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From Mind to Market – Understanding the Influence of Intelligent Virtual Assistants on Advertising Value and Acceptance from a Neurophysiological Perspective

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"*Aim for success, not perfection.*
Never give up your right to be wrong,
because then you will lose the ability to learn new things
and move forward with your life."

Dr. David D. Burns

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This research project is a significant accomplishment, both personally and professionally. When I joined this Ph.D. program, I was unsure what to expect, but certainly not a long, colossal, turbulent, and arduous journey. But at the same time, it turned out to be an extremely fulfilling, passionate, and enriching path. The outcome results from a team effort, with the contribution of many, without whom this would not be a reality and to whom I am profoundly grateful.

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Resumo

Este projeto de investigação teve como objetivo contribuir para uma melhor compreensão do comportamento do consumidor no contexto da neurociência, inteligência artificial (IA) e publicidade. Esta investigação abrange uma revisão da literatura, um novo modelo conceptual e um estudo psicofisiológico para fornecer uma visão global nestes domínios.

No primeiro estudo, é realizada uma revisão abrangente de 75 anos de literatura sobre neurociência do consumidor e *neuromarketing*. Empregando técnicas como *texto mining* e o algoritmo *correlated topic model* (CTM), este estudo identifica ferramentas neurofisiológicas predominantes e temas de investigação, tais como "neurociência do consumidor", "memória de marca", e "vontade de comprar". Além das preocupações éticas e controversas abordadas, diversas oportunidades de investigação são apresentadas, destacando-se o marketing verde, os avanços tecnológicos e as preocupações com a privacidade, como áreas de investigação ainda pouco estudadas. A publicidade ocupa um lugar central, com 10 dos 22 tópicos identificados diretamente relacionados com vários aspetos da publicidade.

Com base nos contributos do primeiro estudo, o segundo estudo introduz um novo modelo conceptual, combinando a tecnologia potenciada pela IA com a eficácia de comunicação da marca, com foco na publicidade ativada por voz veiculada através de assistentes de voz inteligentes (AVIs). Com base na teoria da presença social e no paradigma dos computadores como atores sociais, são explorados diversos fatores que potenciam o valor da publicidade, um território até então desconhecido no contexto de mensagens publicitárias realizadas através de AVI. O estudo enfatiza a importância de imbuir os AVIs com características humanas, de modo a aumentar a sua presença social e maximizar o valor da publicidade.

O terceiro e último estudo complementa o segundo estudo, incorporando dados psicofisiológicos para medir as emoções (prazer e excitação). O estudo disponibiliza contributos sobre os fundamentos emocionais da eficácia da publicidade, expandindo o modelo estímulo-organismo-resposta, a teoria da interação parassocial e o modelo circumplexo do afeto.

Esta pesquisa oferece conhecimentos consolidados sobre neurociência do consumidor, *neuromarketing* e publicidade orientada por IA. As implicações práticas incluem recomendações para melhorar a confiança, o envolvimento emocional, a privacidade e a eficácia na publicidade mediada pelo AVI.

Palavras-chave: Neurociência do Consumidor; Neuromarketing; Inteligência Artificial; Publicidade; Text Mining; PLS-SEM.

Classificação JEL: M31 [Marketing]; M37 [Publicidade]; C12 [Teste de Hipóteses: Geral]; C14 [Métodos Não Paramétricos e Semi-Paramétricos: Geral]

Abstract

This research project aimed at enhancing our understanding of consumer behavior in the context of consumer neuroscience, artificial intelligence (AI), and advertising. The research encompasses a literature review, a novel conceptual model, and a psychophysiological study to provide holistic insights into these domains.

In the first study, a comprehensive review of 75 years of consumer neuroscience and neuromarketing literature is conducted. Employing text mining techniques and the correlated topic model (CTM) algorithm, this study identifies prevalent neurophysiological tools and research themes like “consumer neuroscience”, “brand memory”, and “willingness to buy”. Besides ethical and controversial concerns addressed, an insightful research agenda is presented, highlighting green marketing, technological advances, and privacy concerns as understudied research areas. Advertising takes center stage, with 10 out of 22 identified topics directly related to various aspects of advertising.

Building upon the insights from the first study, Study 2 introduces a novel conceptual model, combining AI-powered technology with brand communication effectiveness, focusing on voice-enabled advertising through intelligent virtual assistants (IVAs). Drawing from social presence theory and the computers are social actors (CASA) paradigm, and it explores factors driving advertising value, a previously uncharted territory in the context of IVA-mediated message delivery. The study emphasizes the importance of imbuing IVAs with human-like cues to enhance social presence and maximize advertising value.

The third and final study complements Study 2 by incorporating psychophysiological data to measure emotions (pleasure and arousal). The study offers insights into the emotional foundations of advertising effectiveness, expanding on the stimulus-organism-response (S-O-R) framework, parasocial interaction theory, and the circumplex model of affect.

This research offers consolidated insights into consumer neuroscience, neuromarketing, and AI-driven advertising. Practical implications include recommendations for enhancing trust, emotional engagement, privacy, and effectiveness in IVA-mediated advertising.

Keywords: Consumer Neuroscience; Neuromarketing; Artificial Intelligence; Advertising; Text Mining; PLS-SEM.

JEL Classification: M31 [Marketing]; M37 [Advertising]; C12 [Hypothesis Testing: General]; C14 [Semiparametric and Nonparametric Methods: General]

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List of Acronyms

AA	Advertising Acceptance
ABS	Association of Business Schools
AC_y	Average Citations per Year
AGI	Artificial General Intelligence
AI	Artificial Intelligence
ANI	Artificial Narrow Intelligence
ANN	Artificial Neural Network
AR	Augmented Reality
ARS	Arousal
ASI	Artificial Super Intelligence
AV	Advertising Value
AVE	Average Variance Extracted
CASA	Computers are Social Actors
CBE	Consumer Brand Engagement
CI	Confidence Interval
CMC	Computer-Mediated Communication
CMV	Common Method Variance
CR	Composite Reliability
CTM	Correlated Topic Models
CY	Citable Years
DH	Digital Human
DL	Deep Learning
ECG	Electrocardiogram
EDA	Electrodermal Activity
EDR	Electrodermal Response
EEG	Electroencephalogram
EFA	Exploratory Factor Analysis
EM	Expectation-Maximization
EMP	Empathy
ERP	Event-Related Potentials
fEMG	Facial Electromyography
fMRI	Functional Resonance Magnetic Imaging

fNIRS	Functional Near-Infrared Spectroscopy
GPT	Generative Pre-Trained Transformer
GSR	Galvanic Skin Response
HAI	Human-AI Interaction
HCI	Human-Computer Interaction
HR	Heart Rate
HRI	Human-Robot Interaction
HRV	Heart Rate Variability
HTMT	Heterotrait-Monotrait
HVL	Humanness-Value-Loyalty
IAT	Implicit-Association Test
ID	Identification
IoT	Internet of Things
IT	Information Technology
IVA	Intelligent Virtual Assistant
IVE	Immersive Virtual Environments
LDA	Latent Dirichlet Allocation
LL	Lower Limit
LLM	Large Language Model
MEG	Magnetoencephalography
ML	Machine Learning
MGA	Multigroup Analysis
MLP	Multilayer Perceptron
M-R	Mehrabian-Russell
MTurk	Amazon Mechanical Turk
NLG	Natural Language Generation
NLP	Natural Language Processing
NLU	Natural Language Understanding
NN	Neural Networks
OLS	Ordinary Least Squares
PAD	Pleasure Arousal Dominance
PET	Positron Emission Tomography
PINT	Perceived Intelligence
PH	Perceived Human-likeness
PSI	Parasocial Interaction
PLES	Pleasure
PLS	Partial Least Squares

PNS	Parasympathetic Nervous System
PSR	Parasocial Relationship
SCR	Skin Conductance Response
SD	Standard Deviation
SEM	Structural Equation Modeling
SJR	Scimago Journal Rank
SN	Social Network
SNS	Sympathetic Nervous System
S-O-R	Stimulus-Organism-Response
SP	Social Presence
SRMR	Standardized Root-Mean-Square Residual
TC	Total Citations
TDM	Term-Document matrix
TF-IDF	Term Frequency and Inverse Document Frequency
TM	Text Mining
TTI	Trust Toward the IVA
UL	Upper Limit
VCA	Voice Assistant
VIF	Variance Inflation Factor
VR	Virtual Reality
WoS	Web of Science

Chapter 1: Introduction

Artificial Intelligence (AI) has subtly entered people's lives, from AI-powered smartphones to personalized social media posts. However, one of the first large-scale uses of AI came with the advent of voice assistants. Amazon's *Alexa*, Apple's *Siri*, *Google Assistant*, Microsoft's *Cortana*, and Samsung's *Bixby* were the first artificially intelligent voice assistants to reach the market. *Siri* was the first voice assistant released as an app for IOS in 2010 and then integrated into Apple's iPhone 4S in 2011. During the following years, Apple spawned this technology on iPads, iMacs and Macbooks, HomePods, iWatchs, and Apple TV. *Siri* is based on natural language processing, speech recognition, and machine learning technology (Hoy, 2018; McLean & Osei-Frimpong, 2019; Moriuchi, 2019). Amazon's *Alexa* (Amazon, 2023) and *Google Assistant* (Google, 2022) soon followed the trend and entered the intelligent assistant market in 2014 and 2016, respectively (Hoy, 2018). *Amelia* – a conversational AI – was also introduced as an AI agent that incorporates the main elements of human interaction (e.g., expressions, emotions, logical conversation, and understanding), enabling its use for creating digital employees that deliver the "most engaging user experiences" (Amelia, 2022). More recently, the commercial availability of large language models such as *ChatGPT* (launched by OpenAI) (OpenAI, 2023a) and *Bard* from Google (Google, 2023), among others, increased the possibilities for intelligent conversational agents to become a preferential communication channel for brands to advertise their products (Machado, 2021; Mariani, Hashemi, et al., 2023; Mishra, 2022).

1.1. The Advertising Market Overview

Advertising is recognized as one of the most noticeable marketing activities (Buil et al., 2013). It intends to communicate a specific message to a predefined target audience to persuade them toward a specific call to action (Rodgers, 2021). The ad revenue reported by media owners worldwide for 2022 was estimated to reach 808 billion USD (GroupM, 2022b), while a 5.4% growth is expected for 2023. The growth is even more expressive in 2024, with an increase of 6.9% fueled by the US Presidential elections and the Olympics. In 2026, the total investment in advertising is expected to surpass the trillion USD mark, thus showing the importance that brands continue to give to communication (Zenith, 2023).

Digital advertising has grown by two digits and is projected to reach 65.13% in 2024 (Zenith, 2022), while only a 20.8% increase will be spent on television[1] (GroupM, 2022a). Advertisers still consider TV a reliable and valuable medium (Hengel, 2021), getting the highest share of advertising investment in several regions. However, innovative advertising strategies, reliable and more effective in reaching the target audience, and able to fuel return on investment are at the epicenter of the relationships between advertisers, agencies, and the media (e.g., AI).

Artificial Intelligence (AI) advertising has become a complex marketing discipline (Li, 2019) pertaining to different meanings. The advertising concept itself varies across authors but can be conceptualized as brand communication to persuade a target audience (Thorson & Rodgers, 2019). A simple way to understand artificial intelligence (AI) relies on a definition from Demis Hassabis, the founder of the AI company DeepMind, currently owned by Google, who stated that AI is the "science of marking machines smart" (Kaput, 2022), or in a more formal way, as a "set of disruptive technologies that allow machines to solve problems, facilitate decision-making, and perform tasks associated with human beings and their intelligence" (Ford et al., 2023, p. 1). Hence, AI advertising can be defined as brand communication that employs several machine functions to execute tasks aiming at target audience persuasion based on inputs from humans and/or machines (S. Rodgers, 2021). AI advertising is a distinctive form of advertising, albeit related to computational advertising (Huh & Malthouse, 2020). Artificial intelligence is reshaping how advertising works (Kaput, 2022), whether from a creation, management, implementation, or effectiveness dimension. However, how will the audience evaluate and relate to advertising through AI? Several researchers and business managers advocate AI as the next best thing in marketing (Vaid et al., 2023), which will undoubtedly contribute to leveraging advertising investment and results. After decades of development, AI captured everyone's attention due to significant investments in the advancing and spreading of machine learning and deep learning algorithms (Chui et al., 2023).

Despite AI advertising taking its first steps, companies are at the right time to decide if they must be cautious and beaten by competition or to be pioneers while defining the path for the future of AI advertising. Advertisers are using artificial intelligence as a back-office operator responsible for ad optimization, market segmentation/targeting, ad generation, or personalization (Ford et al., 2023), improving media planning and buying based on computational advertising and programmatic buying (Huh & Malthouse, 2020).

Even though the funding of AI startups decreased in 2022 versus 2021 from 72,1 to 46,2 billion USD (-35.9%) (CB Insights, 2023), the global AI market size is estimated to reach 142,319.8 million USD and to grow twelvefold by 2030 (Next Move Strategy Consulting, 2023). AI is currently being overly applied in marketing and advertising, with AI-enabled advertising spending estimated to reach almost 400 billion USD worldwide in 2022 (MediaPost, 2022) and potentially grow 250% in ten

[1] Including traditional TV, connected TV, and professional video.

years. Algorithms that mimic human cognitive functions are widely used in marketing and advertising (Huang & Rust, 2021a; Mustak et al., 2021) to provide personalized communications, recommendations, and interactions, fostering a closer relationship between the brand and the consumer (Chandra et al., 2022). However, reliable data must be available, whether provided by consumers themselves or through their endless journeys in the digital ecosystem, as every action is tracked and recorded (Malthouse & Copulsky, 2022).

BigTechs are analyzing the potential of using virtual assistants as advertising media vehicles (Chansky, 2022) by introducing voice-enabled advertising. In September 2022, Amazon presented a new feature called "Customers Ask *Alexa*" at Amazon's Accelerate conference (Wiggers, 2022) that enables brands to submit answers to questions users may ask *Alexa*. Companies must identify every new trend and change in consumer habits and adapt their business accordingly. With voice-enabled advertisements and personalization techniques in marketing, companies expect to build stronger and lasting relationships with their audiences. The hype around voice-enabled advertising is growing, with advertisers such as Uber, Walmart, Spotify, and Burger King, among others, taking this leap of faith into a new way of promoting their businesses with great success (Chansky, 2022). Innovative advertising strategies, reliable and more effective in reaching the target audience, are emerging, resulting in higher returns on investment. Such strategies reshape the relationships between advertisers, agencies, and the media.

1.2. Research Foundations and Research Gap

Prior studies have investigated the progression of AI adoption, its potential consequences, and the opportunities it presents in advertising (Dwivedi et al., 2021; Mustak et al., 2021; Stafford et al., 2023). Recent research has also delved into using AI to identify and promote advertisements within social networks (Shi & Wang, 2023), evaluate virtual influencers' effectiveness (Lou et al., 2022), and apply AI in programmatic advertising (Ciuchita et al., 2023). However, despite the broad implementation of intelligent virtual assistants (IVAs) across various business sectors encompassing sales, customer service, and lead generation, there exists a lack of research concerning the efficacy of advertising through IVAs, particularly in the context of voice assistants and AI avatars. Furthermore, while these initial contributions have greatly enriched the field of AI, practical AI implementation within organizations remains largely unexplored (Ghobakhloo et al., 2023). Even though in-home IVAs have gathered considerable attention, studies centered on advertising through IVAs remain nascent (Cho et al., 2019; Park et al., 2022; Paxton, 2019; Romero et al., 2021).

This research seeks to address this gap in the existing literature by examining the effectiveness of advertising via IVAs by assessing advertising value (AV) and acceptance (AA). Furthermore, it examines other pertinent constructs within human-computer interaction (HCI) and human-AI interaction (HAI) that serve as antecedents to advertising value (AV) and acceptance (AA). These constructs encompass the expected dynamic between non-human agents and users, the levels of empathy and trust extended towards the IVA, and the influence of the anthropomorphic attributes of the IVA on each latent variable. The importance of anthropomorphism remains unclear (Blut et al., 2021; Mariani, Hashemi, et al., 2023), and further research is required (Huang & Rust, 2021b). This research gap has also been appointed by Ford et al. (2023), who stated that future research should focus on AI incorporation in advertising campaigns, assessing their effectiveness.

To delve deeper into consumers' emotions, it is imperative to employ neurophysiological tools to unveil subconscious emotions, overcoming the dependence on self-reported data (Venkatraman et al., 2015). While conventional marketers focused on consciously reported data, growing efforts are acknowledged to investigate consumers' subconscious reactions, providing novel insights into their emotional patterns and motivating factors (Bhardwaj et al., 2023). To assess consumers' responses to advertising via IVA, to our knowledge, only self-reported measurements have been employed. However, the application of neuroscientific techniques in marketing can bring new and richer knowledge to the field (Xu et al., 2023), otherwise unattainable. Understanding consumers' emotions and their subconscious motivations enables the comprehensive decision-making process analysis (Bhardwaj et al., 2023). Traditionally, self-reported data collected through surveys, questionnaires, and interviews have been the primary means of assessing emotional responses in marketing studies (Harris et al., 2018), even though they just capture the conscious response. Additionally, different studies have stated some failed advertisements or product situations caused by the judgmental bias induced by traditional market research methods (Jordão et al., 2017; Vecchiato & Tempesta, 2015). Researchers claim different preferences among the different marketing research methods, typically using a combination of theoretical frameworks and self-reported data to evaluate constructs, such as advertising effectiveness, trust, preferences, attitudes, or even consumer behavior (Manippa et al., 2022). The preference for self-reported data relies upon time, statistical significance, and cost, soon advocated to be complemented with psychophysiological data (Casado-Aranda & Sanchez-Fernandez, 2022).

Neurophysiological instruments have found extensive utility in marketing, consumer behavior, and advertising (Stipp, 2015). Consequently, comprehending the consumer's conscious and subconscious responses becomes paramount within AI-driven advertising. Such comprehension contributes significantly to the formulation of invaluable marketing strategies and plans. To the best of our knowledge, no prior study has ventured into the evaluation of physiological responses within the realm of AI advertising, thus constituting another gap that this research seeks to address.

1.2.1. Research Questions and Goals

This research project comprises three related studies aiming to address the identified research gaps in the literature. Figure 1.1 displays the three studies developed along the research studies, with the corresponding research questions (RQ) and the main goals to be attained for each study.

Figure 1.1. Research questions and main goals

	STUDY 1	STUDY 2	STUDY 3
TITLE	Neuroscience Research in Consumer Behavior: A Review and Future Research Agenda	Let's Go Shopping: Enriching Advertising with Intelligent Voice Assistants	Exploring the Influence of the IVA on Advertising Value and Acceptance – A Psychophysiological Approach
RESEARCH QUESTIONS	**RQ1.** How has consumer neuroscience and neuromarketing-based literature evolved over the years? **RQ2.** Which neuroscience tools have been prioritized in marketing research? **RQ3.** What are the most explored marketing topics in consumer neuroscience and neuromarketing-based literature? **RQ4.** What are the relevant topics and trends in marketing for future research with neurophysiological tools application?	**RQ1.** Do consumers perceive voice-enabled advertising through IVA as valuable? **RQ2.** How do different IVA humanlike attributes influence social responses? **RQ3.** What does trust towards the IVA affect advertising value? **RQ4.** How does the IVA type (Alexa or Anna) affect the different latent factors?	**RQ1.** Are voice-enabled advertising through IVA able to enhance advertising effectiveness via advertising value and acceptance? **RQ2.** How do emotional responses to advertising through IVA influence advertising effectiveness? **RQ3.** Are autonomic responses to stimuli different from those self-reported by participants? **RQ4.** How does the IVA type (Alexa or Anna) affect the different latent factors?
GOALS	• Provide a comprehensive knowledge of previous practices regarding neurophysiological tools application in marketing research and identify opportunities for future research; • Use the text-mining technique to deal with complex and unstructured data to provide a broader knowledge of consumer neuroscience and neuromarketing.	• First, drawing on social presence theory and on trust towards the IVA, this study aims to unveil the key drivers of advertising value; • Secondly, understand how the different levels of antropomorphism displayed by the different IVA affect social and emotional responses and, ultimately, the advertising value.	• This study aims to use an objective measurement of emotional responses through EDA and ECG; • Drawing on PSR theory, understand the drivers of advertising effectiveness; • Extend study 2, and reassess the effect of the anthropomorphic cues featured by the different IVA on advertising outcomes.

Source: Own elaboration.

1.2.2. Research Contributions

A brief description of the main contributions of each study that composes the research project is included below:

1. ***Study 1 – Neuroscientific Research in Marketing Communication: A Review and Future Research Agenda***

   The first study provides a foundational overview of consumer neuroscience and neuromarketing, synthesizing a complex and extensive body of literature spanning approximately 75 years. It emphasizes the importance of employing psychophysiological data to explore the role of emotions in advertising effectiveness, challenging traditional self-reported measures. Furthermore, Study 1 identifies neurophysiological tools borrowed from various scientific domains, highlighting their prevalence in marketing and advertising research. The study underscores the growing significance of consumer neuroscience, given the evolving complexities of consumer attitudes, emotions, and decision-making processes. Employing text mining techniques and the correlated topic model (CTM) algorithm, this study makes a three-fold contribution: (1) it provides a systematic overview of the evolution of consumer neuroscience; (2) it discerns prevailing trends and subjects within this field through topic modeling; and (3) it delineates prospective directions and research inquiries. The interest in consumer neuroscience has witnessed a steady upsurge, with "consumer neuroscience" itself, "brand memory," and "willingness to buy" emerging as the most extensively investigated themes. Additionally, various marketing-related topics have gained recognition as pertinent for forthcoming research opportunities, including (1) green marketing and sustainability, (2) novel technological advancements, and (3) considerations pertaining to privacy and ethics. Moreover, advertising takes center stage within the realm of marketing, firmly establishing itself as the second most frequently occurring term among stemmed terms within the extensive dataset. Notably, it represents the foremost subject matter, with 10 out of the 22 identified topics encompassing facets of advertising to varying degrees;

2. ***Study 2 – Let's Go Shopping: Enriching Advertising with Intelligent Voice Assistants***
   The second study builds upon the insights from Study 1 and introduces a novel conceptual model, analyzed through an online survey from 483 valid respondents recruited via MTurk and social networks. This model combines AI-powered technology with brand communication effectiveness, with a focus on voice-enabled advertising through IVAs. Drawing from social presence (SP) theory (Biocca et al., 2003; Heeter, 1992; Short et al., 1976) and the computers are social actors (CASA) paradigm (Moon, 2000; Nass et al., 1994; Nass & Moon, 2000), Study 2 explores the drivers of advertising value (AV), a previously uncharted territory in the context of IVA-mediated message delivery. Anthropomorphic features, such as perceived intelligence (PINT) and human-likeness, are identified as antecedents of social presence, while empathy and trust play pivotal roles in influencing advertising value (AV) positively. The study underscores the importance of imbuing IVAs with human-like cues to enhance social presence and maximize advertising value. Privacy concerns and data transparency are recognized as crucial factors impacting IVA acceptance. Additionally, the study highlights the significance of emotional responses, emphasizing the role of empathy and trust in shaping advertising effectiveness;

3. ***Study 3 – Exploring the Influence of the IVA on Advertising Value and Acceptance – A Psychophysiological Approach***
   Grounded on the Stimulus-Organism-Response (S-O-R) framework (Mehrabian & Russell, 1974; Russell & Pratt, 1980), on the Parasocial Relationship (PSR) theory (Horton and Wohl,

1956), on the theory of arousal (Mehrabian, 1996; Russell, 1980), and on the Humanness-Value-Loyalty (HVL) theoretical framework (Belanche et al., 2021), the third study represents the final stage of this research project, aiming to complement Study 2 with psychophysiological data to measure emotions. This study introduces parasocial relationships induced by the sense of social presence (SP). Emotional responses of 123 voluntary participants, including pleasure and arousal, were assessed through psychophysiological measures, such as Electrodermal Activity (EDA) and Heart Rate Variability (HRV). The study offers insights into the emotional underpinnings of advertising effectiveness, complementing the previous two by introducing psychophysiological measurements, such as electrodermal activity and heart rate variability, to appraise emotional responses.

1.3. Research Project Outline

This research project comprises six chapters, according to the information displayed in Figure 1.2. Out of these six chapters, Chapter 2 findings were published in a peer-reviewed journal, while Chapters 4 and 5 were also submitted for publication and are under revision by each journal's reviewers.

The first chapter considers the introduction to the current research project, entailing its motivations and scope, as well as the research gaps identified in the literature. To overcome the research gaps, a set of three interdependent studies are described, formulating the different research questions, goals, and contributions of each study.

In Chapter 2, the first study of this project is undertaken. This study considers a systematic review of the literature through text mining and topic models to identify the most relevant topics in the field of marketing communication and neuromarketing.

Chapter 3 dives into the realms of artificial intelligence and its application in the advertising industry by exhibiting the state-of-the-art on the subject for the following Studies 2 and 3 (see Figure 1.3).

Chapter 4 introduces the first experimental study (Study 2) on advertising through intelligent virtual assistants (IVAs), grounded on the social presence theory and self-reported data collected through online surveys. This study aims to develop a conceptual model to map advertising effectiveness and its antecedents. Thus, a large sample is required for the robustness of estimated results. For results' robustness and possible bias mitigation, self-reported data were collected from two different sources: (1) crowdsourcing platforms (MTurk); and (2) social networks. The model estimation was performed using the Partial Least Square Structural Equation Modeling (PLS-SEM) estimation method, revealing advertising value (AV) determinants.

Figure 1.2. Research project outline

CHAPTER 01

Introduction

Provides a context to the research and identifies the main research problems, research questions, and contributions. The research project outline is also presented.

CHAPTER 02

Neuroscience Research in Marketing Communication: A Review and Future Research Agenda

It entails a comprehensive systematic literature review on neuromarketing application in marketing communication through text mining and topic models. The main neuroscientific techniques used in marketing communication and the main areas of study in previous decades are identified. Different future research opportunities are highlighted.

CHAPTER 03

Literature Review on Artificial Intelligence and Its Apllication in Advertising

An overview of related studies in the field of Artificial Intelligence (AI) is provided, including the main topics and taxonomies associated with this technology, including intelligent virtual assistants (IVA) and AI applications in advertising.

CHAPTER 04

Let's Go Shopping: Enriching Advertising with Intelligent Voice Assistants

The first experimental research conducted is presented, with the main purpose of studying voice-enabled advertising through an IVA and understanding how the different anthropomorphic cues affect the sense of social presence, empathy, and perceived value. The model estimation was performed with PLS-SEM, testing the moderation effect of trust toward the IVA.

CHAPTER 05

Exploring the Influence of IVAs on Advertising Value and Acceptance – A Psychophysiological Approach

The second experimental research combined self-reported data and data collected through psychophysiological measures. The emotional responses to advertising through IVA were assessed by recording participants' electrodermal activity (EDA) and cardiac activity registered with the electrocardiogram (ECG). This study aimed to assess the anthropomorphism influence on evoking feelings of trust toward the IVA and parasocial relationship. Advertising effectiveness was assessed through perceived value and acceptance.

CHAPTER 06

Conclusions

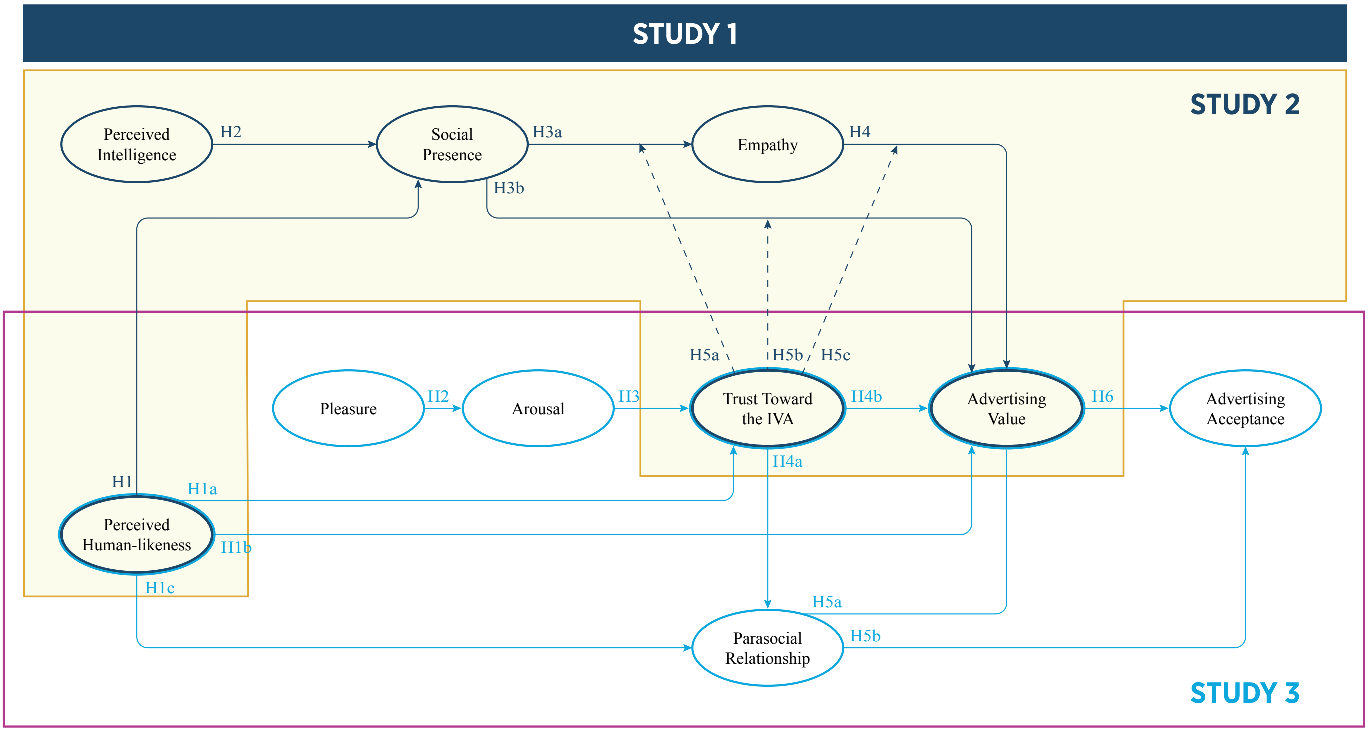
The different studies' main theoretical and managerial implications, limitations, and future research are described.

Source: Own elaboration.

Chapter 5 (Study 3) presents the lab experiment that was undertaken to measure both EDA and ECG to assess the emotional responses, pleasure, and arousal. This study aimed at extending Study 2 by keeping the most significant IVA attribute (perceived human-likeness) and using different theoretical approaches, such as the PSR theory, from which social presence is recognized as an antecedent. The trust towards the IVA was tested for mediation instead of moderator, as in Study 2. As for advertising effectiveness, an additional construct (advertising acceptance – AA) was added to advertising value. The model estimation was also performed with PLS-SEM.

Chapter 6, the final chapter, exhibits the final remarks, describing this research project's main theoretical and managerial implications, limitations, and recommendations for future research.

Figure 1.3. Conceptual models integration



Source: Own elaboration.

Chapter 2: Neuroscience Research in Marketing Communication: A Review and Future Research Agenda[2]

2.1. Introduction

Studying the human brain is no longer interesting just to neurologists and health professionals (Camerer & Yoon, 2015). The last 15 years have seen significant advances in neurosciences, and multiple neurophysiological methods have been used to generate insights into marketing, consumer behavior, and advertising (Stipp, 2015). Samples collected through computational methods can now provide more accurate predictions than self-reported measures (Ariely & Berns, 2010). The human brain hides useful information regarding consumer attitudes that cannot be easily uncovered by assessing self-expressed individual preferences. The widely used questionnaires to register personal preferences and attitudes can lead to biased and inaccurate conclusions (Fisher, 1993).

Shiv et al. (2005) published one of the pioneering articles discussing the relevance of neuroscience and how it could significantly improve future studies on decision-making. In fact, "neuroscience has become both a useful tool and a source of theory development and testing in decision-making research" (Yoon et al., 2012, p. 474). Technological advances provide new computerized neurophysiological recording systems that allow a non-invasive collection of behavioral data, building rich databases for theoretical analysis (National Research Council, 2008).

Over time, scholars have reviewed the existing knowledge in consumer neuroscience and neuromarketing research. However, most previous literature reviews have used systematic approaches based on a limited number of articles, period range, and research fields. For example, Jordão et al. (2017), Lee et al. (2018), Smidts et al. (2014), and Solnais et al. (2013) are limited to studies done more than five years ago. More recently, Rawnaque et al. (2020) studied only papers from 2015 to 2019 and focused on a technological scope, while our time frame and scope are much broader. Our paper is also the first to use a text mining approach to uncover latent topics in the text, removing some potential bias in interpreting the articles. Despite the relevant contributions of past literature reviews, Lin et al. (2018) relied only on studies using EEG, while Lim (2018a) focused exclusively on studies around business-to-business (B2B) marketing without a systematic procedure. The review by Alsharif

[2] Chapter 2 findings were published in an international peer-reviewed journal:
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et al. (2021) was based on advertising research, Vences et al. (2020) limited themselves to studies on social networks and Mandolfo and Lamberti (2021) on impulsive buying. Finally, Alvino et al. (2020) conducted an overview of consumer neuroscience tools based on a traditional review of 15 years and restricted to non-invasive tools. Past studies have also looked at a limited number of articles. For example, the systematic review conducted by Cruz et al. (2016) was based on a selection of 20 indexed journals about consumer behavior, marketing, psychology, and neuroscience, considering a total of 49 articles. Lim (2018b) performed a content analysis on 78 articles from the Association of Business Schools (ABS) list of only 21 marketing publications. Despite the critical literature reviews conducted in the past addressing the use of neuroscience methods, to the best of the authors' knowledge, no study has yet made a comprehensive and integrated review of all the vast and complex information on the topic.

Due to the exponential number of articles published in academic journals on consumer neuroscience and consumer behavior, the traditional or systematic literature review process is a very complex, voluminous, and time-consuming task (Delen & Crossland, 2008) generating a "data deluge" problem (the point where the amount of research on the topic exceeds the ability to manage so much information) (Ananiadou et al., 2009). From a more traditional approach, there is a need to conduct a manual screening of the literature to filter out less relevant papers (Thomas, McNaught, & Ananiadou, 2011), read every single article to identify the topics in a particular publication and evaluate the relevance of the published study (Griffiths & Steyvers, 2004). However, due to the growing number of articles available on several databases, essential knowledge is potentially overlooked in the systematic review process (Delen & Crossland, 2008). To overcome this issue, this paper aims to provide comprehensive consumer neuroscience and neuromarketing knowledge by clustering and systematizing the complex and dispersed textual information available. Therefore, to identify the main topics and theories discussed over more than 70 years of applying neuroscience within social sciences, this paper conducts a comprehensive review of the literature using a text mining (TM) technique.

TM is an efficient and accurate method to extract information, trends, and patterns from extensive collections of documents (Ananiadou, Rea, Okazaki, Procter, & Thomas, 2009; Blei, 2012). This study employs the TM technique through R software, applying the correlated topic model (CTM) algorithm due to its ability to model correlated topics besides topic detection (Lee et al., 2010).

2.2. Theoretical Background on Consumer Neuroscience

Consumer neuroscience and neuromarketing are terms used interchangeably in the literature, though with subtle differences (Kenning & Plassmann, 2008; Lim, 2018; Reimann et al., 2011). Neuromarketing is a broader topic that entails applying neuroscientific methods to understand conscious and unconscious consumer behavior in response to marketing stimuli (Lee et al., 2007, 2018; Solnais et al., 2013; Stipp, 2015). Formerly considered a branch of neuroeconomics (Camerer et al., 2005), the neuromarketing jargon was initially formulated in two papers published in 2007 (Fugate, 2007; Lee et al., 2007) but originally referred to by Ale Smidts in 2002 (Lim, 2018a). Despite the growing interest in and relevance of consumer neuroscience over almost two decades, the use of neuromarketing techniques is still quite controversial due to rising ethical issues concerning the "(1) protection of various parties who may be harmed or exploited by neuromarketing and (2) protection of consumer autonomy" (Murphy et al., 2008, p. 294).

As for consumer neuroscience, Smidts et al. (2014) refer to it as a sub-field of neuromarketing, which applies neuroscience insights to study consumer behavior. Therefore, consumer neuroscience can be defined as an interdisciplinary field combining psychology, marketing, neuroscience, and economics with the main goal of studying neural conditions and processes underlying consumption, physiological meaning, and behavioral consequences (Hansen et al., 2010; Lee et al., 2007; Reimann et al., 2011).

In consumer neuroscience, most studies on the impact of external stimuli on consumer emotions and behavior are grounded on the seminal framework proposed by Mehrabian and Russell (1974). The Stimulus-Organism-Response (S-O-R) model has been used to explain the emotional reactions an individual or organism experiences after exposure to specific stimuli in a particular context. The stimuli are meant to create certain emotional traits in individuals that vary across different dimensions, such as intensity, degree of pleasure, and activation (Russell & Pratt, 1980). As far as responses are concerned, the primary emotions triggered will determine the approach-avoidance response (Vieira, 2013; Vinitzky & Mazursky, 2011) defined by the interest in exploring the environment, willingness to interact with others, or even the level of satisfaction that may lead to specific behavior such as purchase or recommendation. Vieira (2013) ran a meta-analysis identifying the most significant constructs for S-O-R, including brand commitment, attitude toward the advertisement, service quality, and site entertainment. Chan et al. (2017) used the S-O-R framework to study the factors that trigger online impulse buying and classified them into internal and external stimuli, organism, and online impulse-buying response. Wang et al. (2019) developed a research model grounded in S-O-R to analyze the impact of marketing and social media stimuli on participants' message reposting intention. Another example of an adaptive S-O-R framework has been proposed to study the components associated with immersive technology (Suh & Prophet, 2018), concluding that both system features and content topics influence participants' cognitive and affective responses but also identifying which stimuli typologies potentiated these responses.

The most common neuroscientific methods used by academics, researchers, and business practitioners include functional resonance magnetic imaging (fMRI), electroencephalogram (EEG), eye tracking, and magnetoencephalography, among other psychophysiological and brain imaging tools (Lin et al., 2018), as described in Table 2.1 and Figure 2.1.

Biometrics are used to measure automatic responses to external stimuli (Venkatraman et al., 2015) to assess arousal independently. The heart rate is measured through Electrocardiogram (ECG) and is controlled by antagonistic systems, the sympathetic and parasympathetic nervous systems (Potter & Bolls, 2012). The sympathetic nervous system (SNS) increases heart and breathing rates showing evidence of arousal. In contrast, parasympathetic nervous system (PNS) activation leads to heart rate deceleration, enabling greater focus on the stimuli and therefore is used as a measure of attention. In addition, skin conductance response (SCR) is employed to identify SNS activation from sweat level changes (Dimoka et al., 2012).

The main advantage of psychophysiological tools, such as eye-tracking and facial electromyography (fEMG) is their low cost, accessibility, minor intervention, and non-invasiveness. However, SCR has been criticized as having low reliability and small latency (Venkatraman et al., 2015), and ECG is difficult to interpret due to the numerous factors that can influence heart rate. The eye-tracking methodology benefits from identifying visual activities that cannot be self-reported. Nevertheless, it can also be biased because a fixation does not mean the participant has paid attention to a specific stimulus (Dimoka et al., 2012). fEMG is widely used to measure participants' emotional valence (Lajante et al., 2017) continuously and precisely. Still, its limitations include the small number of muscles involved in research, the modification of natural expression as electrodes are positioned on an individual's face, and its susceptibility to bias in interpreting results.

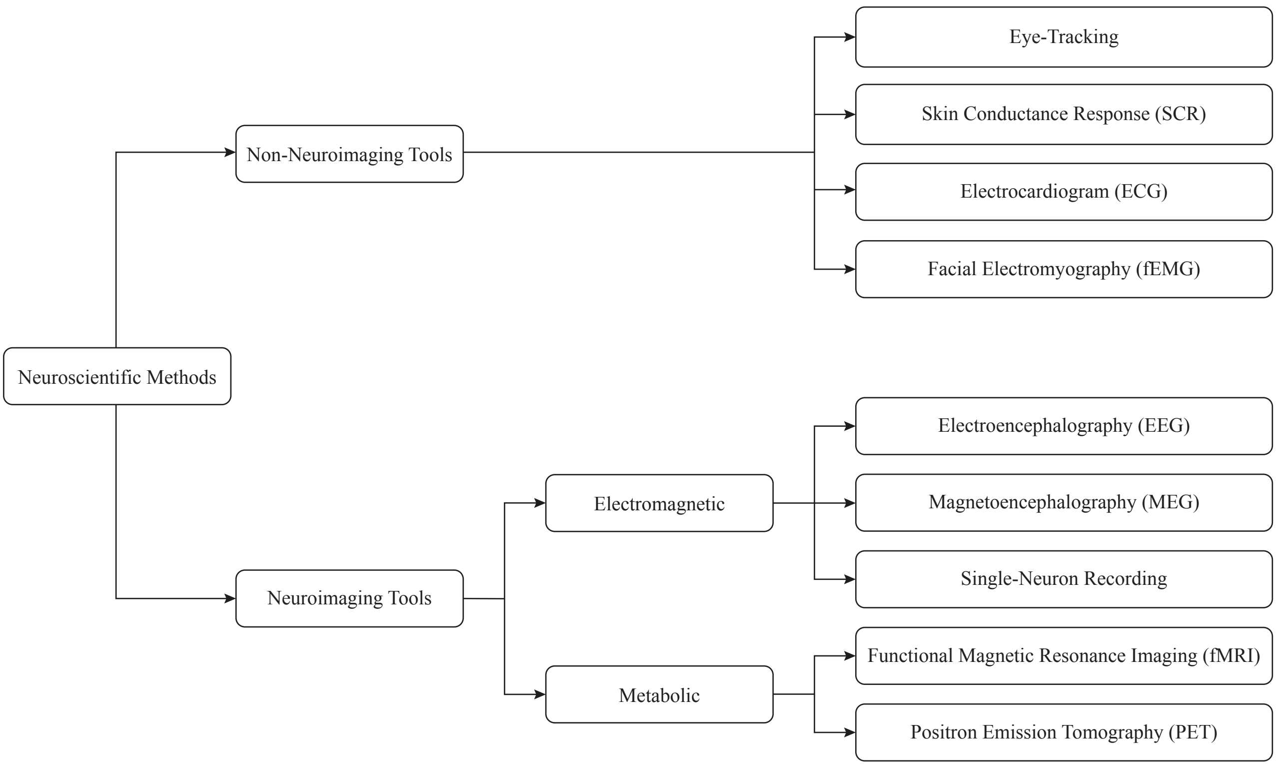
As for brain imaging tools, EEG is the most widely used neurophysiological tool in advertising research (Wang & Minor, 2008). EEG is a non-invasive technique with high temporal resolution, often used to assist in researching cause-and-effect relationships between several marketing stimuli and the associated cognitive response, providing close to real-time data and enabling the understanding of how neurons communicate. Event-Related Potentials (ERP) are a specific application of EEG in which trials are "time locked" aiming to uncover emotional and cognitive brain activity elicited by sensory stimuli (Lin et al., 2018). As ERP signals are small due to signal obstruction by the skull, electrical brain activity amplification is required. These signals are characterized by peaks and troughs, called ERP components (Bastiaansen et al., 2018). ERP has been employed in perception, attention, and memory research (Rugg, 2009). Compared with fMRI, Positron Emission Tomography (PET), and Magnetoencephalography (MEG), EEG is cheaper, easily portable, and tolerant of participants' movements. However, its major limitation is low spatial resolution as "it is restricted to measuring only cortical brain activity" (Venkatraman et al., 2015, p. 339).

	Neuroscientific Methods	Measurement	Application
Non-Neuroimaging Tools	Eye-Tracking	Eye pupil's and cornea's position (eye position) or eye motion relative to the head (eye movement)	Cognitive studies, computer usability, product development, virtual reality, advertising, web usability and design, sponsorship, shelf displays, sporting events, media usage, and human-computer interaction
	Skin Conductance Response (SCR) (Also known as Electrodermal Response or Galvanic Skin Response)	Sympathetic nervous system changes the sweat levels in the eccrine glands of the palms or feet	Arousal, emotion, fear, excitement, and attention
	Electrocardiogram (ECG)	Electrical activity of the heart on the skin and heart rate (heartbeats in a minute)	Anxiety, effort, stress, and arousal evaluation
	Facial Electromyography (fEMG) (Facial Coding)	Muscle activity through electrical impulses caused by muscle fibers during the contraction of the two main facial muscles (the corrugator and the zygomaticus)	Emotional reactions - Activity in the corrugator muscle: negative emotional stimuli and mood states (e.g., anger and disgust) - Activity in the zygomatic muscle: correlated with positive stimuli and mood states (e.g., pleasure and enjoyment)
Neuroimaging Tools	Electroencephalography (EEG)	Electrical brain activity through the multiple electrodes placed on the scalp reveals electrical signals of cortical brain areas	Neuroscience, cognitive science, cognitive psychology, and psychophysiological research, including attention, recall, judgment, emotional engagement, choice behavior, preference ranking, sleeping disorder, coma, and epilepsy
	Magnetoencephalography (MEG)	Magnetic fields induced by synchronized neuronal electrical potentials occurring naturally in the brain	Consumer preferences, reactions, tastes, and choice behavior. Sensory and cognitive brain functions, including perception and memory. It is often used for neuronal changes examination after stroke, trauma, or drug administration
	Single-Neuron Recording	Isolated spike potentials of single neurons, recorded with microelectrodes implanted into the nervous tissue	Memory consolidation, fear, and social behavior, high-level perception, navigation, perception of specific concepts, high-level cognitive control, motor planning
	Functional Magnetic Resonance Imaging (fMRI)	Neural activity by changes in blood oxygenation (blood flow) during cognitive tasks	Value perception, conflict resolution, fear, reward processing, risk perception, prediction, decision-making, self-reflection, disgust, anger, memory, and emotions. Analysis of social perceptions such as trust, envy, cooperation, and reciprocity
	Positron Emission Tomography (PET)	Metabolic activity representing neurochemical changes through radioactive tracer isotopes	Humans' brain patterns that occur over a long period

Source: Adapted from Cerf et al., 2015; Criado et al., 2008; Dimoka et al., 2012; Harris et al., 2018; Lim, 2018; Venkatraman et al., 2015.

Table 2.1. Most common neuroscientific methods, description, and applications

Figure 2.1. Most common neuroscientific method



Source: Adapted from (Lim, 2018a).

In consumer neuroscience research, fMRI has been recurrently used to measure brain activation to different marketing stimuli and in decision-making research (Smidts et al., 2014). This non-invasive technology measures the activation of specific brain regions with an excellent spatial resolution but lacks good temporal resolution, being a good complement to EEG and MEG due to their higher temporal resolution (Dimoka et al., 2012; Harris et al., 2018; Reimann et al., 2011). While EEG mainly measures attention and affect, fMRI can also measure memory and desirability (Venkatraman et al., 2015). With a similar spatial resolution to fMRI, PET's temporal resolution is even lower (2 or 3 minutes) than fMRIs. Notwithstanding, PET i

s not commonly used in consumer neuroscience research due to its invasiveness since subjects are injected with radioactive material (Dimoka et al., 2012; Harris et al., 2018). MEG has also been used to assess cognitive and affective stimuli in advertising research, but to a lesser extent than EEG or fMRI, as it is not a widely accessible tool, being comparable to EEG in terms of temporal resolution. Even though MEG is more effective than EEG in analyzing deeper brain structures, it is a costly and statistically complex device. MEG also has a lower spatial resolution than fMRI (Dimoka et al., 2012).

Single-neuron recording has advantages over other neurophysiological methods due to its finer spatial resolution at a single-neuron level (Cerf et al., 2015). Still, major disadvantages limit its use in neurosciences research, as it requires greater financial and human resources than EEG and fMRI, and because of its intrusiveness and restriction to patients with epilepsy and to a small set of neurons, in which implants are determined by "clinical criteria for epilepsy neurosurgery" (Cerf et al., 2015, p. 533).

