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ENHANCING AI CONVERSATIONAL AGENTS FOR EFFECTIVE ADVICE-GIVING: EXPLORING FACTORS AFFECTING USER-AGENT INTERACTIONS

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Abstract

As conversational agents (CAs) become more ubiquitous in digital interactions, it becomes essential to understand whether their design influences the way users behave. This study investigates the CA communication style in terms of language formality, avatar outfit formality, and advice alignment to see how these factors influence psychological reactance and intention to follow advice. Based on politeness theory, psychological reactance theory, and responsibility attribution theory, three empirical models test some key determinants affecting CA effectiveness in advice-taking situations. Model 1 examines the effect of language and avatar formality on advice adherence. Results indicate that formal language has a significant positive effect on adivce adherence ($F(1,448) = 18.900$, $p = 0.000$), whereas the formality of the avatar outfit has no effect. Mediation tests indicate that formal language increases perceived negative politeness, which in turn has an impact on reactance and adivce adherence. In Model 2, the effect of language directness and advice alignment on adivce adherence is examined. Outcomes show that aligned advice with user's previous preferences reduces psychological reactance (effect = -0.883, $p = 0.000$), thereby increasing adivce adherence. Language directness, nonetheless, does not independently affect adivce adherence, which attests to the importance of alignment in overcoming resistance to AI suggestions. In Model 3, the focus turns to how responsibility attribution and the success or failure of an advice received from a CA impact future adoption of a chatbot. Users put less responsibility on a CA for the outcome when they received advice that is aligned with their previous preference. While the success of the dvice directly affects intention to use the CA positively. In summary, this research advances human-machine interaction literature by clarifying how verbal and nonverbal cues influence user behavior in AI-driven advice settings. Practical implications include strategies for designing persuasive, user-centered CAs that optimize engagement and adherence while managing user resistance and responsibility perceptions.

Keywords: Conversational Agents (CAs), Advice Adherence, Politeness Theory, Psychological Reactance, Responsibility Attribution.

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With heartfelt thanks,
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Introduction

Conversational agents (CAs) have evolved from simple automated systems into advanced artificial intelligence (AI)-driven advisors, significantly impacting customer interactions across industries. These systems simulate human dialogue using natural language processing (NLP) and machine learning (Kolbjørnsrud et al., 2016; McCarthy, 1954). As businesses increasingly integrate CAs in areas such as customer service, healthcare, and e-commerce, the effectiveness of advice-giving CAs becomes a critical research focus (Almzayyen et al., 2022).

This study examines how CA communication styles influence advice adherence, psychological reactance, and post-adoption behavior. Specifically, we investigate how language formality, avatar outfit formality, and advice alignment shape user responses to AI-generated recommendations. Communication styles refer to the verbal and nonverbal elements of interactions, such as formal vs. informal language and visual representations (Liebrecht, Sander, et al., 2021). In contrast, advice-giving strategies focus on how recommendations are framed, including direct vs. indirect communication and whether advice aligns with user preferences.

A key concept in this research is alignment bias, which occurs when advice is tailored to match a user's pre-existing beliefs or preferences (Luo et al., 2024). While alignment can enhance adherence by reducing psychological resistance, excessive alignment may reinforce biases, limiting decision-making quality. For AI-driven recommendation systems, balancing alignment and objectivity is crucial for fostering trust and optimizing user experience.

Additionally, responsibility attribution plays a significant role in shaping post-adoption behavior. When users follow AI-generated advice, they may attribute responsibility for the outcome to the system or themselves (Y. Gu et al., 2024). Successful recommendations can enhance trust and increase future engagement, while failures may lead to blame attribution and disengagement. Understanding these dynamics is essential for designing persuasive, user-centered conversational agents.

To address these questions, this study develops three empirical models:

- Model 1 explores the role of language formality and avatar outfit formality in shaping advice adherence and perceived politeness.
- Model 2 investigates how advice alignment and language directness influence psychological reactance and advice adherence.
- Model 3 examines how advice success or failure, responsibility attribution, and advice alignment impact users' intention to continue interacting with CAs.

This research contributes to the growing field of AI-human interaction by offering insights into the psychological mechanisms underlying advice adherence and long-term CA engagement. The findings inform both theoretical advancements and practical applications, guiding businesses in designing more effective, trustworthy, and persuasive AI advisors.

Chapter 1: Literature Review and Theoretical Background

1. Conversational Agents Implantation in Customer Interaction: A bibliometric analysis and systematic review of the literature

1.1. Introduction

With the advancement of technology, new tools are emerging that allow people and organizations to interact with their target audiences in different fields. A recent tool is Conversational Agents (CAs). A CA is software with which humans interact through natural language (Diederich et al., 2022). CAs are being increasingly implemented in many fields since they can provide a widely accessible service to customers without time limits. Therefore, scholars' attention to this field is rising, and academic studies are focusing on understanding different aspects of human-CA interaction (Maedche et al., 2019). Moreover, many consumers are adapting their shopping and inquiry style to the new change, affecting their expectations and requirements from different service providers. A specific form of CAs is catboats. According to Shukairy (2018), the CCO at Invesp, during the first half of 2021, 67% of the consumers in the world had an interaction with a chatbot (Shukairy, 2018). However, despite their rising popularity, there is still room for improvement because of flaws in the design or a lack of knowledge regarding user experience and expectations (Diederich et al., 2022). Consequently, research in these areas is essential, promising valuable insights for both academic scholars and industry practitioners. This necessity has resulted in an increasing number of publications dedicated to the various dimensions of CA interactions.

As the body of literature continues to expand, it is essential to review and synthesize the accumulated knowledge. This study evaluates users' perceptions of CA implementation by extracting relevant characteristics from existing literature on human-CA interactions. To achieve this objective, a comprehensive bibliometric and scientometric analysis was conducted, along with a systematic review of a dataset sourced from the Web of Science (WoS) and Scopus databases. Due to differences in journal coverage and indexing policies, the two databases were analyzed independently. This allows for accounting for field-specific variations and mitigating potential data biases that may arise from relying on a single source. Subsequently, an aggregated analysis was performed on the combined dataset to ensure the robustness of the findings.

The process of research was guided by an established protocol with defined keywords to search and obtain relevant articles. The outcomes of the 216 shortlisted articles by bibliometric and systematic review were elucidated and presented in tables, charts, and maps, which clearly indicated the development level of the field and future trends. Specifically, this encompassed aspects such as academic impact, predominant journals, influential papers, leading authors, contributing countries, and potential future research areas. Moreover, methodological findings were critically evaluated using a framework previously proposed by Zhang and Li (2005), which identifies four core dimensions of human-CA interactions: Human, Context, Agent, Perception, and Outcome. The methodologies and structures of the reviewed papers within each dimension were thoroughly described. In short, this paper aims to answer the following research question:

RQ: "How do conversational agent (CA) design and communication strategies affect user perceptions and behavioral responses in customer service interactions?"

The study is organized as follows: Section two describes and illustrates the methodology, data collection, and data analysis. Section three discusses the potential for future research and outlines the limitations of this study. Finally, section four provides concluding remarks and summarizes the key points of the research.

1.2. Methodology

In this study, qualitative approaches were employed to thoroughly evaluate the materials and achieve a deeper understanding of the research question (Ahmad et al., 2019). As a result, bibliometric and scientometric analyses, along with a systematic literature review, were conducted to provide a comprehensive overview of the articles addressing the role of Conversational Agents (CAs) in customer interactions. The search was restricted to publications available up to August 2021. Data analysis was conducted using R software's Biblioshiny, which performs science mapping analysis utilizing the primary functions of the bibliometrix package (Aria, 2021), and VOSviewer, a software tool for creating maps based on network data and visualizing and exploring these maps (van Eck & Waltman, 2017). The aim was to find co-occurrences between words and The scientometric analyses include co-author, co-word, and co-citation clusters (Zhao et al., 2019). Afterward, the articles were methodically analyzed to provide an in-depth appraisal (Kupiainen et al., 2015). The subsequent sections detail the data collection process, analysis methodologies, and procedures. Additionally, the analysis of graphs and tables is presented and discussed. Furthermore, co-citation, co-occurrence, and bibliographic coupling analyses are provided, accompanied by relevant graphs and interpretations.

1.3. Data Collection

To gather data, a search protocol was developed to ensure coverage and minimize researcher bias. Searching was carried out in August 2021, and the dataset employed was downloaded from two databases, Scopus and Web of Science (WoS). The two databases were utilized due to their extensive coverage of various publications, subjects, and disciplines. Moreover, they are the most informative sources for various fields and subjects. Moreover, they enable article searching with complex Boolean search strategies that provide more relevant results (Pranckutė, 2021).

As per the established protocol, the formats of publications chosen were limited to reviews and journal articles. The considered publications were English-language only and covered the fields of business, management, psychology, decision-making, social science, and cross-disciplinary fields from core subjects. Data was first extracted independently from WoS and Scopus. The datasets were then merged into a single dataset using the RStudio software to enable a comprehensive analysis. In duplication instances, only the record with complete data fields was retained. Other sources of data were also reviewed to establish any missing records.

PDFs of journal articles were retrieved to enable a thorough analysis of their content and methodologies. If a full-text paper was unavailable, the abstract was used for analysis. Keywords extracted from the literature to assist in collecting relevant papers are presented in Table 1 and Table 2, along with the search terms.

The final search yielded 192 articles indexed in Scopus and 90 in WoS. After removing duplicates using the R program, 216 papers remained for examination. For the analysis, metadata for these 216 articles was obtained, including print features, authors' names, corresponding authors' countries, total number of publications, citation counts including total citations, average article citations, number of citing articles with and without self-citations, journal sources, keywords, countries, references, abstracts, publication dates, authors, and regions (Martynov et al., 2020). These elements were essential for the analyses conducted using relevant software and evaluation tools.

Table 1: Scopus Search Details of The Study

Search Terms in Scopus		
Field Tag	Title, Abstract, and Keywords	TITLE-ABS-KEY ("chatbot" OR "voice assistant" OR "conversational agent") AND
Boolean		AND
Field Tag	Title, Abstract, and Keywords	TITLE-ABS-KEY (user OR consumer OR customer)
Boolean		AND
Document Type	Article, Review	(LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "re")
Boolean		AND

Language		LIMIT-TO (LANGUAGE , "English")
Boolean		AND
Subject Area	Business, Psychology, Decision Making, Economic	(LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "PSYC") OR LIMIT-TO (SUBJAREA , "DECI") OR LIMIT-TO (SUBJAREA , "ECON")

Table 2: WoS Search Details of The Study

Search Terms in WoS		
Field Tag	Abstract	AB=(chatbot OR "voice assistant" OR "conversational agent")
Boolean		AND
	Abstract	AB=(user OR consumer OR customer)
Boolean		AND
LANGUAGE		(English)
Boolean		AND
DOCUMENT TYPES		(ARTICLE OR REVIEW)
Boolean		AND
WEB OF SCIENCE CATEGORIES:		(BUSINESS OR PSYCHOLOGY MULTIDISCIPLINARY OR MANAGEMENT OR PSYCHOLOGY SOCIAL OR PSYCHOLOGY EXPERIMENTAL OR PSYCHOLOGY MATHEMATICAL OR PSYCHOLOGY CLINICAL OR ROBOTICS OR PSYCHOLOGY DEVELOPMENTAL OR COMMUNICATION OR SOCIAL ISSUES OR PSYCHOLOGY APPLIED OR SOCIAL SCIENCES BIOMEDICAL OR SOCIAL

SCIENCES INTERDISCIPLINARY OR SOCIOLOGY OR BUSINESS FINANCE)

1.4. Data Analysis

Biblioshiny was used to extract the key information. The Dataset Summary is presented in Table 3, serving as the initial step in providing a descriptive dataset summary. The same tool was utilized to identify the top ten papers based on total citations and the top ten journals, authors, and countries based on the number of documents. Bibliographic analysis and scientometric techniques were applied to gain deeper insights into the patterns present within the collected data. These techniques made it possible to map scientific knowledge (Zhao et al., 2019). The Biblioshiny bibliometrix package in R (Version 2019) and VOSviewer (Version 2020) are used to create the maps, and the outputs are displayed as the results.

This approach facilitated the creation of network layouts and clustering patterns, utilizing co-occurrence networks based on textual data (Zhao et al., 2019). Furthermore, these efforts facilitated the analysis of key concepts, co-citations, and author networks. Consequently, the scientometric analyses conducted include co-citation, co-occurrence, and bibliographic coupling, with details elaborated in the subsequent subsections.

1.4.1. Descriptive Analysis

The summary of the information about the papers, retrieved from Scopus and WoS, is as mentioned in Table 3, based on each database, WoS and Scopus, and the overall dataset. A total of 216 papers published from 2001 until August 2021, in 108 journals, were evaluated. In addition, the average number of citations per document is 11.4, and the average number of citations per year per document is 3.369.

Table 3: Dataset Summary

Description	WoS	Scopus	Combined

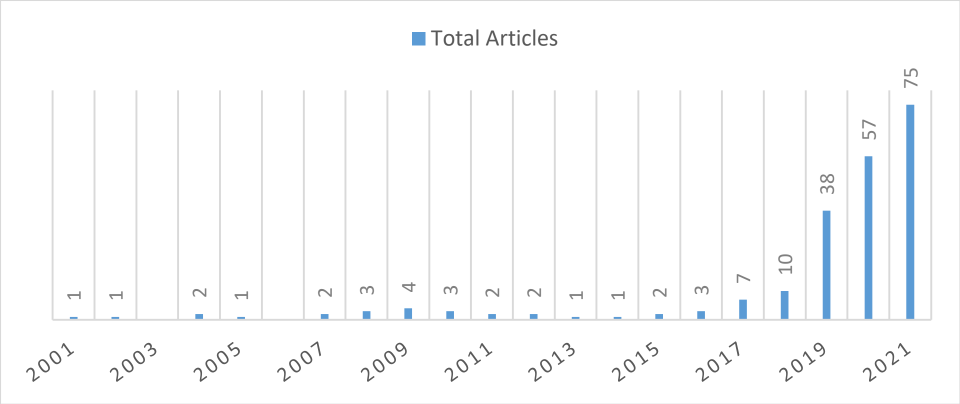
DOCUMENT TYPES			
Article	88	184	207
Review	2	8	9
AUTHORS			
Authors	261	556	609
Author Appearances	280	607	684
AUTHORS COLLABORATION			
Single-authored documents	11	21	24
Documents per Author	0.345	0.345	0.355
Authors per Document	2.9	2.9	2.82
Co-Authors per Document	3.11	3.16	3.17
Collaboration Index	3.18	3.14	3.06

Annual production is shown in Figure 1. According to the dataset's study in terms of annual production, the number of published documents did not significantly fluctuate over time until 2019, when the number of published articles increased significantly, from 10 papers in 2018 to 38 papers in 2019. In 2020 and 2021, the number increased even further, reaching 57 and 75 publications, respectively. This pattern holds true for both databases as well, with Scopus showing a stronger trend.

This might be due to the quick adoption of CAs in many services and enterprises in recent years, as well as the efforts made by corporations to introduce new and more powerful CA forms, including home devices. Additionally, new applications for CAs are being developed daily, and they are embodied in our daily lives through their presence in gadgets like mobile phones, cars, and homes. Furthermore, the COVID-19 pandemic's effects might also play a role. Since 2019, steps have been taken to stop the virus from spreading, including travel limits, quarantines, and smart working.
made it less feasible and convenient for customers and staff to be physically present. As a result, many communications were done via websites and online forums, and companies provided the necessary infrastructure. Consequently, there is an increased focus on comprehending the influence of CAs across many domains. In addition, researchers had obstacles when conducting research during COVID-19. As a result of field research restrictions, online data and platforms became more accessible sources of information during the pandemic in many nations.

This persuaded many researchers to focus on gathering online data and investigating online behaviors. All of these are possible explanations for a great jump in the number of papers published in the field of CAs and human interaction.

Figure 1: Annual Publication



The top 10 nations by total number of papers produced and published are shown in Figure 2. The United States, the United Kingdom, India, Germany, France, the Netherlands, Australia, China, Italy, and Japan are the top-ranked nations. With 110 publications, the USA is the largest contributor, followed by the UK with 38. However, the ten countries with the most referenced publications are not in the same order. as illustrated in Figure 3. The most referenced nations are the US, UK, South Korea, France, Germany, China, Australia, Belgium, India, and Poland, in that order. Belgium has the highest average article citation, at 36.50. Despite having different numbers of published papers, the US and the UK have similar numbers of citations (487 and 463, respectively).

Figure 2: Country Production

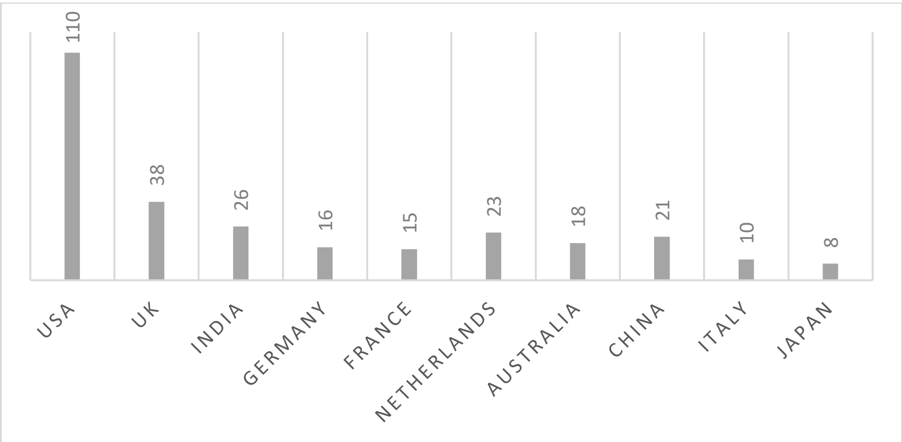


Figure 3: Most Cited Countries

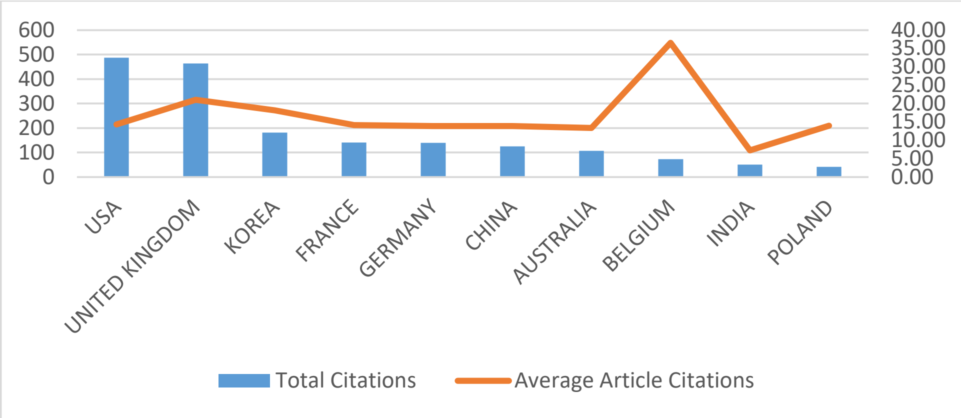


Figure 4 lists the top 10 journals based on the number of published articles. The highest number of studies about CAs have been published in the Journal of "Computers in Human Behavior," a scientific journal devoted to studying computer use from a psychological perspective (Elsevier, 2021). The Journal of Psychology and Marketing, which publishes original research and review articles addressing the application of psychological theories and techniques to marketing, comes in second (Wiley, 2021). The Journal of Computer in Human Behavior held numerous special issues covering a variety of topics, including marketing, consumer behavior, learning, social commerce, and more. Predictably, the journal is at the top because it focuses specifically on the interaction between humans and computers from various angles.

Out of 21 papers published in the Journal of “Computers in Human behaviour”, 16 were published from 2019 to 2021, confirming the previous discussion in the annual publication trend.

Figure 4: Most Relevant Journals

The top 10 journal papers with the most citations overall are presented in Table 4. While all ten top publications were indexed in Scopus, several were also indexed in WoS, with citation numbers in both databases listed separately. Seven highly cited papers were published between 2018 and 2021, whereas the remaining three appeared in 2007, 2009, and 2013, aligning with previously observed publication trends. In the Journal of "Computers in Human Behavior," Dr. Araujo's paper "Living up to the chatbot hype: The Influence of Anthropomorphic Design Cues and Communicative Agency Framing on Conversational Agent and Company Perceptions" received the highest number of citations (140) in 2018. Anthropomorphism's popularity among conversational agent (CA) researchers, along with the emphasis on investigating relevant impacts and requirements of anthropomorphic characteristics in human-computer interaction, may have contributed to the paper's high citation count, in addition to its content and the author's expertise. Consequently, this study is regarded as one of the pioneering investigations in this field.

Table 4: Top 10 Highly Cited Papers

Paper	**Description**	**Total Citations**
Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions	Araujo (2018), Computers in Human Behavior	140
Bringing Chatbots into Education Towards Natural Language Negotiation of Open Learners Models	Kerly et al. (2007), J. of Knowledge-based Systems	99
I Can Help You Change an Emphatic Virtual Agent Delivers Behavior Change Health Interventions	Lisetti et al. (2013), ACM Transactions on Management Information Systems	93
Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions	Go & Sundar (2019), Computers in Human Behavior	91
Frontiers Machines vs. Humans the Impact of Artificial Intelligence Chatbot Disclosure on Customer Purchases	Luo et al. (2019), Marketing Science	75
Frontline Service Technology infusion: conceptual archetypes and future research directions	De Keyser et al. (2019), Journal of Service Management	73

Hey Alexa Examine The Variables Influencing The Use Of Artificial Intelligent in Home Voice Assistants	Mclean and Osei-Frimpong (2019), Computers in Human Behavior	67
Chatbot e-Service and Customer Satisfaction Regarding Luxury Brands	Chung et al. (2020), Journal of Business Research	65
Understanding Emotions in Text Using Deep Learning and Big Data	Chatterjee et al. (2019), Computers in Human Behavior	64
CSIEC A Computer Assisted English Learning Chatbot Based on Textual Knowledge and Reasoning	Jia (2009), Knowledge-based Systems	61

1.4.2. Co-citation analysis

A co-citation analysis was also conducted. It can provide a relevant overview of the semantic similarities in the literature, and the network visualization contributes to sense-making and text summarization (Shiau et al., 2017).