2.3. Methodology

2.3.1. Systematic Review Design

Systematic reviews can be classified in different categories (Paul & Criado, 2020), such as: a *structured review* when focusing on widely used methods, theories and constructs (Canabal & White, 2008; Kahiya, 2018; Paul & Singh, 2017; Rosado-Serrano et al., 2018); *framework-based* when frameworks like ADO (Antecedents, Decisions, and Outcome) employed by Paul and Benito (2018), or TCCM (Theory, Context, Characteristics, and Methodology) developed by Paul and Rosado-Serrano (2019) are used; a *hybrid-narrative review* when a framework is integrated in a narrative discussion leading to a future research agenda (Bahoo et al., 2020; Dabić et al., 2020; Kumar et al., 2020; Paul et al., 2017); a *theory-based review* (Gilal et al., 2019; Paul & Rosado-Serrano, 2019); a *meta-analysis* (Barari et al., 2021; Knoll & Matthes, 2017; Rana & Paul, 2020); a *bibliometric review* (Kumar et al., 2029, 2020; Randhawa et al., 2016); a *method-based review* (Sorescu et al., 2017); a *review aiming for model/framework development* (Paul, 2019; Paul & Mas, 2020); or a *text mining approach* (Bilro et al., 2021; Guerreiro & Rita, 2020; Loureiro et al., 2021; Muñoz-Leiva et al., 2021).

The current study is based on the text mining approach, which extracts valuable information from an extensive data collection in a semi-autonomic way, otherwise considered humanly impossible or unrealistically time-consuming. This technique is much more efficient, accurate, and objective, giving structure to unstructured data, and allows a statistical analysis of the retrieved data (Blei, 2012; Griffiths & Steyvers, 2004; Guerreiro et al., 2016; Moro et al., 2017). Even though a bibliometric analysis also conducts quantitative research on a large dataset and provides reliable indicators for quality, it does not analyze the textual information inside each article. Using a text mining approach, such information can be structured and clustered into different latent topics, which adds valuable context to a quantitative analysis. However, a hybrid approach between these two techniques can lead to results in much greater depth (Donthu et al., 2021; Islam et al., 2021; Paul et al., 2021). Even though this study is a review paper grounded on a text mining analysis, a section detailing future directions was conducted. This section was built upon the most cited articles from 2017 to 2021 to consider the most impactful studies up to date (Aria et al., 2020; Loureiro et al., 2020; Paul & Bhukya, 2021). As the total number of citations is correlated with the year of publication, the Average Number of Citations per Year (AC_y) was calculated.

2.3.2. Text Mining

Text mining is an automated or semi-automated technique that extracts text from a large collection of unstructured documents (Delen & Crossland, 2008). The TM technique is more efficient and accurate than the traditional systematic literature review to extract information, select topics and studies of interest, and identify trends and patterns from a large collection of documents (Ananiadou et al., 2009; Blei, 2012). It reduces the time spent identifying the relevant literature, its description, categorization, and summarization. TM can lead to discovering new, hidden insights from unstructured documents, which is considered an extension of data mining (Ittoo et al., 2015).

In TM, terms are usually represented as a *bag-of-words*, ignoring the lexical co-occurrence, i.e., assumed to occur independently, neglecting their context and order in sentences and documents (Blei et al., 2003; Yang et al., 2015). In this case, terms can be allocated into different topics. Each term frequency is counted and stored in the Term-Document matrix (TDM). In order to deal with the *bag-of-words* approach, the importance of a term in a document and among documents can be calculated based on term frequency and inverse document frequency (*tf-idf*), which considers the relative frequency of a word within a document, and the length of that document (Karl et al., 2015), removing those terms which are frequent in a single document, but not frequent in other documents Guerreiro et al., 2016). The conceptual text mining process encompasses several stages (Feinerer et al., 2008). After collecting the unstructured and heterogeneous corpora, the initial step comprises preprocessing the dataset by tokenization, reformatting, stemming, punctuation, and stop-word removal. Then, a TDM is generated, the most common textual data form for computation, and similar terms are clustered in the same groups, consisting of the underlying topics (Guerreiro et al., 2016; Moro et al., 2017).

2.3.3. Clustering Text via Correlated Topic Models

Topic models are mathematical algorithms grounded on natural language processing and machine learning that cluster text into latent topics (Blei & Lafferty, 2006; Gutierrez & Nakai, 2016). The Latent Dirichlet Allocation (LDA) and the Correlated Topic Models (CTM) are the two topic model algorithms usually used to model extensive collections of documents. Still, they differ in the first step of the generative process. In the case of the topic model LDA, the topic proportions are assumed to follow a Dirichlet distribution (Lee et al., 2010). However, this model fails to incorporate the correlation of topics due to the topic mixture proportion independence assumptions of the Dirichlet distribution for each document. This limitation does not allow the occurrence of a term in more than one topic, which is less realistic when analyzing a real collection of documents (Paisley et al., 2012). To overcome this limitation, CTM uses the logistic normal distribution to capture the relations among topics, enabling a covariance structure between the random variables and topic mixture proportions (Blei & Lafferty, 2007). This distribution on the simplex is a more flexible approach that allows for a pattern of correlation between topics through the covariance matrix of the normal distribution and simplifies the statistical analysis of compositional and probabilistic data (Aitchison & Shen, 1980; Lenk, 1988), mapping a multivariate Gaussian random variable over a *d*-dimensional simplex to obtain a multinomial parameter. However, this enhanced flexibility is obtained at a computational cost as the applied algorithm is not as fast as the one employed on LDA estimation. The estimation of model parameters can be obtained through the variational EM (expectation-maximization) algorithm (Blei & Lafferty, 2006; Gutierrez & Nakai, 2016).

Both CTM and LDA are classified as mixed-membership models, as documents are assumed not to belong to a single topic but to several topics simultaneously (Grün & Hornik, 2011) and grounded on Bayesian probabilistic modeling, aiming for decomposition of the large collection of textual data into multiple latent topics (Blei & Lafferty, 2007). CTM has been employed to accomplish different tasks such as topic extraction (Guerreiro et al., 2016; Loureiro et al., 2020; Loureiro, Guerreiro et al., 2019), query classification (Zhai et al., 2009), motif finding (Gutierrez & Nakai, 2016), human action recognition (Tu et al., 2014), facial expression recognition (Chan et al., 2015), tracking scenes (Rodriguez et al., 2009), and image retrieval (Greif et al., 2008).

In their research, Blei and Lafferty (2007) highlighted the enhanced prediction performance of CTM over LDA and the richer descriptive statistics available. The authors concluded that using likelihood and *perplexity* metrics, the CTM fits the data better and supports more topics than LDA. The *perplexity* of a statistical model is a measure of the uncertainty of predicting a word in a document, evaluating a model's distribution accuracy to predict a sample, being equivalent to the geometric mean per-word likelihood. The lower the *perplexity*, the better the model fits the data (Gutierrez & Nakai, 2016). Blei and Lafferty (2007) found that *perplexity* is nearly 10% lower under CTM than when using LDA. Therefore, the current study uses the CTM algorithm to find hidden topics in the literature.

2.3.4. Data Extraction

A query or search string using neuroscience and neuromarketing keywords was conducted on the Scopus database. Scopus was used instead of Web of Science (WoS) due to its broader range of subject areas and categories (Alvino et al., 2020; Naz et al., 2021; Paul et al., 2021), providing a larger pool of articles since our primary goal is to provide a general overview of the topic. To obtain a sophisticated search string, the Boolean search operators AND and OR were added between different terms, and the search was restricted to specific parts of the article, such as title, abstract, and keywords. The query was built in two parts. In the first part of the query, keywords about consumer neuroscience, neuromarketing, and neuroscientific tools (including derivatives) were used. The second part of the query limited the search based on field specifications (marketing) and inner disciplines (e.g., advertising, branding, promotion). The keywords for the first part of the query were adapted from the studies by Cerf et al. (2015), Criado et al. (2008), Dimoka et al. (2012), Harris et al. (2018), Lim (2018), and Venkatraman et al. (2015). Regarding the keywords for the marketing part of the query, we considered the journals from the Association of Business Schools (ABS) Academic Journal Guide (AJG, 2021) rated with 4*, 4, and 3 in the field of Marketing, such as Journal of Marketing, Journal of Marketing Research, International Journal of Research in Marketing, Psychology & Marketing, and European Journal of Marketing, amongst others. We built a database with all the keywords, analyzed their frequencies, and considered the top 4 terms: Marketing; Advertising; Promotion; and Brand.

The search query retrieved a total of 2,386 articles that were later narrowed down to the results of the top 4 areas, Neuroscience (330), Psychology (260), Business, Management, and Accounting (259), and Social Sciences (254), which generated the following query:

> (TITLE-ABS-KEY ("NEUROSCIENCE*" OR "NEUROMARKETING" OR "NEUROMANAGEMENT" OR "NEUROECONOMIC*" OR "NEUROTOURISM" OR "NEUROETHIC*" OR "NEUROPHYSIOLOG*" OR "NEUROIMAG*" OR "NEUROIS" OR "EYE-TRACK*" OR "FUNCTIONAL MAGNETIC RESONANCE IMAGING" OR "FMRI" OR "ELECTRO-ENCEPHALOGRA*" OR "EEG" OR "ELECTROCARDIOGRA*" OR "ECG" OR "ELECTROMYOGRA*" OR "FEMG" OR "SKIN CONDUCTANCE" OR "SCR" OR "ELECTRODERMAL" OR "EDA" OR "EDR" OR "GALVANIC SKIN*" OR "GSR" OR "BIOMETRIC" OR "HEART-RATE") AND TITLE-ABS-KEY ("MARKETING" OR "ADVERTIS*" OR "PROMOTIONS" OR "BRAND*")) AND (LIMIT-TO (SRCTYPE, "j")) AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "ip")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (SUBJAREA, "NEUR") OR LIMIT-TO (SUBJAREA, "BUSI") OR LIMIT-TO (SUBJAREA, "PSYC") OR LIMIT-TO (SUBJAREA, "SOCI"))

The query revealed 893 articles, which were manually screened to reduce all possible noise and achieve a more robust analysis and coherent results (Ashraf et al., 2018; Moro et al., 2015). This screening procedure followed the quality criteria used by Loureiro et al. (2021, p. 922), adapted from Macpherson and Holt (2007), and presented in Table 2.2. Some terms in the string are also used in different contexts with different meanings. Hence, there was a need to identify and remove articles unrelated to the topic.

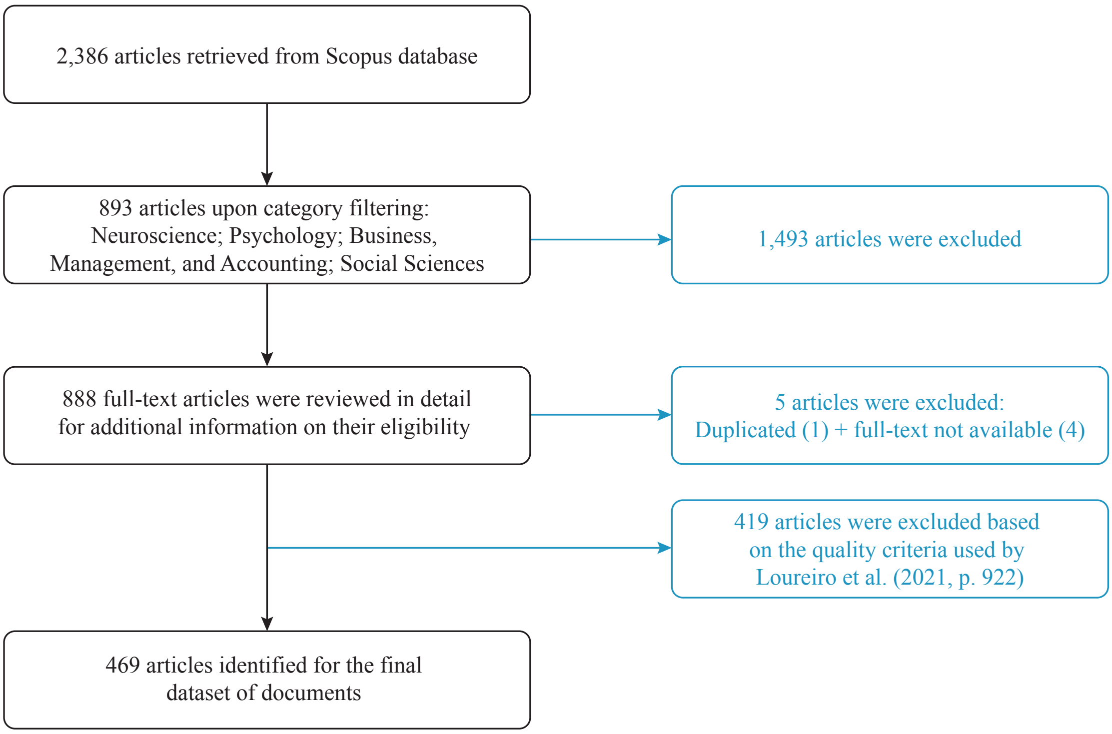
Elements	0: Absence	1: Low Level	2: Medium Level	3: High Level	Not Applicable
1. Directly related to the objective of the research	There is not enough information to evaluate this criterion	Not related	Somehow related	Totally related	Not Applicable
2. Theory robustness	There is not enough information to evaluate this criterion	Weak development of literature	Superficial development of theories and constructs within existing literature	Robust use of theory	Not Applicable
3. Congruence of theory, methodology, and findings	There is not enough information to evaluate this criterion	Incomplete data and not related to theory	Data somehow related to the arguments	Strong link between the arguments presented and data	Not Applicable
4. Contributions to theory and/or practice	There is not enough information to evaluate this criterion	Makes a low contribution	Makes a medium contribution	Makes a high contribution	Not Applicable

Source: Adapted from Loureiro, Guerreiro, and Tussyadiah (2021, p. 922), and from Macpherson and Holt (2007).

Table 2.2. Quality criteria for manual article screening

A final set of 469 articles met all the criteria and were later analyzed using R software. Figure 2.2 shows the process followed to achieve the final set of articles. Articles were copied into a txt file format (the most transversally accepted text format by the different platforms). The text of the articles was either copied directly from the publishers' website or extracted using optical character recognition procedures (OCR).

Figure 2.2. The process of identifying articles for the final dataset



Source: Own elaboration.

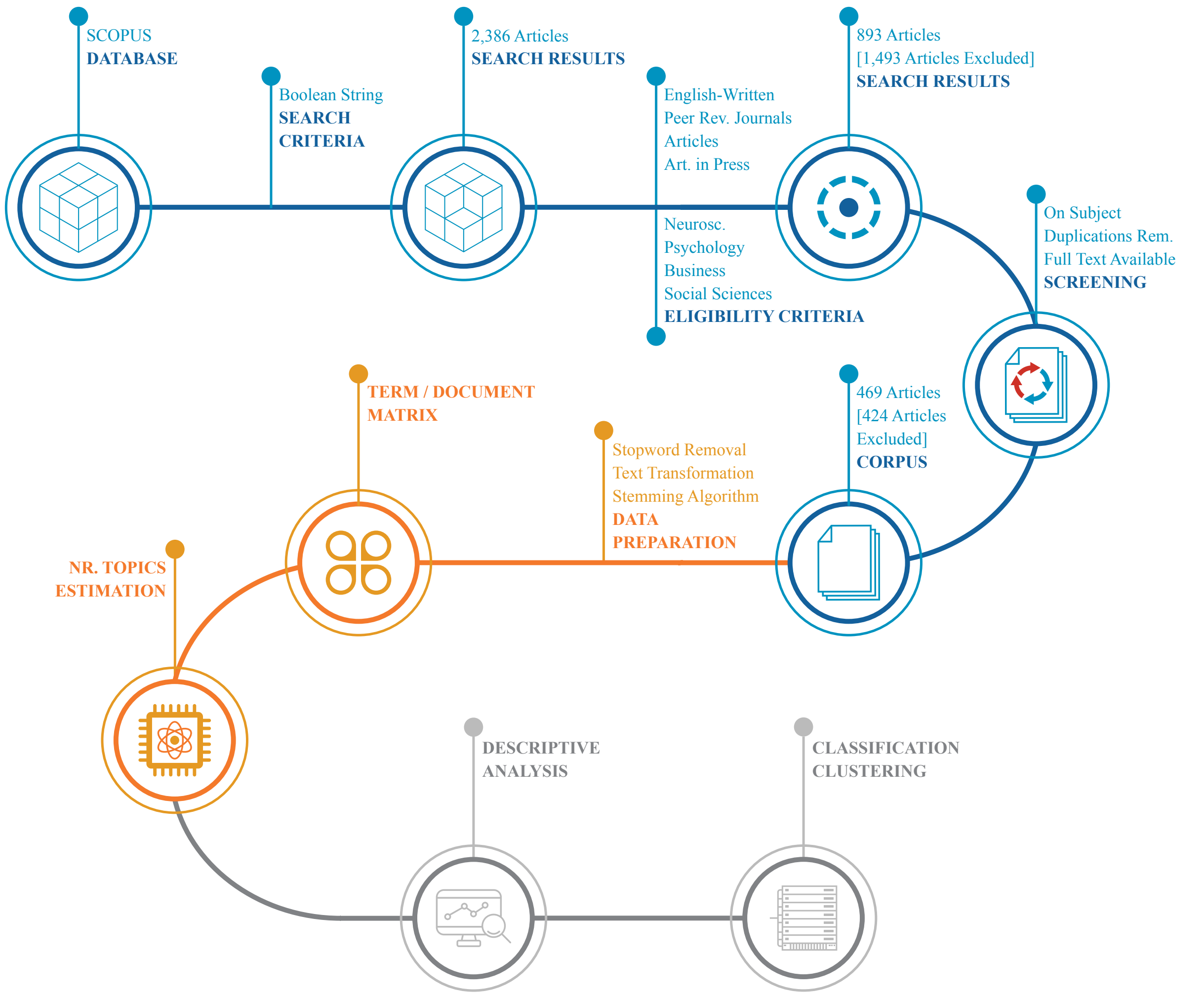
2.3.5. Data Pre-Processing and Model Parameters Estimation

The collected dataset with all the text of the articles was pre-processed to remove punctuation, white spaces, numbers, and stop-words. A stemming algorithm was also applied to each word in the documents (see Figure 2.3). Stemming involves reducing inflected and derived terms into their root base form (Moro et al., 2015; Richardson et al., 2014). Besides stop-word removal, other terms such as, “first”, “will”, “may”, “can”, “one”, “two”, “also”, “use”, “increase”, “however”, “found”, “find” were excluded from the analysis due to their high frequency in the documents, but meaningless for topic/terms interpretation (Guerreiro et al., 2016).

The TDM was then created, in which the columns consisted of the different documents, and the rows had the words and scores based on terms’ frequencies. The TDM matrix had a high sparsity level (98% of the elements are zero), with 35,232 terms in 469 documents. To reduce matrix sparsity, a threshold of 90% was set to retain only the terms that occurred at least 10% of the time, returning a much less sparse set of terms. In order to reduce terms that were very frequent in one document but not in others, the term frequency and inverse document frequency (*tf-idf*) approach was employed and set to values greater than .00260 (*tf-idf* > .0026), which was slightly lower than the median value

(.00266) to guarantee the omission of high frequency terms (Grün & Hornik, 2011; Guerreiro et al., 2016). The new TDM matrix had 1,856 terms in 469 documents.

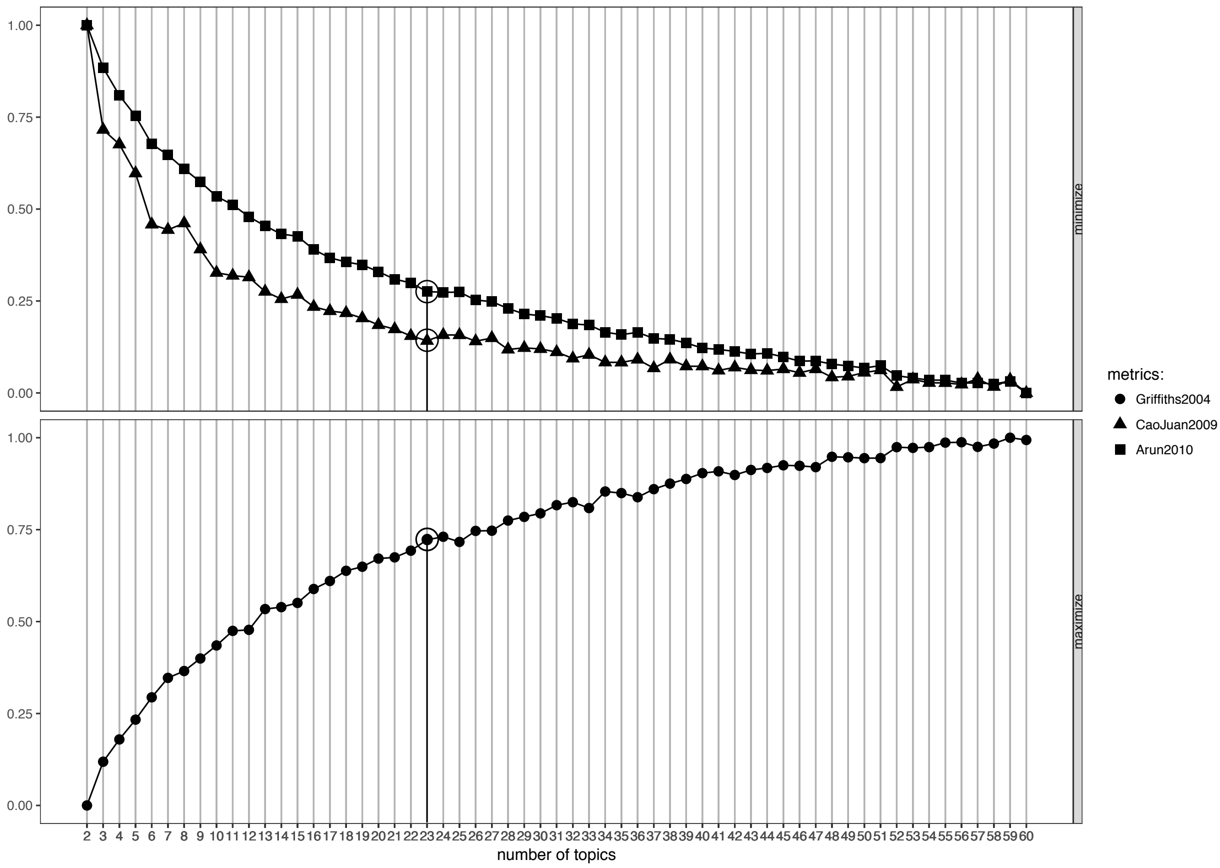
Figure 2.3. Text mining process



Source: Adapted from the framework of Guerreiro et al. (2016), and Moher, Liberati, Tetzlaff, Altman, and The PRISMA Group, (2009).

Before proceeding with the CTM estimation, the appropriate number of topics (*k*) had to be determined. Instead of selecting a *k* value randomly, several simulations were undertaken to find the optimal number of topics using three different approaches simultaneously. Griffiths and Steyvers (2004) employed the Gibbs sampling algorithm by computing the approximated likelihood of the data for each *k*, selecting the *k* value that maximizes the harmonic mean of the log-likelihoods. Cao et al. (2009) used the pairwise average cosine distance (ACD) among topics, reporting the optimal number of topics as the one that minimizes this indicator. Arun et al. (2010) minimized the symmetric Kullback-Lieber divergence between the singular values of the matrix factors. The results of these three metrics are plotted in Figure 2.4. Cao's and Griffiths' measures point to a number of topics of *k* = 140, while Arun's suggest *k* = 145. Multiple inflection points are quite common in cluster analysis (Greene et al., 2014), and it shows different appropriate solutions or topic structures. Several *k* values have been tested, comparing topics' structure for each *k* to identify the most consensual and stable topics among the different analyses, which depicted much broader topics when selecting lower values for *k*. In contrast, higher values returned highly specific and somewhat similar topics, making it difficult to distinguish some of them, an "over-clustering" situation identical to the findings of Greene et al. (2014).

Figure 2.4. Number of topics estimation

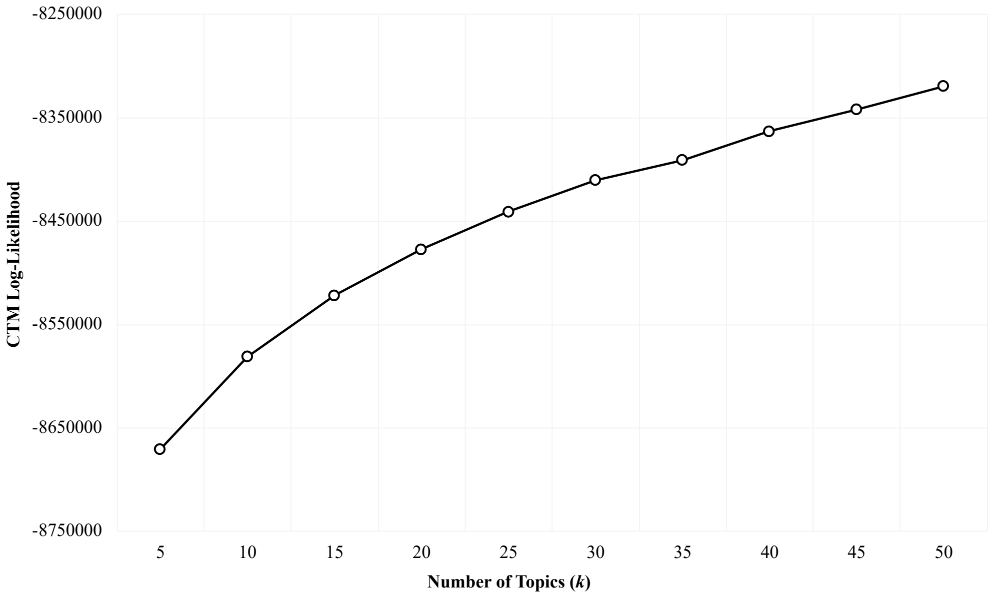


Source: Own elaboration.

To sustain the number of topics selected, the CTM was iteratively estimated for different *k*, storing each model's mean log-likelihood and *perplexity* metrics. The *k*-value that fits the corpus best was chosen based on metrics' variability as *k* increased. The method used to fit the CTM was the Variational EM algorithm, as the marginal likelihood of the data could not be calculated (Blei & Lafferty, 2007; Grün & Hornik, 2011; Wainwright & Jordan, 2007).

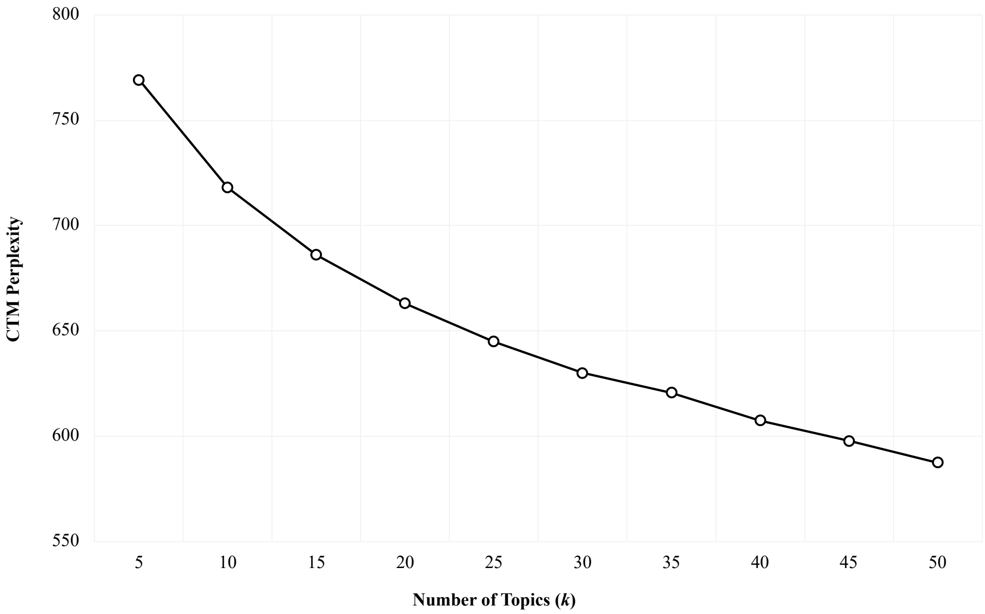
Both log-likelihood and *perplexity* scores show consistency regarding *k* = 23, as for a higher number of topics, the changes in log-likelihood and *perplexity* were quite insignificant, and the increase in explained variability was marginal (see Figures 2.5 and 2.6). The selection of *k* was also sustained by the results described in Figure 2.4, in which *k* = 23 was identified as one of the first inflexion points. Thus, the current paper explored and analyzed 23 topics hidden in the text.

Figure 2.5. Log-Likelihood of the model



Source: Own elaboration.

Figure 2.6. Perplexity scores of the model



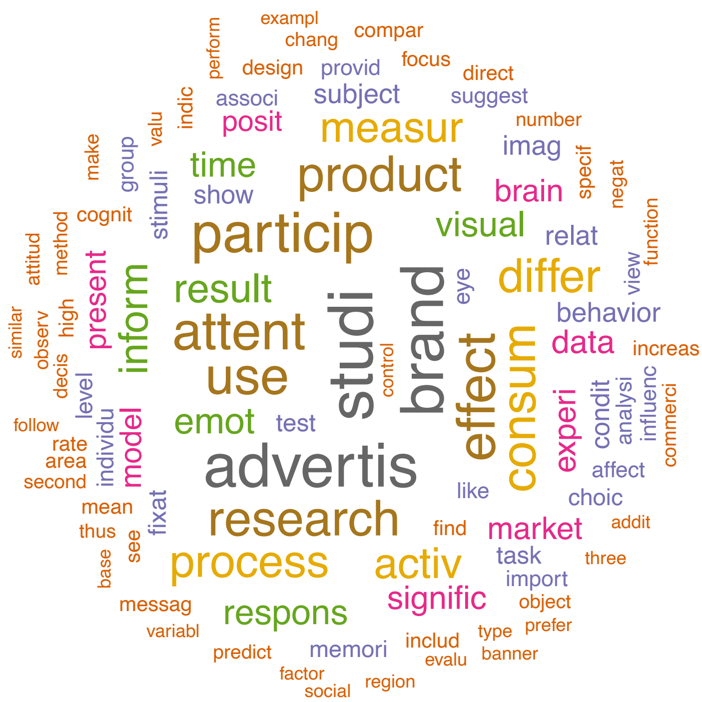
Source: Own elaboration.

2.4. Results

2.4.1. Descriptive Analysis of the Literature

The top 5 most frequent terms were the stemmed terms *studi*, *advertis*, *brand*, *particip*, and *attent*, with an occurrence frequency above 10.000 (see Figure 2.7 and Table 2.3), whereas 35 terms presented a frequency above 4.000. The first term, *studi*, was quite broad, not specific to any area, and related to academic journals (Guerreiro et al., 2016).

Figure 2.7. Word Cloud of the most frequently stemmed terms



Source: Own elaboration.

The second most frequent stemmed term *advertis* comes as no surprise given the focus of the query on Marketing and as one of the major concerns in this field has been advertising effectiveness (e.g., Daugherty et al., 2016; Li et al., 2016; Russell et al., 2017) as well as brand attention and memory as the third and fifth most recurrent terms (e.g., Pieters et al., 2002; Plassmann et al., 2012; Shang et al., 2017). Neurosciences research is highly experiment-driven, so *participants* exposed to a stimulus are overtly present in the collected *corpus*. The interdisciplinary stemmed term *effect* was expected to occur frequently and was related to cause-effect analysis, e.g., whether creative advertising positively affects brand memory.

Nr.	Term	Frequency	Nr.	Term	Frequency
1	studi	12,731	19	time	6,425
2	advertis	12,454	20	respons	6,422
3	brand	12,164	21	data	5,710
4	particip	11,111	22	signific	5,696
5	attent	10,732	23	market	5,504
6	effect	10,560	24	experi	5,454
7	use	10,321	25	brain	5,426
8	product	9,790	26	present	5,209
9	research	9,688	27	model	5,139
10	consum	9,410	28	posit	4,922
11	differ	9,030	29	subject	4,504
12	process	8,743	30	relat	4,494
13	activ	8,305	31	behavior	4,443
14	measur	8,172	32	imag	4,434
15	inform	7,662	33	show	4,296
16	result	7,431	34	condit	4,282
17	emot	6,811	35	test	4,037
18	visual	6,451	36	stimuli	3,903

Source: Own elaboration.

Table 2.3. Top 36 most frequent stemmed terms

Publications classified as Q1 according to Scimago Journal Rank (SJR) Best Quartile (Scimago, 2018) represented 73.56%, against Q2 (14.07%), Q3 (8.32%), Q4 (3.20%), and unindexed articles (0.85%). Results show a 5-Year Journal Impact Factor of 3,36 on average (except for the unindexed 72 articles), with a 2.24 standard deviation (see Table 2.4).

The period from 2013 to 2018 accounted for 58.8% of the articles included in this analysis, showing this field's emergence, importance, and acceptance. Figure 2.8 shows the number of articles by year.

The five main terms most correlated with each topic in Table 2.5 were used to classify each topic with a different name. Table 2.6 shows how each topic evolved.

Journal	Number of Articles	5-Year Impact Factor	SJR Best Quartile	H index
Journal of Marketing Research	19	5.678	Q1	141
Journal of Advertising Research	14	2.709	Q1	71
Computers in Human Behavior	11	4.417	Q1	123
Journal of Neuroscience, Psychology, and Economics	11	1.265	Q1	19
Journal of Advertising	10	3.846	Q1	85
Frontiers in Psychology	10	2.749	Q1	66
International Journal of Advertising	8	2.475	Q1	35
Social Cognitive and Affective Neuroscience	7	4.941	Q1	79
Journal of Consumer Psychology	7	4.427	Q1	84
Journal of Neuroscience	6	6.517	Q1	409
NeuroImage	6	7.079	Q1	307
Journal of Product and Brand Management	6	N/A	Q1	64
Frontiers in Human Neuroscience	6	4.022	Q1	73
NeuroReport	6	1.493	Q3	176
Journal of Business Research	6	3.689	Q1	144
Journal of Consumer Marketing	6	N/A	Q1	79
Frontiers in Behavioral Neuroscience	5	3.553	Q1	50
Journal of Retailing and Consumer Services	5	N/A	Q1	57
Journal of Consumer Behaviour	5	2.270	Q2	28
Neuroscience Letters	5	2.124	Q2	153
Journal of Brand Management	5	N/A	Q2	33
Psychology and Marketing	5	2.631	Q1	90
European Journal of Marketing	5	2.545	Q1	71
Appetite	5	3.691	Q1	110
Journal of the Academy of Marketing Science	4	9.810	Q1	139
Journal of Marketing	4	9.592	Q1	208
Frontiers in Neuroscience	4	4.294	Q1	58
Qualitative Market Research	4	N/A	Q3	42
Journal of Interactive Marketing	4	9.472	Q1	82
Journal of Economic Psychology	4	2.197	Q1	77
Body Image	3	3.534	Q1	62
Marketing Science	3	3.918	Q1	108
Cerebral Cortex	3	6.800	Q1	216
Communication Research	3	4.024	Q1	84
Cogent Psychology	3	N/A	Q3	5
Comunicar	3	3.285	Q1	20
Journal of Marketing Management	3	N/A	Q1	41
Consumption Markets and Culture	3	2.197	Q1	19
Marketing Letters	3	2.080	Q1	55
International Journal of Psychophysiology	3	3.311	Q2	106
Neuropsychological Trends	3	N/A	Q4	4
Journal of Consumer Research	3	6.022	Q1	146
Psychology and Marketing	3	2.631	Q1	90
Applied Cognitive Psychology	3	1.988	Q1	81
Social Neuroscience	3	3.182	Q1	53

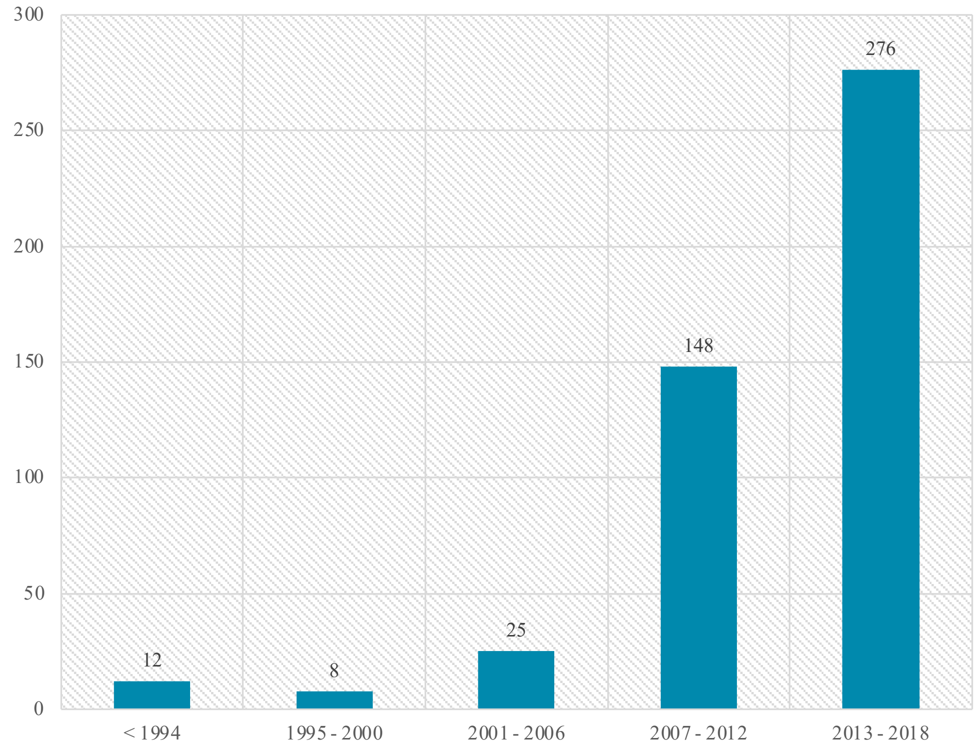
Note: N/A = Not Applicable.

Source: Own elaboration.

Table 2.4. Ranking of journals by number of articles (with more than two articles)

Tables 2.7 and 2.8 show the ranking of the articles by posterior probability regarding their correlation with each topic. In the next section, the classification of topics was created for the first twenty-two. Topic 23 was found to be quite broad, as the article with the highest posterior probability of belonging to this topic showed only a value of 6.3%. Therefore, no articles were assigned to this topic.

Figure 2.8. Number of Articles per Period



Source: Own elaboration.

The most mentioned topic (Topic 1) discusses consumer neuroscience, which corroborates the CTM analysis employed as the identified main subject of this study. This emerging field of study was first discussed in 1984 (Weinstein et al., 1984), and more frequently in 2016.

The second topic (Topic 2) focused on brand memory research, mainly using eye tracking data to acknowledge the process of generating attention and memory toward brands. This has been an active discussion since 1999 but is still relevant in 2018, while the third most frequent topic (Topic 3) is related to willingness to buy, with increasing frequency since 2007, being a major concern from 2015 onwards.

Topic	Nr. Articles	1st Term	2nd Term	3rd Term	4th Term	5th Term
1 - Consumer Neuroscience	21	research	consum	neurosci	studi	brain
2 - Brand Memory	10	brand	memori	process	attent	inform
3 - Willingness to Buy	34	product	consum	choic	price	inform
4 - Hedonic vs. Utilitarian Products	30	activ	brain	brand	studi	cortex
5 - Visual and Neural Cognition for Memory Detection	15	memori	use	imag	face	perform
6 - Models of Data Processing	8	model	refer	data	size	featur
7 - Emotional Responses to Advertisements	20	messag	arous	measur	respons	particip
8 - Advertising Effectiveness	23	advertis	effect	commerci	attitud	brand
9 - Neural Activity in Behavioral Research	13	food	use	activ	behavior	neural
10 - Reliability of Eye-Tracking Data	25	eye	fixat	search	user	use
11 - Visual Attention	23	attent	fixat	visual	gaze	text
12 - Experiment Manipulation	12	particip	imag	use	behavior	studi
13 - Online Advertising	21	banner	anim	effect	game	user
14 - Ethical Concerns in Neuromarketing	51	market	research	neuromarket	brain	custom
15 - Semiotics	22	condit	particip	effect	stimuli	present
16 - Safety Measurements	29	particip	studi	risk	children	group
17 - Neural Response to Reward	20	activ	subject	choic	price	trial
18 - Measuring Emotional vs. Cognitive Appraisal	24	emot	measur	facial	express	use
19 - Visual Design Effects	19	visual	attent	design	effect	complex
20 - Social Comparison	13	social	women	polit	negat	model
21 - TV Commercials Stimuli	26	eeg	activ	commerci	subject	differ
22 - Individual Interaction in Structured Environment	10	focus	system	work	goal	individu
23 - (-)	0	studi	differ	particip	process	effect

Source: Own elaboration.

Table 2.5. The 23 topics and the most frequent terms in each topic

Topic	#	1948	1950	1971	1972	1973	1984	1985	1989	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
1 - Consumer Neuroscience	21						1														1		2	1	2			4	6	3	1
2 - Brand Memory	10											1	1		1		2				1		1		1				1	1	
3 - Willingness to Buy	34																			1	1	1	1		2	3	3	7	4	9	2
4 - Hedonic vs. Utilitarian Products	30																	1	1	4	1	3	4	3	3	2	4	1	2	1	
5 - Visual and Neural Cognition for Memory Detection	15																		1			1	2	3		3	1	2		2	
6 - Models of Data Processing	8																			1		2			1			1	2		1
7 - Emotional Responses to Advertisements	20	1			1	1								1						1		2		2	1	1	2	2	2	3	
8 - Advertising Effectiveness	23		1						1			2									2		1		1	2	2	1	5	5	
9 - Neural Activity in Behavioral Research	13																							1			3	5	2	1	1
10 - Reliability of Eye-Tracking Data	25									1					1	1				2			1	6	1	2	2	1	4	3	
11 - Visual Attention	23																			1	1	1		3		2	2	5	3	4	1
12 - Experiment Manipulation	12							1																1	1	1	1	1	4	1	1
13 - Online Advertising	21															1	1					1	1	1	3	2	2	4	2	3	
14 - Ethical Concerns in Neuromarketing	51																	1	3	5	1	1		8	7	8	3	5	3	6	
15 - Semiotics	22																			2	1		2	1	3	1		4	6	2	
16 - Safety Measurements	29								1		3				1					2			1	3	1	2	2	3	7	3	
17 - Neural Response to Reward	20																1	1	1	3	2			1	3	1		2	1	3	1
18 - Measuring Emotional vs. Cognitive Appraisal	24																			2		1	1		1	1		3	6	7	2
19 - Visual Design Effects	19																1		1			1	1	1	2	2	4	1	1	3	1
20 - Social Comparison	13			1																			2			2	3	1	2	2	
21 - TV Commercials Stimuli	26						2										1				1		5	1	1		2	4	2	7	
22 - Individual Interaction in Structured Environment	10							1									2	1			1	1			1		1		1	1	
23 - (-)	0																														

Source: Own elaboration.

Table 2.6. Relevant topics: yearly frequency evolution

Topic	Authors	Journal	Year	Posterior Prob.
1	Hubert M.	Journal of Economic Psychology	2010	.772
	Plassmann H., Venkatraman V., Huettel S., et al.	Journal of Marketing Research	2015	.604
	Rimkute J., Moraes C., Ferreira C.	International Journal of Consumer Studies	2016	.529
2	Pieters R., Warlop L., Wedel M.	Management Science	2002	.661
	Wedel M., Pieters R.	Marketing Science	2000	.636
	Shang Q., Pei G., Dai S., et al.	Frontiers in Neuroscience	2017	.489
3	Rihn A.L., Yue C.	Agribusiness	2016	.660
	Waechter S., Sütterlin B., Siegrist M.	Journal of Consumer Policy	2017	.628
	Liu C.-W., Hsieh A.-Y., Lo S.-K., et al.	Computers in Human Behavior	2017	.626
4	Schaefer M., Rotte M.	NeuroReport	2007	.868
	Schaefer M., Berens H., Heinze H.-J., et al.	NeuroImage	2006	.829
	Schaefer M., Rotte M.	Brain Research	2007	.824
5	Uncapher M.R., Tyler Boyd-Meredith J., Chow T.E., et al.	Journal of Neuroscience	2015	.878
	Jiang J., Summerfield C., Egner T.	Journal of Neuroscience	2013	.777
	Harding G., Bloj M.	Journal of Vision	2010	.637
6	Brocher A., Chiriacescu S.I., von Heusinger K.	Discourse Processes	2016	.831
	Zhang J., Wedel M., Pieters R.	Journal of Marketing Research	2009	.654
	Yang L., Toubia O., De Jong M.G.	Journal of Marketing Research	2015	.550
7	Leshner G., Bolls P., Thomas E.	Health Communication	2009	.766
	Lee M.J., Shin M.	Journal of Psychology: Interdisciplinary and Applied	2011	.730
	Yegiyan N.S.	Journal of Media Psychology	2015	.707
8	Grigaliunaite V., Pileliene L.	Scientific Annals of Economics and Business	2016	.704
	Russell C.A., Russell D., Morales A., et al.	Journal of Advertising Research	2017	.646
	Boerman S.C., Van Reijmersdal E.A., Neijens P.C.	Journal of Advertising	2015	.593
9	Falk E.B., Berkman E.T., Whalen D., et al.	Health Psychology	2011	.710
	Cerf M., Greenleaf E., Meyvis T., et al.	Journal of Marketing Research	2015	.506
	Falk E.B., O'Donnell M.B., Tompson S., et al.	Social Cognitive and Affective Neuroscience	2016	.505
10	Niehorster D.C., Cornelissen T.H.W., Holmqvist K., et al.	Behavior Research Methods	2017	.912
	Domachowski A., Griesbaum J., Heuwing B.	Proceedings of the Association for Information Science and Technology	2016	.743
	Lam, S. Y., Chau, A. W.-L., & Wong, T. J.	Journal of Interactive Marketing	2007	.718
11	Li Q., Huang Z.J., Christianson K.	Tourism Management	2016	.648
	Hutton S.B., Nolte S.	Applied Cognitive Psychology	2011	.533
	Smit E., Boerman S., Meurs L.	Journal of Advertising Research	2015	.522
12	Hansen K.A., Hillenbrand S.F., Ungerleider L.G.	Frontiers in Neuroscience	2011	.717
	Starcke K., Wiesen C., Trotzke P., et al.	Frontiers in Psychology	2016	.552
	Hüsser A., Wirth W.	Journal of Financial Services Marketing	2014	.514

Source: Own elaboration

Table 2.7. The core three articles from topics 1 to 12

Topic	Authors	Journal	Year	Posterior Prob.
13	Li K., Huang G., Bente G.	Computers in Human Behavior	2016	.818
	Jeong E., Bohil C., Biocca F.	Journal of Advertising	2011	.645
	Hamborg K.-C., Bruns M., Ollermann F., et al.	Computers in Human Behavior	2012	.629
14	Krausová A.	Lawyer Quarterly	2017	.776
	Trocchia P.J., Ainscough T.L.	International Journal of Retail and Distribution Management	2006	.756
	Nijboer F., Clausen J., Allison B.Z., et al.	Neuroethics	2013	.749
15	Mulders I., Szendroi K.	Frontiers in Psychology	2016	.769
	Thomas A., Hammer A., Beibst G., et al.	BMC Neuroscience	2013	.671
	Fudali-Czyz A., Ratomska M., Cudo A., et al.	Neuroscience Letters	2016	.641
16	Seneviratne D., Molesworth B.R.C.	Safety Science	2015	.696
	Dukic T., Ahlstrom C., Patten C., et al.	Traffic Injury Prevention	2013	.664
	Cavalari R.N.S., Romanczyk R.G.	Journal of Behavioral Decision Making	2015	.657
17	Bray S., Rangel A., Shimojo S., et al.	Journal of Neuroscience	2008	.702
	Scult M.A., Knodt A.R., Hanson J.L., et al.	Social Neuroscience	2017	.649
	Staudinger M.R., Erk S., Walter H.	Cerebral Cortex	2011	.620
18	Bellman S.	Australasian Marketing Journal	2007	.608
	Lewinski P.	Journal of Neuroscience, Psychology, and Economics	2015	.575
	Karim A.A., Lützenkirchen B., Khedr E., et al.	Frontiers in Psychology	2017	.572
19	Orth U.R., Crouch R.C.	Journal of Retailing	2014	.707
	Husić-Mehmedović M., Omeragić I., Batagelj Z., et al.	Journal of Business Research	2017	.596
	Kahn B.E.	Journal of Retailing	2017	.540
20	Mischner I.H.S., van Schie H.T., Engels R.C.M.E.	Body Image	2013	.804
	Bury B., Tiggemann M., Slater A.	Body Image	2016	.594
	Bury B., Tiggemann M., Slater A.	Body Image	2014	.588
21	Vecchiato G., Astolfi L., Fallani F.D.V., et al.	Brain Topography	2010	.882
	Vecchiato G., De Vico Fallani F., Astolfi L., et al.	Journal of Neuroscience Methods	2010	.761
	De Vico Fallani F., Astolfi L., Cincotti F., et al.	Clinical Neurophysiology	2008	.755
22	D'Aquili E.G.	Zygon®	1985	.584
	Gillingwater D., Gillingwater T.H.	International Journal of Business Science and Applied Management	2009	.505
	McKhann G.M.	Technology in Society	2004	.448
23	Kilboume W.E., Painton S., Ridley D.	Journal of Advertising	1985	.063
	Golin E., Lyerly S.B.	Journal of Applied Psychology	1950	.059
	Fletcher J.E.	Psychophysiology	1971	.057

Source: Own elaboration.

Table 2.8. The core three articles from topics 13 to 23

2007 became a significant milestone with a 240% increase in articles published on the subject from 2006 and a 120% increase in active topics. Indeed, topics such as Willingness to Buy (topic number 3), Models of Data Processing (topic number 6), Visual Attention (topic number 11), Semiotics (topic number 15), and Measuring Emotional vs. Cognitive Appraisal (topic number 18) originated in 2007. Another important milestone was in 2015 when consumer neuroscience received great attention with special editions from several top journals. By then, twenty of the twenty-two profiled topics were active, with a 50% increase in published articles.

2.4.2. Topics Description

Topic 1 – Consumer Neuroscience

The most correlated terms among the articles on the current topic were *research*, *consum*, *neurosci*, *studi*, and *brain*. The relevant articles discussed the emergence of *consumer neuroscience*, addressing future challenges, and its potential contribution to the marketing theory and practice (Plassmann et al., 2015) (post. prob. = 0.604). Hubert (2010) (post. prob. = 0.772) posited *consumer neuroscience* as a breakthrough in consolidating, validating, or extending economic theories. This author claimed that its conceivable acceptance and integration as a branch of economic and *consumer research* relied on the ability to deal with methodological hitches and practical implementation of outcomes by corporations. Rimkute et al. (2016) (post. prob. = 0.529) developed a systematic literature review on the effects of scent on *consumer* behavior, identifying thematic areas and a major gap related to consumers' scent perception and to what extent it might stimulate their behavior.

Topic 2 – Brand Memory

Brand, *memori*, *process*, *attent*, and *inform* were highly correlated with the current topic. Due to the boom in advertising competition, Pieters et al. (2002) (post. prob. = 0.661) discussed the effects of advertisement originality and familiarity on *brand attention* and *memory*. Through eye fixation data collection, the authors showed that original and familiar ads would grab the greatest *brand attention* and, subsequently, *brand memory*. In addition, eye movements and fixations also have a major role in understanding the *process* by which advertised *brands* are *memorized*, with Wedel and Pieters (2000) (post. prob. = 0.636) finding evidence related to the amount of *information* obtained during eye fixation on an advertisement and the inner negative impact on the latency of *brand memory*. Neuroscience has had a major impact on *brand memory* studies (Venkatraman et al., 2021a) by measuring unconscious responses and thus collecting more credible and effective results for improved ad recall (Plassmann et al., 2015).

Topic 3 – Willingness to Buy

The articles with higher posterior probability within this topic were related to *consumers' choice* of *products* researched in different contexts using eye-tracking devices. This topic grouped the correlated terms *product*, *consum*, *choic*, *price*, and *inform*. The first article analyzed the influence of *products'* label elements, such as *production* method, origin, and nutritional composition, on the willingness to pay for processed foods (Rihn & Yue, 2016) (post. prob. = 0.660), suggesting that *consumers* might be influenced in their *product* selection through the additional *information* about important *product* attributes displayed on labels and in-store promotions. *Consumers' product* preferences for brands, *prices*, and dietary restrictions often juxtapose with what retailers want them to buy (Gidlöf et al., 2017) (post. prob. = 0.597). *Product* packages and in-store displays contain tailored *information* on attributes to increase *consumer* attention, as the authors identified visual attention as the prime purchase predictor. Waechter, Sütterlin, and Siegrist (2017) (post. prob. = 0.628) focused on energy-friendly *product choices* and their reliance on lexicographic strategies. The correct and current *information* on energy consumption leads to easy identification of energy-friendly products, while ambiguous *information* like energy efficiency might result in non-optimal *product choices*. As for online shopping, Liu et al. (2017) (post. prob. = 0.626) concluded that brand awareness had a null effect when *consumers* browse without time pressure. By applying neuroscientific tools, we moved from simply predicting behavior to measuring actual behavior (Ozkara & Bagozzi, 2021). Understanding *consumers*' actual behavior enables brand strategies' adaptation to enhance *consumers*' persuasion and willingness to buy (Harris et al., 2018; Zhang et al., 2021).

Topic 4 – Hedonic vs. Utilitarian Products

The main terms identified with stronger correlations were *activ*, *brain*, *brand*, *studi*, and *cortex*. This topic encompassed fMRI *studies* analyzing subjects' *brain response* when exposed to favorite or familiar *brands* recognized as culturally-based symbols (Schaefer & Rotte, 2007a) (post. prob. = 0.868). The authors acknowledged the *activation* of reward-related areas when individuals were exposed to favorite *brands* by *studying* cortical *activity* using *brand* logos as a stimulus. *Activity* on the striatum was verified for favorite sports and luxury *brands* (hedonic), but the opposite was registered for rational *brands* (utilitarian). In the case of culturally familiar *brands*, Schaefer et al. (2006) (post. prob. = 0.829) reported *activation* in the medial prefrontal *cortex*, also for *brands* highly rated in "social competence" (Schaefer & Rotte, 2010) (post. prob. = 0.753), as well as for sports and luxury *brands* which improved participants' "self-relevant thoughts" (Schaefer & Rotte, 2007b, p. 101) (post. prob. = 0.824). Familiar *brands* revealed *activation* of the bilateral superior frontal gyri, hippocampus, and posterior cingulate. As for value *brands*, the left superior frontal gyrus and anterior cingulate *cortex* were *activated*, which is hypothesized as being relevant for associating actions with consequences. Thus, by applying neuroscientific tools, academics and practitioners can identify *brain* responses and triggers upon hedonic and/or utilitarian *brand* exposure (Audrin et al., 2018; Bettiga et al., 2020; Hubert et al., 2018).

Topic 5 – Visual and Neural Cognition for Memory Detection

This topic's five most correlated terms were *memori*, *use*, *imag*, *face*, and *perform*. The literature on this topic examined visual cognition, neural pattern classifiers, and neural response decoding. Uncapher et al. (2015) (post. prob. = 0.878) tested the vulnerability of *memory* detection with fMRI *using* different strategies to mask *memory* signals (countermeasures). Participants were exposed to several *images* of male *faces*, and measures were undertaken to guarantee suitable behavioral *performance*. The authors concluded that when participants truly reported *memory*, the multivoxel pattern analysis (MVPA) classifiers accurately decoded their *memory* state, but still cognitive strategies could bias classifiers' efficiency for *memory* detection. Visual stimuli were also *used* by Jiang et al. (2013) (post. prob. = 0.777), describing attention and expectation as the "main determinants of visual cognition" (p. 18438). Moreover, attended and expected stimuli increased neural selectivity in the visual cortex. The authors researched the relationship between attention and perceptual prediction error hypotheses. Using not only *images* of *faces* but also outdoor and indoor scenes, the fMRI data revealed attention as an enhancer of neural pattern classifiers' *performance* to distinguish expected from unexpected stimuli while improving the accuracy of prediction errors.

Topic 6 – Models of Data Processing

Model, *refer*, *data*, *size*, and *featur* were the most correlated terms in this topic, discussing several approaches to enhance information understanding and its effects through eye-tracking *data* and statistical *modeling*. The article by Brocher et al. (2018) (post. prob. = 0.831) aimed to study conception and *referent* activation in discourse comprehension and planning. To deal with the dynamic process of language use, these authors developed the Dual-Process Activation *Model,* which proved effective in *referent* management. *Feature* advertising effectiveness was also studied by Zhang et al. (2009) (post. prob. = 0.654) due to the recognized lack of knowledge on how *feature* ad characteristics, such as *size*, color, and location of the advertisement impact sales. The authors proposed a Bayesian statistical *model* accommodating variables' endogeneity and relevance for meditating analyses, showing the positive and considerable effect on sales outcomes of gaze duration on *feature* advertisements. Yang et al. (2015) (post. prob. = 0.550) proposed a "dynamic discrete choice *model* of information search and choice under bounded rationality" (p.166), which showed greater predictive and discriminative performance when compared with benchmarks.

Topic 7 – Emotional Responses to Advertisements

This topic addressed one major purpose of consumer neuroscience: *measuring consumers'* emotional *responses* to different advertising *messages* and content. The combination of methods enables the *measurement* of emotional experiences through three types of data, behavioral (e.g., facial *responses*), self-report (e.g., verbal or written reports), and physiological (e.g., HR, SCR, fEMG) (Bolls et al., 2001) (post. prob. = 0.671). This topic grouped *messag*, *arous*, *measur*, *respons*, and *particip* as the most correlated terms. Emotions such as fear and disgust were often analyzed in the context of anti-tobacco advertisements (Leshner et al., 2009) (post. prob. = 0.766). Through HR data, the authors found evidence of effects on cognitive resources allocated to encoding the *message* and brand recognition in the presence of fear- and disgust-based *message* content. Self-reported emotional *arousal* and valence were also *measured* through the Self-Assessment Mannequin (SAM), a technique employed by Lee and Shin (2011) (post. prob. = 0.730) and also in combination with fEMG to test the emotional *responses* to anti-alcohol advertisements using fear- and humor-related appeals. Individuals with heterogeneous sensation-seeking levels *responded* differently to anti-alcohol abuse advertisements. Self-reports and physiological *measures* were used simultaneously (Yegiyan, 2015) (post. prob. = 0.707). Regarding neurophysiological *measures*, fEMG was used to assess appetitive and aversion activation, while SCR was added to infer the magnitude of activation and *participants' arousal* level during exposure to stimuli. Stimulating emotional *responses* is one key element of success, as emotional cues influence brand memory, ad recall, and future brand choices (Pozharliev et al., 2017). Neuroscience enabled the study of consumers' reactions, providing trustworthy and relevant information so that advertisers can adapt their strategy to increase brand engagement through emotions (Barari et al., 2021; Venkatraman et al., 2021a).

Topic 8 – Advertising Effectiveness

The most correlated terms within this topic were *advertis*, *effect*, *commerci*, *attitud*, and *brand*. In growing and saturated markets, organizations pursue crucial *advertising effectiveness* factors (Grigaliunaite & Pileliene, 2016) (post. prob. = 0.704). In their research, eye-tracking, implicit-association test (IAT), and questionnaires were used to study the *attitude* toward *advertisement*, *attitude* toward the *brand*, and purchase intentions. *Attitudes* regarding emotional *advertisements* for convenience products in print/outdoor media had a much more positive *effect* than rational *advertisements*. Moreover, rational *advertisement* led to a stronger probability of purchasing convenience products. Russell et al. (2017) (post. prob. = 0.646) tested the hedonic contamination process, i.e., how an entertainment experience was influenced by the presence of *advertisements* in different contexts (in-theater *commercials* or watching television), measuring the *attitude* toward the movie using eye-tracking devices. Pre-exposure to *advertising* jeopardized participants' entertainment experience, and they were less receptive to product placement. Boerman et al. (2015) (post. prob. = 0.593) also studied this type of communication using eye-tracking data. This research proved that textual and pictorial disclosure of product placement was most *effective* for *brand* memory but indirectly less promising for *brand attitude*. *Advertisers*' *effectiveness* has been a significant subject in consumer neuroscience research (Couwenberg et al., 2017; Sreejesh et al., 2020). Through the application of neuroscientific tools, valuable data on consumer *attitudes* toward the *advertisement* and the *brand* have been collected. This can improve campaigns' *effectiveness* by unveiling unconscious emotions and preferences (Cummins et al., 2021; Pleyers & Vermeulen, 2021; Simola et al., 2020), also using several measures, such as *brand* memory, to predict this (Pieters & Wedel, 2020).

Topic 9 – Neural Activity in Behavioral Research

The terms *food*, *use*, *activ*, *behavior*, and *neural* had the highest correlation within this topic. Falk et al. (2011) (post. prob. = 0.710) looked for evidence on whether *neural activity* could predict smoking reduction among participants exposed to specific campaigns designed to help smokers quit. The authors found a positive relationship between *neural activity* in the medial prefrontal cortex (data being collected with fMRI) and *behavior* change (successful quitting), reinforcing the prominence of neuroimaging in health promotion, and also that *neural activity* is a valuable complement to self-report measures. Falk et al. (2016) (post. prob. = 0.505) corroborated these results. Public organizations frequently *use* fear appeals in their communication (Cerf et al., 2015) (post. prob. = 0.506). Using the single-neuron method, the authors concluded that messages stimulating consumers' feelings of fear through explicit instructions in the ad would be effective. These authors stated that these insights would be challenging to obtain with self-report measures.

Topic 10 – Reliability of Eye-Tracking Data

This topic has *eye*, *fixat*, *search*, *user*, and *use* as the most correlated terms related to neuroscience studies *using eye*-tracking devices. Niehorster et al. (2018) (post. prob. = 0.912) explored a remote *eye*-tracker, analyzing the performance of five different devices to help researchers choose the most suitable device when unrestrained *users* were their target. *Eye*-tracking was also *used* frequently in online *searching* via mobile (Domachowski et al., 2016) (post. prob. = 0.743) or desktop devices. These authors found that the reliability and validity of *eye*-tracking data can be estimated with behavioral patterns. Linked to online *search* and product display, thumbnails were a helpful resource (Lam et al., 2007) (post. prob. = 0.718), complemented with a short product description. These authors *used eye*-tracking to analyze *users*' *search* behavior. Nevertheless, the results did not reveal significant differences in *users' fixation* patterns, even with different reading directions. Consumers tended to address their focus to the middle of the thumbnail, then to the left, and finally to the right region. The authors also stated that *eye*-movement data is important "for studying consumers' information *search* and processing behaviors in the Web environment" (p. 43). *Eye*-movements are an accurate indicator of stimulus processing intensity.

Topic 11 – Visual Attention

This topic identified the terms *attent*, *fixat*, *visual*, *gaze*, and *text* as highly correlated. Its underlying subject was *visual* processing behavior research regarding *visual attention* through eye-tracking devices. In tourism advertising, photographs have been broadly used (Li, Huang, & Christianson, 2016) (post. prob. = 0.648) with specific design-related guidelines to enhance *visual attention* being suggested: (1) *text* "naturally embedded in landscapes" (p. 254); (2) no more than three *text* elements; (3) and in a known language. Advertisements to be effective need to be seen to grab *attention* (Hutton & Nolte, 2011) (post. prob. = 0.533). *Gaze* cues are key influencers of the focus of human *attention*. The authors used print advertisements to test models' *gaze* direction, whether toward an object or the viewer. In this study, the models' *gaze* toward the product was found more effective, as the viewer spent more time looking at the product and the brand. In print advertising, the context of the advertisement also plays a paramount importance in the reader's *attention* (Smit et al., 2015) (post. prob. = 0.522), as the amount of *text*, page, and color in the direct context of the ad could make the reader less focused on the ad, the brand, the pictorial, and *text*, by addressing less *visual attention* to it.

Topic 12 – Experiment Manipulation

The current topic covered to what extent prior knowledge and emotional *participants*' state of mind influence the lab's experiment outcomes. In some cases, researchers may manipulate the experiment. In these cases, a group of manipulated *participants* is often *used*, and a control group is free of manipulation. The most correlated terms included *particip*, *imag*, *use*, *behavior*, and *studi*. In some *studies*, prior knowledge conditions can bias the experiment's outcome (Hansen et al., 2011) (post. prob. = 0.717). Even when those conditions are no longer applicable, if *participants* experienced *behavioral* training, the prior knowledge conditions would persist. Previous information tended to receive significant attention, even if irrelevant (Hüsser & Wirth, 2014) (post. prob. = 0.514). *Participants* can also be induced into some emotional state before the experiment. Starcke, Wiesen, Trotzke, & Brand (2016) (post. prob. = 0.552) *studied* the effects of stress on executive task performance, having induced stress to some *participants* to infer how their performance would change, and found that the unstressed group (control group) performed better compared with the stressed group.

Topic 13 – Online Advertising

Banner, *anim*, *effect*, *game*, and *user* were the most relevant terms in this topic. In online advertising, the *banner* is the most popular format (Hamborg et al., 2012) (post. prob. = 0.629), but to evaluate its *effectiveness*, it is not enough to measure the click-through rate. *Banners*' properties like format and *animation* speed on *user*'s attention, recall, recognition, and attitude toward the *banner* were also assessed (Hamborg et al., 2012). *Banner*'s *animation* and its inherent speed were revealed to be important. Still, the dichotomy between *animated* and static would depend on the speed and time length (Li et al., 2016) (post. prob. = 0.818). As for the format, horizontal *banners* might grab more attention than skyscrapers. Nevertheless, the *banner*'s *animation* enables the *user* to quickly identify the existence of advertisements. Still, through exposure repetition, the *user* shows a positive attitude merely induced by the exposure *effect* (Lee, Ahn, & Park, 2015) (post. prob. = 0.611). As for *gaming*, a *user*'s arousal level in violent *games* is likely to affect brand attitude positively. However, the level of spatial presence induced a negative change in brand attitude but increased brand logo memory (Jeong et al., 2011) (post. prob. = 0.645).

Topic 14 – Ethical Concerns in Neuromarketing

The most correlated terms in the fourteenth topic were *market*, *research*, *neuromarket*, *brain*, and *custom*, being *ethic* also included as the eleventh most correlated term. This topic embraced the ethical issues in neuromarketing (neuroethics) as the neuroscientific techniques in consumer *research* are considerably controversial (Krausová, 2017) (post. prob. = 0.776). These techniques are considered a way to influence the decision-making process unconsciously, overriding a rational choice by affecting consumers' *brains*. To some extent, some authors classify it as dehumanizing for being scanned like merchandising on non-human objects (Trocchia & Ainscough, 2006) (post. prob. = 0.756). For some individuals, it is a matter of data privacy, autonomy, or violation of civil rights of freedom. Compared with traditional *market research* techniques, *neuromarketing* has a clearer potential for personal autonomy limitation (Krausová, 2017). The current divergent perspectives between neuro engineers and neuro ethicists need to be addressed (Nijboer et al., 2013) (post. prob. = 0.749) in public spheres, and all decisions grounded on ethical principles and regulations based on humans rights and dignity (Ulman et al., 2015) (post. prob. = 0.744). An interdisciplinary ethics committee should be equated to supervise *research* in terms of "scientific and ethical values of nonmaleficence, beneficence, autonomy, confidentiality, right to privacy and protection of vulnerable groups" (p. 1272).

Topic 15 – Visual Stimuli Conditions

This topic grouped *condit*, *particip*, *effect*, *stimuli*, and *present* as the most correlated terms. Mulders and Szendrői (2016) (post. prob. = 0.769) studied sentence processing that included the operator "only", classified as focus-sensitive, and also different pitch accents through eye-tracking data related to early and late stress *conditions*. Thomas, Hammer, Beibst, and Münte (2013) (post. prob. = 0.671) looked to distinguish responses from *participants* to brands and no-name *stimuli* both for congruent and incongruent *conditions* and the inner *effects* on attitudes toward brands, measuring brain activity with Event-Related Potentials (ERP). Brand products were documented to be more arousing than no-name products. For brand extension evaluation in one of the Indo-European language speakers, *participants* were exposed to a randomized *stimuli presentation* along different tasks divided into required response and no response (try to remember) classification *conditions* (Fudali-Czyż et al., 2016) (post. prob. = 0.641). The authors used ERP measurements and found evidence, in response *condition*, that ERP components such as N270, P300, and N400 were affected by the inconsistency between the product category and the *presented* brand.

Topic 16 – Safety

This topic considered *particip*, *studi*, *risk*, *children*, and *group* as the most correlated terms. Safeness was the underlying topic's profile, in which neurophysiological methods were applied to safety in different contexts. Due to poor attention from passengers to pre-flight safety briefing videos, some airlines have used humor and celebrities in their materials. However, their effectiveness was still unknown (Seneviratne & Molesworth, 2015) (post. prob. = 0.696). Each *group* of *participants* watched a sequence of videos with the target video at the end of the sequence. Eye gaze data was collected with an eye-tracking device, revealing humorous pre-flight safety briefing videos as the most effective. Driver's visual attention to electronic advertising billboards has been subject to several *studies* as the number of electronic billboards on major roads is increasing (Dukic et al., 2013) (post. prob. = 0.664). These authors concluded that electronic billboards affected eye gaze by catching greater attention and longer glances than regular traffic signs. Still, no inference was taken on whether this greater attention represented a genuine traffic safety issue. However, the drivers who detected more traffic signs were those who paid more visual attention to roadside advertising (Topolšek et al., 2016) (post. prob. = 0.647). As for *children*'s injury *risk*, most *studies* were based on injured *children*'s self-reported data (Cavalari & Romanczyk, 2015) (post. prob. = 0.657). To overcome this gap, the authors used *children*'s caregivers as *participants* instead in their research, whose results showed an integration of child characteristics and environmental *risk* elements for *risk* assessment and intervention selection.

Topic 17 – Neural Response to Reward

Activ, *subject*, *choic*, *price*, and *trial* were the most correlated terms within the seventeenth topic. Pavlovian cues, in outcome-specific transfer (OST), were associated with rewarding outcomes and exerted a biasing effect on action *choices* (Bray et al., 2008) (post. prob. = 0.702). To understand OST, one may think, for example, about the impact of in-store advertisements on consumer decision-making and addictive behavior. The *subjects* that participated in this research showed behavioral evidence of OST effects through brain *activity* during *trials* measured with fMRI. Regulatory focus can also be used to study individual dissimilarities related to neural responses to rewards (Scult et al., 2017) (post. prob. = 0.649), resulting in a dynamic association between these individual singularities in self-regulation and the rewarding system. Another study researched the presence of a high external *price* reference featured to enhance stated satisfaction associated with the *activation* of mental reward processing (Weber et al., 2007) (post. prob. = 0.589).

Topic 18 – Measuring Different Emotions

This topic highlighted *emot*, *measure*, *facial*, *express*, and *use* as the most correlated terms. Different types of *emotions* can be classified into two levels: type 1 are primary or instinctive reactions that should be *measured* on continuous scales; type 2 *emotions* require a cognitive appraisal (Bellman,

2007) (post. prob. = 0.608). While type 1 *emotions* can be *measured* with psychophysiological tools such as GSR, type 2 *emotions* should rely on a self-reported binary *measure* (yes or no). Lewinski (2015) (post. prob. = 0.575) *used facial expression* patterns to analyze YouTube videos' popularity among *users*, distinguishing between affiliative *facial emotions* (happiness or sadness), non-*emotional facial expressions* (surprise), and disaffiliated *facial emotions* (anger, fear, and disgust). The latter was not predictive of social videos' future performance, and spontaneous *expressions* were a true indicator of internal *emotional*-cognitive conditions. In another study, physiological (SCR, HR, and fEMG), symbolic (ZMET – Zaltman Metaphor Elicitation Technique), and self-report (verbal, visual, and moment-to-moment) *measures* were employed to test TV commercials' effectiveness (Micu & Plummer, 2010) (post. prob. = 0.501). In comparison, self-report captured conscious *emotions*, symbolic *measures* offered the brand's mental mapping, and physiological *measures* traced "peaks of lower-order *emotions*" (p.137).

Topic 19 – Visual Design Effects

The most correlated terms within this topic were *visual*, *attent*, *design*, *effect*, and *complex*. Products and packages are *designed* in a *visually*-appealing way to capture consumers' *attention*, enhancing the brand's value and positioning (Orth & Crouch, 2014) (post. prob. = 0.707). Retailers' *complex visual* environment and noisy background in displaying products and brands also affect their attractiveness. Less appealing packages might also be of interest for promotional purposes or lower prices communication. Both the semantic and physical features of the product have an impact on buyers' *attention*. However, those capturing the most *attention* are not necessarily suitable and likable (Husić-Mehmedović et al., 2017) (post. prob. = 0.596). *Design complexity* revealed stimulus *attention* on pictorial and on the advertisement as a whole (Pieters et al., 2010) (post. prob. = 0.525), improving the "stopping power" of the ad.

Topic 20 – Social Comparison

The group terms *social*, *women*, *polit*, *negat*, and *model* had higher correlation levels within this topic. *Women* often compare themselves with thin media *models*, which can *negatively* affect their self-esteem (Mischner et al., 2013) (post. prob. = 0.804). Using eye-tracker equipment, the authors investigated the visual attention to appearance-related and neutral advertisements, aiming to lower *women's* attention to appearance-related content. As expected, those with high self-esteem paid less attention than those with lower self-esteem. The latter paid less attention upon receiving norm-challenging information. Bury, Tiggemann, and Slater (2016) (post. prob. = 0.594) studied the use of digital modification disclaimer labels attached to digitally modified pictures in fashion magazine advertisements. This study showed that textual disclaimers redirected visual attention to specific body areas, enhancing body dissatisfaction. However, the disclaimer's nature did not affect the time spent looking at specific body parts but did change the gaze direction upon reading the disclaimer (Bury et al., 2014) (post. prob. = 0.588).

Topic 21 – TV Commercials Stimuli

The most correlated terms were *EEG*, *activ*, *commerci*, *subject*, and *differ*. This topic encompasses electroencephalography (*EEG*) to measure and map brain *activity* when *subjects* are exposed to TV *commercial* ads. Vecchiato et al. (2010) (post. prob. = 0.882) also used SCR and HR to measure emotional engagement and *EEG*. The authors found no statistical *difference* in SCR levels during the experiment. Still, they amplified HR values and brain *activity* in areas related to memory and pleasantness judged (theta band in the left hemisphere). *EEG* can easily generate type I errors while executing numerous univariate statistical tests, and it can be managed with proper statistical techniques (Vecchiato et al., 2010) (post. prob. = 0.761). De Vico Fallani et al. (2008) (post. prob. = 0.755) distinguished between *commercials* that will be remembered and those that will be forgotten. For the latter, higher values for the global and local efficiency indexes were revealed in the cortical network, while lower values were exhibited for those to be remembered.

Topic 22 – Individual Interaction in Structured Environment

The most relevant terms within this topic are *focus*, *system*, *work*, *goal*, and *individu*. Several studies have relied on analyzing cognitive effects revealed by *individuals* integrated into different social institutions, such as religion (d'Aquili, 1985) (post. prob. = 0.584), *focusing* on ritual behavior. The author defined this social concept as a succession of structured or patterned, rhythmic, and repetitive behavior occurring regularly and similarly. This type of behavior is recognized to "synchronize affective, perceptual-cognitive, and motor processes within the central nervous *system* of *individual* participants" (d'Aquili, 1985, p. 22). To another extent, organizational analysis is considered one of the most complex areas, but still imperative for business and management research (Gillingwater & Gillingwater, 2011) (post. prob. = 0.505). In this context, organizational performance is compared to biological organisms, incorporating brain's structure and functions as an analogy/metaphor to understand organizational nature and performance.

2.5. Discussion

Although consumer neuroscience research is still in its early days, it has already captured the interest of 80% of the market (Ramsøy, 2019). Neuroscience techniques can shed further insights into consumer behavior studies, and recent articles have discussed some future research avenues. The current section (1) explores these future research proposals and (2) suggests other research questions that can move beyond the existing literature. To summarize the most relevant future research topics discussed in the literature, the articles collected in the current paper, published between 2017 to 2021, were ranked by the Average Number of Citations per Year (AC_y). Then, the top 10 cited articles were selected for further analysis (Aria et al., 2020; Loureiro et al., 2020) (see Table 2.9).

Rank Position	Author	Journal	TC	CY	ACy
1	Szabo, and Webster (2021)	Journal of Business Ethics	22	0	22.0
2	Niehorster, Cornelissen, Holmqvist et al. (2018)	Behavior Research Methods	63	3	21.0
3	Muñoz-Leiva, Hernández-Méndez, and Gómez-Carmona D. (2019)	Physiology and Behavior	41	2	20.5
4	Meyerding, and Mehlhose (2020)	Journal of Business Research	20	1	20.0
5	Kahn (2017)	Journal of Retailing	77	4	19.3
6	Lee, Choi, Han et al. (2020)	Journal of Business Research	18	1	18.0
7	Machín, Curutchet, Gugliucci et al. (2020)	Appetite	18	1	18.0
8	Calogiuri, Litleskare, Fagerheim et al. (2018)	Frontiers in Psychology	53	3	17.7
9	Lim (2018)	Journal of Business Research	52	3	17.3
10	van Reijmersdal, Rozendaal, Hudders et al. (2020)	Journal of Interactive Marketing	17	1	17.0

Note: TC = Total Citations; CY = Citable Years; AC_y = Average Citations per Year.

Source: Own elaboration.

Table 2.9. Top 10 articles (ordered by average citation score per year)

The study by Szabo and Webster (2021) on perceived greenwashing using neuroscience tools achieved the highest average citations per year (AC_y) score with a value of 22.0. The authors suggest using neuroscience techniques to go further in the context of green marketing, namely the impact of green content on interactivity and ethical concerns when green marketing is used to persuade consumers. Niehorster et al. (2018) achieved the second-highest average score in terms of citations per year (AC_y = 21.0). In their research, the authors stress the need to extend studies using eye-trackers in non-optimal conditions in in-depth studies. Muñoz-Leiva et al. (2019) (AC_y = 20.5) analyzed advertising effectiveness in social media in the context of tourism. The authors suggested the study of advertising effectiveness while surfing the web versus during goal-oriented navigation, highlighting the importance of extending eye-tracking techniques specifically for smartphones. Meyerding and Mehlhose (2020) (AC_y = 20.0) examined the feasibility of mobile functional near-infrared spectroscopy (fNIRS) systems in the context of food products. These authors suggested that fNIRS using a cap instead of a headband provides more accurate results and that it should be combined with other methods in the future (e.g., eye-tracking, questionnaires, EEG). Kahn (2017) (average score of 19.3 citations per year) explored the attention patterns on small screens. The study shows how visual design decisions affect consumers' reactions in online environments. These authors propose additional moderators of attention toward small screens such as consumer expectations, individual differences, and expertise. Lee et al. (2020) (AC_y = 18.0) studied green marketing practices in the fashion context using fMRI. They suggested using neuroscience techniques to compare consumer attitudes between luxury and mass-market fashion. Machín et al. (2020) (AC_y = 18.0) explored how consumers make in-store food purchase decisions and identify which information they look for during that process. For future research, these authors suggested scholars should test the impact of in-store environments (e.g., changing the packaging, shelf position, logos, and colors) on changing habits to persuade consumers to have a healthier lifestyle. Calogiuri et al. (2018) achieved a 17.7 average citation score. These authors suggest using immersive virtual environments (IVE) to promote green exercise through simulating outdoor environments. The study by Lim (2018b) (AC_y = 17.3) acted as a roadmap in the neuromarketing context, as it explored what has already been studied and the main priorities for the future. The author stressed the need to address further the ethical issues surrounding consumer neuroscience. Finally, van Reijmersdal et al. (2020) (AC_y = 17.0) conducted an experiment using eye-tracking methods to analyze children's ability to understand sponsored social influencer videos, highlighting the need for more longitudinal studies instead of studies focused only on immediate effects.

Using the previous suggestions for further studies, we categorized the main future research topics into three dimensions and presented additional research questions: (1) green marketing/sustainability; (2) new technology developments; and (3) privacy and ethical concerns.

First, green marketing/sustainability was identified as an emerging topic in neuroscience. Green marketing strategies are becoming important to align the company with consumer expectations (Lee et al., 2020). Such strategies can be applied in different contexts: (i) the luxury industry (perceived as one of the least sustainable industries), in the use of vegetarian leather instead of real leather; (ii) the inclusion of negative environmental cues in ads (Szabo & Webster, 2021); and also (iii) in anti-consumption ads. Using neuroscience techniques, researchers can efficiently study consumers' unconscious responses to such stimuli (Bettiga et al., 2020; Ozkara & Bagozzi, 2021). Hence, we suggest that future studies can explore such problems from a neuroscience perspective.

In the future, brands will increasingly use digital channels to connect with consumers (Hackl, 2021). From blockchain technology to the metaverse, virtual world integration will allow organizations to join larger audiences in a unified virtual location (Cook & Kuczer, 2021; Gleim & Stevens, 2021; Sheth & Kellstadt, 2021). The metaverse arises as the most important futuristic digital environment, combining Artificial Intelligence (AI), Augmented Reality (AR), and Virtual Reality (VR) in one digital place. These engagement-facilitating technologies are emerging and evolving, bringing a revolutionary arena where brands can enhance their interactivity with customers (Hollebeek et al., 2022). Consumer Brand Engagement (CBE) is a pivotal element in marketing strategies that fosters positive attitudes and behaviors toward the brands (Hollebeek et al., 2014; Hollebeek & Belk, 2021).

Recent studies suggest customer engagement is potentiated as interaction experiences increase through AI, AR, and VR (Chen et al., 2022; Kull et al., 2021; Mostafa & Kasamani, 2021). Even though digital channels provide multiple ways of engagement (e.g., likes, comments, public sharing information), for emerging technologies such as AI, VR, AR, 5G, and blockchain (the metaverse subset technologies), the engagement potential is far greater, allowing consumers to experience a brand and explore the space virtually and playfully (McLean et al., 2021; Rauschnabel et al., 2022).

Future Research Avenues	**Dimensions**	**Research Questions**
Green Marketing / Sustainability	Consumer Behavior	– How will green labeling influence visual attention? – What emotional responses may arise in the case of sustainable versus non-sustainable brands (e.g., vegetarian leather vs. real leather products)? – Are eco-friendly products more memorable than non-eco? – Are ads with sustainable practices more appealing than regular ads? – Do anti-consumption ads generate less arousal than traditional commercial ads?
	Luxury Marketing	– Which emotions does sustainable luxury advertising stimulate in individuals? – How will luxury brands' advertisements for sustainable products (e.g., vegetarian leather products by fashion designers) impact brand awareness and engagement?
	New Technology	– Which neuroscientific methods can convey effective messages regarding sustainability?
New Technology Developments	Blockchain	– How can neuroscience be used to assess the blockchain technology impact on perceived trust in retail? – How is blockchain affecting consumer brand attention and engagement, and influencing purchasing intentions? – How will blockchain impact perceived risk and anonymity in financial contexts, whether through SCR or EEG measurement?
	Artificial Intelligence (AI)	– How does AI affect the online shopping experience using biometrics data? – How can neuroscience measure perceived cybersecurity risks with AI? – Is advertising through AI devices creating greater brand memory and attention than traditional media? – Will we ever be able to measure emotions in AI devices?
	Metaverse	– How will brand engagement evolve within a metaverse environment? – Will advertising within a metaverse context trigger different brain responses from other social media? – How can eye-tracking devices optimize social media interaction with metaverse technology?
	Virtual Worlds	– Will the lower physical presence in shops (higher immersive scenarios) cause lower levels of attention and engagement? – Will many-to-many group events improve direct attention and engagement? – Will virtual venues, such as music concerts, ease the relationship with the artists and increase the level of emotions?
	Neuroscientific Tools	– Can mobile devices enabling eye-tracking via front-facing camera accurately measure visual attention? – Will eye-trackers on virtual reality glasses bring more insights to consumer neuroscience due to their portability and real-life application? – Will facial coding software accurately measure other than basic emotions?
Privacy and Ethical Concerns		– Will privacy and anonymity concerns be a major obstacle to consumer neuroscience evolution? – How far can subliminal marketing go? – What shall remain as private data regarding data obtained through neuroscientific tools? – Will blockchain technology impact the definition of private data in consumer neuroscience?

Source: Own elaboration.

Table 2.10. Research Questions in Consumer Neuroscience

Marketing practitioners and academics must understand the groundbreaking technologies for CBE optimization and those that will become obsolete. Furthermore, the ultimate integration of AI and anthropomorphism, such as Ameca, a humanoid with fascinating facial expressions, is also expected to transform how companies and brands engage with their customers (Hollebeek et al., 2021).

Neuroscience techniques are crucial to identify and exploring users' interactions and predicting behaviors and choices (Alsharif et al., 2021; Vences et al., 2020). Such techniques can enable researchers to collect insights and behavioral responses to understand how consumers react in virtual environments.

Finally, even though neuroscience is an emerging field with several advantages for brands and advertisers, it can also negatively impact consumers (Stanton et al., 2017). One such effect derives from the potential bad use of private information, which can lead to confidentiality issues. Second, using fMRI and EEG techniques, brands can understand how consumers´ brains react to different stimuli even before rationalizing such intentions, eventually leading to consumer manipulation (Aicardi et al., 2020; Rainey & Erden, 2020). Third, there is a need to address how to make such important and private information secure (Tham et al., 2021). Potential breaches in data security can represent a major obstacle to further developments in consumer neuroscience research. Table 2.10 summarizes the proposed research questions.

To address these gaps, Study 2 and Study 3 have been designed to investigate two pivotal research avenues: (1) "How does AI influence the online shopping experience through the utilization of biometric data?"; (2) "Does advertising via AI devices contribute to a higher degree of brand retention and attention compared to traditional media?". Our primary objective is to comprehensively examine the intersection of AI and advertising within the context of online shopping, but no comparison with traditional media or memory/attention will be covered in this research project.

Chapter 3: Literature Review – Artificial Intelligence and Its Application in Advertising

3.1. Artificial Intelligence

Artificial intelligence (AI) is the universal field defined as the technological simulation of human intelligence, mimicking human cognitive functions (Huang & Rust, 2022; Schutzer, 1990; Toorajipour et al., 2021), powered by big data, machine learning, and process automation (Lv et al., 2022). Haenlein and Kaplan (2019, p. 17) defined AI as the "system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation", while Huang and Rust (2022, p. 210) described it as "machines that mimic human intelligence computationally and digitally, designed to emulate (or surpass) capabilities inherent in humans, such as doing mechanical, thinking, and feeling tasks".

AI comprises computational systems, data management, and algorithms (Huang & Rust, 2018; Kumar et al., 2021; Rodgers & Nguyen, 2022) and is appointed as the most prominent technology among the four "new-age technologies" (blockchain, Internet of Things (IoT), Machine Learning (ML), and Artificial Intelligence). An essential differentiation from other technologies is its self-learn ability (Haenlein & Kaplan, 2019; Huang & Rust, 2018), as it can recurrently learn from data and adapt autonomously. Latah and Toker (2019) further envisioned the existence of seven subfields of AI: (1) knowledge representation; (2) reasoning; (3) planning; (4) decision-making; (5) optimization; (6) machine learning; and (7) metaheuristic algorithms.

Several early works identified as AI can be easily found, but Alan Turing was appointed the most influential AI precursor (Russell & Norvig, 2016). In his seminal article "Computing Machinery and Intelligence" (Turing, 1950), he introduced the Turing test, machine learning, genetic algorithms, and reinforcement learning, describing how to create intelligent machines and assess their intelligence. However, the term Artificial Intelligence was first employed by the computer scientists John McCarthy, Marvin Minsky, Claude Shannon, and Nathaniel Rochester in their proposal for a two-month workshop on artificial intelligence at Dartmouth College in New Hampshire during the summer of 1956 (McCarthy et al., 1955). Even though no major breakthroughs came out from this workshop, it is still considered a milestone as it set the opportunity for the pioneers of this technology to meet up, who, together with their colleagues and students, dominated this area of study for the next two decades (Russell & Norvig, 2016).

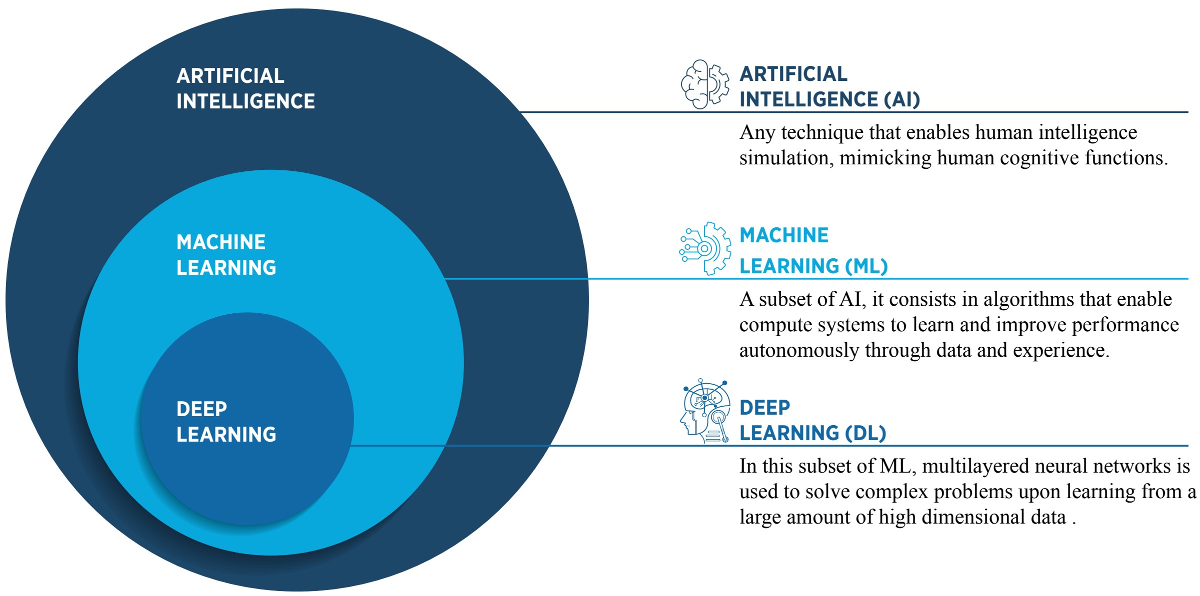
The principle behind AI relies on the knowledge transfer likelihood from humans to machines to execute a multiplicity of tasks, which is sustained by three main concepts, namely, machine learning

(ML), deep learning (DL), and artificial neural networks (ANNs) (Huang & Rust, 2022; Kopalle et al., 2022; Verma et al., 2021) (see Figure 3.1). These concepts are acknowledged as the technological enablers in collecting, analyzing, and correctly interpreting data in different contexts, learning from it, and acting intelligently (Vlačić et al., 2021).

Machine learning consists of "programming computers to optimize a performance criterion using example data or past experience" (Alpaydın, 2014, p. 3), using a set of algorithms that will enable computer systems to be autonomously and continuously updated and adjusted so they can reach an optimal outcome for a specific problematic on its own, based on its "learnings", through trial-and-error, rather than having a programmer intervention (Hollebeek et al., 2021; Huang & Rust, 2022; Mariani et al., 2022; Rodgers & Nguyen, 2022). These learnings are grounded on data from several sources, including sensors and databases (Sharda et al., 2020).

Deep learning is identified as a subset of machine learning, differing from the latter by the type of data it works with and the learning methods. Typically, machine learning algorithms deal with structured data, and deep learning with unstructured data (Alpaydın, 2014; Balducci & Marinova, 2018; IBM Cloud Education, 2020). Machine learning can also work with unstructured data, but in a pre-processing stage, it organizes the data somehow, giving it a structure, while deep learning does not require data pre-processing, hence needing less manual intervention.

Figure 3.1. Deep learning location within AI-based learning methods

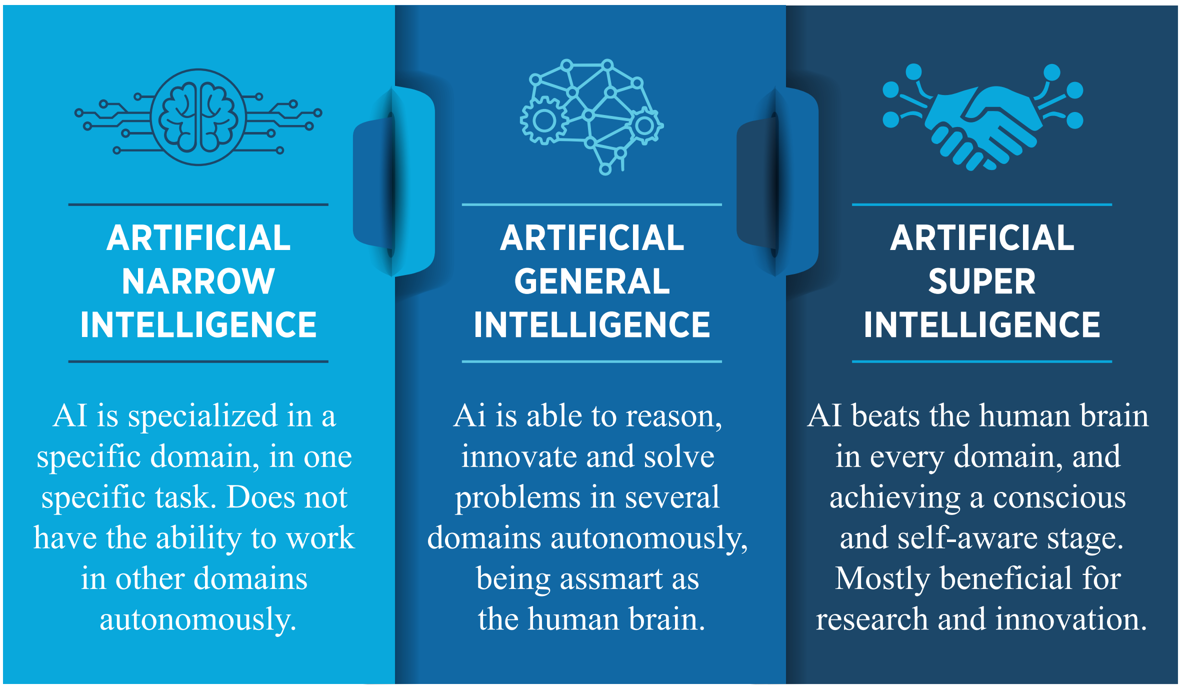


Source: Own elaboration.

Artificial neural networks, or simply neural networks (NNs), are computational systems emulating the biological neural network (Silva et al., 2017), a set of artificial neurons functioning as processing units with the ability to get and maintain knowledgeable data with several interconnections that represent the synaptic connections of the brain. These neural networks are classified as learning systems that can respond to the external responses they obtain (Sterne, 2017).

AI can be categorized into different stages according to its capabilities. The first stage of AI application is referred to as Artificial Narrow Intelligence (ANI) or Weak AI (Al-Shabandar et al., 2019; Gentsch, 2019; Great Learning Team, 2022; Kaplan & Haenlein, 2019), where we currently stand with which the AI is dedicated to a single domain, to execute one task, but unable to solve problems from other domains autonomously. These pervasive AI systems can get closer to or even outperform the human brain in specific and controlled situations. The second generation of AI applications is designated as Artificial General Intelligence (AGI) or General AI, which does not exist yet, maybe in 20 to 25 years (Sharda et al., 2020). This generation will be able to reason and solve problems autonomously in several domains, even for those they were never engineered for. The also non-existent Artificial Super Intelligence (ASI), also known as Super or Strong AI, stands as the third generation, beating the human brain in every domain and achieving a conscious and self-aware stage, which is very beneficial for research and innovation (see Figure 3.2).

Figure 3.2. Types of AI according to its capabilities



Source: Own elaboration.

Unquestionably, AI will change how individuals and corporations make decisions and interact, but the main concern is how humans and AI technologies will coexist beneficially and sustainably (Haenlein & Kaplan, 2019). To fully understand how AI will redefine the workplace and service, Huang and Rust (2018) presented a theory regarding job replacement by AI based on the different types of human intelligence and AI development, ordered by the easiness of an AI-powered system to master each one. The ability to perform different tasks is threatening human jobs, allied with innovativeness, less costly, and timely efficient. Intelligence is the human skill of learning from experience over time to adapt to the environment (Schlinger, 2003). With the technological evolution in the digital era, while initially focused on human intelligence only, the intelligence literature has to deal with the current advances in AI (Steinhoff & Martin, 2023).