The result generated includes publications clustered, formed according to their co-citation similarities on the basis of a matrix developed by the algorithm. This analysis was conducted because Author-based bibliographic coupling aids in identifying theoretical clusters within the field, illustrating different conceptualizations of chatbot interactions by researchers.

These clusters represent dominant themes (Shiau et al., 2017). In network visualization, the lines emphasize the most critical paths between authors, and the figure also demonstrates authors who play a pivotal role in clusters (Nerur et al., 2008). Moreover, the co-citation network structure reveals the most cited authors by considering references used in articles.

To perform the analysis, the number of publications was initially limited to identify the most influential works. A cut-off of a minimum of five citations of cited references in Scopus resulted in 44 publications, while a minimum of seven citations in WoS yielded 33 documents for evaluation.

In the Scopus database, four clusters have emerged. There are 17 articles in the first cluster, which is highlighted in the red color in Figure 5. Based on an overview of the topics and keywords, the papers in the cluster are more focused on Consumer Behaviour.

The second cluster, highlighted in green, includes thirteen papers. In this cluster, It is found that most papers emphasize the Anthrophormisn and Humanlikeness of CAs.

The third cluster, highlighted in blue, instead comprises seven articles that provide insight into the Social Aspects of the interaction with a CA.

Lastly, the fourth cluster, highlighted in yellow, also includes seven papers, closely resembling the first cluster but specifically concentrating only on chatbots rather than other CA types.

In the WoS database, three clusters emerged, closely aligned with those from Scopus. The first cluster, highlighted in blue in Figure 6, contains eleven articles focusing on consumer behavior, similar to the first cluster from Scopus.

The second cluster, highlighted in red, with 13 papers, is more related to psychological and social aspects of the interaction with CAs, again similar to the second cluster in the Scopus database. Finally, the third cluster, highlighted in green, comprises eight articles that investigate the realm of Anthropomorphism and the Humanlikeness of CAs.

Figure 5: Co-Citation Network Based on Scopus Data

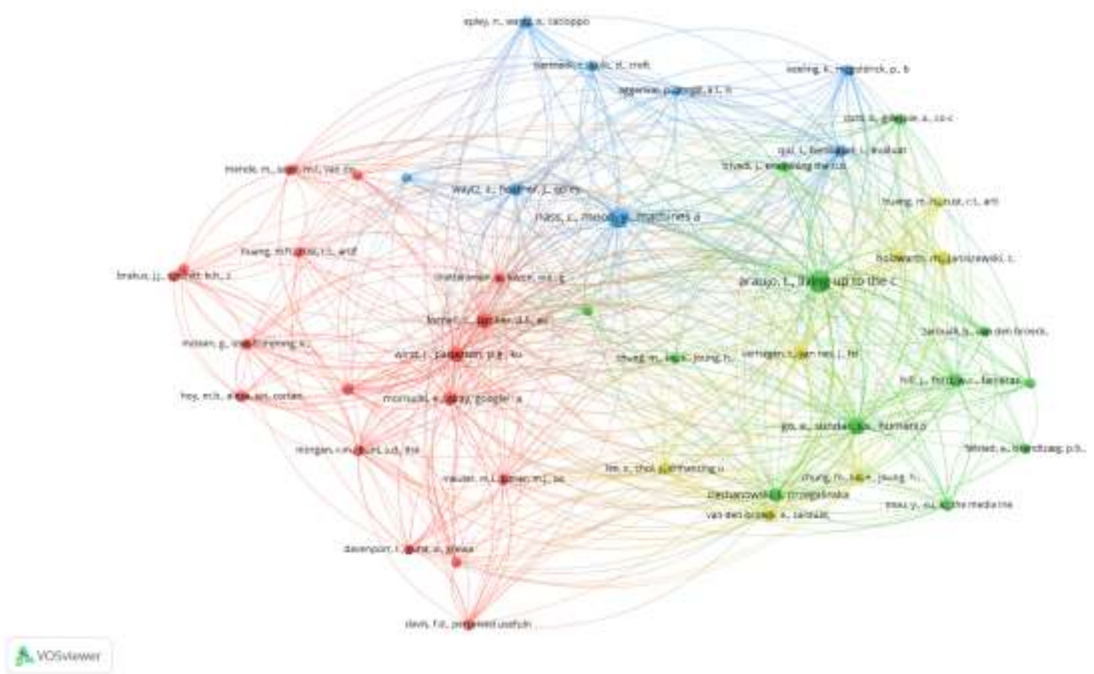
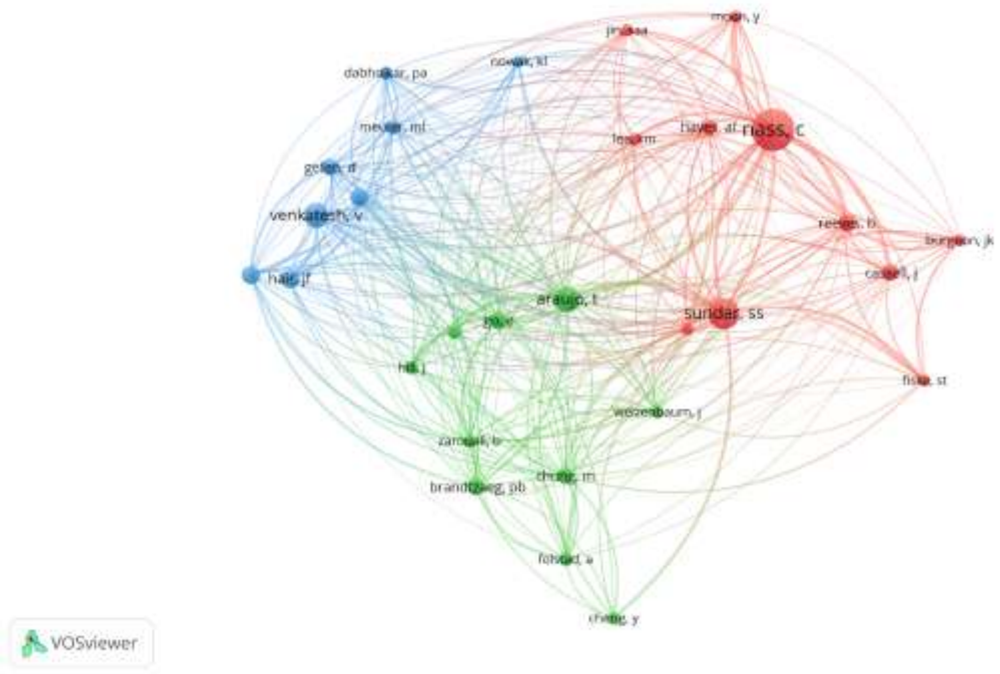


Figure 6: Co-Citation Network Based on WoS Data



1.4.3. Bibliographic Coupling

Building on the previous discussion on citation analysis and its role in mapping intellectual foundations, bibliographic coupling serves as a complementary approach to identifying contemporary research streams.

As opposed to co-citation, where papers are aggregated in clusters of co-cited works, bibliographic coupling pairs papers that have mutual citations (Kessler, 1963). This is particularly helpful to identify emerging areas of research that may not yet be widely cited but have conceptual foundations in common.

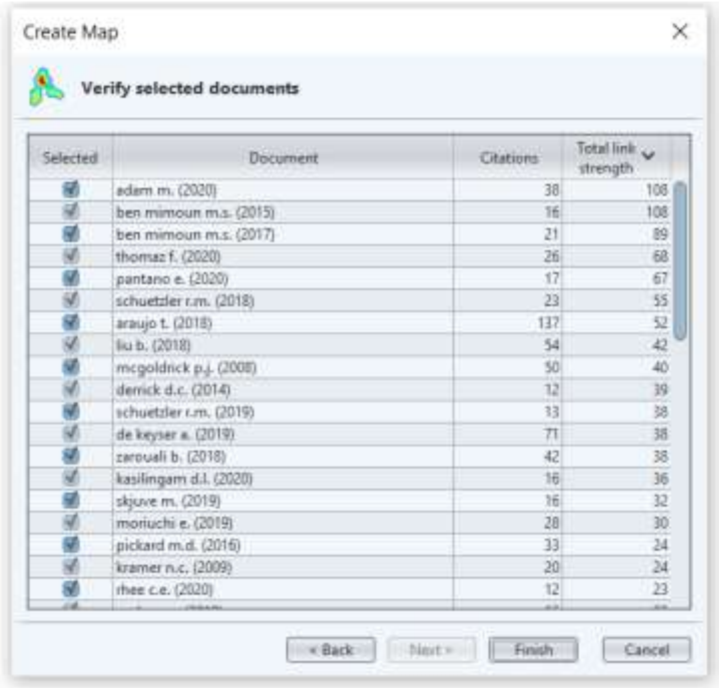
In the context of online marketing and conversational agents, bibliographic coupling helps to identify groups of new research struggling with similar theoretical viewpoints, methods, or areas of application. By looking at how new research is building upon shared references, this method enables a more forward-looking perspective, isolating ongoing fronts of contention and topics of knowledge shortage. Therefore, this section delves deeper into the application of bibliographic analysis to structure the literature review systematically.

In bibliographic coupling analysis, the connection between different authors is determined by evaluating the degree to which they cite the same research publications as references (Shah et al., 2019).

Therefore, the number of common citations within a group of publications was mapped using bibliographic coupling. Unlike co-citation, bibliographic coupling determines whether two publications are linked by assessing if both publications reference a common third publication (Kessler, 1963). Therefore, a stronger bibliographic coupling relationship between two publications indicates a greater number of common references. This approach provides a clearer understanding of the literature's structure. A threshold of at least ten citations was set for the Scopus database, resulting in 48 influential papers, while a threshold of at least four citations for the WoS database yielded 32 influential journal articles. The publication with the strongest link in both databases is "AI-based chatbots in Customer Service and their effects on User Adivce adherence," authored by Adam et al., 2021, and published in the journal Electronic Markets (Figure 5 and Figure 7).

Longitudinal analysis was performed as well to further evaluate the clusters. In Figure 9 and Figure 12, based on the number of citations/papers and the average year, a map of the clusters is presented. The higher the position of the clusters at the top, the greater the citation per paper ratio, therefore, the clusters positioned at the higher levels are more likely to be the most influential research clusters that inspired other authors, while the clusters that are closer to the right end are more recent and are more likely to comprise the topics that could become potential future research trends (Phan Tan, 2022). Therefore, as indicated by Figure 9 and Figure 12, it can be inferred that within the Scopus database, Cluster 2 is the most influential, whereas Cluster 1 likely represents a new direction for future research. Conversely, in the WoS database, Cluster 6 holds the highest influence, while Clusters 2, 3, and 4 potentially outline future research trends.