AI technology's developments aim to mimic or even overcome human intelligence. Four different intelligences can be extracted from the literature, strongly dependent on the task to be executed or service nature (Huang & Rust, 2018). These four intelligence classifications include the mechanical, the analytical, the intuitive, and the empathic. The mechanical task is the easiest to be mimicked. It refers to the capability to undertake repetitive tasks requiring minimum training, for example, the hotel housekeeping service robots (Huang & Rust, 2021b) or any other robot able to perform mechanical tasks autonomously, such as driving or serving at the restaurant (Belanche et al., 2021). Analytical intelligence involves information processing for logical reasoning, evaluating, judging, making comparisons, or even problem-solving (Sternberg, 1999), but it is still classified as weak AI. This requires more training, systematic adaptation, and cognitive thinking, for example, big data analysis to support the decision-making process (Wedel & Kannan, 2016). Analytical AI can analyze cognitive (e.g., online reviews) and emotional data (e.g., sentiment analysis in reviews, voice tone, or facial expressions) and propose recommendations for human actions in several contexts (Huang & Rust, 2022). Intuitive intelligence refers to creative thinking, in which understanding is the main differentiating factor from analytical AI (Huang & Rust, 2018). In the case of intuitive AI, its adaptation is based on intuition and understanding. In the literature, frontline service cyborgs are referred to as an example of intuitive AI, able to interact with customers (Grewal et al., 2020). These cyborgs can also feature empathic intelligence, representing the most advanced form of AI. In this stage, AI could adapt empathetically, based on experience, while recognizing emotions (Rafaeli et al., 2017), similar to the companion chatbot Replika (Pentina et al., 2023). This four-level approach to human intelligence was later simplified by combining the analytical and the intuitive into thinking AI intelligence (Huang et al., 2019).

3.2. Intelligent Virtual Assistants

An artificial intelligence (AI) assistant/agent can be defined as a computational system powered by AI, machine learning, and natural language processing (NLP) algorithms (Lv et al., 2021; Tussyadiah & Miller, 2019; Vimalkumar et al., 2021). It collects and processes complex data in real-time to enable information retrieval or task performance upon users' input through computational commands or voice-based instructions. The AI assistant can execute autonomous actions in a specific domain to achieve its designed goals (Weiss, 2013).

Different AI capabilities are being assigned to these AI assistants, such as: (1) robotics to enable movement and objects manipulation; (2) speech recognition to produce a text dictation based on a sound clip of a conversation; (3) computer vision to extract information from different inputs (images or videos); (4) noise control for voice assistant correctness upon minimizing the risk of misinterpretation users voice request in a noisy environment; (5) Natural Language Processing (NLP), a component of text mining, is used to address the issue with natural human language understanding, simplifying the speech recognition procedure by pre-processing (e.g., parsing, tokenizing, tagging, and standardizing) natural language; (6) Natural Language Understanding (NLU), a subfield of NLP, enables natural language interpretation but contextualizing user’s request and intention behind it; (7) Natural Language Generation (NLG) to convert computer databases into a human-like output; (8) Machine and Deep Learning; (9) emotional intelligence to track non-verbal reactions as facial expressions, body language or speech; (10) augmented reality (AR) to provide an immersive experience, like AR avatars; (11) knowledge representation to store data; and (12) automated reasoning to answer based on stored information (Fuzzy Logic). Hence emulating several human capabilities (Huang & Rust, 2022; Krasnokutsky, 2022; Russell & Norvig, 2016).

There are several types of AI assistants: chatbots; voice assistants; AI avatars; and domain-specific virtual assistants (Krasnokutsky, 2022).

Chatbots are conversational robots, virtual agents based on AI and NLP-driven technology, capable of verbally interacting with humans. Ho et al. (2018, p. 712) define chatbots as “computer programs that can simulate human-human conversations”, while Luo et al. (2019, p. 937) defined this technology as “computer programs that simulate human conversations through voice commands or text chats and serve as virtual assistants to users”. Chatbots retrieve data to proactively predict and assist users’ solicitations and needs (Park et al., 2021; Pizzi et al., 2021). A Chatbot is used to chat with people in human natural language instead of any computer programming language (Sharda et al., 2020), improving customer experience, even though they often fall short of customer expectations (Sheehan et al., 2020).

Eliza, developed by Joseph Weizenbaum between 1964 and 1966, was the first bot, a computer program capable of human interaction using natural language processing (Haenlein & Kaplan, 2019). The bot *Mitsuku* won the Loeber Prize for the world’s most human-like chatbot in 2013, 2016, and

2017. Due to its capability to provide answers almost instantaneously, users get the impression of talking with an actual human (Gentsch, 2019). This technology is facing significant growth, mainly in the E-commerce sector, in which several applications have been developed, mainly in the customer service and product/branding sectors (Huang & Rust, 2021a) where text-based chatbots have real-time conversations with customers, being able to analyze and understand heterogeneous customer voices and to answer accordingly to their emotions and requests, not facing humor volatilities as humans do (Luo et al., 2019), and with a remarkable degree of personalization both for conversation experience and recommendations/offers. Initially, chatbots supported online navigation guidance or purchase assistance (Lind & Salomonson, 2006; McLean et al., 2021). Most recent chatbots are not explicitly assigned to a website but to social media and messaging apps (Letheren & Glavas, 2017; Van den Broeck et al., 2019), performing a variety of tasks (e.g., vacation planning, sleep assistance, or managing a helpline).

In November 2022, OpenAI, a non-profit organization funded by Microsoft in 2015 (Taecharungroj, 2023), launched *ChatGPT* (OpenAI, 2023a), which GPT stands for Generative Pre-trained Transformer, "the best artificial intelligence chatbot ever released to the general public" (Roose, 2022, para. 3), with over a million users signed up *ChatGPT* in its first five days of existence. This model, which was specifically designed for chatbot applications, is a large language model (LLM), a machine-learning-based model that employs NLP techniques to generate human-like text, providing immediate answers to almost every query (Paul et al., 2023; Van Dis et al., 2023). *ChatGPT* started the proliferation of chatbot capabilities (Dwivedi et al., 2023), such as the ability to write essays on a particular subject, develop computer coding, explain concepts, and guess in medical diagnoses (OpenAI, 2022), as well as a variety of other tasks, such as text translation, summarization, and classification. Like its predecessor *InstructGPT*, *ChatGPT* is based on fine-tuning former language models GPT/GPT-3 (GPT-4 is the current version available) through reinforcement learning from human feedback (RLHF) approach with the data collected from OpenAI Application Programming Interface (API), using human preferences as a rewarding signal (Ouyang et al., 2022).

ChatGPT became a new milestone in linguistic intelligence due to decades of research (Wang et al., 2023). With the great demand for generalized deep models, other pre-trained big models were developed beside *ChatGPT* (Wang et al., 2023), including *Vision Transformer* (ViT) to deal with other models' limitations in computer vision (Dosovitskiy et al., 2021). Google launched the *BERT* (Bidirectional Encoder Representations from Transformers) model in 2018, a few months after GPT-1, having announced the new large language model *Bard* (Google, 2023) at the beginning of 2023, now fully powered by PaLM 2, advocated as the next-generation language models (Sharma, 2023). Simultaneously, Microsoft integrated *ChatGPT* into its search engine, Bing, reshaping the use of search engines. Several AI Generated Content models for image/video appeared between 2021 and 2022, like DALL-E, Imagen, or Stable Diffusion, and leveraging AI to a new dimension (Taecharungroj, 2023; Wang et al., 2023).

Google and OpenAI are creating partnerships with other corporations like Adobe or Wolfram and working fiercely with software engineers and developers to integrate their large language models into third-party applications, providing plugins and allowing external developers to create their plugins (Hsiao, 2023; OpenAI, 2023b). Microsoft and Google are also working on integrating these models with their software and apps. Ultimately, the greater the model's spreading and integration with third-party Application Programming Interfaces (APIs), the more strongly enhanced the model's capacities to execute the most numerous tasks.

AI tools such as LLMs are still unable to mimic human intelligence as they still lack reasoning on the outcome provided upon a specific query (Alston, 2023), displaying factual or contextual logic inconsistencies based on their probabilistic interpretation of language patterns from the large corpus with training data (Dwivedi et al., 2023; Lutkevich, 2023; McGowan et al., 2023) to predict the word strings that best fit the query. This phenomenon is known as AI hallucination or confabulation, which may seem plausible due to LLM's capability of producing consistent and fluent text but proved to have been made up when posteriorly checked. One of the most acknowledged hallucinations is the case of non-existing reference listings, historical inconsistencies, or calculation errors (Dwivedi et al., 2023; McGowan et al., 2023). The AI hallucination issue is not limited to LLMs but has also been identified in AI-generated content models for image/video (Lutkevich, 2023).

Voice Assistants or voice-enabled artificial intelligence, operating inside in-home or smartphone devices (Hoy, 2018; Poushneh, 2021), are voice-activated technologies that can perform several tasks on demand and engage in conversations, supported by machine learning and NLP (Hernández-Ortega et al., 2022). This technology is designed to act and be more human-like than ever (Guzman, 2019), assuming a significant role in people's lives. However, using VCAs is far from consensual, as it still holds mixed feelings (Bingaman et al., 2021). Most IoT devices have an embedded AI-powered voice assistant able to help users with several daily tasks, with a customizable voice to foster a bond with the users more easily (Guerreiro & Loureiro, 2023). These AI-based voice assistants store significant amounts of personal data from users for a more tailored experience (Fernandes & Oliveira, 2021; Vimalkumar et al., 2021) but are still a highly demanded form of AI assistants (Aw et al., 2022; Tassiello et al., 2021). The most popular voice assistants, *Google Assistant* (Google, 2022) and Amazon's *Alexa* (Amazon, 2023)*,* can assist the user in online shopping, making hotel reservations, or ordering food, while Apple's *Siri* is still a step behind regarding the tasks it can perform (Chen et al., 2023). While large language models power AI chatbots, voice assistants are question-answering systems (Budler et al., 2023), able to answer a finite number of questions if included in their code. However, AI experts are foreseeing a conversion between chatbots and voice assistants, leveraging voice assistants' skills by incorporating large language models and other technological advances to address security and intelligence issues (Bahmani et al., 2022; Hsu & Lin, 2023; Minder et al., 2023; Rzepka et al., 2022).

AI Avatars are virtual entities or characters with an anthropomorphic appearance (Miao et al., 2022), an embodied digital representation with human-like behavior and qualities (Crolic et al., 2022; Nagendran et al., 2022). Controlled by a human or software, avatars can also have complex text or speech-based interactions with humans (Frank, 2019). Several AI Avatar generator platforms are currently available for entertainment or educational purposes, such as Synthesia, with more than 85 avatars available in more than 120 languages (Synthesia, 2022), Avatar AI (Avatar AI, 2022), or the application Dawn AI developed by Splice Video Editor (Bending Spoons, 2022). The use of these embodied conversational agents and their effectiveness is rising, but their effectiveness changes drastically across companies (Nagendran et al., 2022). Their usage is being globally amplified by firms to enhance customer experience and adopted in several training programs as a matter of cost optimization. However, it has faced several drawbacks in different contexts (Crolic et al., 2022). The more anthropomorphic virtual agent does not necessarily mean a higher customer satisfaction and intention to purchase. Their realistic behavior is expected to lead to more natural interaction with users (Blascovich et al., 2002), even though it can be a double-edged sword as it increases users' expectations of avatars' competence (Miao et al., 2022). A greater negative disconfirmation can potentially occur if expectations are unmet (Oliver, 1980). A sub-category of AI Avatars is the digital human (DH) that looks like a human, while an Avatar can assume different styles, from an illustration to a cartoon or to a human-like character (Lukan, 2023). A DH is a "life-like being, powered by AI, with the capability of conversing, communicating and creating an emotional connection, like any other human being" (Silva & Bonetti, 2021, p. 1). Several companies are developing DHs, such as Soul Machines (Soul Machines, 2023), the leader in AI humanization by creating animated and autonomous digital people like Viola, or Digital Domain (Digital Domain, 2021), with the digital human Douglas. Featuring complex and advanced functionalities, including computer vision or speech recognition, these AI-powered artificial agents can support teams in task management or information search (Baird & Maruping, 2021; Dennis et al., 2023).

Domain-specific virtual assistants are IVAs designed for specific services or industries (Janssen et al., 2020) and trained to provide expert support and advice in their specific domain. The domain-specific focus is not to mimic humans but to automate certain tasks humans do (Bailey, 2019). Domain-specific AI will outperform humans in a specific task, but it does not have the human flexibility to switch from one task to another. Service-based chatbots are an example of domain-specific AI, like the dialogue-based chatbot *Intellibot* (Nuruzzaman & Hussain, 2020), a multi-strategy chatbot that generates responses in specific areas. The *Intellibot* is trained with specific datasets as a custom-built insurance dataset to get specific knowledge for application in the financial area. Other examples of domain-specific AI comprise hotel housekeeping service robots (Huang & Rust, 2021b), frontline service cyborgs (Grewal et al., 2020), or the virtual human social system named "Avatar to Person" (Guo et al., 2021) addressed for disabled people, with which they can perform several tasks, including virtual face repair and simulated voice generation, for more confident video communication.

3.3. Artificial Intelligent Assistants in Advertising

The internet, mobile devices/apps, and social media led to significant changes in how companies would conduct their business (Dwivedi et al., 2023), and currently with AI and ML, which is also reshaping several industries and corporations (Dennis et al., 2023). The advertising industry is widely recognized for its rapid evolution, profoundly impacting more conventional practices (Malthouse & Copulsky, 2023; Shi & Wang, 2023). Emerging technologies are the driving force behind the disruptions and challenges currently experienced within the advertising sector (Stafford et al., 2023). These technologies allow businesses to innovate and thrive in the digital era (Mariani, Machado, et al., 2023). Nevertheless, besides the hype around technology adoption for process automation, the effects of AI-powered technology implementation on firms are still an understudied subject in the literature (Ghobakhloo et al., 2023).

AI adoption within the advertising industry can be performed across different areas and disciplines simultaneously, from advertising research to advertising planning, ad creation and design, media planning and buying, or effectiveness evaluation. This process is envisioned as changing all characteristics of the advertising process as we know it (Rodgers, 2021), creating a more "synthetic advertising" approach (Campbell et al., 2022). Synthetic advertising is when the advertising content and its edition fully rely on AI algorithms and AI-generated content models. AI advertising is "brand communication that uses a range of machine functions that learn to carry out tasks with intent to persuade with input by humans, machines, or both" (Rodgers, 2021, p. 2), even though its definition is considered domain-dependent.

Marketers can rely on social networks to collect large and complex datasets with users' personal and behavioral information and are progressively employing AI/ML-powered systems to transform these data into knowledge or customer insights (Kietzmann et al., 2018; Shi & Wang, 2023). Consequently, advertising content can be personalized and tailored according to customer interests and preferences (Chandra et al., 2022; Zanker et al., 2019), the audiences segmented, leveraging the effectiveness of programmatic advertising through autonomous technology and algorithms (Malthouse & Copulsky, 2023). Programmatic buying has become the most common way of media buying in some regions (Qin & Jiang, 2019). Programmatic advertising refers to targeting consumers in real-time with personalized content associated with the automation of the ad buying and placement process in digital media (Ciuchita et al., 2023; Samuel et al., 2021).

Algorithms and tracking methods, such as third-party cookies and machine learning, have been of paramount relevance for ad targeting services, providing personalized product recommendations in digital communication (Bahmani et al., 2022). The topic of personalized advertising is of major relevance in recent studies. Personalized advertising is related to deeply understanding of consumers' needs, interests, preferences, or lifestyles by tracking and monitoring their online behaviors, including searches, likes, or comments (Deng et al., 2019). Personalization effectiveness can be remarkably enhanced upon customers' willingness to disclose personal data (Chandra et al., 2022), positively impacting click-through intentions (Aguirre et al., 2015), but only if an overt data collection strategy is practiced. Lv and Huang (2022) analyzed the application of AI-powered personalized recommendations for charity advertising. They verified a decreased donation intention when consumers receive personalized recommendations with charity advertising versus when they do not. The authors also suggested that advertisers adopt a servant communication style and provide free options to consumers to maintain their autonomy. Consistent results have been presented by Arango et al. (2023) in the same context of charitable advertising, where the potential benefits of using synthetic content must be weighed against the possible negative effects that may arise when the motives for its usage are not disclosed, and ethical concerns not properly highlighted. Similarly, a cautious and progressive AI adoption for creativity in marketing is also recommended by Ameen et al. (2022), according to which firms should employ a balanced augmentation instead of automation, combining humans with AI capabilities. Drawing from cognitive dissonance theory among Generation Z's strong dependence on social networks sites in the technology customizability context, Wang et al. (2023) analyzed the trade-off between perceived convenience and information privacy concerns as antecedents of technology dissonance and the negative impact of technology dissonance over SN dependence. More positive findings were revealed by Deng et al. (2019), who developed a framework for a smart generation system of personalized advertising copy. This study showed a clear consumer preference for personalized advertising created by the smart generation system over generic ones from retail platforms. Similar results were reported by Wu and Wen (2021), where consumers appreciate significantly and accept AI-created advertisements upon advertisement creation as an objective task. Shumanov et al. (2022) also ascertained AI as a powerful tool for profiling consumers' personality traits, enhancing the persuasiveness of tailored advertising and its effectiveness.

AI advertising is still in its infancy (Wang et al., 2023), and marketers/brands cannot start any communication with IVA users on their own, such as advertising or recommendations. Still, different studies have emerged to unveil the effects of advertisement via IVAs, as this technology will hypothetically evolve to enable a bidirectional relationship with users (Schweitzer et al., 2019), shifting from being merely a servant to a friend or partner (Schweitzer et al., 2019). With every previous interaction between the IVA and the user, the interests and preferences of the latter will be continuously updated. Therefore, more intelligent conversations with the assistant and more accurate responses will enhance the relationship between the two (Smith, 2020). To assess the effects of advertising through chatbots, Van den Broeck et al. (2019) analyzed the mediation effect of message acceptance between perceived intrusiveness and patronage intentions moderated by message relevance. The study of advertising/message acceptance is quite common in advertising through virtual assistants because of the acceptance of the new media (Belanche et al., 2017b; Parreño et al., 2013).

To this extent, different theoretical approaches have been considered, such as the Technology Acceptance Model (TAM) (Davis, 1989; Davis et al., 1989), holding perceived usefulness and perceived ease of use as key determinants for the behavioral intention of new IT (information technology) adoption. As an alternative approach to understand the drivers of new IT adoption, the Unified Theory of Acceptance and Use of Technology (UTAUT) was proposed (Venkatesh et al., 2003), including performance expectation, effort expectation, social influence, and facilitating conditions as antecedents of behavioral intentions, all moderated by social demographic variables as gender, age, experience, as well as voluntariness to use. A third approach is also found in this context, the Use and Gratification theory (U&GT) (Katz et al., 1973, 1974), for understating the motivators for specific media usage and the specific needs people aim to satisfy. Extended versions of these theoretical frameworks have also been applied, such as TAM2 (Venkatesh & Davis, 2000), adding external social factors to TAM, or TAM3 that also included antecedents of the perceived effort regarding technology adoption (TAM3) (Venkatesh & Bala, 2008), and UTAUT2 (Venkatesh et al., 2012) that added the variables hedonic motivation, price value and habit to the previous version of the model.

Van den Broeck et al. (2019) combined two different theoretical frameworks, the TAM and the Consumer Acceptance of Technology model (Kulviwat et al., 2007), identifying perceived helpfulness and perceived usefulness as two cognitive predictors of the attitude toward communication through the chatbot. Considered the future of personalized advertising (Letheren & Glavas, 2017), the effectiveness of chatbot advertising is advocated to rely on perceived intrusiveness and message acceptance. Moreover, the initial experience with the chatbot was also acknowledged to be a determining driver of advertising acceptance, so advertisers should make the chatbot valuable before expecting the advertising through the chatbot to be valuable. Guerreiro et al. (2022) also addressed advertising through smart speakers' acceptance via the TAM framework, reporting perceived ease of use as highly relevant to message acceptance. The message acceptance was identified to be also dependent on its relevance and the entertainment level. To evaluate advertising via IVA effectiveness, Park et al. (2022) used fictitious voice-based advertisements through Amazon's Echo smart speaker, created with Amazon Web services, a total of 12 advertisements, all with contextual relevance. In this study, the authors recognized interactivity and contextual relevance to have a significant role in brand and product recognition, hence a promising platform for improving advertising outcomes, while talker variability did not, possibly due to a trustworthy relationship issue. Following the U&GT framework as an audience-centered approach, Lee and Cho (2020) aimed to analyze the effectiveness of smart speaker advertising, considering attitude toward the ad and the brand for effectiveness assessment, according to different motivations for smart speakers' usage. These relationships were mediated by the parasocial relationship (PSR)[3] construct (Breves et al., 2021; Horton & Wohl, 1956; Schramm, 2008) and moderated by consumer innovativeness. The study retrieved social relationship maintenance and an alternative for social interactions, which can be explained by the social presence theory[4] (Short et al., 1976). Informational learning, play and relaxation, and the pursuit of practicability were identified as the motivators for existing advertising media like radio and the internet. Moreover, the parasocial relationship was reported as a significant factor for smart speaker advertising effectiveness, especially when identical to face-to-face interactions.

Due to the relevance regarding IVAs' valuation by the users on the effects of advertising, other authors analyzed the main drivers of AI-powered technology acceptance, engagement, loyalty, or simply the intention to re-use it (e.g., McLean et al., 2021; Moriuchi, 2019, 2021; Poushneh, 2021). Hence, even though these studies do not directly address the effects of advertising, their conclusions are still of paramount importance in the context of IVA advertising effectiveness. A similar study to Lee and Cho (2020) was developed by McLean and Osei-Frimpong (2019) but focused on voice assistant adoption and not on any advertising effects. This study also aimed to understand the motivators for voice assistant in-home usage, while different motivators were categorized as U&G and social benefits. Still, their findings are relevant, as advertising will only be effective if people deem this technology valuable (Van den Broeck et al., 2019). Utilitarian purposes are the main reason for in-home voice assistants' usage: (1) to help users complete tasks; (2) to search for information; (3) to look for support; and (4) to process orders. Therefore, in-home voice assistants' usage is mainly addressed for goal-directed tasks, so brands should always aim for individuals' convenience for a higher usage propensity. In terms of brand engagement also from a social presence (SP) perspective, McLean et al. (2021) determined that the social attributes related to the AI-enabled voice assistant, such as social presence, perceived intelligence (PINT), and social attraction, motivate consumer brand engagement and technological attributes. The authors also ascertained that users do not engage with voice assistants seeking fun or entertainment but mainly for utilitarian purposes. Still, whereas consumer brand engagement through the voice assistant was established as a predictor of brand usage intention, it does not influence purchase intentions directly. In the service robot context, Fernandes and Oliveira (2021) analyzed social, functional, and relational elements as possible motivators for voice assistant acceptance, in which technology functionality is the primary motivator, namely perceived usefulness, while social norms were found to influence acceptance only through perceived usefulness.

The anthropomorphism of the IVA or the users' perception of IVA's human-likeness is recognized among different studies as an important enabler of a closer relationship and, therefore, of a greater value or acceptance enhancer regarding the intelligent device (Aw et al., 2022; Bahmani et al., 2022; Crolic et al., 2022; Go & Sundar, 2019; Han et al., 2023; Konya-Baumbach et al., 2023; Whang

[3] For more information on the Parasocial Relationship Theory, please read section 5.2.2.
[4] For more information on Social Presence Theory, please read section 4.2.1.

& Im, 2021). For these relationships to be established, consumers' trust in the technology is a fundamental construct (McLean et al., 2020; Pitardi & Marriott, 2021). By adopting a social presence approach, Pitardi and Marriott (2021) advocate for a greater human-like perception of the IVA to raise the virtual perception of competence in users' minds and trust toward the IVA. Furthermore, the current minor IVA's usage in e-commerce is trustworthiness-based, as privacy concerns regarding personal data sharing are still on the table and strongly related to attitudes toward the IVA and the intentions to use it. Perceived privacy risk has a negative impact on perceived trust (Vimalkumar et al., 2021). Hence, companies must address these privacy concerns to potentiate trust in the technology and its adoption.

To assess consumers' responses to advertising via IVA, to our knowledge, only self-reported measurements have been employed. However, the application of neuroscientific techniques in marketing can bring new and richer knowledge to the field (Xu et al., 2023), otherwise unattainable. Understanding consumers' emotions upon their subconscious motivations enables the comprehensive decision-making process analysis (Bhardwaj et al., 2023). Most marketing decisions are grounded on data collected through traditional methods, such as surveys, self-reports, interviews, and focus groups (Harris et al., 2018), even though they just capture the conscious response. Additionally, different studies have stated some failed advertisements or product situations are caused by the judgmental bias induced by traditional market research methods (Jordão et al., 2017; Vecchiato & Tempesta, 2015). Researchers claim different preferences among the different marketing research methods, typically using a combination of theoretical frameworks and self-reported data to evaluate constructs, such as advertising effectiveness, trust, preferences, attitudes, or even consumer behavior (Manippa et al., 2022). The preference for self-reported data relies upon time, statistical significance, and cost, soon advocated to be complemented with psychophysiological data (Casado-Aranda & Sanchez-Fernandez, 2022).

Upon identifying the major gaps in the literature through Study 1 (Chapter 2), technological developments, such as AI, are one of the underexplored topics in neuromarketing. Moreover, according to thematic relevance displayed by the literature review performed in this chapter, AI combined with advertising is of paramount importance for the marketing business, not only due to the significant investment volumes that these two topics are gathering but also to the infancy stage of advertising through intelligent virtual agents. Therefore, recommendations and guidelines on communicating beneficially to ensure positive marketing outcomes are necessary. In Study 2 (Chapter 4), a new conceptual model will be tested for assessing advertising effectiveness of voice-enabled advertising through IVA, which will be the ground for an extended version in Study 3 (Chapter 5), including psychophysiological measurement of emotions. Hence, the research project will follow the complementary and mixed-approach recommended above for a comprehensive analysis of advertising effectiveness with adopting new technology.

Chapter 4: Let’s Go Shopping: Enriching Advertising with Intelligent Voice Assistants

4.1. Introduction

For several decades, the entertainment industry has created an imaginary relationship between humans and non-human beings like robots, humanoids, or other artificial intelligent (AI) devices, some of which could perfectly hold a fluent conversation and respond to voice instructions. From KITT (the car from the 80s TV series) to Star Wars robots *C-3PO* and *R2-D2*, or the *USS Starship Entreprise*’s computer (Start Trek), the examples are innumerous, but back in the real world, Intelligent Virtual Assistants (IVA) are currently identified as the realization of this long-time dream of creating this human-computer interaction (Hoy, 2018).

An IVA can be defined as a computational system powered by AI, machine learning (ML), and natural language processing (NLP) algorithms (Lv et al., 2021; Tussyadiah & Miller, 2019; Vimalkumar et al., 2021). It collects and processes complex data in real-time to enable information retrieval or task performance upon users' input through computational commands or voice-based instructions. The IVA can execute autonomous actions in a specific domain to achieve its designed goals (Weiss, 2013). As AI and NLP featured exponential growth, Intelligent Virtual Assistants are becoming the most prominent technology and are a fast-evolving disruption in human-computer interaction (Moriuchi, 2019). The IVA market size reached 8.1 billion USD worldwide in 2022 (Research and Markets, 2023) and is expected to grow 414% by 2028, with a projected market size of 41.6 billion USD.

With the increasing investment in research and development (R&D) by leading players, such as Google, Microsoft, and Amazon, IVAs are displaying new functionalities at a remarkable pace, which will undoubtedly play a major role for marketers on brands’ communication strategies and advertising effectiveness. Along with the communication automation process, IVA sophistication growth is leading to personalized and assertive recommendations and contextualized conversations with consumers, which will enhance consumer satisfaction, engagement, and loyalty to the brand (Hoy, 2018; McLean et al., 2021; Tassiello et al., 2021).

However, voice-enabled advertising through an IVA is still lacking a reliable and consistent strategy, as this technology is expected to evolve further, possibly incorporating large language models and other technological advances to address privacy concerns (Bahmani et al., 2022; Hsu & Lin, 2023; Minder et al., 2023; Rzepka et al., 2022). Only during Amazon’s Accelerate conference in September 2022 (Wiggers, 2022) the company announced the new feature *Customers Ask Alexa* enabling brands to submit answers to questions posted by customers to *Alexa*. Meanwhile, *Google Assistant* has been reported as running ads in the past for Google devices like the Nest Hub (Schwartz, 2021), but it was back in 2019 that Google added ads to users' experience with *Google Assistant* by displaying sponsored results in some search queries (Williams, 2019). With the emergence of generative AI systems, such as *ChatGPT* (OpenAI, 2023a) and *Bard* (Google, 2023), a new era of virtual assistants is about to begin – one based on large language models that can go beyond simple tasks by learning from millions of unstructured information (Paul et al., 2023). The hype around voice-enabled advertising is growing, with advertisers such as Uber, Walmart, Spotify, and Burger King, among others, taking this leap of faith into a new way of promoting their businesses with great success (Chansky, 2022).

Study 1 (Chapter 2) revealed the technological developments as a research gap in neuromarketing, in which several research questions were presented, including "How does AI affect the online shopping experience using biometric data?" and "Is advertising through AI devices creating greater brand memory and attention than traditional media?". Therefore, we aim to address both technological advances regarding AI and advertising in online shopping. Previous studies highlighted the relevance of future research on IVA features, such as human-like features (McLean et al., 2021; McLean & Osei-Frimpong, 2019; Schanke et al., 2021) or social presence (Park et al., 2022). Although attention is given to in-home IVAs, studies concerning advertisements through IVAs are still in an early stage (Cho et al., 2019; Park et al., 2022; Paxton, 2019; Romero et al., 2021). Besides IVAs' application in different areas like sales, customer service, or lead generation, there is still limited research regarding the effectiveness of advertising through IVA on the advertising value, customer behavior, or brand perception, especially in the specific case of voice assistants and avatars or digital humans.

The current chapter addresses this gap by studying voice-enabled advertising through an Intelligent Virtual Assistant, using the voice assistant *Alexa* (Amazon, 2023) and the digital avatar *Anna* (Synthesia, 2022). In the framework of this study, adding an avatar, a virtual character with an anthropomorphic appearance (Miao et al., 2022), aims to infer the effect of the level of anthropomorphism of the virtual assistant on the advertising value. Anthropomorphism consists of the extent to which customers imbue non-human agents with human features (e.g., characteristics, motivations, emotions, or intentions) (Epley et al., 2007; Mariani, Hashemi, et al., 2023) and is acknowledged as a rapidly expanded meadow in AI adoption in marketing (Mariani et al., 2022). The impact of the IVA's anthropomorphic cues is still far from consistent (Blut et al., 2021; Mariani, Hashemi, et al., 2023). The anthropomorphic cues of the AI assistant are of fundamental importance due to a cultural preference for human-like chatbots and voice assistants being presented as the most competent and advanced technology (Puntoni et al., 2021), creating high expectations on agents' performance (Go & Sundar, 2019). However, existing research has shown mixed findings regarding the presence of anthropomorphic features. While used to stimulate conversation (Araujo, 2018) and foster emotional responses (Kim et al., 2019) between users and virtual assistants, anthropomorphized

IVAs can set unrealistic expectations, leading to a sense of disappointment, frustration, or distrust, and unfavorable behavioral responses to anthropomorphism (Lu et al., 2019; Pentina et al., 2023), as its effects were found to depend on situational factors or customers traits (Alabed et al., 2022). Chatbots' anthropomorphism was determined to negatively impact customer satisfaction during chatbot's service interaction with angry customers (Crolic et al., 2022), while anthropomorphized IVAs enhanced users' privacy concerns (Ha et al., 2021). This ambiguity of results is consistent with the uncanny valley theory (Mori, 1970; Mori et al., 2012) that refers to the non-linear relationship between robotic human-likeness and affinity or emotional response (*shinwakan*) evoked during a human-computer interaction (HCI). The Japanese roboticist Masahiro Mori (Mariani, Hashemi, et al., 2023) found robots more attractive to humans when featuring a greater human-likeness level, but only up to a certain threshold. After this human-likeness threshold, this theory posits that individuals show growing discomfort with humanoids (Mariani, Hashemi, et al., 2023), which marks the beginning of the uncanny valley effect where the benefits of human-likeness drop, and the feeling of eeriness arises.

With simulated voice-enabled ads through IVA, this research also analyzes the inherent ad value perception (advertising value) applied in online shopping, drawing from the social presence (SP) theory (Biocca et al., 2003; Lee, 2004; Lee & Nass, 2003; Lombard & Ditton, 1997; Short et al., 1976) and the computers are social actors (CASA) paradigm (Moon, 2000; Nass et al., 1994; Nass & Moon, 2000). Through online questionnaires administered to a sample of the population of interest, this study aims to map advertising effectiveness in human-AI interaction (HAI), a common practice in marketing research to infer behavioral responses in a population (Dillman, 2007; Malhotra, 2020). Hence, more respondents are required and not easily feasible with the application of psychophysiological measures, which we will dive into in the next chapter.

For this study, the following research questions are proposed:

RQ1: Do consumers perceive voice-enabled advertising through IVA as valuable?

RQ2: How do different IVA's human-like attributes influence social responses?

RQ3: How does trust in the IVA affect advertising value?

RQ4: To what extent does IVAs' anthropomorphism moderate the effectiveness of advertising and the relationships with its drivers?

Therefore, the following research objectives are expected to be tackled in this study: (1) to unveil the main predictors of advertising value when IVAs are used as the advertising media; (2) to understand how the different levels of anthropomorphism affect both social and emotional responses. So forth, the contribution of this study is three-fold. First, it contributes to the existing literature on advertising effectiveness through AI, assessed via the perceived advertising value. Secondly, this study also sheds some light on the impact of IVA's anthropomorphism, here represented by perceived human-likeness (PH) and intelligence (PINT), on social presence (SP). Third, our research examines social presence and empathy as predictors of advertising value (AV), moderated by trust toward the IVA (TTI).

The remainder of this chapter is organized as follows. In section 2, we present the state-of-the-art regarding the social presence theory, empathy in human-AI interaction, advertising value, and trust toward the IVA, as well as the hypotheses formulation and conceptual model. Section 3 describes the methodology, followed by the statistical analysis results in section 4 and discussion in the fifth section.

4.2. Theoretical Background and Hypotheses

4.2.1. Social Presence Theory

Technological advances provide users with a more sophisticated and involving experience during computer-mediated communications (CMC). AI technology is a breakthrough in CMC by powering the stimulation of the sense of social presence while mimicking human-like appearance and behavior (Jiang et al., 2022). High levels of social presence are what the hi-tech industry is promising to users and the ultimate goal of technological evolution (Reeves & Nass, 1996). For several decades, the broader concept of presence has been the "heart" of every mediated communication (Biocca et al., 2003; Lee, 2004; Lee & Nass, 2003; Lombard & Ditton, 1997), from reading a book to using with a computer, and consequently to more advanced human-computer interfaces (Biocca, 1997; Lee & Nass, 2003; Lombard & Ditton, 1997).

Lombard and Ditton theorized the concept of presence as "the perceptual illusion of nonmediation" (1997, sec. Presence Explicated). Moreover, this "illusion nonmediation" comprises two core dimensions: *physical* and *social* presence. Physical presence occurs when the medium is acknowledged as invisible while the same environment is shared between the medium and the user. In this case, communication appears free from artificialness (Heeter, 1992; Lombard et al., 2000). Short et al. (1976, p. 65) initially defined social presence as the "degree of salience of others in mediated interactions and the resulting salience of interpersonal interactions", that is, the feeling of being socially accompanied and connected. Similarly, social presence was also described as the feeling of being with "others" in a mediated environment (Biocca et al., 2003; Heeter, 1992), that is, being together and communicating (Cummings & Wertz, 2018; Oh et al., 2018; Witmer & Singer, 1998; Yoon et al., 2019). Previous consumer research focused on social presence delivered by actual humans in the same environment (Dahl et al., 2001). Currently, in the digital and AI era, the emphasis has moved to a technology-mediated context instead, ranging from the former voice-mail communications to modern AI avatars (Chen et al., 2023; Cummings & Wertz, 2022; Dinh & Park, 2023; Jin & Youn, 2022; Kim et al., 2023; Park et al., 2022). The concept of social presence is considered to rely on two main components, based on the work of Argyle and Dean (1965): (1) *intimacy*, or affiliation, represents the sense of connectedness with others; and (2) *immediacy*, that describes the psychological distance amongst oneself and others during the interaction (Heeter, 1992; Short et al., 1976). Human verbal and nonverbal cues, such as facial expressions, voice, physical appearance, and movements, regulate intimacy and immediacy components (Gunawardena & Zittle, 1997). However, the uniqueness of each medium and heterogeneity regarding its competency to deliver a more or less rich social content (Hassanein & Head, 2007) makes social presence state highly dependent on the features displayed by the medium and therefore strongly related to the media richness theory (Daft & Lengel, 1986; Lombard & Ditton, 1997; Rice, 1992). Therefore, the media can assume different degrees of social presence (Cummings & Wertz, 2022), not only through media richness, as both concepts rely on users' individual attributes and on the communication context (Lee & Nass, 2003; Rice, 1992).

The definitions and conceptualizations of social presence are far from consensual (Kim et al., 2016). Some describe the concept of social presence in a medium-centric way, regarding its features to provide information, while others focus on information richness or media interactivity (Hassanein & Head, 2007). Additionally, a psychological connection approach has been feverously discussed, according to which the social presence concept is concerned with the "warmth" of the medium, conveying the user a sense of human warmth and sociability (Lee, 2004; Nass et al., 1994; Reeves & Nass, 1996), which reinforces the less unusual behavior of attributing a social entity to technology by humans (Heerink et al., 2010). To this extent, the concept of social presence is associated with the sense of humanness of others, given that technological advances are creating different possibilities for human-computer interaction (HCI) (Lim et al., 2022). Following this approach, Gunawardena (1995) described social presence as the extent to which a user is identified as a "real person", aligned with the definition from Lee (2004), according to which "social presence occurs when technology users successfully simulate other humans or nonhuman intelligence" (p. 45). This corroborates Biocca's (1997) description but still complements it by adding that "successful simulation of other intelligence occurs when technology users do not notice either artificiality or para-authenticity of experienced social actors (both humans and nonhuman intelligence)" (Lee, 2004, p. 46).

The breadth of conceptualization about people's social responses to the medium (Reeves & Nass, 1996) is consistent with the Computers are Social Actors (CASA) paradigm (Moon, 2000; Nass et al., 1994; Nass & Moon, 2000). Under this paradigm, humans are socially oriented creatures (Moon, 2000), treating computers as social entities during the interaction, unconsciously associating non-human devices with human attributes and social expectations. This has been acknowledged as the anthropomorphic dimension of the CASA paradigm. Anthropomorphism refers to subconsciously or mindfully imbuing non-human agents (physical entities or not) with human characteristics, appearance, and traits, both affectively and cognitively (Epley et al., 2007). In the current state of artificial intelligence spreading and sophistication, when it comes to intelligent virtual agents, greater anthropomorphized features have been implemented, easily creating emotional bonds (Guerreiro & Loureiro, 2023; Kopalle et al., 2022; Prentice et al., 2023; Schweitzer et al., 2019). Consequently, the higher the anthropomorphism presented by the non-human agent, the stronger the feeling of social presence (Gong, 2008; Jin & Youn, 2022; Kang & Watt, 2013; Kim & Im, 2023; Nass & Moon, 2000; Nowak & Biocca, 2003; Pentina et al., 2023). Several researchers found that AI-powered agents with human-like appearance (Go & Sundar, 2019; Jin & Youn, 2022; Kim et al., 2023; McLean & Osei-Frimpong, 2019) are posited to affect social presence positively. Hence, we suggest that when a user interacts with a more human-like IVA for online shopping purposes, and the IVA responds promptly and accurately, recommending tailored products according to one's interests, the sense of being with another is stronger. Therefore, the following hypothesis is proposed:

H1: Perceived human-likeness positively impacts social presence in the context of advertising through the IVA.

As far as perceived intelligence is concerned, this construct is often linked with AI competence and agents' ability to act intelligently and interact with humans without language barriers. Perceived intelligence can, therefore, be associated with the inner capability of the AI-powered system to mimic human intelligent-based behavior (Qiu et al., 2020). Intelligence is perceived as a human characteristic more challenging to mimic (Bartneck et al., 2009; Yu, 2020) and a comprehensive source of criticism regarding its unfulfillment in AI-powered devices. In their study, Bartneck et al. (2009) developed the five Godspeed dimensions to create a tool to measure human-robot interaction, which comprised anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety. Chattaraman et al. (2019) conceptualized the AI's ability to have a language-based conversation as a critical human-like cue, acknowledged as an intelligence feature, capable of evoking the social presence psychological sense. Moreover, Oh et al. (2018) conceptualized social presence as dependent on how well one perceives to have access "to the intelligence, intentions, and sensory impressions of another" (Biocca, 1997, p. 22). As for voice-enabled advertising through an IVA, we suggest that if the ad is considered meaningful and related to the interaction context, one can easily perceive to be in the presence of an intelligent AI-powered self, enhancing the sense of social presence. Thus, the following hypothesis is formulated:

H2: Perceived intelligence is a positive predictor of social presence in the context of advertising through the IVA.

4.2.2. Empathy in Human-AI Interaction

Empathy is an essential trait in human-to-human communication (Park et al., 2022) and, consequently, in human-AI interaction (HAI), as all technological developments in intelligent virtual assistants aiming for human features mimicking. Empathy is acknowledged as a bi-dimensional reaction to others' experiences and feelings (Cummins & Cui, 2014; Mehrabian & Epstein, 1972; Park et al., 2022; Pelau et al., 2021), which is conceptualized as decomposable in a cognitive and emotional realm. Whereas cognitive empathy involves the ability to understand or recognize others' thoughts and feelings, assuming a more mental-oriented process, emotional or affective empathy refers to an instinctive reaction to others' feelings, a contagious state of feeling the same as others are, in addition to their recognition (Lee et al., 2023; Park et al., 2022; Simon, 2013).

The state of empathy is appointed to be an enabler of social relationships (Leite et al., 2013), hence of extreme importance within the relationship marketing discipline and service industry (Iglesias et al., 2019; Markovic et al., 2018). An empathic employee enhances customers' positive emotions, leading a greater engagement and satisfaction, fostering interaction and stronger relationships (Yun & Park, 2022). Moreover, an empathic entity is also recognized to have several emotional benefits, such as relationship satisfaction, social bonding, closeness, credibility, trust, and partnership, while promoting altruistic behavior. Additionally, behavioral benefits have been admitted, including engagement and compliance (Hwang & Zhang, 2018; Kim et al., 2004).

An empathic agent can change users' behaviors and nurture emotions (Leite et al., 2013), while the lack of personalization and empathy makes users feel frustrated and unwilling to interact with intelligent virtual assistants like conversational chatbots (Ashfaq et al., 2020). Conversational agents have been developed and imbued with the ability to create a therapeutic relationship with patients, including empathy and social dialogue (Bickmore et al., 2010). Emotional recognition and empathy were always pointed out as idealistic goals regarding AI-powered agents, but as technology continues to evolve, IVAs can identify users' specific needs and, therefore, carefully customize their offerings along the interaction, exhibiting recognizable personalization and caring efforts (Ashfaq et al., 2020; Pelau et al., 2021; Skjuve et al., 2021). In recent studies, IVAs such as chatbots were found to have the ability to induce empathy from their users, based on anthropomorphic and social presence qualities, during the interaction process (Gkinko & Elbanna, 2022). Lee et al. (2023) reported that social presence influences empathy positively (both cognitive and affective) in the immersive media context. Therefore, we suggest that the same effect exists during an interaction with an IVA that provides personalized advertising. Hence, the following hypothesis can be formulated:

H3a: Social presence positively affects empathy toward the IVA in the context of advertising through the IVA.

4.2.3. Advertising Value

Perceived value for the consumer is often conceptualized as the exhaustive evaluation of the utility of a product or service or as the trade-off between perceived benefits and perceived costs (Yang & Peterson, 2004), being an important antecedent of customer engagement (Itani et al., 2019). In 1995, Ducoffe developed a framework for advertising effectiveness appraisal on the web, focused on advertising value, claiming that creating or enhancing consumers' perceived value regarding a product or service is one of the major roles of advertising.

As a measure of advertising effectiveness, advertising value can be defined as the "subjective evaluation of the relative worth or utility of advertising to consumers" (Ducoffe, 1995, p. 1), revealing the overall relevance of the advertising content to consumers (Wiese et al., 2020). In other words, Ducoffe reported that the value could potentially be originated from the expectations driven by the offering itself, from experience surrounding the communication exchange between the advertisers and consumers, and the ability to foster engaging behaviors. Hence, advertising value is capable of influencing attitudes toward web advertising and subsequently in platforms such as social media (Yang et al., 2023) or short message service (SMS) (Sharma et al., 2021).

In a previous study by Maroufkhani et al. (2022), social presence was found to influence the perceived value of voice assistants positively. Similarly, Osei-Frimpong and McLean (2018) found social presence a key enabler for voice assistants adoption. In digital retail, this sector employs the most up-to-date technologies to enhance customers' experience, including personalized advertising promoted through ubiquitous technologies and devices (Zimmermann et al., 2023). This ever-evolving technology, including AI-based systems, will reframe the retail industry (Von Briel, 2018) with the ability to add assertive and valuable recommendation systems based on previous browsing and transactions made (Fernández-García et al., 2019).

Stronger feelings of social presence from an online chat agent create positive attitudes toward the associated website (Go & Sundar, 2019). Secondly, social presence was identified with the potential to increase the perceived value of AI-powered devices, such as voice assistants (Maroufkhani et al., 2022), while Chong et al. (2023) found a positive relationship between social presence and perceived value in live streaming commerce platforms. Thirdly, advanced technology is a social presence enabler, but at the same time, capable of providing more assertive recommendations during the interaction (Zimmermann et al., 2023), and therefore, more valuable to the consumer. In the case of an IVA advertising personalized products during an online shopping experience, we argue a greater potential for a positive evaluation of IVA's recommendations whenever a feeling of social presence is elicited during the interaction. Therefore, the following hypothesis is proposed:

H3b: Social presence positively affects advertising value in the context of advertising through the IVA.

The positive feelings or states elicited by using a product or service are related to a positive attitude toward that specific product or service (Martins et al., 2019), and significant determinant of technology adoption (Gkinko & Elbanna, 2022). These emotional cues are also acknowledged to be elicited during advertising visualization (Hyun et al., 2011) and hypothesized to influence advertising value. Moreover, in the context of personalized ads, ads can positively influence advertising value (Abbasi et al., 2021) by matching users' preferences and needs. Perceived service personalization, within the on-demand ridesharing services context, was found to reduce the customers' cognitive process by meeting their needs which, in turn, leads to a more enjoyable experience (Aw et al., 2019) and higher perceived value. Therefore, we suggest that when positive feelings of empathy toward the IVA are elicited, while customers interact with the device, it motivates a positive valuation regarding the personalized ad. Hence, the following hypothesis is proposed:

H4: Empathy toward the IVA has a positive effect on advertising value in the context of advertising through the IVA.

4.2.4. Trust Toward the Intelligent Virtual Assistant

The concept of trust can be defined as the "willingness to rely on an exchange partner in whom one has confidence" (Moorman et al., 1993, p. 82), similar to the definition proposed by Mayer et al. (1995), that posits trust related to how vulnerable is the trustor allowing itself to be regarding the actions to be performed by the trustee. By evaluating and learning the outcomes of previous interactions with the trustee, trustworthiness in the trustee is less of a situational factor but more of a learned factor instead (Esterwood & Robert Jr, 2023). In marketing, trust is usually described as the "confidence in the object of a transaction and the psychological process that accompanies trust in the counterparty" (Sun & Guan, 2022, p. 775). Several authors recognize the crucial role that trust plays currently in technology adoption, especially in human-computer interaction (HCI), human-robot interaction (HRI), or human-AI interaction (HAI) (Chi et al., 2023; Esterwood & Robert Jr, 2023; Khavas et al., 2020; Kim et al., 2021; McLean et al., 2020; Pitardi & Marriott, 2021; Sun & Guan, 2022; Terblanche et al., 2022; Xu et al., 2023), or previously, regarding in-app advertising (Cheung & To, 2017), or internet usage (Corritore et al., 2003; Jarvenpaa et al., 2000).

Trust has been frequently studied as a bi-dimensional construct based on a rational or more emotional-oriented process (Chai et al., 2015; Zur et al., 2012). The first dimension is cognitive trust, a more objective and rational process in which perceived trustworthiness in an agent relies on its expertise, competence, credentials, and reliability. The second trust dimension, the affect-oriented trust, is described as being more subjective, as it depends on others' mood, feelings, or emotional state and is potentiated by the trustee's politeness, friendliness, likeability, and pleasantness (Nicholson et al., 2001).