Figure 7: Publication Link Strengths in Bibliographic-Coupling Based on Scopus Data



Create Map

Verify selected documents

Selected	Document	Citations	Total link strength
☑	adam m. (2020)	38	108
☑	ben mimoun m.s. (2015)	16	108
☑	ben mimoun m.s. (2017)	21	89
☑	thomaz f. (2020)	26	68
☑	pantano e. (2020)	17	67
☑	schuetzler r.m. (2018)	23	55
☑	araujo t. (2018)	137	52
☑	liu b. (2018)	54	42
☑	mcgoldrick p.j. (2008)	50	40
☑	derrick d.c. (2014)	12	39
☑	schuetzler r.m. (2019)	13	38
☑	de keyser a. (2019)	71	38
☑	zarouali b. (2018)	42	38
☑	kasilingam d.l. (2020)	16	36
☑	skjuve m. (2019)	16	32
☑	moriuchi e. (2019)	28	30
☑	pickard m.d. (2016)	33	24
☑	kramer n.c. (2009)	20	24
☑	rhee c.e. (2020)	12	23

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Figure 8: Bibliographic-Coupling Network Based on Scopus Data

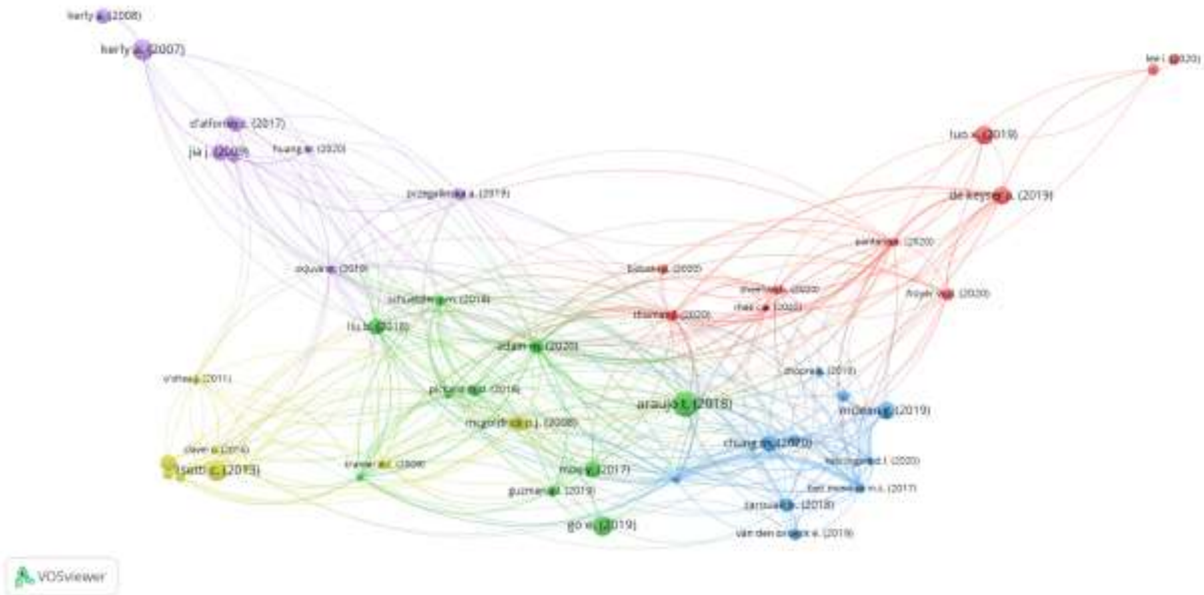
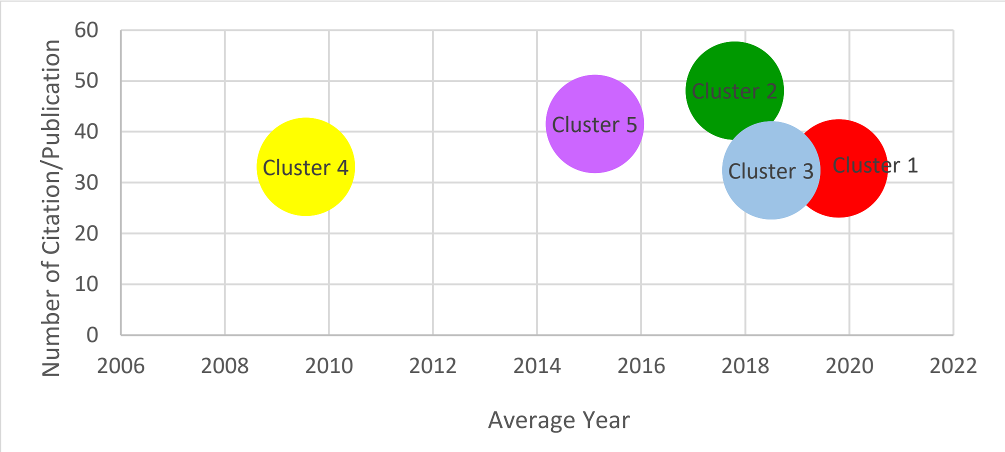


Figure 9: Longitudinal Analysis of The Most Significant Bibliographic Coupling Clusters Based on Scopus Data



Further evaluation of the significant clusters emerging from the longitudinal analysis is provided below:

Cluster 1, which represents future trends, includes the following publications:

- "Assessing long-term user experience on a mobile health application through an in-app embedded conversation-based questionnaire" authored by Biduski D., Bellei E.A., Rodriguez J.P.M., Zaina L.A.M., De Marchi A.C.B. and published in the Journal of Computers in Human Behavior
- "Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential" authored by Canhoto A.I., Clear F. and published in the Journal of Business Horizons
- "Frontline Service Technology infusion: conceptual archetypes and future research directions" authored by De Keyser A., Köcher S., Alkire (née Nasr) L., Verbeeck C., Kandampully J. and published in the Journal of Service Management
- "Transforming the Customer Experience Through New Technologies" authored by Hoyer W.D., Kroschke M., Schmitt B., Kraume K., Shankar V. and published in the Journal of Interactive Marketing
- "Machine learning for enterprises: Applications, algorithm selection, and challenges" authored by Lee I., Shin Y.J. and published in the Journal of Business Horizons
- "Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases" authored by Luo X., Tong S., Fang Z., Qu Z. and published in the Journal of Marketing Science
- "Forecasting artificial intelligence on online customer assistance: Evidence from chatbot patents analysis" authored by Pantano E., Pizzi G. and published in the Journal of Retailing and Consumer Services
- "Effects of personalization and social role in voice shopping: An experimental study on product recommendation by a conversational voice agent" authored by Rhee C.E., Choi J. and published in the Journal of Computers in Human Behavior
- "Customer service chatbots: Anthropomorphism and adoption" authored by Sheehan B., Jin H.S., Gottlieb U. and published in the Journal of Business Research
- "Learning from the Dark Web: leveraging conversational agents in the era of hyper-privacy to enhance marketing" authored by Thomaz F., Salge C., Karahanna E., Hulland J. and published in the Journal of the Academy of Marketing Science

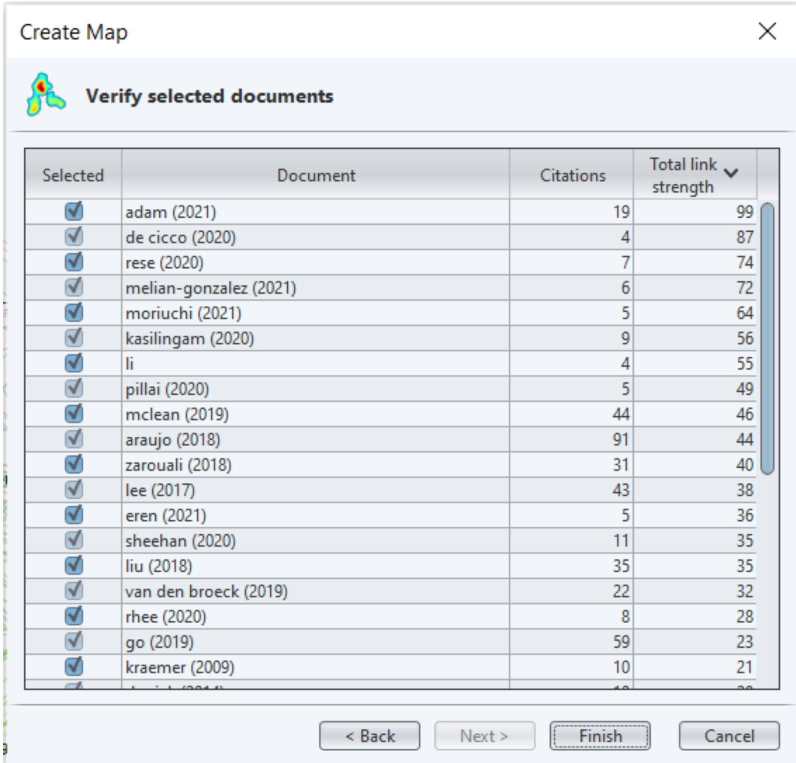
Upon reviewing the abstracts, keywords, and content of the articles listed above, the identified themes are AI, consumer behavior, and consumer adoption of CAs. Consequently, these themes represent promising avenues for future research, anticipated to receive increased attention, and offer valuable insights for both academia and business practitioners utilizing CAs.

Cluster number 2, which represents influential trends, includes the following publications:

- “AI-based chatbots in customer service and their effects on user compliance” authored by Adam M., Wessel M., Benlian A. and published in the Journal of Electronic Markets
- “Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions” authored by Araujo, T and published in the Journal of Computers in Human Behavior
- “The affective outcomes of using influence tactics in embodied conversational agents” authored by Derrick D.C., Ligon G.S. and published in the Journal of Computers in Human Behavior
- “Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions” authored by Go E., Sundar S.S. and published in the Journal of Computers in Human Behavior
- “Voices in and of the machine: Source orientation toward mobile virtual assistants” authored by Guzman A.L. and published in the Journal of Computers in Human Behavior
- “Should Machines Express Sympathy and Empathy? Experiments with a Health Advice Chatbot” authored by Liu B., Sundar S.S. and published in the Journal of Cyberpsychology, Behavior, and Social Networking
- “The media inequality: Comparing the initial human-human and human-AI social interactions” authored by Mou Y., Xu K. and published in the Journal of Computers in Human Behavior
- “Revealing sensitive information in personal interviews: Is self-disclosure easier with humans or avatars and under what conditions?” authored by Pickard M.D., Roster C.A., Chen Y. and published in the Journal of Computers in Human Behavior
- “The influence of conversational agent embodiment and conversational relevance on socially desirable responding” authored by Schuetzler R.M., Giboney J.S., Grimes G.M., Nunamaker J.F., Jr. and published in the Journal of Computers in Decision Support Systems
- “The effect of conversational agent skill on user behavior during deception” authored by Schuetzler R.M., Grimes G.M., Giboney J.S. and published in the Journal of Computers in Human Behavior

In Cluster 2, the review of abstracts, keywords, and content indicates that the prevalent themes among the articles are anthropomorphism, human likeness, and the social presence of Conversational Agents (CAs). Consequently, these topics appear to be receiving significant scholarly attention and are highlighted as primary concerns for ongoing research.

Figure 10: Publication Link Strengths in Bibliographic-Coupling Based on WoS Data


Create Map

Verify selected documents

Selected	Document	Citations	Total link strength
☑	adam (2021)	19	99
☑	de cicco (2020)	4	87
☑	rese (2020)	7	74
☑	melian-gonzalez (2021)	6	72
☑	moriuchi (2021)	5	64
☑	kasilingam (2020)	9	56
☑	li	4	55
☑	pillai (2020)	5	49
☑	mclean (2019)	44	46
☑	araujo (2018)	91	44
☑	zarouali (2018)	31	40
☑	lee (2017)	43	38
☑	eren (2021)	5	36
☑	sheehan (2020)	11	35
☑	liu (2018)	35	35
☑	van den broeck (2019)	22	32
☑	rhee (2020)	8	28
☑	go (2019)	59	23
☑	kraemer (2009)	10	21

< Back Next > Finish Cancel

Figure 11: Bibliographic-Coupling Network Based on WoS Data

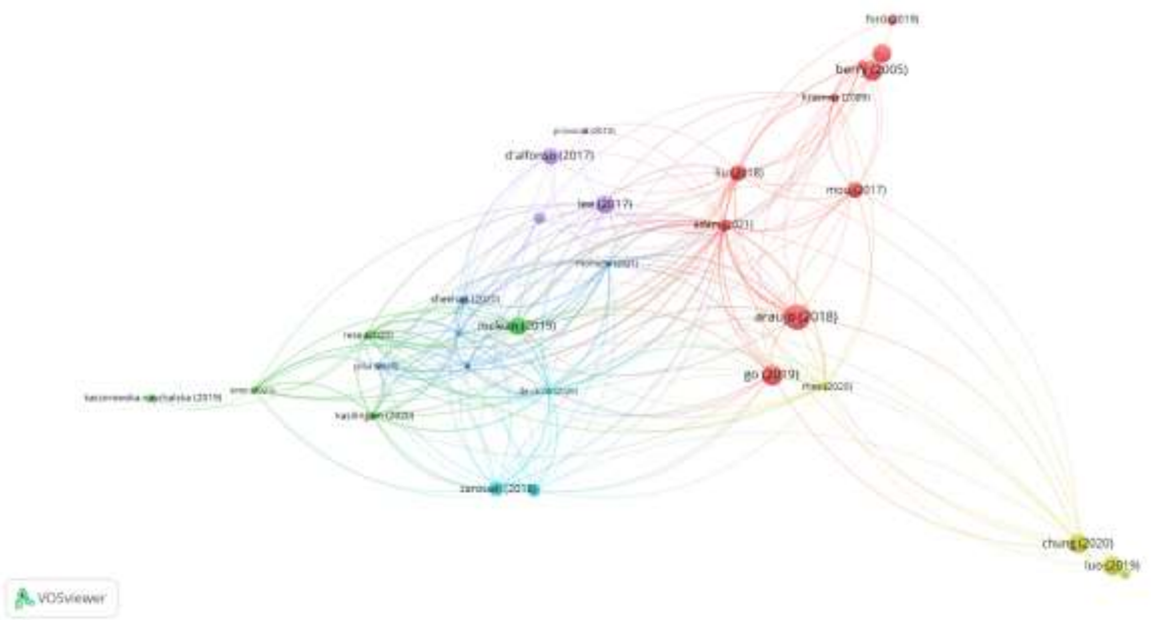
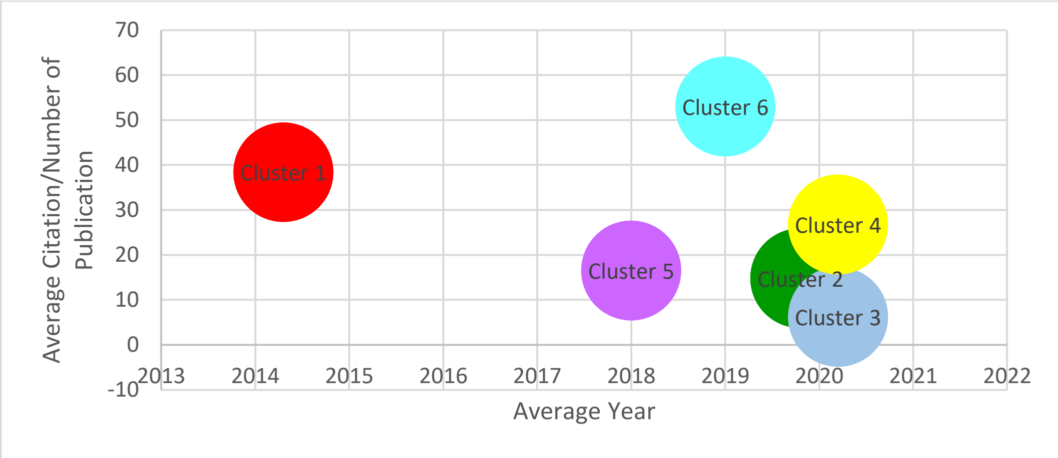


Figure 12: Longitudinal Analysis of The Most Significant Bibliographic Coupling Clusters Based on WoS Data



Additional details and evaluations of the clusters that emerged as significant from the analysis are presented below.

Clusters 2,3, and 4 which represent future trends, include the following publications:

Cluster 2 compromises:

- "Determinants of customer satisfaction in chatbot use: evidence from a banking application in Turkey" authored by Eren B.A. and published in the International Journal of Bank Marketing
- "How chatbots influence marketing" authored by E asilingam D.L. and published in the Journal of Technology in Society
- "Understanding the attitude and intention to use smartphone chatbots for shopping" authored by Kasilingam D.L. and published in the Journal of Technology in Society
- "Hey Alexa … examine the variables influencing the use of artificial intelligent in-home voice assistants" authored by McLean G., Osei-Frimpong K. and published in the Journal of Computers in Human Behavior
- "Chatbots in retailers' customer communication: How to measure their acceptance?" authored by Rese A., Ganster L., Baier D. and published in the Journal of Retailing and Consumer Services

Cluster 3 compromises:

- "What makes you continuously use chatbot services? Evidence from chinese online travel agencies" authored by Li L., Lee K.Y., Emokpae E., Yang S.-B. and published in the Journal of Electronic Markets
- "Predicting the intentions to use chatbots for travel and tourism" authored by Melián-González S., Gutiérrez-Taño D., Bulchand-Gidumal J. and published in the Journal of Current Issues in Tourism
- "An empirical study on anthropomorphism and engagement with disembodied AIs and consumers' re-use behavior" authored by Moriuchi E. and published in the Journal of Psychology and Marketing
- "Adoption of AI-based chatbots for hospitality and tourism" authored by Pillai R., Sivathanu B. and published in the International Journal of Contemporary Hospitality Management

- “Customer service chatbots: Anthropomorphism and adoption” authored by Sheehan B., Jin H.S., Gottlieb U. and published in the International Journal of Conte Business Research

Finally, cluster 4 includes:

- “Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential” authored by Canhoto A.I., Clear F. and published in the Journal of Business Horizons
- “Chatbot e-service and customer satisfaction regarding luxury brands” authored by Chung M., Ko E., Joung H., Kim S.J. and published in the Journal of Business Research
- “Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases” authored by Luo X., Tong S., Fang Z., Qu Z. and published in the Journal of Marketing Science
- “Effects of personalization and social role in voice shopping: An experimental study on product recommendation by a conversational voice agent” authored by Rhee C.E., Choi J. and published in the Journal of Computers in Human Behavior
- “Managing the human–chatbot divide: how service scripts influence service experience” authored by Sands S., Ferraro C., Campbell C., Tsao H.-Y. and published in the Journal of Service Management

The common themes identified across the publications in each cluster are summarized as follows: Cluster two emphasizes marketing and consumer behavior concepts, cluster three concentrates on adoption factors, particularly anthropomorphism, and the final cluster is dedicated to artificial intelligence (AI). It can be concluded that these themes will likely be subject to further analysis and continue to attract scholarly attention, given the ongoing expansion and numerous opportunities within this evolving research field.

Cluster number 6, which represents influential trends, includes the following publications:

- “millennials' attitude toward chatbots: an experimental study in a social relationship perspective” authored by De Cicco R., e Silva S.C., Alparone F.R. and published in International Journal of Retail and Distribution Management (2020)
- Chatbot advertising effectiveness: when does the message get through? Authored by Van den Broeck E., Zarouali B., Poels K. and published in the Journal of Computers in Human Behavior (2019)
- “predicting consumer responses to a chatbot on facebook” authored by Zarouali B., Van Den Broeck E., Walrave M., Poels K. Cyberpsychology, and published in the Journal of Behavior, and Social Networking (2018)

By evaluating the keywords and content of the papers, common themes emerged. Three of the papers specifically examine chatbots in commercial contexts targeting young users, particularly millennials. Furthermore, these studies developed chatbots designed for experimenting with service sales. Based on the current dataset, these topics are recognized as dominant themes in the existing scholarly literature.

1.5. Systematic Analysis

Building upon the insights gained from bibliographic coupling, this section outlines the systematic approach employed to structure the literature review. A systematic literature review (SLR) ensures a rigorous and replicable process for identifying, selecting, and synthesizing relevant research (Tranfield et al., 2003). This method allows for an objective assessment of the existing body of knowledge, providing a foundation for hypothesis development and research design.

In order to ensure comprehensiveness and methodological excellence, the systematic review was conducted in this research, which follows three key stages:

1. Selection of Pertinent Literature: Peer-reviewed journals were retrieved from premier research databases utilizing pre-determined search terms. Scopus and Web of Science were used as databases since they offer extensive coverage of marketing, consumer behavior, and artificial intelligence literature.
2. Screening and Inclusion Criteria: Articles were screened for relevance to conversational agents, consumer decision-making, and digital persuasion. Exclusion criteria were non-human-agent-related studies, non-peer-reviewed material, and publications with no empirical support.
3. Thematic Analysis and Categorization: The final dataset was analyzed to identify the dominant themes, theoretical traditions, and methodological orientations.

This thematic mapping enabled the studies to be clustered according to the aims of this study. Hence, through the integration of bibliometric analysis and systematic review of a structured format, this approach ensures a comprehensive synthesis of the literature and identification of gaps to be filled by future research. The findings are elaborated upon in the following chapter, which outlines the conceptual model and research hypotheses underpinning empirical analysis.

A systematic review is characterized by formulated research questions, identification of relevant studies, appraisal of study quality, and summarization of evidence through explicit methodology (Khan et al., 2003). The systematic literature review (SLR) was chosen as the research method to comprehensively understand the structure of methodologies and topics regarding the implementation of Conversational Agents (CAs) in human interaction. Initially, a methodological analysis was conducted to identify the primary research methodologies employed. Subsequently, an analysis of methods and topics across various dimensions of interaction was performed.

1.5.1. Methodology Analysis

The methodology used in the majority of the studies was Quantitative (61%). (Table 5) As for the analysis tool, consequently, in most of the papers, SEM and different types of Analysis of the Variance were applied to derive the results.