In the context of human-AI interaction for online shopping, trust is a barrier mover for technology adoption, as the intention to use an AI-powered agent is endogenously related to the agent's competence to provide richer information (Hassanein & Head, 2007), but also to security and privacy issues, as IVA will be acting on user's behalf (Feng et al., 2017). However, the more human-like the IVA is, such as AI Avatars, the stronger customers' trust toward the technology is (Crolic et al., 2022; Terblanche et al., 2022). Trust is also a socialness enabler through personalization, able to foster emotions (Leite et al., 2013) and feelings of closeness with the other self, enhancing an empathic relationship (Ashfaq et al., 2020; Pelau et al., 2021; Skjuve et al., 2021). In the specific case of voice-enabled advertising through an IVA, if the AI agent is found to be competent and reliable, trust toward the agent is attained, reinforcing positive emotions toward the IVA, such as empathy. Thus, the following hypothesis is proposed:

H5a: Trust toward the IVA moderates the impact of social presence on empathy in the context of advertising through the IVA.

Additionally, trust was determined to positively shape attitudes toward in-app and Facebook advertising (Cheung & To, 2017; Wiese et al., 2020). Moreover, trust increases the willingness to watch in-app advertising (Cheung & To, 2017) and advertising effectiveness (Crolic et al., 2022). In this study, IVA's advertising effectiveness is assessed through advertising value. Therefore, we expect trust toward the IVA to moderate the relationships with advertising value. Hence, the following hypotheses are proposed:

H5b: Trust toward the IVA moderates the impact of social presence on advertising value in the context of advertising through the IVA.

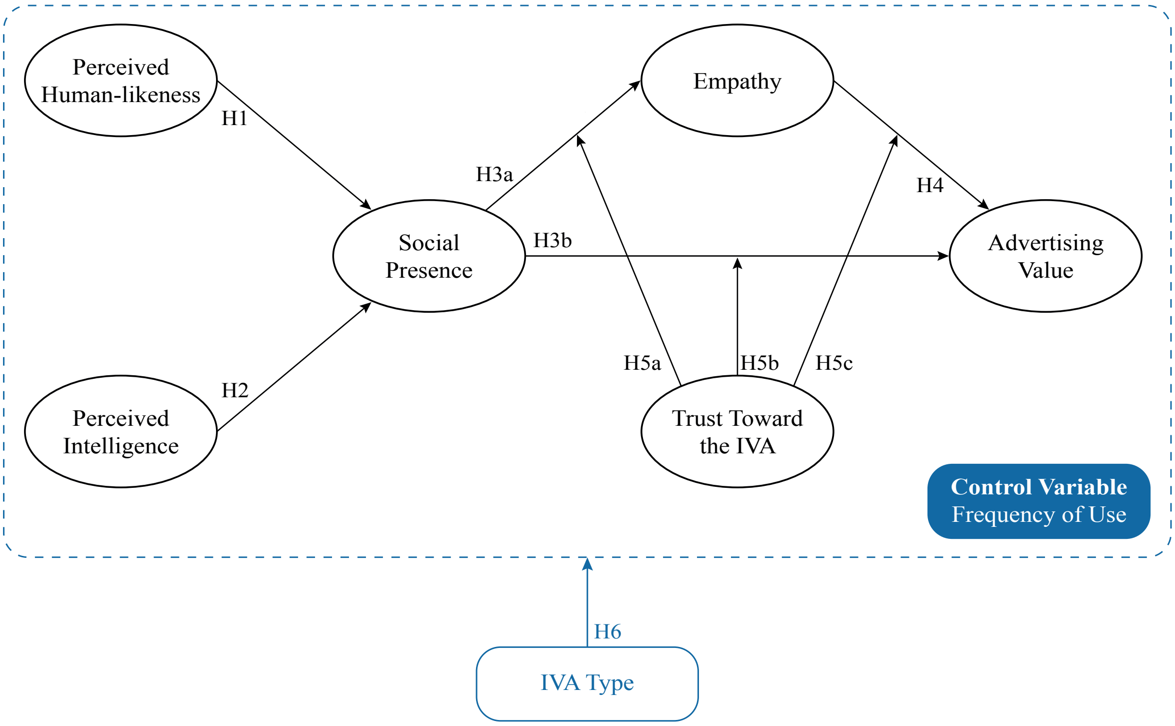
H5c: Trust toward the IVA moderates the impact of empathy on advertising value in the context of advertising through the IVA.

Highly anthropomorphic technology has been determined to improve marketing outcomes (Crolic et al., 2022; Munnukka et al., 2022), such as social interaction (Kim et al., 2023; Nass & Moon, 2000) and customers' preference for products (Wan et al., 2017) or robots (Stroessner & Benitez, 2019). Hence, significant differences are expected for the different model paths, according to the anthropomorphic degree featured by each IVA (*Alexa* vs. *Anna*). To analyze IVAs' anthropomorphism effect among the different relationships considered in the conceptual model and to determine the existence of the uncanny valley effect (Mori, 1970; Mori et al., 2012), the following hypothesis is formulated in the context of advertising through IVA.

H6: IVA's anthropomorphism moderates the relationships in the model in the context of advertising through the IVA.

The proposed research model and formulated hypotheses are displayed in Figure 4.1.

Figure 4.1. Conceptual Model



Source: Own elaboration.

4.3. Methodology

4.3.1. Sampling and Data Collection

A structured online questionnaire was created on the Qualtrics platform, including a brief introduction on the first screen of the survey. The online questionnaire was first deployed to a random sample of individuals with 18 years old or older, recruited from the crowdsourcing platform Amazon Mechanical Turk (MTurk) in August 2022 that voluntarily accepted to participate in the survey and paid between $0.85 to $1.00, if their participation was considered as valid. The questionnaire was also deployed on social networks (SNs), such as Facebook, Instagram, and LinkedIn. Participants were excluded if: (1) they have never used or owned any IVA device (did not accomplish the eligibility criteria); (2) they failed to answer correctly to any of the three attention check questions distributed along the questionnaire; (3) they failed to complete the survey; (4) their answers would indicate a carelessness behavior, with slight variances along the questionnaire; (5) or the random ID number of five digits, automatically generated by Qualtrics at the end of the questionnaire, was not correctly submitted on MTurk (Kim & Im, 2023).

Variables	**Characteristics**	**Frequency**	**Percentage**
Gender	Female	328	67.91%
	Male	155	32.09%
Age Group	Under 18	0	0.00%
	18 – 24	127	26.29%
	25 – 34	167	34.58%
	35 – 44	102	21.12%
	45 – 54	57	11.80%
	55 – 64	27	5.59%
	65 or more	3	0.62%
Household Annual Income	Less than $20,000	97	20.28%
	$20,000 – $39,999	112	23.19%
	$40,000 – $59,999	127	26.29%
	$60,000$ – $79,999	73	15.11%
	$80,000$ – $99,999	46	9.52%
	$100,000 – $124,999	15	3.11%
	$125,000 or more	13	2.69%
Education	High-school graduate	41	8.49%
	Vocational training	15	3.11%
	Bachelor's degree	320	66.25%
	Master's degree	102	24.03%
	Doctoral degree	5	21.12%
	No formal qualification	0	1.04%
Occupation	Retired	4	0.83%
	Employed	313	64.80%
	Self-employed	50	10.35%
	Homemaker	4	0.83%
	Student	108	22.36%
	Unemployed	4	0.83%
Frequency of IVA Usage	Multiple times daily	148	30.64%
	Once daily	69	14.29%
	Multiple times weekly	140	28.99%
	Once weekly	59	12.22%
	At least once a month	43	8.90%
	Less than once a month	24	4.97%

Source: Own elaboration.

Table 4.1. Sample demographic characteristics

A pre-test with 142 IVA users was performed before the main study to mitigate any issues with stimulus correct comprehension and with the questionnaire.

For the main study, 991 (574 MTurk + 417 SNs) respondents started the survey, but only 483 (251 MTurk + 232 SNs) participants were considered valid after analyzing each of the five quality criteria mentioned above. Table 4.1 displays the participant's demographic characteristics.

MTurk is a crowdsourcing platform often used by researchers and is considered a reliable and valid data source (Aksoy & Yazici, 2023; Hasan et al., 2021; Kim & Im, 2023; Mills et al., 2022), already compared with other samples, such as student and professional samples, and found of equal or of better quality (Kees et al., 2017). The use of this platform was particularly relevant to this study, as participants were required to have some experience with an IVA.

4.3.2. The Stimuli

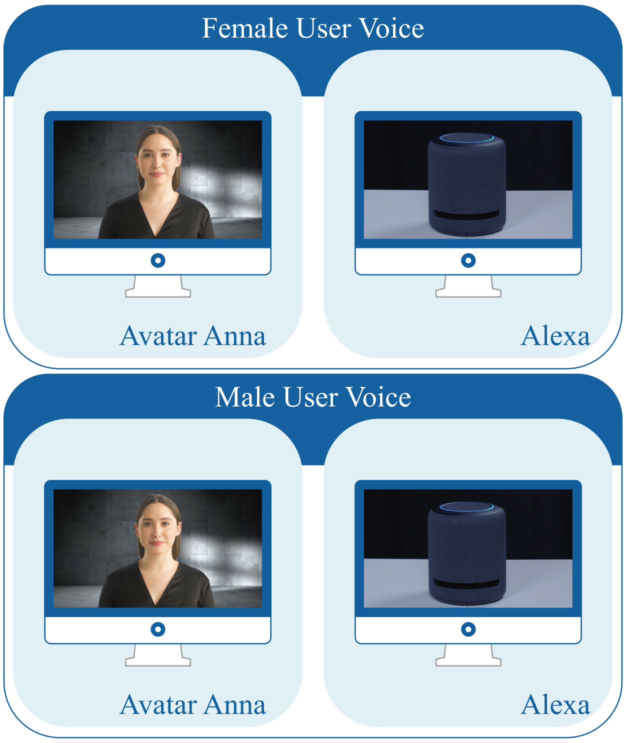
The stimuli used in this study portray an interaction between a human (male or female) with one of two possible AI agents (see Figure 4.2) during an online shopping experience. The intelligent virtual agents used in this research were: (1) the popular *Alexa*, Amazon's voice assistant, here embedded in the Amazon Echo Studio smart speaker, which interaction was programmed via routines' creation in the Amazon *Alexa* app for the operating system IOS (AMZN Mobile LLC, 2022); (2) the digital human *Anna*, a human-like AI avatar, which video, script, and animacy were created on the Synthesia website (Synthesia, 2022). A single-factor approach (IVA Type: *Alexa* vs. *Anna*) between-subject was considered for this research design.

During the experience, participants had a passive observation of the interaction through the video, so they were asked to imagine themselves as the IVA user in the video. In each video, only the IVA was visible, as displayed in Figure 4.2, contributing to a more realistic simulation of a first-person interaction with the virtual assistant. Therefore, the human voice gender in the video always matched the participant's gender for gender congruency purposes. IVA's voice was always feminine and precisely the same for *Alexa* and *Anna*. The type of IVA (AI Avatar *Anna* or Voice Assistant *Alexa*) was randomly assigned to each participant by Qualtrics to ensure an even distribution per type and gender. To increase the probability of a complete visualization of the video, the button to move forward only became available at the end of the video.

The user asked IVA to reorder digestive biscuits and to add cream cheese on sale to the shopping cart, upon which the IVA played a voice-enabled ad to promote peanut butter on sale. The ad was clearly identified by the message "Your shopping will continue after the following advertising message" and by a jingle at the beginning and the end of the ad. After the ad, the user was asked if he/she would like to add the advertised product to the shopping cart. As soon as the user informed the

IVA that he/she was not willing to shop for any other products, the IVA informed the user of the order's total amount and the estimated days for delivery. Then IVA asked the user to proceed to the check-out and about his/her preferred payment method.

Figure 4.2. The video ads stimuli



Source: Own elaboration.

4.3.3. Measurement Scales

Participants were asked to assess the IVA they watched in the video according to their perception of intelligence and human-likeness. *Perceived Intelligence* (PINT) was measured using a five-item scale adapted from McLean et al. (2021), while *Perceived Human-likeness* (PH) was assessed through the selection of four out of the five-item semantic differential scale borrowed from Ho and MacDorman (2010) as the fifth item (Moving rigidly – Moving elegantly) was considered as not applicable to the current context. This study was manipulated by *IVA Type* (voice assistant versus AI avatar). To assess that the participants correctly perceived the manipulation, a manipulation check was done by asking respondents to rate IVA's appearance, according to the video they just watched, with a seven-point scale with one (1) as "Human-like" and seven (7) as "Smart Speaker-like". They were also asked to "indicate whether the human's voice (not the AI assistant's voice) sounds female or male".

The measurement of *Social Presence* (SP) was also adapted from McLean et al. (2021), and *Empathy* (EMP) was assessed through the eleven-item scale from Pelau et al. (2021). The scale for

Empathy includes items related to IVA's ability to understand the user, care about the user, and perceived emotions regarding the relationship between the user and the IVA. To measure the *Advertising Value* (AV) scale, items were adapted from Martins et al. (2019), and for *Trust Toward the IVA* (TTI), a four-item scale was adapted from Pitardi and Marriott (2021). All other constructs were assessed with a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree) except for *Perceived Human-likeness*. As for control variables, the *Frequency of IVA Use* (Low, Medium, and High) was also collected, following Kim et al. (2022), which used *AI-driven interactive recommendation agents* (IRA) *usage duration* as a single control variable, acknowledged as the most significant control variable for model's estimation.

Three attention check questions were displayed along the questionnaire:

- Please indicate your agreement with the following statement: "I love my profession." Please respond with "Strongly agree" (1): 7-point Likert scales (1 = *strongly disagree*, 7 = *strongly agree*);
- "What color is grass? The fresh, uncut grass, not leaves or hay". Make sure to select "Purple" as the answer: (1) Red; (2) Green; (3) Yellow; (4) Purple; and (5) Pink;
- "What is your favorite drink? The most refreshing non-alcoholic drink you can have at breakfast". Make sure to select "Apple juice" as the answer: (1) Vodka; (2) carrot juice; (3) Orange juice; (4) Red wine; and (5) Apple juice.

The questionnaire used in this study is displayed in Appendix A.

4.4. Results

In this study, SmartPLS 4 (Ringle et al., 2022) was employed to estimate the reflective model illustrated in Figure 4.3, using partial least squares structural equation modeling (PLS-SEM), a variance-based path modeling technique. As a distribution-free multivariate data analysis, PLS-SEM does not rely on a specific data distribution assumption. Instead, it aims to maximize explained variance, enabling the estimation of causality between latent variables across the conceptual model (Hair et al., 2011, 2020, 2022; Henseler et al., 2015; Sarstedt, Hair, et al., 2022). The PLS path model consists of two key components, such as the structural model (or inner model) and the measurement models (or outer models), assessed through composite reliability, convergent validity, and discriminant validity (Hair et al., 2021).

The sample of 483 participants adheres to the 10-times rule, which stipulates that the sample size should be at least ten times the maximum number of arrowheads pointing toward a latent variable in the path model (Hair et al., 2012, 2022). These recommendations are based on the Ordinary Least

Square (OLS) regression properties. Moreover, Cohen's sample size recommendation (Cohen, 1992) for a statistical power of 80% and a significance level of 0.05 is also satisfied.

4.4.1. Measurement Model

The first stage of model assessment is focused on the measurement model (Hair et al., 2022) by evaluating the constructs' reliability and validity. For each item's reliability, the outer loadings were determined, and only the items EMP1, EMP3, and EMP4 were below the recommended threshold of 0.70 (Sarstedt, Ringle, et al., 2022). To assess internal consistency reliability, Jöreskog's (1971) composite reliability ρ_C (CRρ_C) was computed (Hair et al., 2011). Composite reliability is posited as more suitable for PLS-SEM estimation, as it does not assume all items with equal reliability, unlike Cronbach's Alpha (CA) metric that postulates a common factor model (Rönkkö et al., 2023; Sarstedt, Hair, et al., 2022), and therefore a less precise and too conservative measure of reliability. The minimum and maximum thresholds of 0.70 and 0.95 (Hair et al., 2019) were verified for CRρ_C and CA (see Tables 4.2 and 4.3).

Convergent validity and discriminant validity must be established for reflective models' validity measurement. The Average Variance Extracted (AVE) was calculated for discriminant validity, with all latent variables showing values above the recommended 0.5 threshold. Therefore, an adequate convergent validity level can be postulated, meaning that more than 50% of the items' variability is explained by the associated latent variable itself (Hair et al., 2014, 2019).

Discriminant validity assessment was done using the Fornell-Larcker criterion (Fornell & Larcker, 1981), in which the latent construct's AVE has to be higher than the highest squared inter-construct correlation, which was established for all latent constructs (see Table 4.4).

However, several researchers have shown this criterion's underperformance and limitations for discriminant validity evaluation (Henseler et al., 2015), as it overestimates items' loadings. Henseler et al. (2015) proposed a new criterion for discriminant validity evaluation, the heterotrait-monotrait (HTMT) ratio of correlations, a more robust and reliable approach (Franke & Sarstedt, 2019; Voorhees et al., 2016). This method relies on the ratio of the average of the heterotrait-heteromethod correlations to the geometric mean of constructs' average monotrait-heteromethod correlations. The HTMT criterion is strongly encouraged for a variance-based approach to SEM like PLS-SEM (Hair et al., 2020; Henseler et al., 2015). Discriminant validity was then established with all HTMT ratios below the recommended value of 0.90 (Franke & Sarstedt, 2019) (see Table 4.5).

Constructs	Scale Items	Factor Loadings	CA	CR(ρ_C)	AVE
Perceived Human-likeness			**0.880**	**0.918**	**0.736**
PH1	Machine-like – Human-like	0.823			
PH2	Artificial – Lifelike	0.894			
PH3	Fake – Natural	0.911			
PH4	Unconscious – Conscious	0.799			
Perceived Intelligence			**0.862**	**0.901**	**0.646**
PINT1	The AI assistant in the video appears to be competent	0.814			
PINT2	The AI assistant in the video is knowledgeable	0.821			
PINT3	The AI assistant in the video provides relevant information	0.828			
PINT4	The AI assistant in the video is intelligent	0.742			
PINT5	The AI assistant in the video provides accurate information	0.809			
Social Presence			**0.869**	**0.911**	**0.721**
SP1	When there is an interaction with the AI assistant in the video, it feels like someone is present in the room	0.740			
SP2	The interactions with the AI assistant in the video are similar to those with a human	0.892			
SP3	During the communication with the AI assistant in the video, it feels like one is dealing with a real person	0.883			
SP4	The communication with the AI assistant in the video is similar to the way I communicate with humans	0.873			
Trust Toward the IVA			**0.875**	**0.914**	**0.727**
TTI1	I feel that the AI assistant in the video makes truthful claims	0.777			
TTI2	I feel that the AI assistant in the video is trustworthy	0.870			
TTI3	I believe what the AI assistant in the video tells	0.878			
TTI4	I feel that the AI assistant in the video is honest	0.882			

Notes:
* items removed as corresponding factor loadings were below the cutoff value of 0.70 (Hair et al., 2022).
CA = Cronbach's Alpha; CR(ρ_C) = Composite Reliability ρ_C; AVE = Average Variance Extracted; AV = Advertising Value; EMP = Empathy; PH = Perceived Human-likeness; PINT = Perceived Intelligence; SP = Social Presence; TTI = Trust Toward the IVA.
Source: Own elaboration.

Table 4.2. Measurement scales validity and reliability results (1/2)

Constructs	Scale Items	Factor Loadings	CA	CR(ρ_C)	AVE
Empathy			**0.936**	**0.947**	**0.693**
EMP1	The AI assistant in the video is capable of understanding consumers' needs	*			
EMP2	The AI assistant in the video is capable of understanding consumers' feelings	0.846			
EMP3	The AI assistant in the video follows the interests of the consumer	*			
EMP4	The AI assistant in the video can adopt user's perspective and recommend the desired products	*			
EMP5	The AI assistant in the video can take care of me	0.849			
EMP6	The AI assistant in the video is preoccupied with offering the best products	0.712			
EMP7	The AI assistant is preoccupied with user's wellbeing	0.821			
EMP8	I feel comfortable depending on the AI assistant in the video	0.828			
EMP9	The AI assistant in the video makes a strong impression on me	0.881			
EMP10	I have positive feelings toward the AI assistant in the video	0.865			
EMP11	I feel I can have a good connection with the AI assistant in the video	0.847			
Advertising Value			**0.919**	**0.948**	**0.860**
AV1	I feel that advertising through the AI assistant in the video is useful	0.906			
AV2	I feel that advertising through the AI assistant in the video is valuable	0.935			
AV3	I feel that advertising through the AI assistant in the video is important	0.941			

Notes:
* items removed as corresponding factor loadings were below the cutoff value of 0.70 (Hair et al., 2022).
CA = Cronbach's Alpha; CR(ρ_C) = Composite Reliability ρ_C; AVE = Average Variance Extracted; AV = Advertising Value; EMP = Empathy.
Source: Own elaboration.

Table 4.3. Measurement scales validity and reliability results (2/2)

As HTMT assumes all items' loadings (λ or *tau*) for each construct as equal, which is quite improbable in most cases, an improved technique named HTMT2 was proposed by Roemer et al. (2021) based on an initial idea from Henseler (2021). Whenever the items' loadings are not *tau*-equivalent, the modified coefficient HTMT2 should be used instead, considering the geometric mean instead of the arithmetic mean, for the items' average correlation computation. The HTMT2 results for discriminant validity assessment are indicated in Table 4.6. No significant differences against HTMT were identified, as values slightly changed (still lower than 0.90), which seems not to be a major improvement over the original HTMT metric (Sarstedt, Hair, et al., 2022).

Variables	AV	EMP	PH	PINT	SP	TTI
AV	0.927					
EMP	0.732	0.833				
PH	0.575	0.647	0.858			
PINT	0.504	0.532	0.402	0.804		
SP	0.605	0.673	0.702	0.491	0.849	
TTI	0.559	0.587	0.471	0.739	0.547	0.853

Note: AV = Advertising Value; EMP = Empathy; PH = Perceived Human-likeness; PINT = Perceived Intelligence; SP = Social Presence; TTI = Trust Toward the IVA.
Source: Own elaboration.

Table 4.4. Discriminant validity results using the Fornell-Larcker criterion

Variables	AV	EMP	PH	PINT	SP	TTI
AV	—					
EMP	0.787	—				
PH	0.637	0.709	—			
PINT	0.568	0.596	0.464	—		
SP	0.672	0.744	0.798	0.564	—	
TTI	0.616	0.637	0.533	0.851	0.619	—

Note: AV = Advertising Value; EMP = Empathy; PH = Perceived Human-likeness; PINT = Perceived Intelligence; SP = Social Presence; TTI = Trust Toward the IVA.
Source: Own elaboration.

Table 4.5. Discriminant validity results using the HTMT ratio of correlations

Variables	AV	EMP	PH	PINT	SP	TTI
AV	—					
EMP	0.786	—				
PH	0.637	0.708	—			
PINT	0.566	0.591	0.461	—		
SP	0.671	0.746	0.800	0.563	—	
TTI	0.612	0.622	0.528	0.852	0.617	—

Note: AV = Advertising Value; EMP = Empathy; PH = Perceived Human-likeness; PINT = Perceived Intelligence; SP = Social Presence; TTI = Trust Toward the IVA.
Source: Own elaboration.

Table 4.6. Discriminant validity results using the HTMT2 ratio of correlations

4.4.2. Common Method Variance

It is not unusual for the variance in the model to be attributed not to the constructs but to the measurement method when the same instrument is used for all participants at once, both for dependent and independent variables (Malhotra et al., 2006; Podsakoff et al., 2003). This phenomenon is widely known as Common Method Variance (CMV), and it can severely bias the results for the construct's validity and reliability (Podsakoff et al., 2012; Williams et al., 2010), often leading to inflated correlations among observed variables. Several authors advocate using multiple statistical techniques to detect CMV (Lindell & Whitney, 2001; Podsakoff et al., 2003; Podsakoff & Organ, 1986).

One *post hoc* statistical approach for CMV detection relies on a full collinearity test, assessing whether one or more predictors measure the same construct (Kock, 2015). This procedure involves calculating the Variance Inflation Factors (VIF) for all observed variables in the model. If all factor-level VIF values are below the 3.3 threshold, the model is considered CMV-free (Kock et al., 2012; Kock, 2015). Table 4.7 displays VIF values, which were lower than 3.3, indicating no evidence of the CMV phenomenon in this study.

Harman's single-factor test is another commonly used technique for assessing CMV (Aguirre-Urreta & Hu, 2019; Malhotra et al., 2006; Podsakoff et al., 2003). This approach computes an exploratory factor analysis (EFA) by loading all model's observed variables. If the first or single unrotated factor extracted accounts for a significant percentage of the variance, it may indicate the presence of the CMV phenomenon. Podsakoff et al. (2003) recommended a more conservative threshold of less than 50% of the variance, while Fuller et al. (2016) suggested a less conservative threshold of less than 60% for CMV. Harman's single-factor test conducted for all latent variables in our model shows that the single extracted factor accounted for 46.192% of the model's variance. Therefore, this test also provides no evidence of the data being significantly affected by CMV.

Variables	**AV**	**EMP**	**PH**	**PINT**	**SP**	**TTI**
AV		1.912	2.360	2.337	2.353	2.325
EMP	2.324		2.749	2.888	2.765	2.889
PH	2.210	2.134		2.236	1.814	2.243
PINT	2.292	2.265	2.291		2.297	1.514
SP	2.480	2.396	2.024	2.475		2.462
TTI	2.546	2.539	2.562	1.687	2.561	

Note: AV = Advertising Value; EMP = Empathy; PH = Perceived Human-likeness; PINT = Perceived Intelligence; SP = Social Presence; TTI = Trust Toward the IVA.
Source: Own elaboration.

Table 4.7. VIF results for the inner model

4.4.3. Structural Model

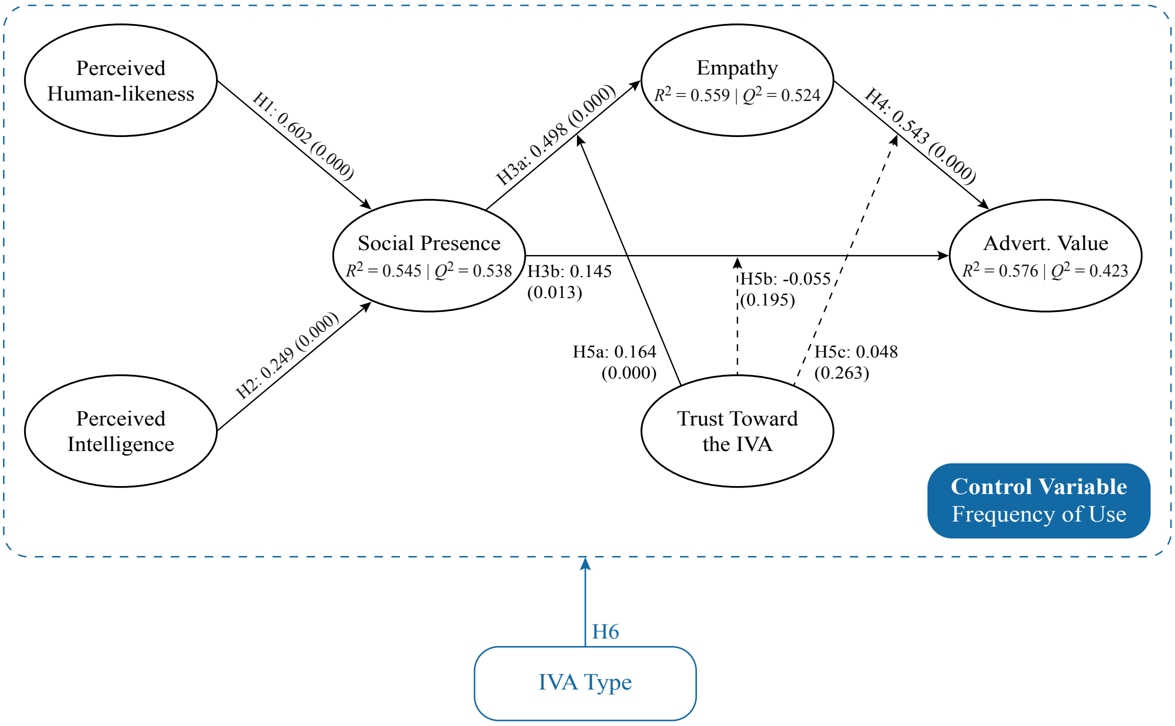
After analyzing the measurement model, the results of the structural model were assessed. Due to the nonparametric nature of the PLS-SEM technique, a bootstrapping procedure with 10,000 subsamples was conducted to estimate path coefficients (β), determine their significance and relevance, and assess the explanatory and predictive power of the model (Hair et al., 2019, 2020; Sarstedt, Hair, et al., 2022). The percentile bootstrap approach was used for estimating confidence intervals, as it has demonstrated superior performance compared to other available methods (such as studentized or bias-corrected and accelerated bootstrap) in terms of balance and coverage (Aguirre-Urreta & Rönkkö, 2018). For the path's significance analysis, the *p*-values were determined using a two-tailed test and a significance level of 5%, while the estimated coefficients' stability was tested through confidence interval inference (Hair et al., 2022). The model's explanatory power was evaluated with the coefficient of determination R^2, which measures the variance in a specific endogenous construct explained by all connected exogenous constructs (Henseler et al., 2009; Shmueli & Koppius, 2011). This statistic is known as within-sample predictive power (Rigdon, 2012). For the model's predictive power appraisal, the Q^2 statistic was computed using the blindfolding procedure PLSpredict algorithm and considering a *ten*-fold cross-validation (Shmueli et al., 2019). The results are presented in Figure 4.3 and Table 4.8.

The model's standardized root-mean-square residual (SRMR) is 0.064, lower than the cutoff value of 0.08. This indicates a good fit of the model to the data (Henseler et al., 2016; Hu & Bentler, 1999).

According to Stones-Geisser's statistics for assessing the model's out-of-sample predictive power assessment, if $Q^2 > 0$, there is evidence of the model's predictive relevance (Chin et al., 2020). The f^2 was computed to measure the effect sizes of the predictors (Henseler et al., 2016). Effect sizes higher than 0.35, 0.15, and 0.02 can be classified as a strong, moderate, and weak predictors of the dependent construct, respectively (Cohen, 2013; Henseler et al., 2009). The effect sizes related to hypotheses H2, H3b, and H5a are deemed weak, while the effect size related to H4 can be classified as moderate. The strongest effect sizes are those associated with hypotheses H3a ($f^2 = 0.394$) and H1 ($f^2 = 0.667$). Furthermore, no evidence of collinearity effects was established among the predictor constructs, as the VIF values range from 1.171 to 2.268, below the cutoff value of 5 (Hair et al., 2022).

Upon coefficients' estimation of the structural model using bootstrapping with the complete dataset, perceived human-likeness ($\beta_1 = 0.602$; $p < 0.001$) and perceived intelligence ($\beta_2 = 0.249$; $p < 0.001$) exhibit significant and positive effects on social presence, thereby supporting hypotheses H1 and H2. In this case, the predictors perceived human-likeness and perceived intelligence explain 54,5% (R^2) of social presence variance.

Figure 4.3. Conceptual model bootstrapping results



Note: Values correspond to path coefficients (β), and p-values in parentheses.
Source: Own elaboration.

Hypothesis	**Paths**	**Std. β**	***p*-value**	**95% CI [LL ; UL]**	**f^2**	**Decision**
H1	PH → SP	0.602	0.000^{***}	[0.533 ; 0.671]	0.667	Supported
H2	PINT → SP	0.249	0.000^{***}	[0.167 ; 0.331]	0.114	Supported
H3a	SP → EMP	0.498	0.000^{***}	[0.429 ; 0.569]	0.394	Supported
H3b	SP → AV	0.145	0.013^{*}	[0.030 ; 0.258]	0.024	Supported
H4	EMP → AV	0.543	0.000^{***}	[0.443 ; 0.642]	0.307	Supported
H5a	TTI × (SP → EMP)	0.164	0.000^{***}	[0.116 ; 0.212]	0.084	Supported
H5b	TTI × (SP → AV)	-0.055	$0.195^{n.s.}$	[-0.141 ; 0.024]	0.005	Not Supported
H5c	TTI × (EMP → AV)	0.048	$0.263^{n.s.}$	[-0.036 ; 0.132]	0.003	Not Supported

Notes:
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; n.s. = not significant.
CI = Confidence Interval; LL = Lower Limit; UL = Upper Limit; AV = Advertising Value; EMP = Empathy; PH = Perceived Human-likeness; PINT = Perceived Intelligence; SP = Social Presence; TTI = Trust Toward the IVA.
Source: Own elaboration.

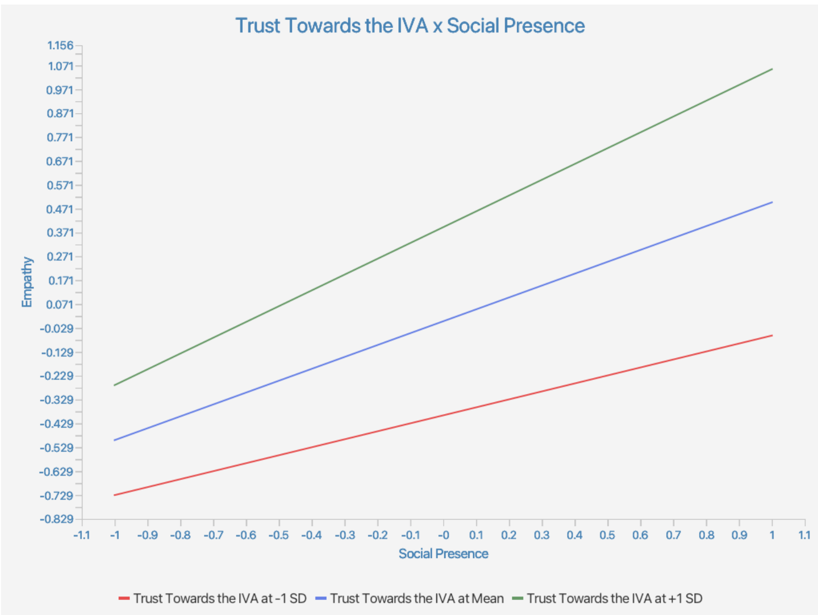
Table 4.8. Structural model results

A direct and positive relationship is observed between social presence and empathy (β_{3a} = 0.498; p < 0.001), with social presence accounting for 55.9% (R^2) of the variance in empathy. Advertising value is positively influenced by social presence (β_{3b} = 0.145; $p < 0.05$) and by empathy (β_4 = 0.543; $p < 0.001$), while its variance is moderately explained by its antecedents (R^2 = 0.576). Substantial explanatory power is typically established for R^2 values of 0.75, while moderate and weak explanatory power corresponds to R^2 values of 0.5 and 0.25, respectively (Hair et al., 2021). Therefore, hypotheses H3a, H3b, and H4 are supported.

4.4.4. Moderation and Mediation Analysis

Regarding the moderation effects of trust toward the IVA, only hypothesis H5a is found to be significant (β_{5a} = 0.164; $p < 0.001$). This finding suggests that trust toward the IVA influences the strength of the interaction between social presence and empathy, but none of the direct effects on advertising value ($p > 0.1$). The path coefficient β_{5a} represents the impact of a one-unit standard deviation (SD) change in the moderator trust toward the IVA on β_{3a} (Hair et al., 2022). This moderation effect can be illustrated through a slope plot representation (see Figure 4.4).

Figure 4.4. Moderation effect of trust toward the IVA on the interaction between social presence and empathy



Source: SmartPLS 4.

This is a case of a moderated mediation, also known as conditional indirect effect, as the indirect effect (mediation) of social presence on advertising value is conditioned by the moderator trust toward the IVA (Hayes, 2015).

The significance of indirect relationships over direct paths was assessed for mediation analysis of the intervening constructs, social presence, and empathy (Hair et al., 2022; Henseler et al., 2009). The mediation analysis must be conducted after performing measurement and structural model evaluation. Different types of mediation effects can be assumed, such as partial mediation (complementary or competitive), full mediation (indirect-only), or no mediation (direct-only or no-effect mediation) (Zhao et al., 2010). All intervening mediators will be analyzed simultaneously in a single model. It is not recommended to perform several mediation analyses for each mediation to avoid biased results and to account for the total indirect effect through multiple mediators (Sarstedt et al., 2020). Thus, multiple mediation analysis is required to test the hypothesized effects through more than one mediator (Cepeda-Carrión et al., 2017). The bias-corrected (BC) confidence intervals were computed using a two-tailed approach with a significance level of 5%. The bias-corrected bootstrap confidence intervals are postulated as the best approach for identifying mediating effects (Nitzl et al., 2016).

Both total indirect effects (see Table 4.9) and specific indirect effects (see Table 4.10) obtained from the bootstrap analysis were tested for significance. For total indirect effects, all relationships were found to be significant. Specifically, perceived human-likeness to advertising value ($\beta = 0.250$; $p < 0.001$), perceived human-likeness to empathy ($\beta = 0.300$; $p < 0.001$), perceived intelligence to advertising value ($\beta = 0.104$; $p < 0.001$), perceived intelligence to empathy ($\beta = 0.124$; $p < 0.001$), and social presence to advertising value ($\beta = 0.270$; $p < 0.001$). These results indicate that all mediations in the model are supported. Additionally, all specific indirect effects were also found to be significant.

Paths	**Std. β**	**Std. Error**	***p*-value**	**95% BC CI [LL ; UL]**
Perceived Human-likeness → Empathy	0.300	0.029	0.000	[0.245 ; 0.358]
Perceived Human-likeness → Advertising Value	0.250	0.035	0.000	[0.184 ; 0.321]
Perceived Intelligence → Empathy	0.124	0.023	0.000	[0.082 ; 0.172]
Perceived Intelligence → Advertising Value	0.104	0.021	0.000	[0.067 ; 0.150]
Social Presence → Advertising Value	0.270	0.032	0.000	[0.211 ; 0.336]

Note: BC = Bias-Corrected; CI = Confidence Interval; LL = Lower Limit; UL = Upper Limit.
Source: Own elaboration.

Table 4.9. Total indirect effects

The strength of the mediation effect on the total variance of the dependent variable needs to be determined using the ratio of the indirect-to-total effect, known as the variance accounted for (VAF) (Cepeda-Carrión et al., 2017; Nitzl et al., 2016). When VAF values fall between 20% and 80%, partial mediation can be assumed, whereas VAF values above 80% suggest full mediation, and values below 20% indicate no mediation effect. A direct effect was added to the model when non-existent between two constructs being assessed for mediation, according to Shrout and Bolger (2002). The new direct effect between perceived human-likeness and advertising value was not significant (β = 0.105; p > 0.05), so an indirect-only effect is established.

Paths	Std. β	Std. Error	p-value	95% BC CI [LL ; UL]	VAF (%)	Mediation Type
PH → SP → EMP	0.300	0.029	0.000	[0.245 ; 0.358]	58.03	Partial Mediation
PH → SP → AV	0.087	0.036	0.015	[0.018 ; 0.159]	22.54	Partial Mediation
PI → SP → EMP	0.124	0.023	0.000	[0.082 ; 0.172]	38.27	Partial Mediation
PI → SP → AV	0.036	0.016	0.023	[0.008 ; 0.072]	10.29	No Mediation
PH → SP → EMP → AV	0.163	0.022	0.000	[0.124 ; 0.211]	42.23	Partial Mediation
PI → SP → EMP → AV	0.067	0.014	0.000	[0.043 ; 0.098]	19.14	No Mediation
SP → EMP → AV	0.270	0.032	0.000	[0.211 ; 0.336]	76.27	Partial Mediation

Note: BC = Bias-Corrected; CI = Confidence Interval; LL = Lower Limit; UL = Upper Limit; VAF = Variance Accounted For; AV = Advertising Value; EMP = Empathy; PH = Perceived Human-likeness; PINT = Perceived Intelligence; SP = Social Presence.
Source: Own elaboration.

Table 4.10. Specific indirect effects

According to Table 4.10, every 95% confidence interval computed for the indirect effects exclude the value zero. Therefore, it can be assumed the significance of these indirect effects. However, VAF values returned a no mediation effect for both paths connecting perceived intelligence and advertising value. In all other relationships, there is evidence of a partial mediation effect with VAF values ranging from 22.54% to 76.27%.

4.4.5. Moderation of IVA Type

A bootstrap multigroup analysis (MGA) was conducted to check for differences in the moderating variable IVA type (H6), considering 10,000 subsamples. The MGA analysis examined path coefficients for significant differences among the different groups (Hair et al., 2018; Klesel et al., 2022; Sarstedt et al., 2011).

To understand the impact of the IVA type presented in the video (Voice Assistant *Alexa* or AI Avatar *Anna*) among the different latent variables and paths in the structural model, the MGA analysis was performed, distinguishing between participants who watched the video with *Alexa* and those who watched *Anna* instead (see Table 4.11).

The analysis reveals significant differences between the two groups in one out of three moderated mediation effects performed by trust toward the IVA. Specifically, in *Alexa*'s group, the moderation effect of trust toward the IVA remains nonsignificant for both interactions leading to advertising value, consistent with the complete dataset.

Paths	β_{Alexa} (*p*-value)	β_{Anna} (*p*-value)	MGA β Dif.	MGA *p*-value
PH → SP	0.606 (0.000)	0.603 (0.000)	0.002	0.972
PINT → SP	0.279 (0.000)	0.206 (0.001)	0.072	0.385
SP → EMP	0.534 (0.000)	0.462 (0.000)	0.071	0.315
SP → AV	0.166 (0.064)	0.107 (0.153)	0.059	0.617
EMP → AV	0.559 (0.000)	0.529 (0.000)	0.030	0.761
TTI × (SP → EMP)	0.177 (0.000)	0.137 (0.000)	0.040	0.415
TTI × (SP → AV)	0.017 (0.806)	-0.125 (0.014)	0.143	0.097
TTI × (EMP → AV)	-0.050 (0.474)	0.134 (0.013)	-0.183	0.037

Note: AV = Advertising Value; EMP = Empathy; PH = Perceived Human-likeness; PINT = Perceived Intelligence; SP = Social Presence; TTI = Trust Toward the IVA.
Source: Own elaboration.

Table 4.11. MGA results for moderation effects

However, in the group of participants who watched the video with *Anna*, all moderations remain significant. This difference in significance may be attributed to the heightened level of anthropomorphism exhibited by the avatar *Anna*, compared to the smart speaker *Alexa*. Moreover, when evaluating each IVA type separately, the direct effect between social presence and advertising value is no longer significant for either group, representing a full mediation by empathy. Hence, empathy toward the IVA fully mediates the social presence effect over advertising value.

According to the MGA *p-values* associated with the null hypothesis regarding the differences between (H_0: $\beta_{Alexa} = \beta_{Anna}$), except for the moderated mediation H5c, all other paths show a *p-value* greater than 0.05. Hence the null hypotheses are not rejected for these paths, and no evidence of significant statistical differences was found between the two groups.

4.4.6. Control Variables

In what concerns the control variables, using the MGA analysis, no significant differences in coefficients were found for the frequency of IVA usage (see Table 4.12), following the same approach proposed by Kim et al. (2022), that considered AI-driven interactive recommendation agents (IRA) usage duration as the most relevant control variable for model estimation. For the multigroup analysis, the six original classifications of frequency of IVA usage were grouped into three categories, with a similar number of cases per each, resulting in a categorical scale varying from low (once weekly or less), moderate (once daily or multiple times weekly), to high (multiple times daily).

Paths	MGA $\beta_{high} - \beta_{low}$	MGA $\beta_{high} - \beta_{mod}$	MGA $\beta_{low} - \beta_{mod}$	*p*-value (High vs Low)	*p*-value (High vs Mod.)	*p*-value (Low vs Mod.)
PH → SP	-0.021	-0.042	-0.021	0.834	0.623	0.793
PINT → SP	0.106	0.100	-0.006	0.327	0.304	0.961
SP → EMP	0.089	-0.003	-0.092	0.372	0.986	0.314
SP → AV	-0.078	-0.111	-0.033	0.628	0.481	0.795
EMP → AV	0.043	-0.099	-0.142	0.788	0.466	0.214

Note: AV = Advertising Value; EMP = Empathy; PH = Perceived Human-likeness; PINT = Perceived Intelligence; SP = Social Presence.
Source: Own elaboration.

Table 4.12. MGA results for frequency of IVA usage

4.5. Discussion

Intelligent virtual assistants are an ever-evolving technology, that is being widely employed in different industry sectors, with different purposes (Guerreiro & Loureiro, 2023; Statista, 2023). The AI-enabled systems are experiencing exponential growth in terms of their users' massification and capabilities. However, worldwide heated debates are taking place to discuss AI systems development and the potential threats to human life (Rough & Sutherland, 2023; Susskind, 2023; Vynck, 2023).

In this study, the voice assistant *Alexa* and the AI avatar *Anna* were the focal characters in understanding how these different AI-enabled systems, imbued with different human-like features, are seen by participants as assertive and empathic vehicles for advertising communication. This research also aims to contribute to the debate on advertising effectiveness using AI-powered systems, using advertising value as a measure of effectiveness in the online shopping context, addressing trust toward the medium, in this case, toward intelligent virtual assistants, and how the hypothesized relationships change when moderated by trust. The theory of social presence (Biocca et al., 2003; Lee, 2004; Lee & Nass, 2003; Lombard & Ditton, 1997; Short et al., 1976) and the computers are social actors (CASA) paradigm (Moon, 2000; Nass et al., 1994; Nass & Moon, 2000), were employed as pivotable theories along HCI, HRI, and HAI.

Two major primary human cues, perceived human-likeness (H1) and perceived intelligence (H2), were hypothesized as social presence predictors in the context of advertising through the IVA, similar to the research developed by Jin and Youn (2022) but applied in the AI-Chatbot continuance intention context. Regarding the first hypothesis, in which perceived human-likeness was postulated as an antecedent and predictor of social presence, it came up as supported, corroborating Jin and Youn's (2022) findings, but also similar to those from other studies, such as Kim et al. (2020), and Munnukka et al. (2022) that considered anthropomorphism as an antecedent of social presence, in the context of consumer-brand relationship and of virtual service assistants, respectively. As for perceived intelligence as a predictor of social presence (H2), this hypothesis was supported in our study, differing to the findings of Jin and Youn (2022), possibly due to the fact of the IVA being a “not-so-smart”, non-animated (static) chatbot. Possibly, intelligence expectations from participants about this specific IVA were lower, derived from the less innovative appearance.

In the current study, empathy refers to the cognitive and emotional response to the IVA in the video (Cummins & Cui, 2014; Mehrabian & Epstein, 1972; Park et al., 2022; Pelau et al., 2021), which comprises the recognition of the feelings revealed by the IVA in the video, and the contagious state of feeling the same as the IVA in the video (Lee et al., 2023; Park et al., 2022; Simon, 2013). Empathy is of paramount importance in this study. Recent studies have stated its relevance in relationship marketing, as it promotes positive marketing outcomes like engagement, compliance, and satisfaction, creating stronger relationships (Hwang & Zhang, 2018; Yun & Park, 2022). Our study retrieved a positive and significant relationship between social presence and empathy (H3a), coherent with the findings of Shin (2018) for the high VR immersive groups. Cohen et al. (2021) also identified social presence mediating the experiment’s VR condition (versus 2D video) and empathic care. Moreover, social presence was also inferred to influence advertising value positively in the current study. Therefore, hypothesis H3b was supported and consistent with the findings from Chong et al. (2023) and Maroufkhani et al. (2022) which were applied in the live streaming commerce platforms and voice assistants contexts, respectively.

In immersive journalism via VR, Shin & Biocca (2018) determined a positive correlation between satisfaction and perceived value and posited empathy's significant and positive influence on satisfaction. Kim and Huh (2021) referred to empathy with amateur video creators as an intrinsic motivation to enhance intentional ad-viewing, directly dependent on advertising value. In fact, according to previous studies from Ducoffe (1995, 1996) and Ducoffe and Curlo (2000), ad-viewing predisposition relies on the expected advertising value by consumers as potentially addressing their personal interests. An indirect effect between empathy and perceived value, being mediated by perceived quality, was described by Keshavarz and Jamshidi (2018), whereas Shanshan and Wenfei (2022) corroborated an indirect effect between empathy and perceived value, but in this case, mediated by confirmation, based on the Expectation Confirmation Model applied in the massive open online courses context. To a similar extent, our study retrieved H4 as significant, establishing empathy toward the IVA as a predictor for the perceived value of advertising.