Table 5: Methodologies Implemented

Research Type	Scopus	WoS	Total	%
Qualitative	46	13	54	31%
Quantitative	95	61	107	61%
Mixed Method	12	7	14	8%
Total	153	81	175	100%

The majority of the studies that completely or partially used quantitative methods, implemented an Experimental Study (63%) to investigate the interaction between a user and a CA. and the next most implemented method is Survey (33%) (Table 6). This trend is logical due to the nature of the subject of the studies. To understand the interactions between a user and CAs and characteristics related to them, an experiment could provide the most relevant information regarding an experience.

Table 6: Quantitative Methods Implemented

Quantitative Methods	Scopus	WoS	Total	%
survey	36	25	40	33%
Experimental	62	40	78	63%
meta-analysis	2	0	2	2%
text analysis, a personality analysis tool	1	0	1	1%
Bayesian classifier	1	1	1	1%
analysis hierarchy process method	1	0	1	1%
Total	101	66	123	100%

Among Qualitative and mixed-method papers, the most common methods are Review of the articles (54%) and interviews (22%) (Table 7).

Table 7: Qualitative Methods Implemented

Qualitative Methods	Scopus	WoS	Freq.	%
interview	8	5	15	22%
literature review	31	5	36	54%
case study	4	2	6	9%
conceptual	3	3	5	7%
Focus Group	2	0	2	3%
Other	17	7	24	35%

1.5.2. Content Analysis

Approximately 15% of the reviewed papers explored the development and design of chatbots through various software engineering methodologies, while other studies addressed different aspects of interactions with Conversational Agents (CAs). The subsequent sections discuss the topics and methodological structures of the papers based on the four primary dimensions related to human-CA interactions, initially proposed by Zhang & Li (2005) in Human-Computer Interaction and subsequently revised by Diederich et al. (2022). These dimensions include Human, Context, Agent, and Perception and Outcome.

1.5.2.1. The user as the Human Dimension

The human dimension refers to individuals who interact with Conversational Agents (CAs), representing the sample population chosen for interaction. In the reviewed literature, researchers selected specific participant characteristics either because the CA was explicitly designed for a particular group or to investigate behaviors within a certain demographic. Examples of groups targeted by specialized CAs included older adults, individuals with special needs, and victims of cyberbullying. Other studies focused on broader groups such as millennials, students, or particular nationalities. Additionally, a smaller number of studies aimed to cluster users into homogeneous groups.

A few numbers of pieces of research have been dedicated to this dimension so far. The fact that CAs are still in the first phases of adoption could be the reason that still the investigations are still trying to provide insight regarding other dimensions in general terms than the human characteristics of the users (Table 8).

Table 8: Articles Researching The Human Dimension

Dimension	CA type		Methodology	
Human	Generic	9	Qualitative	8
	Developed	11	Quantitative	19
	Branded	10	Mix method	0

1.5.2.2. Context of the study

CAs could be implemented in a certain context or have a general purpose. In the research, some authors specifically focused on a certain context to evaluate the interaction-related categories or a simple context. In our sample, 39% of the papers designed their study for a certain context, such as healthcare, travel, news, service, insurance, etc. The dominant methodology used was Quantitative methods, and the type of CA studies is varied, as can be seen in Table 9. However, it is worth mentioning that the majority of the papers have focused on the service industry, and in very few papers where the context is related to product shopping, it is in the realm of e-commerce and online shopping. This could be because CAs are now more accepted in the service industry, and customers are not ready to adopt them as a shopping tool and reveal their information to a CA to order physical goods.

The highest percentage of Qualitative papers is found in this dimension since it requires the most explanation of the phenomenon in its environment. Still, the number of quantitative papers conducted is increasing.

Table 9: Articles Researching Context Dimension

Dimension	CA type		Method	
Context	Generic	30	Qualitative	17
	Developed	24	Quantitative	40
	Branded	30	Mixed method	9

1.5.2.3. The chatbot as the Machine Dimension

Studies also examined either the characteristics or the design of Conversational Agents (CAs). Approximately 26% of the reviewed articles assessed various characteristics or designs related to specific CA types. These studies addressed multiple aspects, such as the impact of the platform used (e.g., mobile devices, laptops) or the type of user input (text-based or voice-based). A significant amount of research emphasized anthropomorphism and human-like features exhibited by CAs during interactions. This focus aligns with broader technological trends, wherein advancements in Artificial Intelligence increasingly incorporate human-like attributes into technological tools, including CAs. Understanding customer preferences is crucial to ensuring user satisfaction with CA services or interactions.

In this dimension, the highest proportion of quantitative analyses and the lowest proportion of qualitative papers were identified. This is likely due to the nature of the analysis required, as studies aiming to describe the characteristics of a phenomenon and their effects on interactions typically necessitate clear definitions and structured observations to effectively test well-constructed hypotheses (Table 10).

Table 10: Articles Researching Agent Dimension

Dimension	CA Type		Method	
	Generic	14	Qualitative	3
Agent	Developed	18	Quantitative	44
	Branded	25	Mixed method	4

1.5.2.4. Conversational Interaction

During interactions with Conversational Agents (CAs), users form specific perceptions and outcomes. Most studies investigated characteristics across various dimensions to identify users' overall perceptions and outcomes, aiming to provide guidance for improved customer management. Consequently, this dimension has the highest number of related publications. In total, 52% of the reviewed articles explored variables within this domain, with particular emphasis on user experience, adoption, acceptance, trust, ethics, and attitude (Table 11).

Table 11: Articles Researching Perception and Outcome Dimension

Dimension	CA Type	Method

Perception	Generic	36	Qualitative	16
and	Developed	28	Quantitative	74
Outcome	Branded	49	Mixed method	10

1.6. Conclusion and Future Research Direction

A content analysis of 90 papers indexed in WoS, 192 papers indexed in Scopus, and a merged dataset of 216 papers after duplicates were removed was conducted. The content analysis of the review was founded on the discussion of the results concerning the application of Conversational Agents (CAs) in customer engagement, prioritizing the inclusion of publications across the fields of business, management, decision-making, psychology, social science, and allied interdisciplinary disciplines. The results reveal exponential growth of research on CA implementation in customer interactions, particularly from 2018-2019 onwards. The dominant areas of research are still relatively limited, however, with home devices and chatbots being the most researched categories. Chatbots, particularly, are of significant interest considering their versatility in application for some purposes, such as education and mental health, to signal the stage of development of CA as well as its application across different industries.

A majority of the reviewed articles utilized quantitative methods, with the large majority being experimental methods, reflecting the interaction-orientation of CA research, which is advantaged by observations in controlled, semi-realistic environments like laboratories or field experiments. US scholars dominate the market of publication, and therefore, the majority of samples comprise predominantly US respondents. Drawing conclusions from studies using respondents who cover a range of cultural and geographic places may add significantly to the literature by creating a richer description of customer behavior in alternative settings.

Research is primarily focused on retail service and mental health environments, suggesting dominant CA use patterns. Nevertheless, exploring present and future uses of CAs can provide valuable insights into their future potential and capabilities. Figure 14 is a thematic map constructed from the entire dataset, using author keywords to visually represent significant research themes (Garfield, 1990).

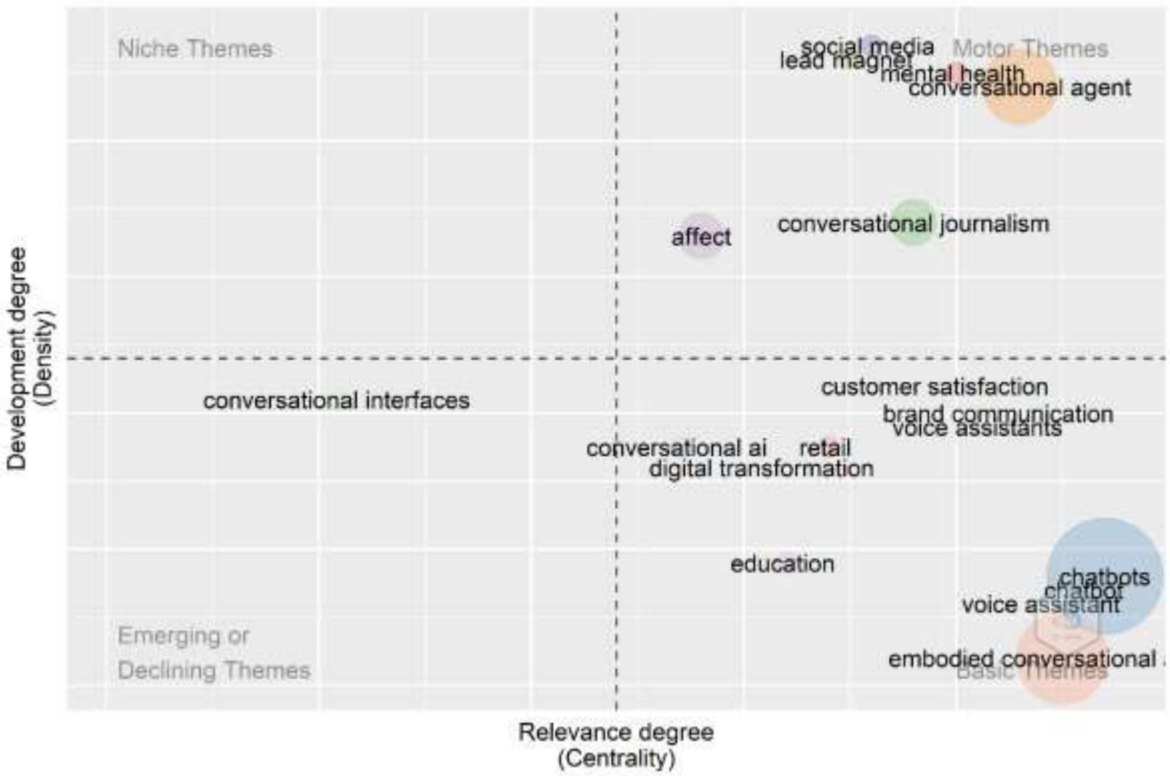
In the upper-left quadrant, there are no Niche Themes, the highly developed and isolated themes with well-developed internal links (high density) but unimportant external links, and so with only limited importance for the field (low centrality) (Della Corte, Del Gaudio, Sepe, & Sciarelli, 2019).

In the lower-left quadrant, emerging or declining themes are represented, characterized by low centrality and density, indicating that they are weakly developed and marginal. This quadrant includes only Conversational Interfaces, highlighting a potential emerging topic for future research (Della Corte et al., 2019).

In the upper-right quadrant, several motor themes exhibit high centrality and density, indicating that these themes are both well-developed and significant for the research field (Della Corte et al., 2019). It includes Social Media, Lead Management, Mental Health, Conversational Agents, Conversational Journalism, and Affect.

Finally, in the lower-right quadrant, there are basic and transversal themes that have high centrality and low density. These themes are also important for a research field and concern general topics transversal to the different research areas of the field (Della Corte et al., 2019). This quadrant comprises Chatbots, Voice Assistants, Embodied Conversational Agents, Education, Digital Transformation, Conversational AI, Retail, Brand Communication, and Customer Satisfaction.

Figure 13: Thematic Map Based on Overall Data



Comparing the thematic map with bibliographic coupling reveals common trends, notably highlighting significant topics such as AI and consumer behavior variables, including customer satisfaction, chatbots, retail, and commerce.

Synthesizing the results indicates that AI-enabled and human-like conversational agents, specifically those chatbots capable of mimicking human dialogue, represent critical areas for future research.

Based on the studies, what is essential in these sorts of chatbots is to design them in a way that they provide useful advice for the audience. Which leads to persuading users to follow what is suggested by the chatbot. The success of the chatbots is persuading users, which can eventually lead to the future adoption of the chatbot by users.

1.6.1. Significant Aspects of Human_Chatbot Interaction

Hence, based on the literature review, particularly the cluster analysis, content analysis, and mapping, it can be summarized that the multifaceted interplay between the chatbot (CA), the conveyed message, user attributes, and context highlights the importance of designing chatbots that effectively motivate users to follow their recommendations. Each component contributes in the following ways:

1.6.1.1. The Chatbot as The Agent

Physical aspect: CAs should be designed in a way that they possess the appropriate physical and psychological features, allowing the creation of trust, engagement, and credibility of the chatbot to advise users. On the physical side, there is the TAM, including ease of use, perceived usefulness, and the accuracy of responses, as highlighted in the U&G and UAUT frameworks, respectively. These attributes allow the users to feel that the CA is trustworthy, easy to use, and precise, which can have a direct influence on the intention of users to adhere to its recommendations (Huang & Chueh, 2021; McLean & Osei-Frimpong, 2019; Pitardi & Marriott, 2021).

Psychological aspect: the establishment of anthropomorphism in CAs-like social presence and empathy can help in establishing a social bond (Blut et al., 2021). Users tend to accept any advice provided by a CA as long as the responses are seen to be empathetic and responsive. Studies have also shown that when CAs mimic human behavior, users seem to be at ease and open to suggestions. Moreover, the kind of relationship established by the chatbot with the user-whether the chatbot is there as a virtual assistant or as a friend, may also influence how persuasive the advice would look to the user, adding another layer to user receptivity (Youn & Jin, 2021).

1.6.1.2. The Interaction Style as Main Factor Influencing Perception

A CA's effectiveness also depends on how efficiently it conveys its message. The initiation style, interactivity, and customized responses are some of the message aspects that affect how well the CA's recommendations are received (Weber & Ludwig, 2020). Here, personalization is particularly important since messages that feel specifically suited to the user resonate more deeply, increasing the perceived usefulness and relevance of the CA (Go & Sundar, 2019; Schuetzler et al., 2020).

The style of the conversation also plays a major influential role in the users' adherence to suggestions. Such is the case with social-oriented conversations, which give more social presence to CA by making the system more relatable and trustworthy, while task-oriented conversations are better in terms of efficiency. According to De Cicco et al. (2020), a CA designed to modulate its conversational style based on user needs and contexts can enhance user adherence to advice significantly.

1.6.1.3. The User as the Human Dimension

User traits, such as computer anxiety, trust, and innovativeness, on the part of the user also play a role in the propensity to accept recommendations (Bawack et al., 2021; Pillai & Sivathanu, 2020). Traits such as these could therefore be addressed through modifications in the approach of the CA-for example, reassuring in tone in the case of users anxious with technology or innovative and playful in users open to new technologies. This would make it easier for users to engage at a deeper level and be more willing to adopt recommendations.

Personalization is not only important in message design but also in matching the CA's personality to the user's. Research proves that during an interaction with a CA whose tone and style correspond to the user's personality or preference, the process feels easier and more natural; thus, the user is more likely to be deeply involved and will be more likely to act on advice provided by it (Shumanov & Johnson, 2021; Nawaz et al., 2020).

1.6.1.4. Context and environment

Few studies focused on the contextual and environmental aspects that may impact the user's intention to adopt CAs. One example is the work done by Ramadan, who explains that the strategy of the Amazon firm leads to the AI addition in the users of Alexa (Ramadan et al., 2021). Then there are some papers that investigated a certain context, therefore, their results are more context-specific. For instance, scholars frequently investigated topics related to CA implementation in health, news, and interview processes more than in other fields.

These four main domains were covered by the articles evaluated in the literature review. To provide a roadmap for future research, several potential research questions are proposed in Table 12.

Table 12: Future Research Questions

Research categories	Suggested Research Questions
The Chatbot as The Agent	1. What are the factors influencing different types of CAs to be effective in communication? 2. Is there any difference between different types of CAs? 3. Which type of CA is better suited to different business strategies? 4. What are the potential implications of CAs in marketing that are still underdeveloped? 5. What is the process of knowledge creation ina purchase decision-making process through CAs?

	6. A comprehensive evaluation of the offering features in the service vs goods industry that suits the implementation of CA in the purchase process? 7. how does human-AI collaboration influence the effectiveness of CA in creating effective communication? 8. What type of offerings are best suited for CA presentation? 9. Do users' reactions to anthropomorphism change over time? 10. Does users' perception of anthropomorphism vary while implementing different types of CAs? 11. more insight into brand strategies that More specific characteristics of the chatbots will be taken into consideration 12. What are the differences difference between humans and machines in communicating with a consumer that affects the adoption? 13. What are the various kinds of impact of the physical or psychological features of a CA on the decision-making process of users? 14. What are the differences between CAs behavior used in different domains (e.g. healthcare, sharing economy, news, e-commerce). 15. how auditory and visual factors may influence conventional conversational interactions still is warranted
The Interaction Style as the Main Factor Influencing Perception	1. What are the specific factors in a conversation style that influence the adoption of a CA significantly? 2. What are the specific factors in a conversation style that influence adherence to suggestions from a CA significantly? 3. What are the differences between languages in messaging behavior? 4. How should the message strategy fall into the company's overall communication strategy? 5. How to align conversation strategy with target customer preference regarding different aspects such as tone, appeal, clarity, appropriateness of length, and layout? 6. What are the possible conversation personalization opportunities in different target groups that facilitate communication quality?
The User	1. What are the factors affecting human intention to prefer a certain CA brand or type? 2. Does previous experience with a brand affect user expectations from CA?

	3. How does previous experience affect the behavior of different demographic groups? 4. Does consumer communication skill affect his/her preference in communication with a CA (message initiation, information requirements, etc)
Context and Environment	1. How, are the differences in communication across different geographical settings affecting human and machine communication? 2. How does the firm culture affect communication through machines with users? 3. Is there any relation between management strategies and CA adoption by users? 4. What are the business fields with the highest and lowest opportunities to implement CA? 5. How does the technology gap between different societies affect CA adoption?

However, the research also shows that little research still exists in this field, with several points emerging for future consideration. For instance, existing studies emphasize the value of both physical attributes (e.g., appearance, voice, and text presentation) and psychological factors (e.g., social presence, anthropomorphism) in facilitating user interaction with Conversational Agents (CAs). For example, studies of auditory characteristics and the impact of embodied conversational agents have shown that such design characteristics have strong impacts on user adoption and perception of CAs. Continuance intention studies suggest that user satisfaction, trust, and perceived usefulness are key drivers influencing their continuance intention to use chatbots for advice and recommendations. Furthermore, advice adherence is enhanced by different factors, some of which were the focus of the studies, such as personalization, a critical factor in user engagement and trust-building in long-term interactions with CAs. Consequently, understanding how to design CAs that users perceive as personalized, empathetic, and supportive fosters sustained engagement and adherence to advice and suggestions. Therefore, the study will continue by focusing on advice-giving communication with chatbots, specifically investigating methods to enhance their design and communication effectiveness.

1.6.2. Research Question refinement based on the literature review

Building upon the literature review, this section refines the original research question, "How do conversational agent (CA) design and communication strategies affect user perceptions and behavioral responses in customer service interactions?", breaks it into three categories, and justifies the structure of the three interrelated research models. The previous discussion highlighted key theoretical constructs related to chatbot politeness strategies, advice adherence, and user autonomy. This study aims to investigate how these factors interact and shape user responses.

Based on the literature review presented earlier in this chapter, it is evident that Artificial Intelligence (AI) constitutes a foundational pillar in the evolving landscape of research on conversational agents (CAs).

Among the many applications for AI-driven chatbots, recommender system chatbots are perhaps the most critical and rapidly growing type. They are designed to mimic human conversation by including anthropomorphic traits and natural dialogue structure, which enables them to support users through complex decision-making tasks with customized guidance. A review of current literature suggests that AI-powered conversational agents with the ability to simulate human conversation are a crucial frontier for future research. Chatbots are not only characterized by their ability to disseminate information but also by how they can influence users toward certain behaviors. Their success therefore hinges on how much they can build trust, achieve social presence, and engage in ways that are aligned with the expectations and intentions of users. Above all, the technical design of recommender system chatbots must be directed towards providing actionable and contextually relevant advice. If such advice is perceived as helpful and customized, it has the potential to raise user compliance, improve overall interaction quality, and facilitate long-term adoption. As a result, the channels through which such chatbots are able to influence user attitudes and behavior through either technical design or communication patterns constitute a core domain of current research in academia. Further, findings from the literature review point to the core position of interaction effectiveness, not only in driving chatbot adoption, but also in securing user acceptance of the recommended proposals. Effective interaction thus determines user trust, engagement, and compliance in behavioral aspects of human-chatbot communication environments. This insight requires sharpening the general research objective to more focused investigation of how communication strategies in recommender system chatbots can be optimized to improve user outcomes.

As discussed in Section 1.6.1.1, chatbots may function as social agents, and their interaction style, as highlighted in Section 1.6.1.2, plays a decisive role in determining communication efficacy. Specifically, a chatbot’s physical and psychological design (e.g., ease of use, anthropomorphism, empathy) and its interaction approach (e.g., task-oriented vs. socially-oriented dialogue) significantly shape user trust and engagement, which are fundamental to fostering advice adherence in recommender systems. For example, trust and perceived social presence are linked to increased compliance, while conversational style and personalization contribute directly to advice persuasiveness.

Further, as outlined in Sections 1.6.1.3 and 1.5.2.1, user characteristics such as trust propensity, innovativeness, and computer anxiety influence how users receive and respond to chatbot-generated advice. These findings underscore the importance of tailoring communication to individual user traits. For instance, a reassuring tone may be more effective for users with higher levels of anxiety, while a playful tone might engage more technologically adept individuals. This supports the notion that user autonomy and psychological distance are critical moderating factors in chatbot-user interactions.

Additionally, Sections 1.4, 1.5.2, and 1.6.2 provide evidence from a content analysis that identified four key thematic dimensions—Human, Context, Agent, and Perception and Outcome—which map the dynamics of user interaction with CAs. Several studies within these dimensions emphasize the importance of design features such as visual appearance and tone of voice in shaping trust, engagement, and compliance. Section 1.6.2, in particular, reinforces the value of advice-giving communication, showing that human-like CAs endowed with empathy and emotional sensitivity contribute to improved user outcomes across various service domains.