As for the interaction moderation here hypothesized in terms of trust toward the intelligent virtual assistant over the relationship between social presence and empathy (H5a), between social presence and advertising value (H5b), and between empathy and advertising value (H5c), only H5a turned out to be significant. Therefore, as trust in the IVA is enhanced, the relationship between social presence and empathy will be strengthened. Trust has been established in different studies as endogenously dependent on social presence in different contexts, such as e-commerce (Attar et al., 2023; Su et al., 2021), social media branded content (Liu et al., 2022), and HAI (Sun & Guan, 2022; Toader et al., 2019). Nevertheless, trust and empathy are also postulated as social enablers and crucial elements in relationship building. The relevance of trust in moderating the relationship between social presence and empathy is reinforced by other studies (Mangus et al., 2020; Pelau et al., 2021; Sun & Guan, 2022). Both paths connected to advertising value were not significantly moderated by trust towards the IVA (H5b and H5c), possibly due to the lack of fit regarding the advertised products and participants interests or needs. Online generic ads are reported to be losing effectiveness (Bleier & Eisenbeiss, 2015), while personalized advertising may also cause privacy concerns, a sense of distrust and intrusiveness (Van Doorn & Hoekstra, 2013), upon the amount of personal data disclosed in tailored ads. These negative effects potentially brought by personalized advertising are only partially mitigated if highly fitting consumer current needs but not by offered discounts.

To understand how IVA's anthropomorphic cues influence the hypothesized relationships (H6), a complete model moderation assessment was undertaken, according to the IVA that each participant watched in the video. *Alexa* is represented by the smart speaker Echo Studio, with voice as the most salient anthropomorphic cue. The AI avatar *Anna*, besides its voice, possesses an advanced and realistic human resemblance, capable of moving her mouth when interacting with the user. In this case, *Anna* has a much stronger level of anthropomorphism than *Alexa.* Estimating the model separately for each IVA's dataset, the results exhibited distinctive path coefficients and significances (*p*-values) of the different paths that came out considerably different from each other versus the complete model. For *Alexa*'s dataset, the model performs similarly performance to the complete dataset with trust only significantly moderating the relationship between social presence and empathy. For *Anna*'s dataset all trust toward the IVA moderation hypotheses came out supported, even though the direct path from social presence to advertising became not significant for both IVAs. Therefore, MGA results found a significant difference between the two IVAs' subsamples for the moderation by trust toward the IVA on the relationship between empathy and advertising value. A plausible explanation for this result relies on the uncanny valley theory (Mori, 1970; Mori et al., 2012), as different anthropomorphic degrees of the technology evoke different emotional responses, also applicable in the context of advertising through an IVA. This corroborates the findings from Blut et al. (2021) that proceeded with a meta-analysis of physical robots and virtual chatbots regarding the effect of their anthropomorphism and customer's intention to use the technology. The authors found technology's anthropomorphism to have a strong and positive impact, as suggested by the anthropomorphism theory (Duffy, 2003). Moreover, participants have had different experiences with AI devices, and the stimulus may not have guaranteed personal, direct, and temporal sufficient contact with the IVA, which can partially explain the lack of significance regarding the direct path from social presence to advertising value.

One of the most important results from this study is related to the relevance of empathy in human-AI interaction. In both individual estimations, social presence no longer directly influences advertising value, only indirectly through empathy, revealing itself as a full mediator in this path. Therefore, the perceived value of advertising is strongly dependent on the empathy that the IVA can foster with the user, which is established as dependent on the IVA level of anthropomorphism, consistent with the findings of existing literature (Bickmore et al., 2010; Go & Sundar, 2019; Park et al., 2022; Pelau et al., 2021; Sun & Guan, 2022). Regarding the interaction with *Alexa*, there was a significant moderating role of trust toward the IVA on the relationship between social presence and empathy, as for the complete model. In contrast, when interacting with *Anna*, all interaction moderations were significant.

Chapter 5: Human, Am I Accepted? Exploring the Influence of Intelligent Voice Assistants on Advertising Value and Acceptance – A Psychophysiological Approach

5.1. Introduction

Advertising is acknowledged as one of the most critical fields in marketing (Buil et al., 2013) due to the investment efforts made by brands to capture audience attention and preference. The worldwide ad revenue by media owners for 2022 was estimated to surpass 800 billion USD (GroupM, 2022b), with a positive trend for the following years, and is expected to exceed the trillion USD mark in 2026 (Zenith, 2023). Self-reports have been extensively used in marketing research to understand and predict consumer behavior relying on conscious feelings and thoughts (Alsharif et al., 2023) concerning a different marketing mix, with advertising as one of the most sought-after. Different studies advocate for a mixed-method approach, combining self-reports with psychophysiological data (Casado-Aranda & Sanchez-Fernandez, 2022) to avoid possible advertising or product development failures induced by the judgmental bias attained from the most traditional marketing research methods (Jordão et al., 2017; Vecchiato & Tempesta, 2015). The application of neuroscientific methods to marketing can provide a deeper understanding of consumer behavior regarding their true and unconscious preferences, feelings, and motivations surrounding their decision-making process (Plassmann et al., 2012; Xu et al., 2023). In more traditional research methods, such as questionnaires, interviews, and focus groups (Harris et al., 2018), individuals' "stated preferences are influenced by conscious cognitive control rather than true subconscious attitudes" (Xu et al., 2023, p. 2).

Consumer neuroscience and neuromarketing are two disciplines derived from neuroscience that have featured a significant development in marketing, recognized as playing a major impact in understanding and assessing consumer cognitive and affective mechanisms that are triggered by marketing stimuli (Bell et al., 2018; Casado-Aranda & Sanchez-Fernandez, 2022; Costa-Feito et al., 2023; Kakaria et al., 2023). Neuromarketing aims to go beyond the traditional methods, making use of still-evolving neuroscientific tools that may be grouped into two main categories following Lim (2018) and Oliveira et al. (2022): (1) non-neuroimaging or physiological tools, such as Eye-Tracking, Skin Conductance Response (SCR), Electrocardiogram (ECG), and Facial Electromyography (fEMG); and (2) neuroimaging or neurophysiological tools, such as Electroencephalography (EEG), Magnetoencephalography (MEG), Single-Neuron Recording, and Functional Magnetic Resonance Imaging (fMRI).

This study was designed to address major gaps and research avenues identified in Study 1 (Chapter 2) and Study 2 (Chapter 4). Technological developments, such as AI, were determined in Study 1 as an underexplored topic in neuromarketing. Moreover, even though AI-enabled technology has been getting attention from scholars, the effectiveness of advertising through intelligent virtual assistants (IVA) needs to be further researched, especially with the combination of self-reported and psychophysiological data.

An intelligent virtual assistant (IVA) refers to a computational system powered by AI, machine learning, and natural language processing (NLP) algorithms (Lv et al., 2021; Tussyadiah & Miller, 2019; Vimalkumar et al., 2021). This system can process a large volume of data in real time, enabling tasks based on user input through commands or voice-based instructions. These assistants possess diverse capabilities, including robotics for movement, speech recognition, computer vision, and emotional intelligence (Huang & Rust, 2022; Krasnokutsky, 2022; Russell & Norvig, 2016).

Voice-enabled advertising is still unavailable globally, limited to some pioneer advertisers and concrete business cases, such as Burger King, Domino's Pizza, or Tide in the United States of America (Infomo Global, 2023). Advertising in voice interfaces is still an untapped field as the big companies owning the main intelligent virtual assistants face challenges, including limited user adoption, targeting options, and privacy concerns. Moreover, there is hesitation in advertising through IVAs regarding how these devices are made available to the general public (RDW Group, 2018), as consumers have to pay for the smart technology in which the virtual assistants operate. However, Amazon is reported to have *Alexa* as an advertising vehicle in 2023 (Schwartz, 2022), which makes this research even more appealing to managers and practitioners for a sustained and deeper understanding of how to use this technology effectively.

Pertaining to emotional response assessment, this study considered the dimensional theory of emotions (Russell, 1980; Russell & Pratt, 1980; Wundt, 1904) approach. The two-dimensional space comprising pleasure and arousal (Citron et al., 2014; Donovan et al., 1994; Sherman et al., 1997) was undertaken and appraised through psychophysiological measures, which included the analysis of participants' Electrodermal Activity (EDA) and Heart Rate Variability (HRV) data. Although conventional self-report instruments are commonly employed in experimental research (Guerreiro et al., 2015), it is highly recommended to complement these with psychophysiological data (Bell et al., 2018). Neuroscientific methodologies have been extensively acknowledged as valuable tools for comprehending consumers' spontaneous and unconscious emotional reactions (Liu & Huang, 2023; Rita et al., 2021). These approaches offer insights less reliant on participants' conscious and potentially biased self-reports (Venkatraman et al., 2015). Electrodermal activity (EDA) or SCR is established as appropriate for arousal measurement (Höfling et al., 2020; Oliveira et al., 2022; Rita et al., 2023) and HRV for emotional valence and arousal levels (So et al., 2021).

Building upon a conceptual foundation rooted in various theoretical frameworks, including the Stimulus-Organism-Response (S-O-R) framework (Mehrabian & Russell, 1974; Russell & Pratt, 1980), parasocial interaction (PSI) theory (Horton and Wohl, 1956), the theory of arousal (Mehrabian, 1996; Russell, 1980), the circumplex model of affect (Russell, 1980; Xu et al., 2023), mediated relationship development theory (Rubin & McHugh, 1987), and the humanness-value-loyalty (HVL) theoretical framework (Belanche et al., 2021), the objective of the third study is to make a significant contribution to the literature regarding the fundamental determinants of advertising effectiveness. This effectiveness is assessed based on advertising value (AV) and advertising acceptance (AA), according to the proposed framework from Wu (2016), providing valuable insights into the impact of various factors on consumer responses to advertising stimuli. Furthermore, to our knowledge, only one study has analyzed ad acceptance antecedents using IVAs (Guerreiro et al., 2022), but with no psychophysiological measures application.

One central point of contention regards the anthropomorphism of the virtual assistant for optimal results, whether it shall be more machine-like or human-like (Han et al., 2023), a topic that has been discussed in previous literature but that is still lacking findings consistency (Blut et al., 2021; Mariani, Hashemi, et al., 2023). Anthropomorphism refers to how customers attribute non-human agents with human features (Epley et al., 2007; Mariani, Hashemi, et al., 2023). However, research on the presence of anthropomorphic features has yielded mixed findings (Blut et al., 2021; Mariani, Hashemi, et al., 2023), one question this research addresses. The study of anthropomorphism within the scope of parasocial interaction with an intelligent virtual assistant has not provided clear strategic guidelines on how brands should engage with users during a human-AI interaction (Han et al., 2023; Huang & Rust, 2021b). The anthropomorphic attributes of AI assistants hold significant cultural importance, as there is a prevailing preference for chatbots and voice assistants to exhibit human-like features, often perceived as more competent and sophisticated (Puntoni et al., 2021), setting unrealistic expectations for these agents' performance (Go & Sundar, 2019), leading to disappointment, frustration, or distrust (Lu et al., 2019; Pentina et al., 2023). These conflicting results align with the uncanny valley theory (Mori, 1970; Mori et al., 2012). According to this theory, humans find robots more appealing as they become more human-like, but only up to a certain threshold (Mariani, Hashemi, et al., 2023). Beyond this threshold, individuals experience discomfort with humanoids, marking the onset of the uncanny valley effect, where the benefits of human-likeness decline, and an eerie feeling emerges.

For this study, the following research questions are proposed:

- RQ1: Can voice-enabled advertising through IVA enhance advertising effectiveness via advertising value and acceptance?
- RQ2: How do social and emotional responses to advertising through IVA influence advertising effectiveness?
- RQ3: Will autonomic responses to stimuli complement participants' self-reported data?
- RQ4: How does IVAs' anthropomorphism (*Alexa* or *Anna*) affect the relationships between the different latent variables?

The rest of this chapter is organized as follows. In section 2, we present the state-of-the-art regarding the stimulus-organism-responses (S-O-R) model theory, parasocial interaction (PSI) theory, emotional responses assessment through psychophysiological measures, advertising affect, as well as the hypotheses formulation and conceptual model. Section 3 describes the methodology, followed by a fourth section with the statistical analysis results and a discussion in the fifth section.

5.2. Theoretical Background

5.2.1. The Stimulus-Organism-Response Theory

The Stimulus-Organism-Response (S-O-R) framework (Mehrabian & Russell, 1974; Russell & Pratt, 1980), also known as the Mehrabian-Russell (M-R) model, has become an important tool in experimental research. This framework originated in environmental psychology, considered valuable for studying the impact of store atmosphere on individuals' shopping behavior (Donovan & Rossiter, 1982). At the time, environmental psychologists mainly focused on work, residential, and entertainment environments. Donovan and Rossiter (1982) formally presented a proper extension of the M-R model to the retail context years later.

In the context of the S-O-R framework, the stimulus (S) is conceptualized as external factors that elicit, incite to action, or increase action, acknowledged as enablers of consumers' internal states (Bagozzi, 1986; Gu et al., 2023; Mehrabian & Russell, 1974; Pantano & Viassone, 2015). Influenced by its environmental roots, most stimuli consider environmental loads, that is, the novelty and complexity degree depicted in the environment (Donovan & Rossiter, 1982; Mehrabian, 1977; Mehrabian & Russell, 1974; Vieira, 2013). The knowledge an individual has of the environment (novelty) and the assortment of elements, features, or changes (complexity) is used for the stimuli classification (Mehrabian, 1977), enabling an internal or external descriptive assessment of the location in which the interaction takes place (Bitner, 1992; Vieira, 2013; Zhang et al., 2014). In technological contexts, the stimuli are often represented by features exhibited by the technology itself (e.g., website, apps, software, AI-powered devices), comprising a wide range of factors such as perceived coolness (Chen & V.G., 2022), anthropomorphic appearance (Elsharnouby et al., 2023), innovativeness (Kautish et al., 2023), immersion or telepresence (Suh & Prophet, 2018), interactivity (Herrando, Jiménez-Martínez, Martín-De Hoyos, Asakawa, et al., 2022), integration (Pantano & Viassone, 2015), realism/authenticity (Kim et al. 2020), or the level of online customer engagement (Perez-Vega et al., 2021).

The organismic (O) variables designate internal processes mediating the external environmental stimuli and the approach-avoidance behavioral responses (Bagozzi, 1986; Eroglu et al., 2001; Qin et al., 2021; Sherman et al., 1997). The M-R model proposed three-dimensional emotional states that consumers experience: (1) pleasure; (2) arousal; (3) dominance (PAD) (Bagozzi et al., 1999; Donovan & Rossiter, 1982; Mehrabian & Russell, 1974; Vieira, 2013). The PAD emotional theory was initially proposed by Wilhelm Wundt (Wundt, 1904), also known as the father of psychology. However, Russell and Pratt (1980) suggested a two-dimensional representation of emotions, discarding the dominance dimension, whose approach found support from other authors due to its marginal or null contribution to the model's variance explanation in different studies (Donovan et al., 1994; Donovan & Rossiter, 1982; Sherman et al., 1997).

According to the M-R theory, every environmental stimulus is actively processed by organisms, evoking cognitive, affective, and psychological-driven traits that, in turn, produce behavioral responses (R) based on the approach-avoidance taxonomy (Perez-Vega et al., 2021; Sherman et al., 1997; Vieira, 2013). Stimuli with positive valence would foster the approach behaviors (e.g., act, purchase intention), whereas aversion behaviors (e.g., not to act) would be evoked by negative emotional traits (Gu et al., 2023; Jang & Namkung, 2009; Sherman et al., 1997). These approach-avoidance responses are postulated as comprising four features (Donovan & Rossiter, 1982; Mehrabian & Russell, 1974): (1) the willingness to physically stay in (approach) or out (avoid) of the environment; (2) the desire to explore the environment (approach), or to not interact with it (avoid); (3) the disposition to interact with others in the environment (approach), or to avoid and ignore any communication with others (avoid); (4) satisfaction level enhancement (approach) or obstruction (avoid) regarding task performance.

In the last decade, the number of S-O-R framework applications to the technological industry is reinforcing its relevance, with studies covering diverse technological advances such as social networking sites (SNS) (Hsieh, 2023), social commerce (Herrando et al., 2022; Wang et al., 2019b; Zhang et al., 2014; Zhang & Benyoucef, 2016), e-commerce (Chan et al., 2017; Fu et al., 2018; Wang et al., 2023), augmented and virtual reality (Animesh et al., 2011; Kim et al., 2020; Liu & Huang, 2023; Qin et al., 2021), live streaming (Gao et al., 2023; Gu et al., 2023), and AI-enabled technologies (Perez-Vega et al., 2021), where intelligent virtual agents are playing the major protagonists' role (Elsharnouby et al., 2023; Frank & Otterbring, 2023; Kautish et al., 2023; Maduku et al., 2023).

This study is grounded on the S-O-R framework, aiming to analyze consumers' reactions to video advertising through two different IVAs (*Alexa* and *Anna*) exhibiting different anthropomorphic levels (stimuli). The popular voice assistant *Alexa* portrays a lower anthropomorphic level due to its smart speaker-like appearance but still reveals some human-like cues, such as a female voice and a name, as well as the ability to interact with the user, which might be perceived as resembling human intelligence. On the other hand, *Anna* is an AI Avatar, so in addition to all *Alexa*'s human-like cues, *Anna* displays a human figure and, therefore, a greater anthropomorphic level. Anthropomorphism refers to the attribution of human features, traits, or behaviors to non-human beings, either visible or non-visible, consciously or not (Guerreiro & Loureiro, 2023; Li & Sung, 2021; Munnukka et al., 2022). In summary, anthropomorphism assigns human-like appearances and actions to humanoids or nonhuman agents (Kim & Im, 2023). In previous studies, humanness was identified as fostering emotional connections in the HAI (Adam et al., 2021; Kopalle et al., 2022; Prentice et al., 2023), reinforcing the sense of confidence and compelling trust toward the IVA.

To a broader extent, trust can be ascribed as the psychological state related to the willingness to rely on an object or being (human being or not), in which one deposits confidence, and before which one can show greater vulnerability (Mayer et al., 1995; Moorman et al., 1993; Rousseau et al., 1998). Previous research has reported trust as being positively influenced by the degree of human-likeness exhibited by an intelligent agent (Alboqami, 2023; McLean et al., 2021; Pelau et al., 2021). Therefore, the following hypothesis is proposed in the context of advertising through IVA:

H1a: Perceived human-likeness positively influences trust toward the IVA in the context of advertising through the IVA.

IVA's appearance has been the focus of several studies (Crolic et al., 2022; Go & Sundar, 2019; Kim & Im, 2023), in addition to its technological, cognitive, or behavioral capabilities. No one is certainly indifferent to what IVA looks like, whether more machine-like or more human-like. In order to ascertain the possible impact exerted by perceived human-likeness on the advertising value perception, the humanness-value-loyalty (HVL) theoretical framework proposed by (Belanche et al., 2021) was considered. The HVL model is grounded on the uncanny valley concept from Masahiro (Mori, 1970; Mori et al., 2012) and posits that an agent with more human-like features leads to higher value expectancy (Pizzi et al., 2023). Previous studies identified that people tend to treat differently intelligent agents with a more human appearance from those with an inanimate and more machine-like appearance (Chari et al., 2016), which is supported by the HVL model, as individuals attribute to these agents a greater competence, sophistication, and warmth, and thereby higher expectations regarding the service value (Belanche et al., 2021). In the specific context of advertising, the perceived value of advertising is conceived as the assessment of its relative utility, relevance, or significance regarding the information provided to consumers (Ducoffe, 1995, 1996). Based on the HVL framework, we suggest that when people perceive the communicator of an ad as more human-like, they tend to perceive a higher value in the advertisement. Therefore, the following hypothesis can be formulated in the context of advertising through IVA:

H1b: Perceived human-likeness positively affects advertising value in the context of advertising through the IVA.

The stimuli are then intervened by the emotional states experienced by the participants in terms of pleasure, arousal, trust toward the IVA, parasocial relationship (organism), and the relationship with both advertising value and advertising acceptance (response).

5.2.2. From Parasocial Interaction to Parasocial Relationship Theory

Research on Parasocial Interaction (PSI) and Parasocial Relationship (PSR) has frequently been overlapping even though these terms account for different types of social connections (Schramm, 2008). Parasocial interaction, for example, was first proposed by Horton and Wohl (1956), which designated it as a "simulacrum of conversational give and take" (p. 215) between the media spectator and media performer (the persona). In other words, PSI is an illusionary face-to-face interaction between individuals and a persona or character in the context of the media exposure drawn by the "new" mass media (television, radio, and movies) (Greenwood, 2008; Horton & Wohl, 1956; Pitardi & Marriott, 2021). This concept relies on a mediated, one-sided, cognitive, affective, and conative interaction, in which only the persona's actions can be observed by the spectator, whereas the spectator's reactions cannot be directly observed by the persona but only anticipated instead (Breves et al., 2021; Horton & Wohl, 1956; Schramm, 2008). Hence, there is a lack of mutuality or reciprocity during the interaction in PSI (Greenwood, 2008; Horton & Wohl, 1956; Schramm & Hartmann, 2008; Zheng et al., 2020). PSI was found to be driven by different mechanisms (Labrecque, 2014; Schramm & Hartmann, 2008), including, for example, persona's attractiveness, duration and repetition of exposure to the persona, identity similarity, verbal and non-verbal addressing style, and the spatial distance regarding the persona (Chung & Cho, 2017; Labrecque, 2014; Pradhan et al., 2023; Schramm, 2008; Schramm & Hartmann, 2008).

Horton and Strauss (1957) first attempted distinguishing PSI and PSR concepts. Recent studies also contributed to this differentiation by designating PSI as an ephemeral interpersonal process limited to a one-time exposure to the media. PSR, however, is grounded on the PSI concept but not limited to a single exposure, and therefore, enduring beyond the exposure (Dibble et al., 2016; Gleason et al., 2017; Pradhan et al., 2023; Yuan & Lou, 2020). PSR is acknowledged to be a longer-term relationship than PSI. According to Schramm (2008), "PSR stands for a cross-situational relationship that a viewer or user holds with a media person, which includes specific cognitive and affective components" (p. 3503). PSR is fostered upon continuous and repetitive exposure to the media, delving into a deeper imaginary connection sustained by feelings of intimacy, friendship, and identification with the persona (Breves et al., 2021; Cummins & Cui, 2014; Pitardi & Marriott, 2021; Vazquez et al., 2020).

The media has been evolving, whether by the number of TV channels, but also by current new media brought by emerging technology (Kumar et al., 2021; Potter, 2004; Shi & Wang, 2023), such as the web, mobile devices, and even AI-power systems. Moreover, with increasing media formats and devices, individuals spend more time-consuming media content. Hence, the potential for parasocial behaviors is greater than ever before and, for example, individuals may experience a greater sense of closeness and personal acquaintance with celebrities (Chung & Cho, 2017; Ghosh & Islam, 2023; Kim, 2021), as celebrities who are active on social media appear to have greater openness about their lives, and more interactive with their fans and followers, resembling a one-to-one communication, which would make fans feel as if they have a genuine bond with these celebrities (Breves et al., 2019; Hwang & Zhang, 2018; Kim & Song, 2016; Labrecque, 2014). In addition to traditional media and SNS, with a considerable focus on influencer marketing, the PSI and PSR concepts have also been adopted in different contexts, such as e-commerce (Li & Wang, 2023), social commerce (Xiang et al., 2016; Zheng et al., 2020), multi-screening mobile marketing (Vazquez et al., 2020), and intelligent virtual agents (Aw et al., 2022; Han & Yang, 2018; Hsieh & Lee, 2021; Pentina et al., 2023; Pitardi & Marriott, 2021; Whang & Im, 2021).

In the case of artificial intelligence, PSR is an appropriate theory to address the potential bonds elicited during a computer-mediated interaction (Li & Wang, 2023; Pitardi & Marriott, 2021), explaining how feelings of closeness, friendship, or intimacy can be evoked while engaging with intelligent virtual assistants with human-like features (Ki et al., 2020; Pitardi & Marriott, 2021). According to Levy (1979), media figures with a warmth and conversational tone would easily create stronger feelings of parasocial relationship. In the context of intelligent voice assistants, able to keep a personalized conversation with the user, as these agents assume a more human-like appearance and behavior, people tend to develop relationships with a sense of closeness and intimacy with them (Whang & Im, 2021). Therefore, considering the context of advertising through IVA, the following hypothesis is proposed:

H1c: Perceived human-likeness positively influences parasocial relationship in the context of advertising through the IVA.

5.2.3. Behind Emotional Responses

Measuring an individual's emotional state has been recognized as one of the most puzzling problems among different research fields (Mauss & Robinson, 2009). Several theoretical models have been proposed over the years, aiming at emotional response assessment, including the discrete or categorical theory (Darwin, 1872; Ekman & Friesen, 1971; Izard et al., 1993; James, 1884, 1994; Tomkins, 1962), the appraisal theory (Arnold, 1960; Frijda, 1986; Lazarus, 1991; Moors, 2017; Scherer, 2009; Smith & Ellsworth, 1985), and the dimensional theory (Mehrabian, 1977; Reisenzein, 1994; Russell, 1980, 2003; Russell & Pratt, 1980; Wundt, 1904) of emotions. The discrete theory of emotion states that emotions can be categorized by a diverse yet limited set of basic emotions, which list varies between authors (e.g., sadness, joy, anger, contempt, fear, shame, disgust, and surprise). Each emotion is distinguishable from another and exhibits unique characteristics and specific motivational and neurophysiological properties (Bradley & Lang, 2007; Levenson, 2011). According to the appraisal theory, emotion is assumed as a mental reaction to a cognitive appraisal of events, objects, or thoughts (Bagozzi et al., 1999), a coherent and "organized system of coping responses" (Roseman, 2013, p. 141). As for the dimensional emotion theory, it presumes an emotional space composed of an unspecific but limited set of dimensions (Citron et al., 2014), for example, pleasure, arousal, and dominance (Bigné et al., 2005; Mehrabian & Russell, 1974). The latter corresponds to the organismic emotional responses considered in the S-O-R framework (Bagozzi et al., 1999; Donovan & Rossiter, 1982; Mehrabian & Russell, 1974; Vieira, 2013). In advertising research, the dimensional theory of emotion is assumed as appropriate for assessing consumers' emotional responses to advertising (Li et al., 2018).

The PAD affect theory is a popular framework in environmental psychology, as it considers the three basic dimensions (pleasure, arousal, and dominance) to assess individuals' emotional responses to stimuli (Bakker et al., 2014). Pleasure involves feelings of contentment, happiness, delightfulness, or enjoyment (Loureiro, Bilro, et al., 2019; Moon et al., 2016), whereas arousal refers to whether an individual feels active, attentive, stimulated, or excited, driven by his surroundings (Russell & Carroll, 1999; Wu et al., 2008). Dominance regards the perception of control, autonomy, or influence over a specific situation (Mehrabian, 1996; Shah et al., 2023).

However, numerous studies have reached a consensus regarding the insufficient theoretical or empirical evidence to support the inclusion of dominance. Instead, emotions are better explained in a two-dimensional space comprising pleasure and arousal (Citron et al., 2014; Donovan et al., 1994; Sherman et al., 1997). Moreover, pleasure and arousal have been reported as the strongest predictors of consumer behavior (Guo et al., 2017; Russell, 1980; Russell & Pratt, 1980) while positing that "any affect word could be defined as some combination of the pleasure and arousal components" (Russell, 1980, p. 1163), giving place to the Circumplex Model of Affect. Recent studies have supported this bi-dimensional emotional assessment framework (Genevsky et al., 2017; Herrando, Jiménez-Martínez, Martín-De Hoyos, & Constantinides, 2022; Kranzbühler et al., 2020; Laroche et al., 2022; Xu et al., 2023), and therefore, this framework will be assumed in this current study. Russell's (2003) seminal work emphasized this bi-dimensionality approach, designating *core affect* as the combination of both valence (or pleasure) and arousal (or energy) dimensions (Barrett & Bliss-Moreau, 2009; Russell, 2003). The author formerly defined *core affect* as the conscious and non-reflective neurophysiological state, described by both valence and arousal dimensions, and usually not object-oriented. To this extent, emotional valence describes whether an emotion is positive or negative, while arousal refers to its intensity (Cacioppo et al., 2018; Citron et al., 2014). *Core affect* provides a common currency, as designated by neuroeconomists, useful for a qualitative comparison of events, moral judgments, or language comprehension (Barrett & Bliss-Moreau, 2009). The core affective circuitry involves the amygdala and ventral striatum, brain areas usually evoked by emotional events (Barrett & Bliss-Moreau, 2009; Cacioppo et al., 2018).

Selecting the most suitable method is paramount to retaining the most accurate results for individuals' emotional responses to the stimuli (Li et al., 2018). Even though self-reported methods to measure "conscious" emotions have been evolving and overly accepted in marketing research, they are not free from criticism. The conventional self-reports are still acknowledged as more prone to bias given the fact that: (1) emotions are not language-based, requiring a cognitive effort to recall it and to verbalize it, affecting the experienced affective reaction, making it a result of mental process and appraisal, instead of an autonomic, involuntary and unconscious process (Dasborough et al., 2008; Kassam & Mendes, 2013); (2) individuals may be unwilling to disclose their real emotions due to social desirability concerns (Paulhus, 2002).

Emotions are a complex phenomenon involving multiple channels, with ubiquitous effects underlying interactions (Hatfield et al., 1993), while lacking a consensual definition among the different research areas (Ramsøy, 2019). Social psychologists found evidence of emotions contagiousness effect, from observed to observer, and among observers, influencing their behavior (Russell, 1980; Tombs & McColl-Kennedy, 2003). Emotional contagion refers to responses to emotional stimulus not only in an observational stance (face, voice, or posture) but also in the neurophysiological and autonomic nervous system (ANS) responses (Hatfield et al., 1993). Neural activity is triggered whenever one experiences an emotional event, leading to changes in the autonomic and neuroendocrine systems (Kassam & Mendes, 2013). The arousal theory (Mehrabian, 1996; Russell, 1980) assumes a pivotable role in emotional contagion research by describing how emotional arousal is a consequence of emotional valence/pleasure. According to the arousal theory, emotional pleasure can activate or deactivate emotional arousal, which was also validated by Kumar et al. (2021) in the food delivery apps context. Therefore, the following hypothesis is proposed in the context of advertising through IVA:

H2: Emotional pleasure influences emotional arousal in the context of advertising through the IVA.

Limited research has examined the effect of emotional arousal on trust (Song et al., 2023). Trust judgments are considered an affective and complex process as emotions are crucial for trust (McAllister, 1995) but are highly related to individual traits (Mayer et al., 1995). Positive and negative emotional states are acknowledged to influence one's judgments. Dunn and Schweitzer (2005) established that different emotions evoke different trust levels, as happier participants revealed higher levels of trust, whereas angry participants showed lower trust. According to the circumplex model of affect, every emotional state arises from a bi-dimensional space due to a linear combination of pleasure and arousal (Russell, 1980; Xu et al., 2023). Therefore, considering the context of advertising through IVA, we can hypothesize that:

H3: Emotional arousal can influence trust toward the IVA in the context of advertising through the IVA.

Trust is key in interpersonal interactions (Choi et al., 2019; Rotter, 1967) and HAI (McLean et al., 2020; Pitardi & Marriott, 2021), fostering socialness through personalization (Leite et al., 2013). Trust development is only conducted over a certain period, grounded on consistent and predictable actions from the trustor and trustee (Wu & Chang, 2005). The sense of trust is also an enabler of closeness and intimacy states between active participants involved in the interaction (Ashfaq et al., 2020; Pelau et al., 2021; Skjuve et al., 2021). This study is grounded on the commitment-trust theory (Morgan & Hunt, 1994), which relies on trust as predicting relationship commitment, and on the model of trust proposed by Mayer et al. (1995), supported in recent studies (Casaló et al., 2011; Choi et al., 2019). The model of trust defines trust as a multidimensional construct comprising honesty, benevolence, and competence, as trusting beliefs, and proven to be related to PSI in the context of online travel communities. PSI is considered the embryonic stage of PSR, developed after repetitive exposure to the medium. Rungruangjit (2022) also reported a positive and significant relationship between trustworthiness, a dimension of source credibility, and PSR for the streaming industry. Therefore, the following hypothesis is proposed in the context of advertising through IVA:

H4a: Trust toward the IVA positively influences parasocial relationship in the context of advertising through the IVA.

Additionally, attitudes toward the advertisement are positively influenced by trust (Cheung & To, 2017; Wiese et al., 2020). Moreover, perceived trust is also reported as positively influencing perceived value in online shopping (Kim et al., 2012). Hence, the following hypothesis is presented in the context of advertising through IVA:

H4b: Trust in the IVA positively influences advertising value in the context of advertising through the IVA.

5.2.4. Advertising Effectiveness Through Advertising Value and Advertising Acceptance

Advertisers and their advertising agencies constantly pursue more effective ads, using various formats in different media channels to reach the proper target audience at the right time (Belanche et al., 2017a; Eckler & Bolls, 2011). Technological advances are creating new opportunities to communicate in unprecedented ways (Campbell et al., 2022; Kim et al., 2022), claiming the target's attention (Fay et al., 2019) while dodging feelings of intrusiveness, privacy violation, and distrust (Maduku et al., 2023; Natale & Cooke, 2021; Niu et al., 2021; Van den Broeck et al., 2019). Advertising has assumed different formats over the last decades, moving from static to dynamic ads, from offline to online media, and from massified to personalized messages (Baabdullah et al., 2022; Canhoto et al., 2023; Zimmermann et al., 2023), with the ultimate purpose of enhancing advertising effectiveness (Chandra et al., 2022; Liu & Yu, 2022; Santoso et al., 2022).

Artificial intelligence is emerging as a powerful tool to enhance advertising effectiveness (Lv & Huang, 2022; Shumanov et al., 2022), among other processes, through personalization that connects the customers with marketers, able to foster an emotional bond, leading to a state of engagement (Kumar et al., 2019) and creating a sense of individual customer experience (Aksoy et al., 2021; Chandra et al., 2022; Lv & Huang, 2022). Advertisers frequently use the Cognition–Affect–Conation model (Lavidge & Steiner, 1961) to measure advertising effectiveness. This model is a popular framework for describing the primary responses from consumers to advertising messages, grounded on the classification of advertising functions into the three main psychological behavioral dimensions: (1) *cognitive responses* that refer to the thinking, intellectual and mental stages (e.g., attention, awareness, perceived value, perceived quality, brand image, brand trustworthiness); (2) *affective responses*, the emotional and feelings-related stage (e.g., brand likability, preferences, satisfaction); (3) and *conative responses*, in which feelings change into actions (e.g., purchase intentions, word of mouth intention, continuance intention, acceptance, willingness, brand loyalty) (Bart et al., 2014; Grewal et al., 1997; Lavidge & Steiner, 1961; Vakratsas & Ambler, 1999; Valenti et al., 2023; Wu, 2016; Zeng et al., 2023). Other quantitative measures such as sales or share impact, audience-related metrics, or the campaign's relative costs (cost per impression, per click, per rating, per thousands of contacts) should only be assessed for advertising effectiveness when a goal has been previously set up.

This study assesses advertising effectiveness by measuring advertising value and acceptance, following Wu's (2016) framework. Advertising value can be ascribed as a cognitive response to advertising, according to its conceptualization as the relative utility or significance of the information provided (Ducoffe, 1995, 1996) and a reliable behavior predictor (Ha et al., 2014). Drawn on the grounds of the uncertainty reduction theory (Berger & Calabrese, 1975), the mediated relationship development theory (Rubin & McHugh, 1987) posits parasocial interaction as a form of intimacy that the audience establishes with the media persona in which social attractiveness of the latter is fundamental. In the context of television, social attraction will lead to rewarding relationship development based on the anticipated rewards appraisal from the social exchange theory (Cook et al., 2013). Moreover, theorized as preceded by PSI, PSR was found to positively affect the evaluation of the product recommended by a voice assistant (Whang & Im, 2021), which is similarly conceptualized regarding the perceived value of the recommendations provided by the IVA. Therefore, the following hypothesis is proposed in the context of advertising through IVA:

H5a: Parasocial relationship positively affects the advertising value in the context of advertising through the IVA.

Advertising acceptance, identified as a conative response to advertising, refers to the sense of appropriateness and fairness that a particular advertisement elicits among its audience (Van den Broeck et al., 2017) or to the willingness to receive more information and to put effort into establishing or reinforcing the relationship with the advertised brand or company (Belanche et al., 2017b; Sultan et al., 2009). In this case, depending on the interactions available in the specific type of advertising in analysis, customers can freely choose their coping behavior with advertising (avoidance or acceptance) (Lee et al., 2022). The technology of acceptance model (TAM) proposed by Davis et al. (1989) is a popular model to predict technology adoption and usage, developed as an adaptation of the theory of reasoned action (TRA). Fishbein and Ajzen (1975) established behavioral intentions as the extent to which the individual is willing to perform a task or to assume a coping behavior. In this study, behavioral intention refers to advertising acceptance, consistent with the framework used by Parreño et al. (2013). Within the TAM framework, customers' attitudes toward the technology will predict their intentions regarding technology adoption, which, in turn, are determined by the technologies' perceived usefulness and ease of use (Davis, 1989).

TAM is recognized in different studies as one of the most suitable frameworks for interactive advertising acceptance research (Belanche et al., 2017b; Parreño et al., 2013), even though some authors stand for the adoption of multiple theories simultaneously due to the multidisciplinary environment of digital advertising (Bakr et al., 2019). TRA is stated as solely focusing on predicting behavioral intentions rather than studying any drivers of attitudes, whereas TAM is also criticized for the limited drivers of attitudes, excluding other variables pertaining to the advertising process and message features, from which interactivity (Kim et al., 2023; Lee et al., 2022; Liu et al., 2019) and personalization of the message (Murillo-Zegarra et al., 2020; Van den Broeck et al., 2017; Yang & Gao, 2021) are currently key constructs. More recent models, such as TAM2 and UTAUT2 (the extended Unified Theory of Acceptance and Use of Technology), have also been employed (Guerreiro et al., 2022) in advertising acceptance drivers research, in addition to Ducoffe's web advertising model (Ducoffe, 1995, 1996), Persuasion Knowledge Model (Friestad & Wright, 1994; Lee et al., 2022), or even Uses and Gratification Theory (Katz et al., 1973; Sultan et al., 2009). Advertising acceptance is not a widely studied concept in the literature, covering mainly two contexts, such as mobile advertising (Kim et al., 2023; Liu et al., 2019; Merisavo et al., 2007; Parreño et al., 2013; Sultan et al., 2009) and social media advertising (Belanche et al., 2017b; Lee et al., 2022; Van den Broeck et al., 2017; Yang & Gao, 2021; Zeng et al., 2017), with a quite limited number of studies in IVA context (Guerreiro et al., 2022; Van den Broeck et al., 2019).

Limited studies have analyzed a direct relationship between parasocial relationship and advertising acceptance. One study on parasocial interaction and message acceptance (Nah, 2022) concluded that the more the performer is perceived as authentic, the greater the parasocial friendship, which, in turn, would increase the audience's acceptance of the performer's message. Therefore, in the context of advertising through the IVA, the following hypothesis is formulated:

H5b: Parasocial relationship positively influences advertising acceptance in the context of advertising through the IVA.

The direct relationship between the two stimulus responses considered in the current S-O-R framework, advertising value, and advertising acceptance, was tested by Wu (2016), in which advertising value was established as a positive predictor of advertising acceptance in mobile social network advertising. Hence, in the context of advertising through IVA, the following hypothesis is formulated:

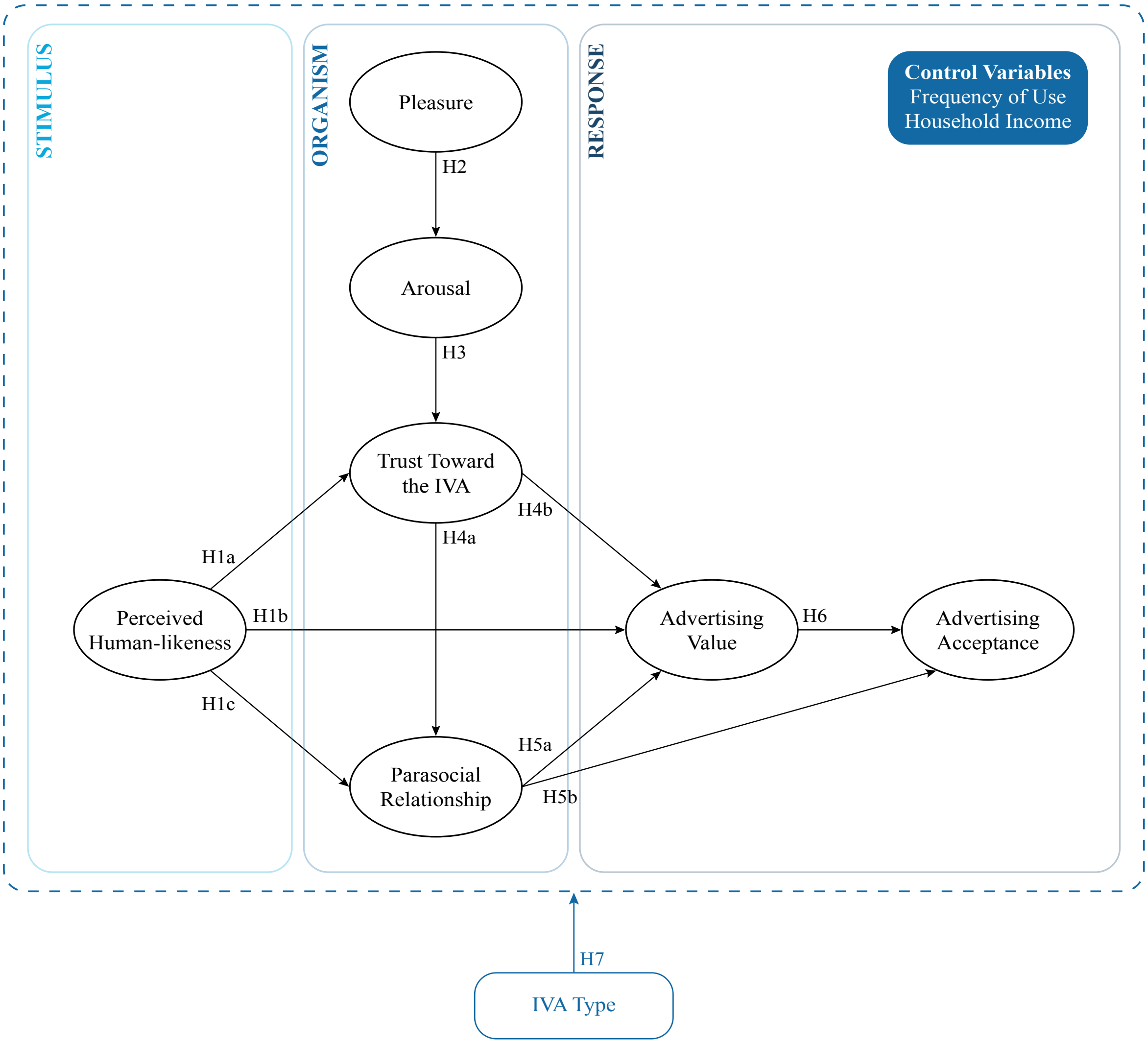
H6: Advertising value positively impacts advertising acceptance in the context of advertising through the IVA.

Based upon the uncanny valley (Mori, 1970; Mori et al., 2012) and anthropomorphism (Duffy, 2003) theories, highly anthropomorphic technology has been reported to induce improved marketing outcomes (Crolic et al., 2022; Munnukka et al., 2022). Therefore, significant differences are foreseen for the different model relationships upon the divergent anthropomorphic salience featured by each IVA (*Alexa* vs. *Anna*). To this extent, the following hypothesis is proposed in the context of advertising through IVA:

H7: IVA's anthropomorphism moderates the relationships in the model in the context of advertising through the IVA.

Following the concepts above and hypothesized relationships, the conceptual model with all formulated hypotheses is displayed in Figure 5.1:

Figure 5.1. Conceptual Model



Source: Own elaboration.

5.3. Methodology

5.3.1. Participants

The ethical committee of Iscte – Instituto Universitário de Lisboa (IUL) approved this study in accordance with the Helsinki Declaration of Ethical Principles (World Medical Association, 2023). This study took place in the Laboratory of Social and Organizational Psychology (LAPSO) at Iscte-

IUL. Before participating, all participants signed a written informed consent, demonstrating their voluntary contribution to the research.

One hundred thirty-four individuals (82 women and 52 men) participated in the study between July and September 2022. Participants were recruited through social media and within the university campus. For their participation, they could win tickets for different summer music festivals. Participants were considered valid only if: (1) they were 18 years old or older; (2) they signed the informed consent; (3) they had not been diagnosed with any heart or other health condition that might influence HR or SCR data; (4) they have regular cardiac activity; (5) the electrodermal activity exhibited usable responses; (6) they completed the survey, without evidence of a carelessness behavior.

Variables	**Characteristics**	**Frequency**	**Percentage**
Gender	Female	75	61.0%
	Male	48	39.0%
Age Group	Under 18	0	0.0%
	18 – 24	76	61.8%
	25 – 34	14	11.4%
	35 – 44	16	13.0%
	45 – 54	12	9.8%
	55 – 64	2	1.6%
	65 or more	3	2.4%
Household Annual Income	Less than €20,000	21	17.1%
	€20,000 – €39,999	46	37.4%
	€40,000 – €59,999	32	26.0%
	€60,000$ – €79,999	10	8.1%
	€80,000$ – €99,999	8	6.5%
	€100,000 – €124,999	2	1.6%
	€125,000 or more	4	3.3%
Education	High-school graduate	59	48.0%
	Vocational training	3	2.4%
	Bachelor's degree	41	33.3%
	Master's degree	16	13.0%
	Doctoral degree	4	3.3%
	No formal qualification	0	0.0%
Occupation	Retired	3	2.4%
	Employed	38	30.9%
	Self-employed	5	4.1%
	Homemaker	0	0.0%
	Student	77	62.6%
	Unemployed	0	0.0%
Frequency of IVA Usage	Multiple times daily	15	12.2%
	Once daily	7	5.7%
	Multiple times weekly	42	34.1%
	Once weekly	15	12.2%
	At least once a month	21	17.1%
	Less than once a month	23	18.7%

Source: Own elaboration.

Table 5.1. Sample demographic characteristics

The final sample comprises 123 participants. Their demographic characteristics are displayed in Table 5.1.

5.3.2. Experimental Design

A laboratory experiment was conducted to test the formulated hypotheses using a mixed-method approach for triangulation purposes. This study addresses some drawbacks of self-report research by collecting psychophysiological measures, such as biometric data. While conventional self-reports are regularly used in experimental research (Guerreiro et al., 2015), the combination with biometrics is enormously beneficial to research (Bell et al., 2018) as a valuable source able to unravel the spontaneous and unconscious emotions in consumer neuroscience, measuring autonomic responses to stimuli (Liu & Huang, 2023; Rita et al., 2021). The psychophysiological measures are identified as a more accurate prediction of participants' emotions, and less dependent on their conscious and potentially biased responses (Venkatraman et al., 2015), and allow for the identification of involuntary changes in cognitive and affective processes (Wang & Minor, 2008).

Emotional arousal (ARS) was measured as the autonomic changes in participants' electrodermal activity (EDA) (Bettiga et al., 2017; Rodero & Potter, 2021), also known as Skin Conductance Response (SCR). The emotional pleasure (PLES) was assessed through participants' cardiac activity registered by the electrocardiogram (ECG). The heart rate variability (HRV) was obtained, consisting of the variation, in time (time domain method), between each heartbeat (Casado-Aranda & Sanchez-Fernandez, 2022), associated with both components of the autonomic nervous system (ANS): (1) the sympathetic nervous system (SNS), related with "fight or flight" response in situations of danger; and (2) the parasympathetic nervous system (PNS), related with "rest or digest", restoring the body back to a calm and relaxed state. HRV provides relevant data on central and peripheral autonomic control (Cacioppo et al., 2018). EDA only registers SNS activity (Boucsein, 2012), whereas HR is influenced by SNS and PNS (Chen & Nowak, 2023). EDA parameters have been strongly correlated with emotional arousal in marketing research (Barnett & Cerf, 2017; Barquero-Pérez et al., 2020; Bettiga et al., 2017; Boucsein, 2012; Caruelle et al., 2019; Guerreiro et al., 2015; Kuijsters et al., 2015; Pozharliev et al., 2022; Rita et al., 2021), while cardiac activity (HR) is posited as being a sensitive measure of emotional valence (i.e., pleasure) (Kakaria et al., 2023; Liu & Huang, 2023; Maxian et al., 2013; Orazi & Nyilasy, 2019; So et al., 2021; Sung et al., 2021; Venkatraman et al., 2015).

The importance of the simultaneous employment of ECG and EDA relies on data sensitivity and difficulty distinguishing between positive or negative reactions to stimuli in a single-method approach (Dawson et al., 2016).

5.3.3. Design and Procedure

This study was conducted in two different stages. In the first stage, which relied on the autonomic physiological measurement, participants were called individually to a quiet room after signing the informed consent. Room light and temperature (22–24 ºC) were controlled and kept unchanged along the data collection process (Boucsein, 2012; Dawson et al., 2016). Each participant was asked to sit comfortably at a 60 cm distance from the desk with a computer screen and presented with further instructions and any clarifications to what they read in the informed consent.

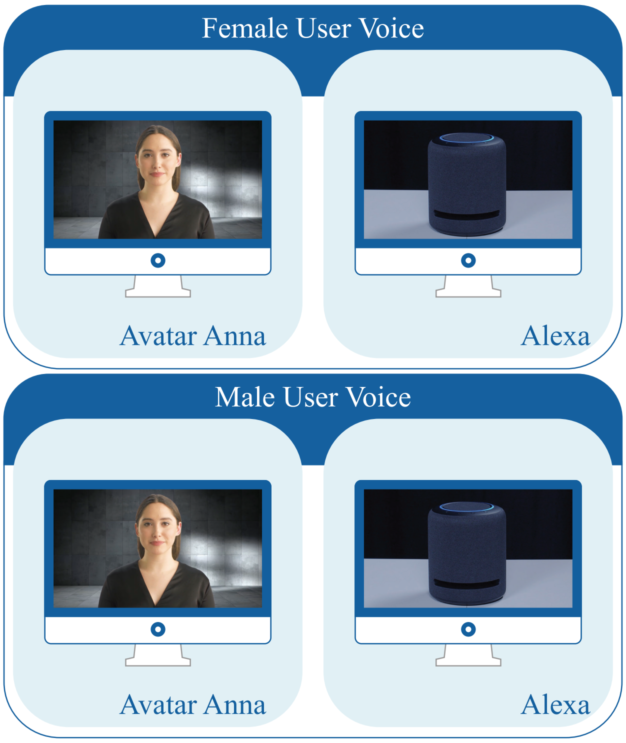
ECG data were collected with a Lead II configuration with three Ag-AgCl disposable electrodes after preparing the skin for better electrode adherence. The BIOPAC MP150 (Biopac Systems Inc.) with the ECG100C amplifier was used and set with a band-pass finite impulse response (FIR) filter of 35 Hz and 0.5 Hz to dodge phase distortion. A 50 Hz notch filter was applied to prevent power-line interference, sampled at a 2,000 Hz rate (Chen & Nowak, 2023).

An isotonic NaCl gel solution was applied to the non-disposable electrodermal electrodes for EDA data recording (Boucsein, 2012). These electrodes were attached to each medial phalanx of the middle and index fingers of the non-dominant hand. The BIOPAC MP150 with the GSR100C amplifier was used and set to a 5,000 μƱ gain rate and a low-pass filter of 10 Hz to detect sweating peaks more accurately. High-pass filters were set to direct current (DC) for absolute conductance values measurement, such as the skin conductance level (SCL) (Boucsein, 2012). Both EDA and ECG signals were recorded with the software AcqKnowledge version 4.1. To check if all signals were being appropriately recorded properly, the participant was asked to inhale deeply to confirm whether the signals would react to it or not.

During the first 288 seconds for baseline measurement, participants were solely listening to relaxing and calm music. After that, task instructions were displayed on the screen, in which the participants were asked to observe a video, imagining themselves in the role of the IVA user in the video. Therefore, a gender congruence condition was imposed so that the voice of the IVA user in the video would match the gender of the participant. The video simulated an interaction between a human and a virtual assistant in an online shopping context for groceries. The type of IVA (AI Avatar *Anna* or Voice Assistant *Alexa*) was randomly assigned to each participant by Qualtrics to ensure an even distribution per type for each gender (see Figure 5.2). The video with the Avatar *Anna* was created with Synthesia (Synthesia, 2022), while the interaction with the voice assistant *Alexa* was created in a studio with an Amazon Echo Studio device. In each video, only the IVA was visible to help a more realistic simulation of a first-person interaction with the virtual assistant. IVA's voice was always feminine, and the same for *Anna* and *Alexa*. This study used a single-factor (IVA Type: *Alexa* vs. *Anna*) between-subject research design.

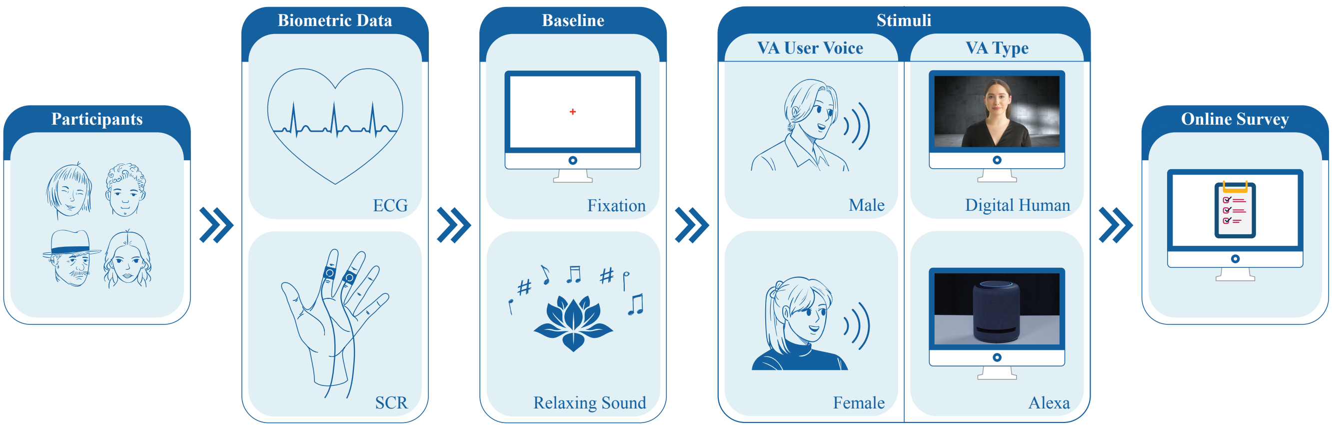
In the second stage of the experiment, participants were asked to move to an adjacent room and to complete the online survey (see Appendix B) with the supervision of another researcher to clarify any possible questions they might have (see Figure 5.3).

Figure 5.2. The video ads stimuli



Source: Own elaboration.

Figure 5.3. Experimental design



Source: Own elaboration.

For electrodermal activity measurement, the tonic SCL was selected (Chen & Nowak, 2023; Dawson et al., 2016; Rita et al., 2021; Shoval et al., 2018) to capture spontaneous electrodermal activity (Stern et al., 2001). As SCL is expressed in microsiemens (μs) units, in which data distribution shape is usually leptokurtic and positively skewed, the logarithmic transformation was applied (*log* SCL) to standardize and normalize the data among participants (Boucsein et al., 2012). In what concerns cardiac activity, the heart rate variability (HRV) was collected, a known measure of pleasure (Bell et al., 2018; Dulleck et al., 2011; Kakaria et al., 2023; Task Force, 1996). Data were normalized with the logarithmic transformation (*log* HRV) (Bos et al., 2013). *Log* SCL and *log* HRV reactivity were analyzed by subtracting the score obtained during the video from the baseline score (Chen & Nowak, 2023). Therefore, the physiological responses collected are not uniquely based on the stimulus but also the individual baseline level for arousal and pleasure (Beck & Egger, 2018; Liu & Huang, 2023).

5.3.4. Non-Physiological Measurement Scales

A semantic differential scale adapted from Ho and MacDorman (2010) assessed *perceived human-likeness* (PH). However, only four items of this five-item scale were employed, as the fifth item (Moving rigidly – Moving elegantly) was classified as non-applicable in the context of this research.

For the construct *trust toward the IVA* (TTI), the measurement scale was adapted from Pitardi and Marriott (2021), while the measurement scale for *parasocial relationship* (PSR) was modified upon the proposed scale from Whang and Im (2021). To measure *advertising value* (AV), the scale's items were adapted from Martins et al. (2019), and for *advertising acceptance* (AA), the three-item scale from Parreño et al. (2013) was used. Besides *perceived human-likeness*, a seven-point Likert scale was used for every construct (1 = strongly disagree, 7 = strongly agree).

Control variables were determined with the constructs *frequency of IVA usage* (Low, Medium, and High) and *annual household income* (< €40,000 and ≥ €40,000).

5.4. Results

For exploratory or causality research of the postulated hypotheses, this study utilized the partial least squares structural equation modeling (PLS-SEM) technique, performed with SmartPLS 4 (Ringle et al., 2022). PLS-SEM was chosen based on its nonparametric nature (Henseler et al., 2009; Sarstedt, Hair, et al., 2022) but also for its adequacy for predictive applications, mainly when human interaction is a reality (Avkiran & Ringle, 2018). Moreover, it is commonly used in laboratory experimental research, in which sample sizes are usually smaller (Amorim et al., 2022; Chattaraman et al., 2019; Lv et al., 2021; Rzepka et al., 2022).

To keep with best practices, the recommended ten-times rule is verified (Hair et al., 2012, 2022), given that the dataset comprises 123 valid participants, and the maximum number of connections pointing to a latent variable is 3 (see Figure 5.1). Therefore, the minimum sample size threshold of 30 participants for each between-subject condition is established. Furthermore, Cohen's sample size recommendation (Cohen, 1992) for a statistical power of 80% and a significance level of 0.05 is also satisfied.

The sample was previously analyzed with IBM SPSS Statistics 29 and found to be free of outliers and missing data. Consequently, the proposed reflective model will be assessed for measurement and structural models.

5.4.1. Measurement Model

To evaluate the measurement model validity, item's reliability, internal consistency, convergent validity, and discriminant validity were calculated (Avkiran & Ringle, 2018; Hair et al., 2022). The PLS-SEM estimation results for the first three procedures can be found in Tables 5.2 and 5.3.

The outer loadings were analyzed to evaluate the model's reliability. Those that did not meet the minimum threshold of 0.70 were excluded (Sarstedt, Ringle, et al., 2022), which was the case for the items PSR1, PSR3, PSR7, PSR8, PSR9, and PSR11. Regarding internal consistency, both Cronbach's Alpha (CA) and Jöreskog's (1971) composite reliability ρ_C (CRρ_C) were computed for each construct, with CRρ_C being considered more appropriate as CA relies on the common factor model assumption (Rönkkö et al., 2023; Sarstedt, Hair, et al., 2022). The minimum and maximum thresholds of 0.70 and 0.95 (Hair et al., 2019) were confirmed for both CA and CRρ_C, establishing the model's internal consistency.

A preliminary analysis of potential collinearity issues among the data was performed through the outer model's variance inflation factor (VIF). In this case, the items TTI2 and TTI3 presented values exceeding the maximum threshold of 5 (Hair et al., 2012, 2022). In this case, the item TTI2 was removed as its VIF value was higher than TTI3's, and its exclusion would cause a lower impact on the construct's reliability.

The third procedure for evaluating the measurement model relies on assessing convergent validity for each latent variable in the model using the Average Variance Extracted (AVE). AVE quantifies the amount of items' variance captured by the construct itself (Hair et al., 2011, 2021), indicating stronger convergent validity with larger AVE values, as it represents that the construct explains a more significant proportion of items' variance. The minimum AVE threshold of 0.5 (Hair et al., 2014, 2019) was verified for all latent constructs, ranging from 0.580 to 0.868.

Constructs	Scale Items	Factor Loadings	CA	CR(ρ_C)	AVE
Perceived Human-likeness			**0.819**	**0.881**	**0.650**
PH1	Machine-like – Human-like	0.777			
PH2	Artificial – Lifelike	0.898			
PH3	Fake – Natural	0.812			
PH4	Unconscious – Conscious	0.728			
Trust Toward the IVA			**0.907**	**0.942**	**0.843**
TTI1	I feel that the AI assistant in the video makes truthful claims	0.880			
TTI2	I feel that the AI assistant in the video is trustworthy	*			
TTI3	I believe what the AI assistant in the video tells	0.947			
TTI4	I feel that the AI assistant in the video is honest	0.927			
Parasocial Relationship			**0.822**	**0.873**	**0.580**
PSR1	I would like to compare my ideas with what the AI assistant in the video says	**			
PSR2	Interacting with the AI assistant in the video makes one feel comfortable, as if he is with friends	0.727			
PSR3	If the AI assistant in the video was a human, I imagine the AI assistant as a natural, down-to-earth person	**			
PSR4	I would like to hear the opinion of the AI assistant in the video at home	0.807			
PSR5	The AI assistant in the video keeps someone company while using it	0.728			
PSR6	I look forward to using an AI assistant like the one in the video	0.791			
PSR7	When the AI assistant in the video responds to the request, it seems to understand the kinds of things one wants to know	**			
PSR8	If there was a story about the AI assistant in the video, in a newspaper or magazine, I would read it	**			
PSR9	I would miss using an AI assistant like the one in the video when I can't use it because it needs to be repaired	**			
PSR10	I think the AI assistant in the video is like an old friend	0.752			
PSR11	I find the AI assistant in the video to be attractive	**			

Notes:
* Item removed due to collinearity issues with item TTI3.
** Items removed as corresponding factor loadings were below the cutoff value of 0.70 (Hair et al., 2022).
CA = Cronbach's Alpha; CR(ρ_C) = Composite Reliability ρ_C; AVE = Average Variance Extracted; AA = Advertising Acceptance; AV = Advertising Value; PH = Perceived Human-likeness; PSR = Parasocial Relationship; TTI = Trust Toward the IVA.
Source: Own elaboration.

Table 5.2. Measurement scales validity and reliability results (1/2)

Constructs	Scale Items	Factor Loadings	CA	CR(ρ_C)	AVE
Advertising Value			**0.924**	**0.952**	**0.868**
AV1	I feel that advertising through the AI assistant in the video is useful	0.930			
AV2	I feel that advertising through the AI assistant in the video is valuable	0.923			
AV3	I feel that advertising through the AI assistant in the video is important	0.942			
Advertising Acceptance			**0.893**	**0.933**	**0.823**
AA1	I feel positive about the advertising through the AI assistant in the video	0.913			
AA2	I am willing to receive advertising through the AI assistant like the one in the video in the future	0.927			
AA3	I would listen to all the advertising messages I receive in the future from the AI assistant as the one in the video	0.882			

Notes:
CA = Cronbach's Alpha; CR(ρ_C) = Composite Reliability ρ_C; AVE = Average Variance Extracted; AA = Advertising Acceptance; AV = Advertising Value.
Source: Own elaboration.

Table 5.3. Measurement scales validity and reliability results (2/2)

For the analysis of discriminant validity, the Fornell and Larcker criterion was computed (see Table 5.4), and the square root of the AVE for each construct (values in diagonal) was found to be higher than their correlation with any other constructs in the research model (Fornell & Larcker, 1981). Therefore, all constructs are assumed to be distinct from each other. To confirm these results, the heterotrait-monotrait (HTMT) ratio of correlations was also calculated (Henseler et al., 2015). The Fornell and Larcker criterion has been reported to have limitations in assessing discriminant validity, while the HTMT ratio is known as a less constrained, more robust, and reliable approach, recommended for variance-based statistical techniques (Franke & Sarstedt, 2019; Hair et al., 2020; Voorhees et al., 2016).

The HTMT ratios in Table 5.5 do not exceed the maximum 0.90 threshold (Franke & Sarstedt, 2019; Hair et al., 2020), also showing evidence of discriminant validity. Nevertheless, as the HTMT ratio of correlations assumes unlikely equal items' loadings (λ or *tau*) for each construct (*tau*-equivalency), the modified technique HTMT2 was computed (Henseler, 2021; Roemer et al., 2021). In most cases, as the items' loadings are not *tau*-equivalent, the improved coefficient HTMT2 should be used instead. The items' average correlation is calculated by the geometric mean instead of the arithmetic mean. The HTMT2 results for discriminant validity assessment are indicated in Table 5.6. In general, HTMT2 values are lower than the HTMT ratio of correlations, revealing itself as a more flexible technique in comparison to the latter (Sarstedt, Hair, et al., 2022).

Variables	AA	AV	ARS	PH	PLES	PSR	TTI
AA	0.907						
AV	0.737	0.932					
ARS	0.076	0.021	1.000				
PH	0.507	0.443	-0.066	0.806			
PLES	0.050	0.023	0.173	0.157	1.000		
PSR	0.588	0.604	-0.095	0.426	0.027	0.762	
TTI	0.501	0.545	-0.196	0.229	-0.036	0.417	0.918

Note: AA = Advertising Acceptance; ARS = Arousal; AV = Advertising Value; PH = Perceived Human-likeness; PLES = Pleasure; PSR = Parasocial Relationship; TTI = Trust Toward the IVA.
Source: Own elaboration.

Table 5.4. Discriminant validity results using the Fornell-Larcker criterion

Variables	AA	AV	ARS	PH	PLES	PSR	TTI
AA	—						
AV	0.810	—					
ARS	0.081	0.026	—				
PH	0.594	0.501	0.086	—			
PLES	0.053	0.024	0.173	0.175	—		
PSR	0.661	0.675	0.106	0.512	0.027	—	
TTI	0.555	0.591	0.204	0.256	0.044	0.459	—

Note: AA = Advertising Acceptance; ARS = Arousal; AV = Advertising Value; PH = Perceived Human-likeness; PLES = Pleasure; PSR = Parasocial Relationship; TTI = Trust Toward the IVA.
Source: Own elaboration.

Table 5.5. Discriminant validity results using the HTMT ratio of correlations

Variables	AA	AV	ARS	PH	PLES	PSR	TTI
AA	—						
AV	0.809	—					
ARS	0.076	0.019	—				
PH	0.593	0.502	0.077	—			
PLES	0.052	0.021	0.173	0.173	—		
PSR	0.644	0.670	0.080	0.510	0.014	—	
TTI	0.553	0.586	0.200	0.247	0.035	0.432	—

Note: AA = Advertising Acceptance; ARS = Arousal; AV = Advertising Value; PH = Perceived Human-likeness; PLES = Pleasure; PSR = Parasocial Relationship; TTI = Trust Toward the IVA.
Source: Own elaboration.

Table 5.6. Discriminant validity results using the HTMT2 ratio of correlations

5.4.2. Common Method Variance

Common Method Variance (CMV) refers to the potential bias in data arising from the same source of measurement, both for the dependent and independent variables, causing the variance in the constructs to be attributed more to the method rather than to the constructs in the model (Kock et al., 2021; Kock, 2015; Podsakoff et al., 2012).

This research employed both procedural and statistical approaches to address the potential issue of CMV. Procedurally, different methods for data collection were used, including self-report and autonomic physiologic measurements. Furthermore, all questions underwent thorough checks for simplicity and clarity during the pre-test stage (Chin et al., 2012; Podsakoff et al., 2003). In addition, two professionals accompanied each participant during all phases of data collection. From a statistical perspective, two *post hoc* approaches were utilized. The first *post hoc* statistical technique consists of the collinearity tests (Kock, 2015) by determining the VIF values for all constructs in the model. All factor-level VIF values in Table 5.7 are below the cutoff value of 3.3. Therefore, there is no evidence of a significant CMV phenomenon. Secondly, we conducted Harman's single-factor test (Aguirre-Urreta & Hu, 2019; Malhotra et al., 2006; Podsakoff et al., 2003) by performing an exploratory factor analysis in SPSS, using the principal component method for factor extraction, without any factor rotation, and extracting a single factor. The single factor extracted accounted for 39.58% of the total variance in the model. This result is lower than both recommended thresholds of 50% (Podsakoff et al., 2003) and 60% (Fuller et al., 2016).

Variables	AA	AV	ARS	PH	PLES	PSR	TTI
AA		2.144	2.325	2.462	2.598	2.545	2.616
AV	2.095		2.206	2.614	2.432	2.440	2.448
ARS	1.117	1.156		1.143	1.145	1.147	1.087
PH	1.334	1.465	1.413		1.354	1.435	1.459
PLES	1.064	1.064	1.028	1.034		1.068	1.067
PSR	1.698	1.634	1.646	1.685	1.879		1.781
TTI	1.537	1.480	1.413	1.583	1.562	1.595	

Note: AA = Advertising Acceptance; ARS = Arousal; AV = Advertising Value; PH = Perceived Human-likeness; PLES = Pleasure; PSR = Parasocial Relationship; TTI = Trust Toward the IVA.
Source: Own elaboration.

Table 5.7. VIF results for the inner model

5.4.3. Structural Model

After the measurement model satisfactory results were obtained, the structural model evaluation was conducted. This study employed the bootstrapping technique with 10,000 subsamples to estimate path coefficients (β) and test their significance with *p*-values, as well as to determine whether the model has a reasonable explanatory and predictive power (Hair et al., 2019, 2020; Sarstedt, Hair, et al., 2022). Confidence intervals were estimated by the percentile method, which is superior to the bias-corrected or the studentized approach (Aguirre-Urreta & Rönkkö, 2018). The two-tailed test was performed for path coefficients significance analysis and *p*-values determined, using the same 5% significance level as for the confidence intervals estimation (Hair et al., 2022). The coefficient of determination R^2 was calculated for explanatory power assessment. This statistic determines the amount of variance of a specific latent variable that is explained by all exogenous variables connected to it (Henseler et al., 2009; Shmueli & Koppius, 2011). The blindfolding procedure PLSpredict algorithm was used to determine the model's predictive power, using a *ten*-fold cross-validation for Q^2 statistic computation (Shmueli et al., 2019). The results of the postulated hypotheses are displayed in Figure 5.4 and Table 5.7.

The model has a standardized root-mean-square residual (SRMR) of 0.076, below the recommended threshold value of 0.08. This result indicates a good fit of the model to the data (Henseler et al., 2016; Hu & Bentler, 1999). Further assessments of the structural model's adequacy will be addressed by evaluating the model's explanatory and predictive power, but beforehand, the different regressions that compose the structural model must be examined for possible collinearity problems. The variance inflation factor (VIF) was calculated for the inner model, with values ranging from 1.000 to 1.574. Therefore, VIF is lower than the recommended cutoff value of 5 (Hair et al., 2022) and below the more conservative value of 3 (Becker et al., 2015), suggesting that collinearity is not an issue.

According to PLS path coefficients estimation and the inherent *p*-values, perceived human-likeness positively influences trust toward the IVA (β_{1a} = 0.217; p < 0.05), advertising value (β_{1b} = 0.206; p < 0.01), and parasocial relationship (β_{1c} = 0.349; p < 0.001), thus supporting hypotheses H1a, H1b, and H1c. However, the relationship between pleasure and arousal was deemed statistically insignificant, considering a significance level of 5% (β_2 = 0.173; p > 0.05). Hence, H2 is not supported. Arousal was found to have a negative but significative influence on trust toward the IVA (β_3 = -0.182; p < 0.05), and therefore, H3 is supported.

Trust toward the IVA is shown to positively affect parasocial relationship (β_{4a} = 0.337; p < 0.001) and advertising value (β_{4b} = 0.342; p < 0.001), which also gets positively influenced by trust (β_{5a} = 0.373; p < 0.001). Hence, hypotheses H4a, H4b, and H5a are supported. As for advertising acceptance, this latent variable is positively affected by parasocial relationship (β_{5b} = 0.225; p < 0.05) and advertising value (β_6 = 0.602; p < 0.001), supporting hypotheses H5b and H6.

Path coefficients' stability is established as all model coefficients fall into the lower and upper bounds of 95% confidence intervals (see Table 5.8) (Hair et al., 2022). In terms of the model's explanatory power, PLS-SEM reports the amount of variance explained for each of the endogenous constructs (Hair et al., 2011), whose thresholds of 0.75, 0.50, and 0.25 can be interpreted as substantial, moderate, and weak explanatory power, respectively. A limitation of the coefficient of determination R^2 is its dependence on the number of explanatory variables introduced in the model. The alternative statistic (adjusted R^2) corrects the R^2 value regarding the number of predictors concerning the sample size but produces less accurate results (Hair et al., 2021). Their independent variables weakly explain arousal and trust toward the IVA, with R^2 values of 0.030 and 0.085, respectively. As for the parasocial relationship, its predictors explain 28.9% of the total variance of this construct (R^2 = 0.289), while advertising value and advertising acceptance show a more substantial explanatory power by their respective antecedents, with a coefficient of determination above 0.50 (R^2 = 0.503 and R^2 = 0.576, respectively).

Hypothesis	**Paths**	**Std. β**	***p*-value**	**95% CI [LL ; UL]**	**f^2**	**Decision**
H1a	PH → TTI	0.217	0.029*	[0.025 ; 0.410]	0.051	Supported
H1b	PH → AV	0.206	0.006**	[0.056 ; 0.351]	0.069	Supported
H1c	PH → PSR	0.349	0.000***	[0.211 ; 0.489]	0.162	Supported
H2	PLES → ARS	0.173	0.068$^{\text{n.s.}}$	[-0.017 ; 0.355]	0.031	Not Supported
H3	ARS → TTI	-0.182	0.020*	[-0.327 ; -0.021]	0.036	Supported
H4a	TTI → PSR	0.337	0.000***	[0.189 ; 0.477]	0.152	Supported
H4b	TTI → AV	0.342	0.000***	[0.189 ; 0.472]	0.194	Supported
H5a	PSR → AV	0.373	0.000***	[0.237 ; 0.518]	0.199	Supported
H5b	PSR → AA	0.225	0.029*	[0.021 ; 0.418]	0.076	Supported
H6	AV → AA	0.602	0.000***	[0.428 ; 0.761]	0.542	Supported

Notes:
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; n.s. = not significant.
CI = Confidence Interval; LL = Lower Limit; UL = Upper Limit; AA = Advertising Acceptance; ARS = Arousal; AV = Advertising Value; PH = Perceived Human-likeness; PLES = Pleasure; PSR = Parasocial Relationship; TTI = Trust Toward the IVA.
Source: Own elaboration.

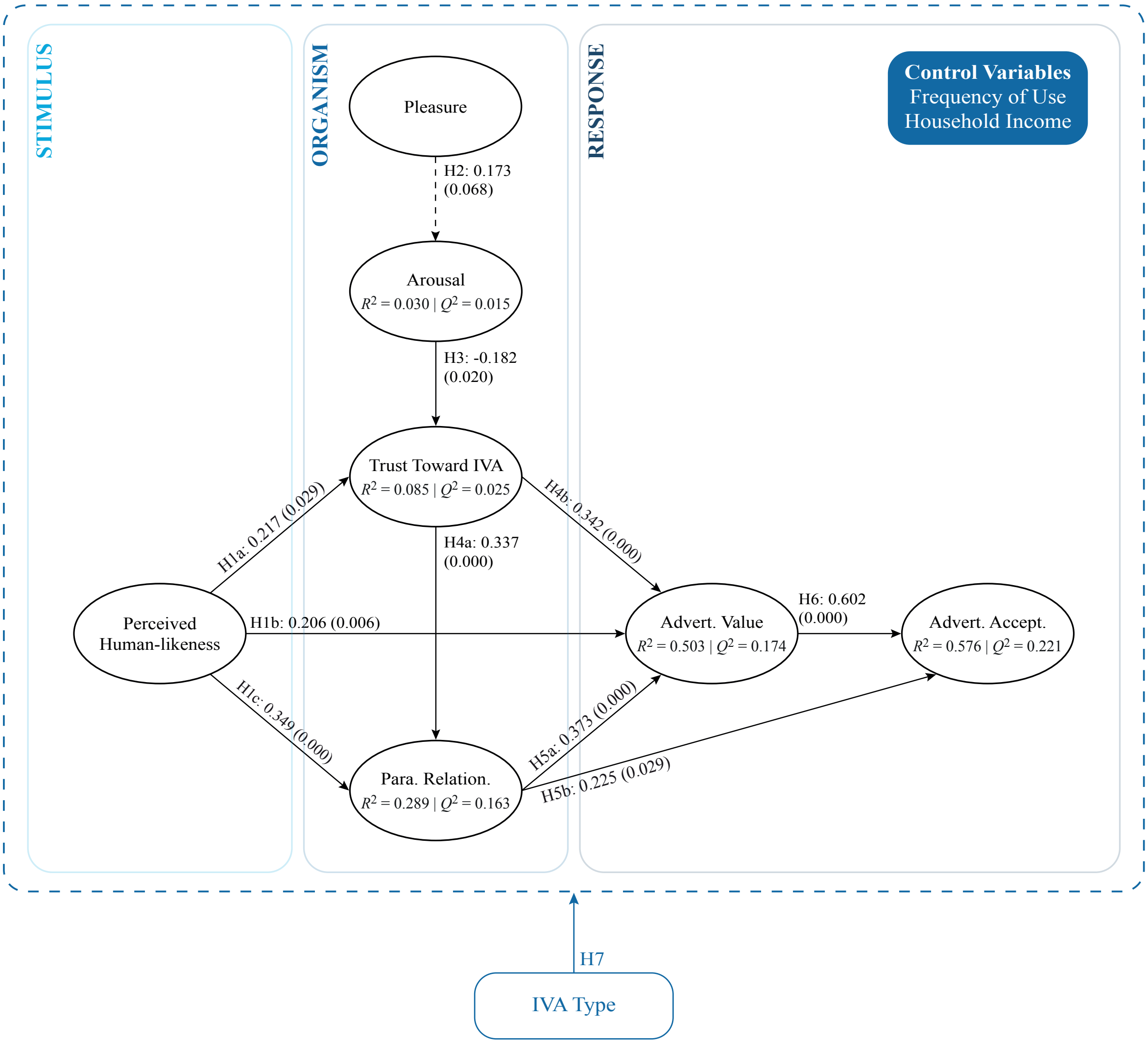
Table 5.8. Structural model results

The f^2 measure was calculated to specify the effect size for each exogenous construct (Henseler et al., 2016). f^2 values of 0.35, 0.15, and 0.02 can be inferred as strong, moderate, and weak predictors, respectively (Cohen, 2013; Henseler et al., 2009). The hypotheses H1a, H1b, H2 (not supported hypothesis), H3, and H5b have a f^2 value between 0.02 and 0.15. For hypotheses H1c, H4a, H4b, and

H5a, the f^2 values fall between 0.15 and 0.35, while H6 is the only hypothesis exceeding 0.35 (f^2 = 0.542).

The out-of-sample predictive power of the model was evaluated with Stones-Geisser's statistics Q^2. For $Q^2 > 0$, the predictive relevance of the model is established (Chin et al., 2020), which is the case as displayed in Figure 5.4.

Figure 5.4. Conceptual model bootstrapping results



Note: Values correspond to path coefficients (β) and p-values in parentheses.

Source: Own elaboration.

5.4.4. Mediation Analysis

Based on the direct effects of bootstrap estimations, the indirect relationships can also be computed as the product of the different coefficients accompanying the path between the two constructs (Cepeda-Carrión et al., 2017; Nitzl et al., 2016; Streukens & Leroi-Werelds, 2016). Hence, trust toward the IVA, parasocial relationship, and advertising value will be analyzed for mediation. Arousal, even though included in the total indirect effects (see Table 5.9) and in the specific indirect effects (see Table 5.9) calculation, will not be considered for mediation purposes as the direct relationship from pleasure was not significant for the complete dataset.

A multiple mediation analysis was employed to test the paths that run through more than one mediator (Cepeda-Carrión et al., 2017). The confidence intervals for both total and specific indirect effects were computed according to the bias-corrected method recommended by Nitzl et al. (2016) for mediation effects identification, considering a two-tailed test type and a significance level of 5%.

Paths	**Std. β**	**Std. Error**	***p*-value**	**95% BC CI [LL ; UL]**
Perceived Human-likeness → Parasocial Relationship	0.073	0.040	0.064	[0.006 ; 0.158]
Perceived Human-likeness → Advertising Value	0.232	0.057	0.000	[0.117 ; 0.339]
Perceived Human-likeness → Advertising Acceptance	0.358	0.062	0.000	[0.222 ; 0.466]
Pleasure → Trust Toward the IVA	-0.031	0.025	0.206	[-0.102 ; 0.000]
Pleasure → Parasocial Relationship	-0.011	0.009	0.254	[-0.039 ; -0.000]
Pleasure → Advertising Value	-0.015	0.012	0.227	[-0.051 ; 0.000]
Pleasure → Advertising Acceptance	-0.011	0.009	0.234	[-0.040 ; -0.000]
Arousal → Parasocial Relationship	-0.061	0.032	0.054	[-0.133 ; -0.008]
Arousal → Advertising Value	-0.085	0.039	0.030	[-0.168 ; -0.013]
Arousal → Advertising Acceptance	-0.065	0.030	0.033	[-0.130 ; -0.010]
Trust Toward the IVA → Advertising Value	0.126	0.039	0.001	[0.058 ; 0.209]
Trust Toward the IVA → Advertising Acceptance	0.358	0.055	0.000	[0.246 ; 0.464]
Parasocial Relationship → Advertising Acceptance	0.225	0.058	0.000	[0.119 ; 0.342]

Note: BC = Bias-Corrected; CI = Confidence Interval; LL = Lower Limit; UL = Upper Limit.
Source: Own elaboration.

Table 5.9. Total Indirect Effects

The total indirect effects analysis indicates that not all paths are significant. As expected, none of the relationships starting on the latent variable pleasure were deemed significant ($p > 0.05$). Moreover, the indirect effect from perceived human-likeness to parasocial relationship, and from arousal to parasocial relationship were also non-significant ($p > 0.05$). All the remaining indirect effects are significant. In this case, there is evidence that trust toward the IVA does not mediate any relationship to parasocial relationship. However, there is a mediating role of parasocial relationship on advertising value and on advertising acceptance.

Following the proposal from Zhao et al. (2010), all non-significant indirect effects were excluded from the mediation analysis. Hence, in Table 5.10 only significant specific indirect effects are represented. To classify the different types of mediation, the intensity of the mediation effect over the endogenous variable's total variance needs to be calculated using the variance accounted for (VAF), also known as the ratio of the indirect-to-total effect (Cepeda-Carrión et al., 2017; Nitzl et al., 2016). A full mediation can be assumed for VAF values above 80%, while values ranging from 20% to 80% suggest partial mediation. VAF values below 20% may denote the absence of mediation. No effect is attained if neither a direct nor an indirect effect is significant (Nitzl et al., 2016; Zhao et al., 2010). If the specific indirect effect is not significant but the direct effect is, then the hypothesized mediator variable has no impact on the dependent variable. When both the direct and indirect effects are significant, a partial mediation scenario is reached. In the past, only complementary partial mediation was often considered (Zhao et al., 2010), whereas competitive partial mediation is currently considered a second type of partial mediation. If the direct effect and indirect effect have the same signal (positive or negative), a complementary partial mediation is observed. A competitive partial mediation is determined if these effects present opposite signals. The rule of thumb for VAF interpretation is only clear when the direct effect and indirect effect point in the same direction. However, some authors recommend considering inconsistent mediation when VAF yields a negative value (Hayes, 2009).

According to Shrout and Bolger (2002), to compute VAF, a direct effect was added to the model when unavailable in the initial conceptual model. As the path between pleasure and arousal was found to be non-significant, no mediation effect was assessed from pleasure to any other construct (Zhao et al., 2010). Regarding the newly created direct paths, the path from parasocial relationship to advertising acceptance ($\beta = 0.174$; $p > 0.05$), and from arousal to parasocial relationship ($\beta = -0.008$; $p > 0.05$) were also determined as non-significant.

Competitive mediation was observed in the path from arousal to advertising value, and from arousal to advertising acceptance, which is acknowledged by the negative VAF value (Nitzl et al., 2016; Zhao et al., 2010). All other partial mediation were deemed complementary.

Paths	Std. β	Std. Error	p-value	95% BC CI [LL ; UL]	VAF (%)	Mediation Type
PH → TTI → AV	0.074	0.035	0.036	[0.010 ; 0.150]	16.67	No Mediation
PH → PSR → AV	0.130	0.038	0.001	[0.065 ; 0.214]	29.28	Complementary Med.
PH → TTI → AV → AA	0.045	0.022	0.039	[0.007 ; 0.093]	8.69	No Mediation
PH → AV → AA	0.124	0.052	0.016	[0.033 ; 0.236]	23.94	Complementary Med.
PH → PSR → AV → AA	0.078	0.026	0.003	[0.037 ; 0.137]	15.06	No Mediation
ARS → TTI → AV	-0.062	0.030	0.036	[-0.131 ; -0.012]	-129.17	Competitive Med.
ARS → TTI → AV → AA	-0.037	0.019	0.046	[-0.083 ; -0.008]	-33.94	Competitive Med.
TTI → PSR → AV	0.126	0.039	0.001	[0.058 ; 0.209]	25.40	Complementary Med.
TTI → PSR → AV → AA	0.076	0.028	0.008	[0.031 ; 0.140]	17.19	No Mediation
TTI → PSR → AA	0.076	0.037	0.042	[0.012 ; 0.159]	17.19	No Mediation
TTI → AV → AA	0.206	0.050	0.000	[0.115 ; 0.313]	46.61	Complementary Med.
PSR → AV → AA	0.225	0.058	0.000	[0.119 ; 0.342]	65.79	Complementary Med.

Note: BC = Bias-Corrected; CI = Confidence Interval; LL = Lower Limit; UL = Upper Limit; VAF = Variance Accounted For; AA = Advertising Acceptance; ARS = Arousal; AV = Advertising Value; PH = Perceived Human-likeness; PLES = Pleasure; PSR = Parasocial Relationship; TTI = Trust Toward the IVA.
Source: Own elaboration.

Table 5.10. Specific indirect effects

5.4.5. Moderation of IVA Type

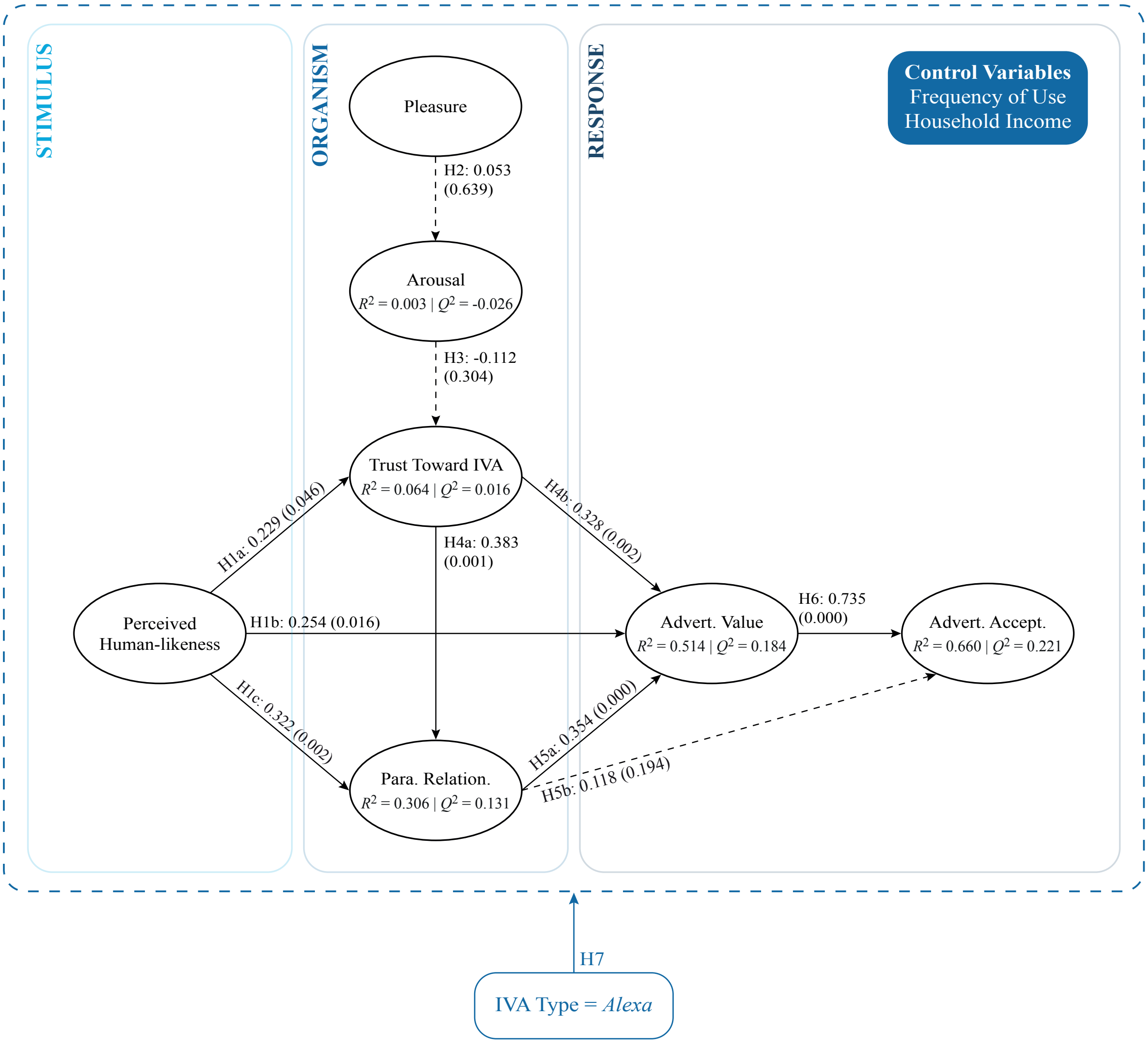
This study employed the bootstrap multigroup analysis (MGA) with 10,000 subsamples to compare results between two groups of participants, according to the IVA type (voice assistant *Alexa* or AI avatar *Anna*) they watched in the video to test H7 (see Table 5.11, and Figures 5.5 and 5.6) (Hair et al., 2018; Klesel et al., 2022; Sarstedt et al., 2011).

Paths	β_{Alexa} (p-value)	β_{Anna} (p-value)	MGA β Dif.	MGA p-value
PH → TTI	0.229 (0.046)	0.272 (0.109)	-0.043	0.812
PH → AV	0.254 (0.016)	-0.037 (0.732)	0.291	0.059
PH → PSR	0.322 (0.002)	0.454 (0.000)	-0.132	0.350
PLES → ARS	0.053 (0.639)	0.271 (0.052)	-0.218	0.885
ARS → TTI	-0.112 (0.304)	-0.223 (0.033)	0.111	0.230
TTI → AV	0.328 (0.002)	0.421 (0.000)	-0.093	0.742
TTI → PSR	0.383 (0.001)	0.262 (0.011)	0.121	0.218
PSR → AV	0.354 (0.000)	0.487 (0.000)	-0.133	0.840
PSR → AA	0.118 (0.194)	0.376 (0.030)	-0.258	0.899
AV → AA	0.735 (0.000)	0.418 (0.004)	0.318	0.027

Note: AA = Advertising Acceptance; ARS = Arousal; AV = Advertising Value; PH = Perceived Human-likeness; PLES = Pleasure; PSR = Parasocial Relationship; TTI = Trust Toward the IVA.
Source: Own elaboration.

Table 5.11. MGA results for IVA type moderation effects

Figure 5.5. Conceptual model bootstrapping results considering the sub-group of IVA Alexa

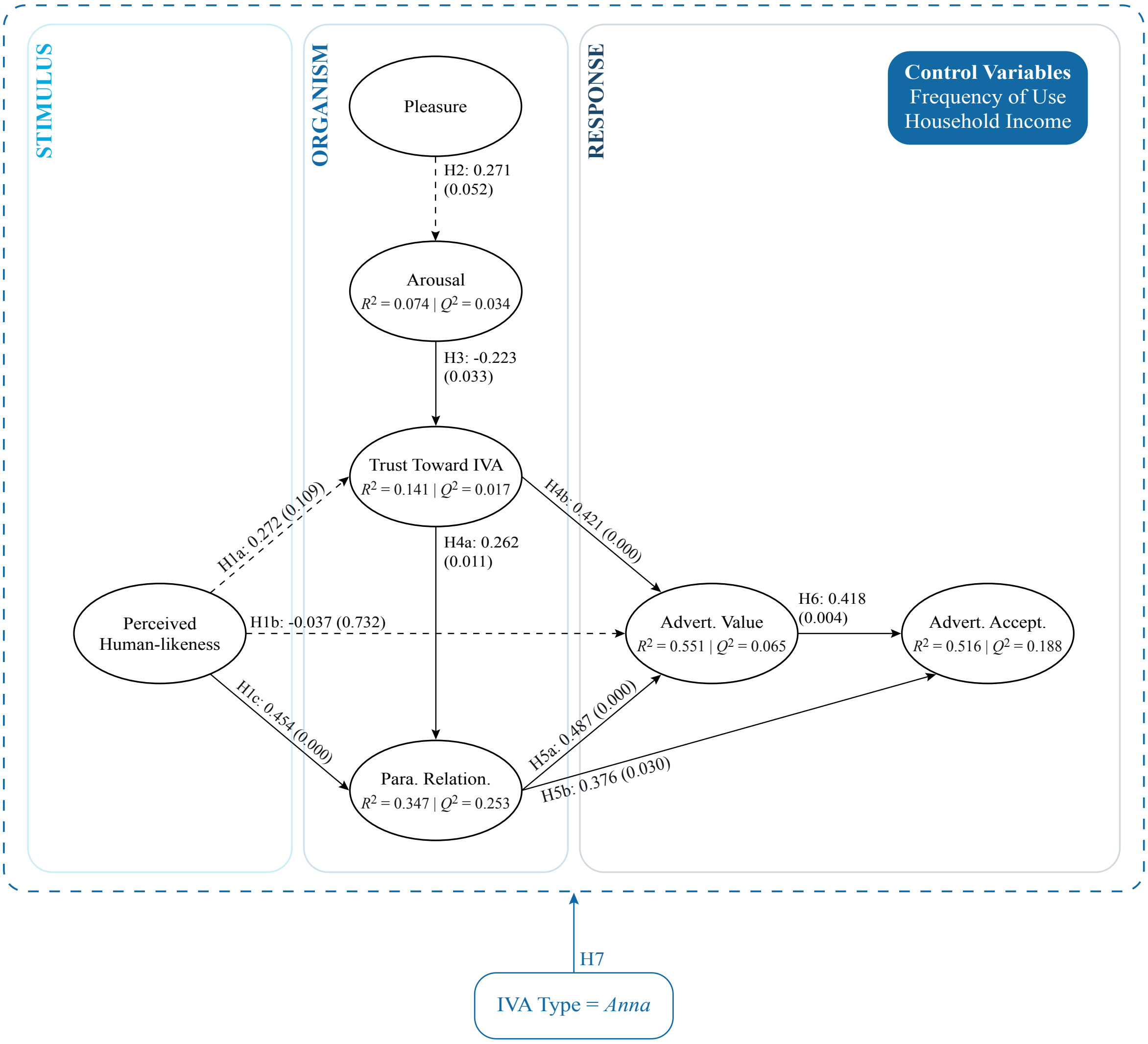


Note: Values correspond to path coefficients (β) and *p*-values in parentheses.

Source: Own elaboration.

By testing the null hypothesis of no significant differences between the results among these two groups (i.e., H_0: $\beta_{Alexa} = \beta_{Anna}$), against the alternative hypothesis of the existence of significant differences (i.e., H_1: $\beta_{Alexa} \neq \beta_{Anna}$), this research examines the moderation effects analysis regarding IVA type among all relationships hypothesized in the structural model (Esposito Vinzi et al., 2010). For the sub-group that watched *Alexa*, both physiological measures for pleasure and arousal became not significant, as well as the direct effect of parasocial relationship on advertising acceptance. In this case, there is only an indirect effect of parasocial relationship on advertising acceptance through a full mediation by advertising value. For the sub-group that watched *Anna*, the AI avatar with greater human resemblance, pleasure is now positively affecting arousal, and the latter happens to have a negative but significant effect on trust toward the IVA. However, the relationship between perceived human-likeness and advertising value is now fully mediated by parasocial relationship. Moreover, despite the differences, the MGA only found the path from AV to AA significantly different between groups.

Figure 5.6. Conceptual model bootstrapping results considering the sub-group of IVA Anna



Note: Values correspond to path coefficients (β) and p-values in parentheses.

Source: Own elaboration.

5.4.6. Control Variables

Secondly, the MGA analysis was employed to test for control variables. Household income was transformed into a binary variable with one category considering incomes below €40,000 and another one with incomes greater than or equal to €40,000. No significant differences were found between these two groups of participants (see Table 5.12).

The frequency of IVA usage was also reclassified into three categories, varying from low (once weekly or less), moderate (once daily or multiple times weekly), and high (multiple times daily). A comparison between these three groups of participants was performed, and no significant differences were found among the three groups of participants (see Table 5.12).

Paths	**MGA** $\beta_{low} - \beta_{high}$	***p*-value** (Low vs. High)
PH → TTI	0.147	0.472
PH → AV	0.308	0.051
PH → PSR	-0.207	0.122
PLES → ARS	0.028	0.881
ARS → TTI	0.084	0.614
TTI → AV	-0.044	0.755
TTI → PSR	0.092	0.544
PSR → AV	-0.047	0.769
PSR → AA	-0.208	0.322
AV → AA	0.087	0.650

Note: AA = Advertising Acceptance; ARS = Arousal; AV = Advertising Value; PH = Perceived Human-likeness; PLES = Pleasure; PSR = Parasocial Relationship; TTI = Trust Toward the IVA.
Source: Own elaboration.

Table 5.12. MGA results for household income

Paths	**MGA** $\beta_{high} - \beta_{low}$	**MGA** $\beta_{high} - \beta_{mod}$	**MGA** $\beta_{low} - \beta_{mod}$	***p*-value** (High vs. Low)	***p*-value** (High vs. Mod.)	***p*-value** (Low vs. Mod.)
PH → TTI	0.249	0.056	-0.193	0.263	0.684	0.367
PH → AV	-0.069	0.172	0.240	0.851	0.489	0.171
PH → PSR	-0.241	-0.266	-0.026	0.347	0.309	0.861
PLES → ARS	0.354	0.207	-0.147	0.224	0.466	0.457
ARS → TTI	-0.140	-0.280	-0.140	0.485	0.243	0.438
TTI → AV	-0.017	-0.066	-0.049	0.953	0.787	0.767
TTI → PSR	0.150	0.268	0.118	0.534	0.365	0.468
PSR → AV	0.063	0.023	-0.039	0.791	0.938	0.826
PSR → AA	-0.445	-0.391	0.054	0.326	0.393	0.772
AV → AA	0.152	0.053	-0.099	0.567	0.836	0.576

Note: AA = Advertising Acceptance; ARS = Arousal; AV = Advertising Value; PH = Perceived Human-likeness; PLES = Pleasure; PSR = Parasocial Relationship; TTI = Trust Toward the IVA.
Source: Own elaboration.

Table 5.13. MGA results for frequency of IVA usage

The frequency of IVA usage was also reclassified into three categories, varying from low (once weekly or less), moderate (once daily or multiple times weekly), and high (multiple times daily). A comparison between these three groups of participants was performed, and no significant differences were found among the three groups of participants (see Table 5.13).

5.5. Discussion

Due to the proliferation of AI-enabled devices, their inclusion as advertising media vehicles portrays a major opportunity for brands, similar to the challenges faced in the past with the rise of the internet, social media, mobile devices, and apps (Dwivedi et al., 2021; Stafford et al., 2023). In this context, parasocial interactions and relationships are paramount in the contemporary mediated environment (Nah, 2022), advocated by many as the ultimate goal of technology evolution (Breves et al., 2021; Horton & Wohl, 1956; Pitardi & Marriott, 2021).

This study was designed according to the stimulus-organism-response framework (Mehrabian & Russell, 1974), but considering the Circumplex Model of Affect (Russell, 1980; Xu et al., 2023), and therefore assuming a bi-dimensional space composed of pleasure and arousal, measured through the psychophysiological techniques ECG and EDA, instead of the conventional self-reported measurements. Two agents (*Alexa* and *Anna*) with different anthropomorphic levels were used as stimuli, providing personalized recommendations during an online shopping experience. The emergent contactless shopping scenario, supported by AI for a more personalized experience, is leveraging both advertising and AI technology in the e-commerce industry (Kim et al., 2022; Li, 2019) and directly linked to companies' revenues increase from 5% to 15% (Chandra et al., 2022).

The results show that the results regarding the influence of the humanness perception over trust toward the intelligent virtual agents (H1a), on advertising value (H1b), and the parasocial relationships (H1c) are all consistent with previous literature applied in other contexts. Different studies found the same positive relationship between PH and trust (Følstad et al., 2018; Kim & Im, 2023; Pal et al., 2022; Pitardi & Marriott, 2021), a relevant construct in interpersonal relations in contexts characterized by potential risks (Schoorman et al., 2007), such as personal information disclosure, both for the ability of the IVA providing personalized recommendations, as well as for shopping payment. The value perception of the message advertised is also recognized as positively dependent on the perceived human-likeness of the IVA. This study extended the HVL for assessing how the value assessment gets affected by the PH of the intelligent agent, as did Belanche et al. (2021) for service robots in the hotel industry, in which value expectancy was found to mediate the relationship between robot human-likeness in loyalty intentions fully. As for the effect of PH on PSR, the positive relationship corroborates the findings of Aw et al. (2022) for PSI, a former stage of PSR, and Whang and Im (2021) for PSR.

The organismic stage of the S-O-R model was formerly assessed for a possible relationship between emotional valence (pleasure), whose data were gathered with ECG recordings, and the EDA measurement of emotional arousal, collected simultaneously while the participant watched the video. Neurophysiological methods are posited as having the ability to explain a greater proportion of the variance in advertising elasticities (Venkatraman et al., 2015), being a far superior predictor of advertising success. Considering the complete dataset for the bootstrapping estimation, this relationship (H2) was deemed not significant, hence not consistent with the arousal theory (Mehrabian, 1996; Russell, 1980), which establishes emotional arousal as a consequence of emotional valence, nor with the findings from Kumar et al. (2021). This lack of validation might be due to the different measurement techniques (self-reports versus psychophysiological tools). This study corroborated the existence of a relationship between emotional arousal and trust, supporting H3, as emotional arousal was established to affect trust negatively (H3), validating that positive and negative emotions are key components for trust formation (Dunn & Schweitzer, 2005; McAllister, 1995). Higher emotional arousal can be activated by either positive or negative valence. A low level of valence with high arousal is associated with feelings of agitation, fear, or anxiousness (Barrett & Bliss-Moreau, 2009; Xu et al., 2023), leading participants to be more prone to mistrust the information (Herrando et al., 2022) or the medium.

Trust is crucial in interpersonal relationships and their success (Choi et al., 2019; Rotter, 1967; Youn & Jin, 2021) and in technology-mediated environments (Kim et al., 2021). This study validates the existence of a positive relationship between trust and PSR (H4a), extending the results from different studies that only examined the relationship with PSI (Abdul Latif & Abdul Aziz, 2021; Choi et al., 2019; Yılmazdoğan et al., 2021), corroborating the results from Rungruangjit (2022) for the relationship with PSR. Hence, both theoretical frameworks used for this hypothesis formulation, the commitment-trust theory (Morgan & Hunt, 1994) and the trust model (Mayer et al., 1995), were of paramount relevance. Also, the relationship between trust and advertising value (H4b) was significant and consistent with the results from Yuan et al. (2020), a study developed for third-party organization endorsement.

The contribution to the PSR literature is conceived through verifying relationships with advertising value (H5a) and acceptance (H5b), deemed statistically significant and supported. These two constructs for advertising effectiveness appraisal were adopted from the work of Wu (2016). The relationship between PSR and advertising value was determined as supporting the study from Whang and Im (2021), assuming the evaluation of the recommended product as a concept equivalent to the assessment of the value of the advertised message. To the best of our knowledge, the study of self-disclosure from an unfamiliar media performer during the primary PSI (Nah, 2022) was the first to establish a direct relationship between parasocial relationship in the form of parasocial friendship (interpersonal liking) and message acceptance. His results were validated by the significative relationship between PSR and advertising acceptance, considering a significance level of 5%. The direct relationship between the advertising effectiveness measures, advertising value, and acceptance (H6) returned significant and consistent with the findings of the existing literature on mobile advertising (Murillo-Zegarra et al., 2020; Wu, 2016).

In the case of the model moderation by IVA type (H7), some of the hypotheses above do not hold as significant. Considering the sub-sample of participants shown the video with the IVA *Alexa*, represented by Amazon's Echo Studio smart speaker, displaying less human-like features, no emotional responses were found significant (H2 and H3). In this case, any variability in trust toward the IVA would be only explained by PH and not by pleasure nor by arousal, which is in accordance with the emotional contagion theory (Hatfield et al., 1993), possibly related to a lower affect evoked during the ad exposure (Bakalash & Riemer, 2013). The direct relationship between PSR and advertising acceptance becomes insignificant, in which advertising value fully mediates the relationship with other independent latent variables.

For the sub-sample of participants that watched the video with the AI avatar *Anna*, presenting more anthropomorphic cues, compared to *Alexa*, the PH construct only exhibits a significant relationship with PSR, with hypotheses H1a and H1b turning out as insignificant. In this case, as the IVA shows a more human-like appearance, participants have higher expectations regarding IVA's skills, whereas *Alexa* is no longer a novelty for most participants, so people are more aware of its performance. Therefore, as expectations may not be met with *Anna*, an issue of source credibility may arise due to a lack of authenticity regarding the medium and, consequently, the message (Alboqami, 2023; Corritore et al., 2003; Yılmazdoğan et al., 2021), as some synchronization problems may have been identified in the video between speech and mouth movement. This source's credibility, attractiveness, and competence will harm interpersonal trust development (Calvo-Barajas et al., 2020; Choi et al., 2019; Mayer et al., 1995; Pizzi et al., 2023) and perceived value, according to the HVL model (Belanche et al., 2021), grounded in the uncanny valley theory (Mori, 1970; Mori et al., 2012), which correlates the agent's human resemblance and the elicited emotional responses. It is also interesting to notice that there is evidence of greater affect being evoked while watching the video, as pleasure influences positively arousal with a p-value much closer to 5% (5.2%), hence significant at a 10% confidence level. In this case, arousal negatively influences trust toward the IVA, so lower electrodermal activity (EDA) levels elicit higher levels of trust, consistent with the findings of Walker et al. (2019) that reported a moderate, yet significant, negative correlation between EDA and self-reported trust toward a simulated vehicle.

Chapter 6: Conclusions

This chapter comprises the final remarks of this dissertation by ascertaining the main theoretical contributions and managerial implications obtained from the different studies included in this research project. Limitations and challenges experienced along this journey are also documented, as well as recommendations for future research. In this study, intelligent virtual agents were found to have considerable potential as a media vehicle to spread brand information. Although these devices still have a servant posture (Schweitzer et al., 2019) – on-demand devices that interact upon request – consumers may perceive information spread through IVA as valuable and are willing to receive more information from the device, implying its acceptance.

6.1. Theoretical Contributions

Consumer neuroscience has been assuming a growing relevance in academia, especially over the last decade, in which several technological innovations are considered disruptive regarding consumer behavior. To this end, the first study contributed primarily to the knowledge of consumer neuroscience and neuromarketing. It provides a synthesized and structured overview of this matter among the existing, dispersed, complex, and vast literature. It also presents how the topic has evolved over approximately 75 years. Although traditional measures of advertising effectiveness have been collected using self-reported measures, the first study highlights the need to use psychophysiological data to address the topic, especially to study the role of emotions in the process.

The first study also identifies the available neurophysiological tools borrowed from other scientific areas, such as psychology, psychiatry, or neuroscience, to identify the most used ones in marketing and advertising, along with the most prominent trends and topics in which these tools have been overly applied. Consumer neuroscience has been paid attention to as consumer attitudes, emotions, and decision-making are becoming overly complex (Plassmann et al., 2007; Steenkamp & Maydeu-Olivares, 2015). This field of consumer research has been mostly devoted to (1) the preference for objective versus subjective measurement and (2) a more cost-effective way to develop new products and advertising material more likely to engage consumers Daugherty et al., 2016). Further advances in consumer neuroscience will depend on the success of its translation into practice both for marketing academics and business practitioners (Levallois et al., 2012).

Using the correlated topic model algorithm, a text mining technique was employed to analyze the literature. Twenty-three topics emerged from the literature review on consumer neuroscience and neuromarketing. Each topic was then profiled exhaustively with the five most relevant terms and the most relevant articles. The results show that "consumer neuroscience", "brand memory", and "willingness to buy" are the most relevant topics in the field. This study also reveals that the literature has focused on ethical concerns and controversial concerns in the use of consumer neuroscience techniques.

The contributions of the first study are two-fold. First, to the best of the author's knowledge, this study was the first to group many papers on consumer neuroscience and neuromarketing. Despite the important literature reviews conducted in the past, no study has yet performed a comprehensive and integrated review of the vast and complex information around the topic. Second, the paper contributes to the literature by suggesting research questions on three dimensions that cover green marketing/sustainability, new technology developments, and privacy and ethical concerns, providing researchers with several understudied topics and relevant research questions. Besides virtual reality, this technological gap in the literature also considers the subjects of artificial intelligence, blockchain, metaverse, and new advances in neuroscientific tools. Indeed, the study launched the roots for the remaining studies by showing that the combination of AI and neuroscience should be explored to improve the effectiveness of brand communication (Bhardwaj et al., 2023).

The second study took upon the research gaps and avenues from Study 1 and aimed to develop and test a new conceptual model, combining AI-powered technology with brand communication (digital advertising) effectiveness, that would serve as the primary framework for the more complex one in Study 3. The need for statistical significance to map advertising effectiveness and its drivers required a larger sample size for the robustness of results, so only self-reported data was used to guarantee, with data collected from crowdsourcing platforms and social networks to dilute possible bias as much as possible. This second study makes a three-fold theoretical contribution. Grounded in social presence theory (Biocca et al., 2003; Heeter, 1992; Short et al., 1976), and on the computers are social actors (CASA) paradigm (Moon, 2000; Nass et al., 1994; Nass & Moon, 2000), the drivers for advertising value are explored. The study of advertising value, as a measure of advertising effectiveness, in the context of message/recommendations delivery via IVA has not been previously addressed by other researchers. Most of the studies on advertising value were focused on social media (Gupta et al., 2021; Wiese et al., 2020; Yang et al., 2023) or mobile advertising (Hsu et al., 2023; Martins et al., 2019; Sharma et al., 2021), or in the study of customer engagement instead (Itani et al., 2019; Jiang et al., 2022; Zaib Abbasi et al., 2022), whereas artificial intelligence is still in an embryonic stage as an advertising medium. Secondly, anthropomorphic features, such as perceived intelligence and human-likeness, were ascertained as antecedents of social presence, consistent with the results from previous studies. Kim et al. (2020) and Munnukka et al. (2022) considered anthropomorphism a single construct. In contrast, Jin and Youn (2022) conceptualized perceived intelligence, human-likeness, and animacy, similarly to our study, even though animacy and intelligence were not established as significant determinants of social presence. Thirdly, social presence and empathy were found to influence advertising value positively. The relationship between the former two constructs is moderated by the sense of trust toward the IVA, while empathy assumes a full mediation role in advertising value determination when estimating the model paths by IVA type. Therefore, the effects of the different anthropomorphic features displayed by each intelligent virtual assistant on the social and emotional responses and the advertising outcome are addressed.

The third study refers to the final research stage of this project, aiming to complement Study 2 with psychophysiological data to measure emotions. From a social interaction standpoint, this study aimed to move further by introducing the parasocial relationship construct acknowledged as being induced by the sense of social presence (Tsai et al., 2021). The emotional responses evoked by the stimulus (pleasure and arousal) were assessed via psychophysiological measures registered with participants' EDA and HRV data. While traditional self-reports are frequently used in experimental research (Guerreiro et al., 2015), the combination with psychophysiological data is strongly recommended (Bell et al., 2018). Neuroscientific tools are well documented as valuable techniques to understand consumers' spontaneous and unconscious emotions (Liu & Huang, 2023; Rita et al., 2021), less dependent on their conscious and potentially biased responses (Venkatraman et al., 2015), unraveling involuntary changes from cognitive and affective processes (Wang & Minor, 2008). With a foundation on the Stimulus-Organism-Response (S-O-R) framework (Mehrabian & Russell, 1974; Russell & Pratt, 1980), the parasocial interaction theory (Horton and Wohl, 1956), the theory of arousal (Mehrabian, 1996; Russell, 1980), the circumplex model of affect (Russell, 1980; Xu et al., 2023), the mediated relationship development theory (Rubin & McHugh, 1987), and the humanness-value-loyalty (HVL) theoretical framework (Belanche et al., 2021), the third study aims to give a significant contribution for the literature on the critical antecedents of advertising effectiveness, evaluated via advertising value and advertising acceptance.

The contributions from Study 3 are also three-fold. First, this study contributes to the literature on advertising through IVA effectiveness, assessed as Wu (2016) suggested in the context of mobile social networks. Second, regarding the IVA's anthropomorphism, this research provides a more profound knowledge regarding its role as a social and emotional response enhancer and marketing outcomes. Thirdly, our research sheds light on emotional appraisal via psychophysiological tools. In this study, IVA's humanness perception is established as positively influencing its dependent constructs, hence an essential variable for enhancing advertising effectiveness. Additionally, the parasocial relationship is considered one of the mediators between emotional responses and ad effectiveness. Emotional pleasure and arousal were registered with ECG and EDA while participants were exposed to the stimulus in this laboratory experiment, aiming for a more objective measurement of emotions. This research did not support the theory of arousal, as emotional pleasure shows no significant relationship with arousal, whereas arousal was reported as negatively influencing the sense of trust toward the IVA. This negative effect may be related to a high level of arousal and possibly a lower valence (pleasure). According to the circumplex model of affect, participants were probably anxious, nervous, or simply annoyed, leading to untrustworthiness toward the IVA. This finding is potentiated when considering the subsample related to the AI avatar *Anna*, despite its humanness resemblance. According to the uncanny valley theory (Mori, 1970; Mori et al., 2012), which correlates the agent's human resemblance and the elicited emotional responses, the performance of this avatar still needs further development. Even though this avatar is a superior version to others available during the period of the stimulus production, participants may have found some creepiness motivated by synchronization issues between its mouth and speech or the slightly strange facial expressions presented when it was pretending to be listening to the user. The parasocial relationship is revealed to have an important role both for the advertising value and acceptance and to be dependent on PH and from the trust toward the IVA. Also, in this study, the IVA type plays a vital role as a complete model moderator by changing the way and the strength of the relationship between several constructs.

6.2. Managerial Implications

As for practical implications, this research project aimed at providing managers and marketers with recommendations for more assertive and effective communication strategies and techniques in the specific context of advertising through intelligent virtual assistants (IVA). Even though companies and investors are allocating billions of dollars to AI-powered systems (CB Insights, 2023), advertising through IVA is still in the early stages. Therefore, it is crucial to understand how to use this technology to create a closer relationship between brands and customers, with emotional responses assessed through self-reported and biometric data, imbuing the results and recommendations with practical validity for its implementation by practitioners. Hence, the different studies contribute in a specific manner to this up-to-date goal, leading to a better knowledge of the field, taking the most beneficial usage of the technology to enhance brands' visibility and awareness, as well as attention and positive responses from the target audience. By studying conscious and unconscious responses, managers can adapt their future strategies to meet their target expectations (Ozkara & Bagozzi, 2021).

The text mining analysis employed in the first study unveiled the most relevant topics in the literature, some having received more attention from researchers than others. No immersive technology research, whether virtual, augmented, or mixed reality, has been captured by the search string developed for this study, revealing a substantial gap for future research. Consumer neuroscience was determined to be the most explored topic due to its broader application as a breakthrough in the marketing practice (Plassmann et al., 2015). Moreover, brand memory is of paramount importance in advertising, especially in a competitive environment (Pieters et al., 2002; Venkatraman et al., 2021b), and is often considered a measure of advertising effectiveness assessment (Pleyers & Vermeulen, 2021). Advertising aims to catch consumers' attention to the information displayed on labels and product packaging. Besides product price, sustainability-related information (Lee et al., 2020; Loureiro, Guerreiro, & Han, 2021), their composition and origin (Machín et al., 2020; Rihn & Yue, 2016) are currently a significant concern to consumers and an eye-catcher, strong drivers for willingness to buy (Zhang et al., 2021).

Due to the current fervorous market competition, companies must develop the best strategies to overcome their main competitors. Therefore, besides scholars, managers can benefit from this research by identifying the strengths regarding the implementation of neuroscientific tools to assess advertising effectiveness before running a campaign. In this case, due to the significant investment most managers put in brand communication, they should rest assured about the return on their investment and, more specifically, guarantee a suitable response from their target audience. By combining self-reported data, either collected via questionnaires, interviews, or focus groups, with neurophysiological data, managers can understand consumers' possible undisclosed or unconscious feelings and preferences. Eye-tracking, heart rate variability or electrodermal activity are cheaper neurophysiological tools but still strongly beneficial to assess visual attention to advertising and/or product packaging or to measure emotional pleasure and arousal toward the marketing mix (Alsharif et al., 2023). The future research agenda included in Study 1 can be used by researchers, managers, or psychologists as a base for discussion with their teams and to address new directions for innovativeness. With the advent of online retailing, understanding consumer behavior is becoming much more difficult (Bhardwaj et al., 2023). New technologies are disrupting in the marketing business. Traditional media have been losing effectiveness, reach, and acceptance, bringing new challenges to marketers who need new ways to get consumers' attention, hearts, and minds. Therefore, managers should proactively test novel advertising content and using innovative media while building a disruptive strategy properly assessed adequately for efficacy and effectiveness with different neuroscientific tools, hence significantly reducing biased results or less accurate responses.

The second study provides valuable implications for managers regarding adopting intelligent virtual assistants as a medium for delivering voice-enabled advertising or recommendations. To our knowledge, even though these new ways of reaching target audiences are still in their infancy, in an experimental stage, in which only a small number of advertisers took advantage of these new vehicles in specific markets, reporting great results. Therefore, understanding the factors influencing positively the perceived value of advertising is an important added value for advertisers, creative agencies, and manufacturers. Virtual assistants should be imbued with several human cues like voice, appearance, and intelligence to elicit social presence. Otherwise, the information spread by these devices may be assessed as lacking utilitarian benefits, and no value perception would be motivated by the branded content delivered. Marketers should also address the concerns regarding data privacy, which are deemed a noteworthy blocker for IVAs' adoption by consumers, and a key driver of untruthfulness regarding the technology. If consumers are more prone to experience positive social and emotional responses toward anthropomorphic IVAs, marketers and technology designers/developers shall imbue AI-powered technology with a suitable anthropomorphic degree, matching consumer expectancies and enhancing trust toward the IVA. When the suitable human-like salience is not met, the uncanny valley effect may arise (Mori, 1970; Mori et al., 2012), leaving a counterproductive technological device to take over brand communication as consumers will not evaluate brands' content as valuable due to the sense of discomfort, eeriness, and distrust brought by technology. The correct use of AI-enabled technology is advocated to enhance social responses like social presence (Dinh & Park, 2023; Short et al., 1976). Most technology is still not able to show complex emotions, which will weaken social presence judgment (Chen et al., 2023) and empathy creation toward the technology. Empathy toward the IVA was acknowledged in our research as paramount for the greater perception of advertising value Ducoffe (1995, 1996). Therefore, AI avatars are possibly the most easily anthropomorphizable IVAs, so they would be most recommended for brand interaction with consumers due to their ability to feature more complex facial expressions. This would allow consumers to recognize IVAs' emotions and emotional contagion, eliciting a sense of empathy (Park et al., 2022; Pelau et al., 2021). AI is being further used for digital advertising creation, aiming for a more tailored, one-to-one communication with actual consumers and prospects due to the ability to analyze a growing volume of data collected. However, special care has to be taken when developing personalized ads to avoid the excessive disclosure of personal info on the ads, which will raise privacy concerns, along with a strong distrustful attitude toward the technology and the brand (Van Doorn & Hoekstra, 2013).

As for the third study, several contributions to practitioners are acknowledged. The physical resemblance to the user motivates a more substantial and closer relationship, which is an important learning for corporations, especially those responsible for AI-powered device development, but also for the branded content creators. The ability to measure objectively the emotional responses provides a more profound knowledge of the expected reactions to the communication. In this study, there were no special activation moments along the video, which may have affected the EDA results and did not stimulate trust toward the intelligent virtual agent. Consequently, technology adoption blockers may arise, depending on how the audience perceives the message as interesting and not dull. This study provides insights regarding intelligent virtual assistant usage in business practice. With salient technological advances, marketing is going through disruptive ways of interacting with consumers, assembled in a one-to-one framework instead of a one-to-many, as in the previous decades. To this extent, firms must be better equipped with AI-enabled systems to exploit the emerging AI momentum (Aw et al., 2022). To promote voice assistants' usage in the online shopping context, retailers could use influencer marketing but select real customers to bring credibility and trust. On the other hand, as a common practice for online shopping, retailers could use specific promotions for those who order via IVA, whether employing monetary savings for users or simply making specific products or variants available for customers shopping through IVA. Moreover, technology designers, developers, and programmers should pursue IVA’s embodiment, providing highly anthropomorphic assistants to enhance customer trust toward them, using AI avatars instead of simple smart speakers. Anthropomorphic assistants were reported to elicit the adoption of the technology (Pentina et al., 2023), leading to greater emotional attachment like arousal, a predictor of trust. EDA negatively influences trust towards the IVA, so not only does the appearance have to be developed cautiously, but software engineers shall also develop the platform appropriately to avoid expectancy disconfirmation (Oliver, 1980; Spreng et al., 1996) regarding IVA’s capabilities. Customers' expectancy disconfirmation regarding IVA’s skills will lead to distrust and a negative evaluation of the advertised content (its value and acceptance). To enhance trust toward the IVA, IVA’s manufacturers and other companies using IVAs to interact with their target audience should disclose the data collection procedure, featuring higher transparency and potentiating consumer’s confidence in the technology. The advertising content shall also be developed attentively by understanding customers’ interests and needs, as far as personalized advertising is concerned, avoiding the excessive disclosure of customer’s personal data in the ad, which may raise privacy concerns and a sense of intrusiveness (Van Doorn & Hoekstra, 2013), also negatively influencing the advertising outcomes. Besides potentiating the humanness perception of the IVA, developing authentic and truthful IVA is, not only a decisive factor for a positive assessment of the advertising value and acceptance, but also a relationship enhancer (Pentina et al., 2023). Marketers shall also carefully test customers emotions evoked by the technology, not only with self-reported data, but always complementing with neurophysiological tools, at least for the main launches/challenges of the firm.

6.3. Limitations and Directions for Future Research

Several limitations in the studies have been identified, readily presenting themselves as potential avenues for future research.

One of the limitations encountered in the first study, which concurrently offers a valuable research opportunity, pertains to the data collection and sampling methods employed. Although Scopus encompasses a broader array of articles compared to WoS, and other studies have adopted a similarly single-sourced approach, including additional databases, such as WoS, which can enhance the comprehensiveness and representativeness of the subject matter. Moreover, this study could have been further enriched by incorporating alternative analytical techniques, including bibliometric analysis, or using established theories and frameworks (Bhukya & Paul, 2023; Paul & Rosado-Serrano, 2019). A promising avenue for future research lies in exploring the potential application of meta-analysis techniques to investigate the primary and significant relationships among the constructs commonly addressed within this subject area.

Regarding Studies 2 and 3, similar limitations have been identified, which concurrently present promising avenues for future research. These studies utilized the voice assistant *Alexa* and the AI Avatar *Anna* as distinct IVA types. While *Alexa* predominantly finds application in smart speakers, *Google Assistant* and *Siri* hold prominence in mobile devices (Vixen Labs & Open Voice Network, 2022). Within this context, the prior experience of each participant with an assistant and their familiarity with Alexa, compared to the AI Avatar, may play pivotal roles in shaping advertising effectiveness by eliciting social and emotional responses during stimulus presentation. A pertinent area for exploration involves comparing different virtual assistants, such as *Alexa* and *Google Assistant*. In such a scenario, while the moderation by the IVA model could still be administered, the differences observed would not hinge on the anthropomorphic attributes of the assistants, as they possess similar human cues.

Another salient facet during Studies 2 and 3 pertains to the stimuli employed. It would be interesting to conduct further research investigating how participants' responses might evolve in the event of direct interaction with the virtual assistant. Regrettably, such interactions were not implemented due to technological constraints related to voice recognition in the case of the voice assistant. As for the AI Avatar, the study's design precluded direct interactivity, given that the interactions were scripted. Nonetheless, the potential for direct interactivity with the technology is a catalyst for its adoption, potentially fostering a more robust relationship with the device compared to passive observation of a simulated interaction. A longitudinal research approach, as opposed to a cross-sectional study, presents an intriguing avenue for exploration. In this scenario, it would be possible to assess how participants' responses evolve over time, considering the influence of continuous technology usage instead of capturing responses at a specific moment in time.

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Appendices

Appendix A: Script for *Alexa*[5] Ad

User: *Alexa*! Reorder digestive biscuits.

Alexa: Based on your order history, I can add a pack of digestive biscuits for 5 dollars and 99 cents or a pack of 3 for only 16 dollars and 97 cents. Which one do you prefer?

User: *Alexa*! The pack of three.

Alexa: Done! What else?

User: Add any cream cheese on sale to my cart.

Alexa: I have found an option for cream cheese on sale, 200 grams for 2 dollars and 99 cents instead of 3 dollars and 29 cents. Can I add it to your shopping cart?

User: Sure.

Alexa: Your shopping will continue after the following advertising message.

Ad Start – Jingle

Alexa: While you are buying cream cheese, why don't you also try peanut butter from Mr. Portnut? It is Gluten Free and has no added sugar. It uses non-genetically modified organisms and verified ingredients. This peanut butter can be enjoyed anywhere, anytime.
A pack of 3 jars with 454 grams each is just 27 dollars and 99 cents.

Ad End – Jingle

Alexa: Do you want to add this product to your shopping cart?

User: Yes, please.

Alexa: Done. Do you want to shop for anything else?

User: No, that's it.

Alexa: To purchase these items, say, "buy it now".

User: Buy it now.

Alexa: Your total is 47 dollars and 95 cents, including tax, and will be delivered in 2 business days to your address.

Alexa: Shall I proceed to checkout and use your preferred payment method?

User: Yes, sure.

[5] The script for *Anna* ad is exactly the same. Just replace the name of the IVA from *Alexa* to *Anna*. There is no difference on ads' scripts for the different gender.

Alexa: OK! Order placed!

User: Thank you.

Alexa: My pleasure! Just doing my job!

Appendix B: Online Questionnaire for Study 2

Start of Block: Introduction

Dear participant,

This study aims to analyze the future of digital advertising through artificial intelligence (AI) assistants.

The most popular AI Assistants are Amazon's *Alexa*, Apple's *Siri*, Google's *Google Assistant*, Microsoft's *Cortana*, Samsung's *Bixby*, and even the AI assistant on Google Maps app. These AI assistants can be used in diverse smart devices/systems or through robots with/without a human resemblance.

Only participants who own an AI assistant and/or who have used one in the last year should answer this survey.

During your participation, it is important that the device you are using to answer the questionnaire has the sound turned on. Otherwise, your participation cannot be considered.

Note that some questions may seem similar to others, but please answer all of them. You will also find questions that may seem out of context and aim to analyze your attention during the survey. Thus, read each question carefully and respond thoughtfully.

We expect the survey will take approximately 10 minutes to complete, although response times may differ between participants.

All the collected data will be treated confidentially and anonymously. The data will only be used for the purpose of this study. Therefore, please answer honestly and spontaneously.

Thank you in advance for your cooperation. Your participation will be much appreciated.

Click the button below to move forward and begin with the survey. By doing so, you agree to participate in the survey, consenting to the terms and conditions described above. Please close your browser if you do not wish to participate in the survey.

End of Block: Introduction

Start of Block: Participants' Eligibility

1. *Eleg*

   Please indicate whether you have already used an AI assistant.

   ○ Yes (1)

   ○ No (2)

Skip To: End of Survey If Eleg = 2

End of Block: Participants' Eligibility

Start of Block: Demographic Data

2. *Age*

   Please indicate whether you have already used an AI assistant.

   ○ Under 18 (1)

   ○ 18 - 24 (2)

   ○ 25 - 34 (3)

   ○ 35 - 44 (4)

   ○ 45 - 54 (5)

   ○ 55 - 64 (6)

   ○ 65 or more (7)

3. *Gender*

   Please identify your gender:

   ○ Male (1)

   ○ Female (2)

4. *Nationality*

   Please select the country of your nationality:

▼ Afghanistan (1) ... Zimbabwe (1357)

5. *Residence*

Please select the current country of residence:

▼ Afghanistan (1) ... Zimbabwe (1357)

6. *Education*

What is the highest education level you completed?

- ○ High-school graduate (1)
- ○ Vocational training (2)
- ○ Bachelor's degree (3)
- ○ Master's degree (4)
- ○ Doctoral degree (5)
- ○ No formal qualification (6)

7. *Occupation*

What is your current occupation?

- ○ Retired (1)
- ○ Employed (2)
- ○ Self-Employed (3)
- ○ Homemaker (4)
- ○ Student (5)
- ○ Unemployed (6)

8. *Income*

What is your household annual income (approximate value before taxes)?

- ○ < 20,000$ (1)
- ○ 20,000$ - 39,999$ (2)
- ○ 40,000$ - 59,999$ (3)
- ○ 60,000$ - 79,999$ (4)
- ○ 80,000$ - 99,999$ (5)
- ○ 100,000$ - 124,999$ (6)
- ○ ≥ 125,000$ (7)

End of Block: Demographic Data

Start of Block: AI Assistant Usage

9. *Frequency*

   Please indicate your frequency of usage of an AI assistant:

   ○ Multiple times daily (1)
   ○ Once daily (2)
   ○ Multiple times weekly (3)
   ○ Once weekly (4)
   ○ At least once a month (5)
   ○ Less than once a month (6)

10. *Persona*

    What's the name of your AI assistant persona?

    ○ *Alexa* (Amazon) (1)
    ○ *Bixby* (Samsung) (2)
    ○ *Cortana* (Microsoft) (3)
    ○ *Google* (Google) (4)
    ○ *Siri* (Apple) (5)
    ○ Other (6)

11. *Attention Check 1* (Att1)

    Please indicate your agreement with the following statement (1 = Strongly disagree and 7 = Strongly agree):

	1 = Strongly disagree (1)	2 = Disagree (2)	3 = Somewhat disagree (3)	4 = Neither agree nor disagree (4)	5 = Somewhat agree (5)	6 = Agree (6)	7 = Strongly agree (7)
I love my profession. Please respond with "Strongly agree" (1)	○	○	○	○	○	○	○

End of Block: AI Assistant Usage

Start of Block: Stimulus

Stimuli Description

Before continuing, check that your device has the sound turned on.

Please watch the following video carefully.

The video depicts an interaction between a human and an artificial intelligence (AI) assistant.

Pay attention to the interaction and **imagine yourself in the role of the user (human) interacting with the AI assistant.**

NOTE: The button to move forward will only become available by the end of the video.

Stimulus Presentation

End of Block: Stimulus

Start of Block: Stimulus Manipulation Check

12. *IVA's Appearance*

    According to the video you just watched, please rate the **artificial intelligent (AI) assistant's appearance**, using a seven-points scale with 1 as "Human-like" and 7 as "Sound Speaker-like":

	1 = Human-like (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 = Sound Speaker-like (7)
Artificial intelligent agent's appearance (1)	○	○	○	○	○	○	○

13. *User's Voice*

    According to the video you just watched, please indicate whether the **human's voice of the user (not the AI assistant's voice)** sounds rather female or male:

    ○ Female (1)

    ○ Male (2)

End of Block: Stimulus Manipulation Check

Start of Block: Main Questionnaire

14. *Perceived Human-likeness* (PH)

    Please rate the appearance of the AI assistant in the video according to the following scales:

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	(7)	
Machine-like	○	○	○	○	○	○	○	Human-like
Artificial	○	○	○	○	○	○	○	Life-like
Fake	○	○	○	○	○	○	○	Natural
Unconscious	○	○	○	○	○	○	○	Conscious

15. *Perceived Intelligence* (PINT)

    Taking into consideration the video you just watched, please indicate your level of agreement with the following sentences (1 = Strongly disagree and 7 = Strongly agree):

	1 = Strongly disagree (1)	2 = Disagree (2)	3 = Somewhat disagree (3)	4 = Neither agree nor disagree (4)	5 = Somewhat agree (5)	6 = Agree (6)	7 = Strongly agree (7)
The AI assistant in the video appears to be competent (1)	○	○	○	○	○	○	○
The AI assistant in the video is knowledgeable (2)	○	○	○	○	○	○	○
The AI assistant in the video provides relevant information (3)	○	○	○	○	○	○	○
The AI assistant in the video is intelligent (4)	○	○	○	○	○	○	○
The AI assistant in the video provides accurate information (5)	○	○	○	○	○	○	○

16. *Attention Check 2* (Att2)

    What color is grass? The fresh, uncut grass, not leaves or hay. Make sure to select "Purple" as the answer:

    - ○ Red (1)
    - ○ Green (2)
    - ○ Yellow (3)
    - ○ Purple (4)
    - ○ Pink (5)

17. *Social Presence* (SP)

    Please indicate your level of agreement with the following sentences (1 = Strongly disagree and 7 = Strongly agree):

	1 = Strongly disagree (1)	2 = Disagree (2)	3 = Somewhat disagree (3)	4 = Neither agree nor disagree (4)	5 = Somewhat agree (5)	6 = Agree (6)	7 = Strongly agree (7)
When there is an interaction with the AI assistant in the video, it feels like someone is present in the room (1)	○	○	○	○	○	○	○
The interactions with the AI assistant in the video are similar to those with a human (2)	○	○	○	○	○	○	○
During the communication with the AI assistant in the video, it feels like one is dealing with a real person (3)	○	○	○	○	○	○	○
The communication with the AI assistant in the video is similar to the way I communicate with humans (4)	○	○	○	○	○	○	○

18. *Trust Toward the IVA* (TTI)

Taking into consideration the video you just watched, please indicate your level of agreement with the following sentences (1 = Strongly disagree and 7 = Strongly agree):

	1 = Strongly disagree (1)	2 = Disagree (2)	3 = Somewhat disagree (3)	4 = Neither agree nor disagree (4)	5 = Somewhat agree (5)	6 = Agree (6)	7 = Strongly agree (7)
I feel that the AI assistant in the video makes truthful claims (1)	○	○	○	○	○	○	○
I feel that the AI assistant in the video is trustworthy (2)	○	○	○	○	○	○	○
I believe what the AI assistant in the video tells (3)	○	○	○	○	○	○	○
I feel that the AI assistant in the video is honest (4)	○	○	○	○	○	○	○

19. *Empathy* (EMP)

Taking into consideration the video you just watched, please indicate your level of agreement with the following sentences (1 = Strongly disagree and 7 = Strongly agree):

	1 = Strongly disagree (1)	2 = Disagree (2)	3 = Somewhat disagree (3)	4 = Neither agree nor disagree (4)	5 = Somewhat agree (5)	6 = Agree (6)	7 = Strongly agree (7)
The AI assistant in the video is capable of understanding consumers' needs (1)	○	○	○	○	○	○	○
The AI assistant in the video is capable of understanding consumers' feelings (2)	○	○	○	○	○	○	○
The AI assistant in the video follows the interests of the consumer (3)	○	○	○	○	○	○	○
The AI assistant in the video can	○	○	○	○	○	○	○

adopt user's perspective and recommend the desired products (4)							
The AI assistant in the video can take care of me (5)	O	O	O	O	O	O	O
The AI assistant in the video is preoccupied with offering the best products (6)	O	O	O	O	O	O	O
The AI assistant in the video is preoccupied with user's wellbeing (7)	O	O	O	O	O	O	O
I feel comfortable depending on the AI assistant in the video (8)	O	O	O	O	O	O	O
The AI assistant in the video makes a strong impression on me (9)	O	O	O	O	O	O	O
I have positive feelings toward the AI assistant in the video (10)	O	O	O	O	O	O	O
I feel I can have a good connection with the AI assistant in the video (11)	O	O	O	O	O	O	O

20. *Attention Check 3* (Att3)

What is your favorite drink? The most refreshing non-alcoholic drink you can have at breakfast. Make sure to select "Apple juice" as the answer:

O Vodka (1)

O Carrot juice (2)

O Orange juice (3)

O Red wine (4)

O Apple juice (5)

21. *Advertising Value* (AV)

Taking into consideration the video you just watched, please indicate your level of agreement with the following sentences (1 = Strongly disagree and 7 = Strongly agree):

	1 = Strongly disagree (1)	2 = Disagree (2)	3 = Somewhat disagree (3)	4 = Neither agree nor disagree (4)	5 = Somewhat agree (5)	6 = Agree (6)	7 = Strongly agree (7)
I feel that advertising through the AI assistant in the video is useful (1)	o	o	o	o	o	o	o
I feel that advertising through the AI assistant in the video is valuable (2)	o	o	o	o	o	o	o
I feel that advertising through the AI assistant in the video is important (3)	o	o	o	o	o	o	o

End of Block: Main Questionnaire

Appendix C: Online Questionnaire for Study 3[6]

Start of Block: Introduction

Dear participant,

Having completed the first task in the lab, we invite you to complete the second task, which consists of filling out a questionnaire about the video you just watched during the first task.

Some questions may seem similar to others, but please answer all of them. You will also find questions that may seem out of context and aim to analyze your attention during the survey. Thus, read each question carefully and respond thoughtfully.

We expect the survey will take approximately 15minutes to complete, although response times may vary, depending on how quickly you answer to each question.

All the collected data will be treated confidentially and anonymously. The data will only be used for the purpose of this study. Therefore, please answer honestly and spontaneously.

Thank you in advance for your cooperation. Your participation will be much appreciated.

Click "Next" to start the survey. By doing so, you agree to participate in the survey, consenting to the terms and conditions described above. Please close your browser if you do not wish to participate in the survey.

End of Block: Introduction

[6] For self-reported data collection purposes in Study 3, this questionnaire was deployed in Portuguese. For a matter of document's consistency, its English version is presented.

Start of Block: Participants' Eligibility

1. *Eleg*

   Please indicate whether you have already used an AI assistant.

   - ○ Yes (1)
   - ○ No (2)

Skip To: End of Survey If Eleg = 2

End of Block: Participants' Eligibility

Start of Block: Demographic Data

2. *Age*

   Please indicate whether you have already used an AI assistant.

   - ○ Under 18 (1)
   - ○ 18 - 24 (2)
   - ○ 25 - 34 (3)
   - ○ 35 - 44 (4)
   - ○ 45 - 54 (5)
   - ○ 55 - 64 (6)
   - ○ 65 or more (7)

3. *Gender*

   Please identify your gender:

   - ○ Male (1)
   - ○ Female (2)

4. *Nationality*

   Please select the country of your nationality:

▼ Afghanistan (1) ... Zimbabwe (1357)

5. *Residence*

Please select the current country of residence:

▼ Afghanistan (1) ... Zimbabwe (1357)

6. *Education*

What is the highest education level you completed?

- ○ High-school graduate (1)
- ○ Vocational training (2)
- ○ Bachelor's degree (3)
- ○ Master's degree (4)
- ○ Doctoral degree (5)
- ○ No formal qualification (6)

7. *Occupation*

What is your current occupation?

- ○ Retired (1)
- ○ Employed (2)
- ○ Self-Employed (3)
- ○ Homemaker (4)
- ○ Student (5)
- ○ Unemployed (6)

8. *Income*

What is your household annual income (approximate value before taxes)?

- ○ < 20,000€ (1)
- ○ 20,000€ - 39,999€ (2)
- ○ 40,000€ - 59,999€ (3)
- ○ 60,000€ - 79,999€ (4)
- ○ 80,000€ - 99,999€ (5)
- ○ 100,000€ - 124,999€ (6)
- ○ ≥ 125,000€ (7)

End of Block: Demographic Data

Start of Block: AI Assistant Usage

9. *Frequency*

   Please indicate your frequency of usage of an AI assistant:

   - ○ Multiple times daily (1)
   - ○ Once daily (2)
   - ○ Multiple times weekly (3)
   - ○ Once weekly (4)
   - ○ At least once a month (5)
   - ○ Less than once a month (6)

10. *Persona*

    What's the name of your AI assistant persona?

    - ○ *Alexa* (Amazon) (1)
    - ○ *Bixby* (Samsung) (2)
    - ○ *Cortana* (Microsoft) (3)
    - ○ *Google* (Google) (4)
    - ○ *Siri* (Apple) (5)
    - ○ Other (6)

End of Block: AI Assistant Usage

Start of Block: Stimulus Manipulation Check

11. *IVA's Appearance*

    According to the video you just watched, please rate the **artificial intelligent (AI) assistant's appearance** using a seven-point scale with 1 as "Human-like" and 7 as "Sound Speaker-like":

	1 = Human-like (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 = Sound Speaker-like (7)
Artificial intelligent agent's appearance (1)	○	○	○	○	○	○	○

12. *User's Voice*

According to the video you just watched, please indicate whether the **human's voice of the user (not the AI assistant's voice)** sounds rather female or male:

○ Female (1)

○ Male (2)

End of Block: Stimulus Manipulation Check

Start of Block: Main Questionnaire

13. *Perceived Human-likeness* (PH)

Please rate the appearance of the AI assistant in the video according to the following scales:

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	(7)	
Machine-like	○	○	○	○	○	○	○	Human-like
Artificial	○	○	○	○	○	○	○	Life-like
Fake	○	○	○	○	○	○	○	Natural
Unconscious	○	○	○	○	○	○	○	Conscious

14. *Trust Toward the IVA* (TTI)

Taking into consideration the video you just watched, please indicate your level of agreement with the following sentences (1 = Strongly disagree and 7 = Strongly agree):

	1 = Strongly disagree (1)	2 = Disagree (2)	3 = Somewhat disagree (3)	4 = Neither agree nor disagree (4)	5 = Somewhat agree (5)	6 = Agree (6)	7 = Strongly agree (7)
I feel that the AI assistant in the video makes truthful claims (1)	○	○	○	○	○	○	○
I feel that the AI assistant in the video is trustworthy (2)	○	○	○	○	○	○	○
I believe what the AI assistant in the video tells (3)	○	○	○	○	○	○	○
I feel that the AI assistant in the video is honest (4)	○	○	○	○	○	○	○

15. *Parasocial Relationship* (PSR)

Taking into consideration the video you just watched, please indicate your level of agreement with the following sentences (1 = Strongly disagree and 7 = Strongly agree):

	1 = Strongly disagree (1)	2 = Disagree (2)	3 = Somewhat disagree (3)	4 = Neither agree nor disagree (4)	5 = Somewhat agree (5)	6 = Agree (6)	7 = Strongly agree (7)
I would like to compare my ideas with what the AI assistant in the video says (1)	○	○	○	○	○	○	○
Interacting with the AI assistant in the video makes one feel comfortable, as if he is with friends (2)	○	○	○	○	○	○	○
If the AI assistant in the video was a human, I imagine the AI assistant as a natural, down-to-earth person (3)	○	○	○	○	○	○	○

I would like to hear the opinion of the AI assistant in the video at home (4)	o	o	o	o	o	o	o
The AI assistant in the video keeps someone company while using it (5)	o	o	o	o	o	o	o
I look forward to using an AI assistant like the one in the video (6)	o	o	o	o	o	o	o
When the AI assistant in the video responds to the request, it seems to understand the kinds of things one wants to know (7)	o	o	o	o	o	o	o
If there was a story about the AI assistant in the video, in a newspaper or magazine, I would read it (8)	o	o	o	o	o	o	o
I would miss using an AI assistant like the one in the video when I can't use it because it needs to be repaired (9)	o	o	o	o	o	o	o
I think the AI assistant in the video is like an old friend (10)	o	o	o	o	o	o	o
I find the AI assistant in the video to be attractive (11)	o	o	o	o	o	o	o

16. *Advertising Value* (AV)

Taking into consideration the video you just watched, please indicate your level of agreement with the following sentences (1 = Strongly disagree and 7 = Strongly agree):

	1 = Strongly disagree (1)	2 = Disagree (2)	3 = Somewhat disagree (3)	4 = Neither agree nor disagree (4)	5 = Somewhat agree (5)	6 = Agree (6)	7 = Strongly agree (7)
I feel that advertising through the AI assistant in the video is useful (1)	○	○	○	○	○	○	○
I feel that advertising through the AI assistant in the video is valuable (2)	○	○	○	○	○	○	○
I feel that advertising through the AI assistant in the video is important (3)	○	○	○	○	○	○	○

17. *Advertising Acceptance* (AA)

Taking into consideration the video you just watched, please indicate your level of agreement with the following sentences (1 = Strongly disagree and 7 = Strongly agree):

	1 = Strongly disagree (1)	2 = Disagree (2)	3 = Somewhat disagree (3)	4 = Neither agree nor disagree (4)	5 = Somewhat agree (5)	6 = Agree (6)	7 = Strongly agree (7)
I feel positive about the advertising through the AI assistant in the video (1)	○	○	○	○	○	○	○
I am willing to receive advertising through the AI assistant like the one in the video in the future (2)	○	○	○	○	○	○	○

I would listen to all the advertising messages I receive in the future from the AI assistant as the one in the video (3)	o	o	o	o	o	o	o

End of Block: Main Questionnaire

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From Mind to Market
Understanding the Influence of Intelligent Virtual Assistants on Advertising Value and Acceptance from a Neurophysiological Perspective

Pedro Miguel Oliveira