To systematically investigate these relationships, the following research questions are proposed:

- How does the communication style of chatbots affect users' willingness to adhere to their recommendations?
- What is the impact of conversational language on users' intention to comply with chatbot-generated recommendations?
- To what extent does the outcome of recommendation acceptance (i.e., success or failure) influence users' subsequent reactions and behavioral responses?

These research questions are directly grounded in the literature and logically extend from the theoretical and empirical findings presented. They serve to bridge the gap between emerging chatbot technologies and user-centered design, ensuring the study's alignment with both academic objectives and real-world applicability.

Chapter 2: Recommender system chatbots in advice-giving communication: literature review and hypothesis development

2. Advice Giving, Communication, and Recommender System Chatbots Background

2.1. Advice-Giving Communication Literature Review:

In general, CAs with human-like conversational qualities are becoming increasingly important in various domains, including customer service, education, and healthcare. For instance, in healthcare, CAs need to balance social and transactional elements to effectively deliver health advice, a concept termed "Practical Empathy" (Ghosh & Faik, 2020).

For academic advising, CAs can assist with multiple tasks using natural language, improving student retention and graduation rates (Latorre-Navarro & Harris, 2015).

Research shows that users prefer agents with the capability of perceiving, responding to, and simulating emotions. This is particularly important where human interaction, emotional support, and creative works are concerned (Hernandez et al., 2023). Human-like conversational agents are especially critical in advice-giving communication due to their ability to positively influence user engagement and trust. The presence of human-like interactional capabilities in CAs, including cognitive, relational, and emotional capabilities, facilitates user interaction (Chandra et al., 2022). The capabilities provide a natural and personal interaction environment for users seeking advice. The language used by CAs in advice-taking scenarios plays a major role in user experience and outcomes. In addition, research has established that the language strategies employed by such agents will have a significant impact on users' satisfaction, interaction, and overall efficiency of the conversation (Wang et al., 2024).

In total, CAs have much potential for enhancing advice-giving relationships across various areas, but careful design should be undertaken to strike a good balance between social and functional considerations. A brief literature review on chatbot advice-giving is thus also included.

Based on the established protocol, the review was limited to journal articles and reviews published exclusively in English, focusing on fields related to business, management, psychology, decision-making, social science, and associated interdisciplinary areas. Initially, data were separately extracted from the Web of Science (WoS) and Scopus databases. Subsequently, these datasets were merged into a single comprehensive dataset using Rstudio software, retaining only entries with complete data fields in cases of duplication. The keywords extracted from the literature that could assist us in collecting relevant papers are presented in Table 13 and Table 14, together with the search terms.

The final search resulted in 50 articles indexed in Scopus and 9 articles indexed in WoS. After cleaning up duplicates using R' software, 56 articles in total remained for evaluation.

Metadata for these 56 articles were downloaded, including print features, authors' names, corresponding authors' countries, the total number of publications, citation counts with total citations, average article citations, numbers of citing articles with and without self-citations, journal sources, keywords, countries, references, abstracts, publication dates, authors, and regions for analysis (Martynov et al., 2020). all of which were necessary for the analysis conducted using relevant software and evaluation tools. Although the initial analysis was conducted in 2021, the dataset was subsequently updated to include additional data up to 2024. The final search identified 50 articles indexed in Scopus and 9 articles indexed in WoS through 2021. After removing duplicates using R software, a total of 56 articles remained for evaluation.

Table 13: Scopus Search Details for Advice-Giving with Chatbots

Search Terms in Scopus		
Field Tag	Title, Abstract, and Keywords	TITLE-ABS-KEY ("chatbot" OR "voice assistant" OR "conversational agent") AND
Boolean		AND
Field Tag	Title, Abstract, and Keywords	TITLE-ABS-KEY ("advice" OR "recommendation")
Boolean		AND
Field Tag	Title, Abstract, and Keywords	TITLE-ABS-KEY ("user*" OR "consumer*" OR "customer *")
Boolean		AND
Document Type	Article, Review	(LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "re")
Boolean		AND
Language		LIMIT-TO (LANGUAGE, "English")
Boolean		AND
Subject Area	Business, Psychology, Decision Making, Economic	LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "PSYC") OR LIMIT-TO (SUBJAREA , "DECI") OR LIMIT-TO (SUBJAREA , "ECON")

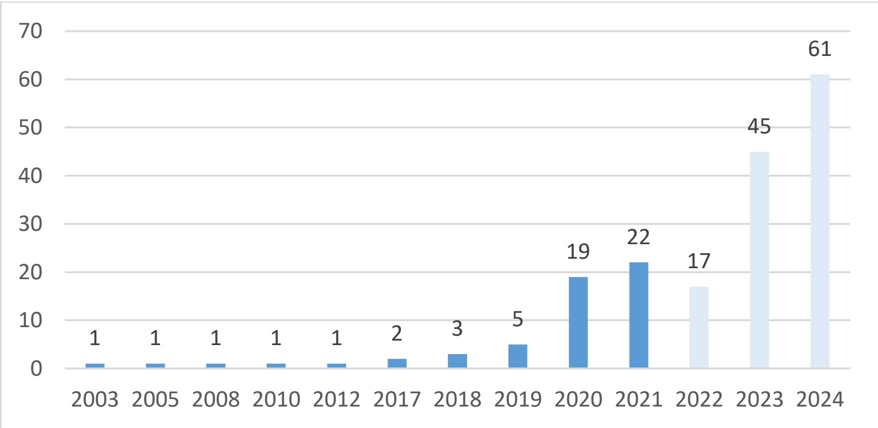
Table 14: WoS Search Details for Advice-Giving with Chatbots

Search Terms in WoS		
Field Tag	All	All=(chatbot OR "voice assistant" OR "conversational agent")
Boolean		AND
Field Tag	All	All=("advice" OR "recommendation")
Boolean		AND
Field Tag	All	All=(user OR consumer OR customer)
Boolean		AND
LANGUAGE		(English)
Boolean		AND
DOCUMENT TYPES		(ARTICLE OR REVIEW)
Boolean		AND
WEB OF SCIENC E CATEGORIES:		(BUSINESS OR PSYCHOLOGY MULTIDISCIPLINARY OR MANAGEMENT OR PSYCHOLOGY SOCIAL OR PSYCHOLOGY EXPERIMENTAL OR PSYCHOLOGY MATHEMATICAL OR PSYCHOLOGY CLINICAL OR ROBOTICS OR PSYCHOLOGY DEVELOPMENTAL OR COMMUNICATION OR SOCIAL ISSUES OR PSYCHOLOGY APPLIED OR SOCIAL SCIENCES BIOMEDICAL OR SOCIAL SCIENCES INTERDISCIPLINARY OR SOCIOLOGY OR BUSINESS FINANCE)

The annual number of publications on this topic demonstrates a significant increase starting in 2020, followed by a second surge in 2023, indicating a growing academic interest (Figure 14). This trend may be attributed to the introduction of AI-enabled chatbots, such as ChatGPT, which facilitate advice-driven dialogues across a range of subjects.

In Table 15, additionally, the list of the most cited articles in this area was compiled, highlighting a predominant focus on chatbot design aimed at enhancing user perception and increasing the willingness to follow provided advice.

Figure 14: Annual Publications on Advice-Giving Communication with Chatbots



As shown in Table 15, the most cited articles in this area mostly discuss how to design effective communication between the user and the chatbot to persuade the user to follow or adopt the chatbot. This shows the importance and growth of this aspect in research.

Table 16, which includes articles up to 2024, indicates that while many papers remain consistent, newer studies focusing on AI-enabled chatbots such as ChatGPT are gaining prominence and becoming highly cited, signalling an emerging trend. Therefore, subsequent chapters will concentrate on this area, particularly exploring the appropriate linguistic and visual design elements of chatbots that could enhance advice adherence and promote chatbot adoption

Table 15: Most Cited Articles on Advice-Giving in Chabots Until 2021

Article	**Author and year**	**Published Journal**	**Total Citations**
• Chatbots for learning: A review of educational chatbots for the Facebook Messenger	Smutny & Schreiberova (2020)	Computers & Education	378

• Enhancing user experience with conversational agent for movie recommendation: Effects of self-disclosure and reciprocity	S. Lee & Choi, (2017)	International Journal of Human-Computer Studies	242
• Should Machines Express Sympathy and Empathy? Experiments with a Health Advice Chatbot	Liu & Sundar, (2018)	Cyberpsychology, Behavior, and Social Networking	237
• Negotiated Collusion: Modeling Social Language and its Relationship Effects in Intelligent Agents	Cassell, (2003)	User Modeling and User-Adapted Interaction	183
• Chatbot advertising effectiveness: When does the message get through?	Van den Broeck et al., (2019)	Computers in Human Behavior	153
• "Phantom Friend" or "Just a Box with Information": Personification and Ontological Categorization of Smart Speaker-based Voice Assistants by Older Adults	Pradhan et al., (2019)	Proceedings of the ACM on Human-Computer Interaction	149
• Effects of personalization and social role in voice shopping: An experimental study on product recommendation by a conversational voice agent	Rhee & Choi, (2020)	Computers in Human Behavior	129
• User Experiences of Social Support From Companion Chatbots in Everyday Contexts: Thematic Analysis	Ta et al., (2020)	Journal of Medical Internet Research	105
• Artificial Intelligence Chatbot Behavior Change Model for Designing Artificial Intelligence Chatbots to Promote Physical Activity and a Healthy Diet: Viewpoint	Zhang et al., (2020)	Journal of Medical Internet Research	103
• Conversational robo advisors as surrogates of trust: onboarding experience, firm perception, and consumer financial decision making	Hildebrand & Bergner, (2020)	Journal of the Academy of Marketing Science	99

Table 16: Most Cited Articles on Advice-Giving in Chabots Until 2024

Article	**Author and year**	**Published Journal**	**Total Citations**
• ChatGPT: Bullshit spewer or the end of traditional assessments in higher education?	Rudolph et al. (2023)	Journal of Applied Learning & Teaching	538
• Chatbots for learning: A review of educational chatbots for the Facebook Messenger	Smutny & Schreiberova (2020)	Computers & Education	378
• BenchCouncil Transactions on Benchmarks, Standards and Evaluations	Haleem et al. (2022)	BenchCouncil Transactions on Benchmarks, Standards and Evaluations	265

• Enhancing user experience with conversational agent for movie recommendation: Effects of self-disclosure and reciprocity	Lee & Choi, (2017)	International Journal of Human-Computer Studies	242
• Should Machines Express Sympathy and Empathy? Experiments with a Health Advice Chatbot	Liu & Sundar, (2018)	Cyberpsychology, Behavior, and Social Networking	237
• Negotiated Collusion: Modeling Social Language and its Relationship Effects in Intelligent Agents	Cassell, (2003)	User Modeling and User-Adapted Interaction	183
• Chatbot advertising effectiveness: When does the message get through?	Van den Broeck et al., (2019)	Computers in Human Behavior	153
• "Phantom Friend" or "Just a Box with Information": Personification and Ontological Categorization of Smart Speaker-based Voice Assistants by Older Adults	Pradhan et al., (2019)	Proceedings of the ACM on Human-Computer Interaction	149
• Effects of personalization and social role in voice shopping: An experimental study on product recommendation by a conversational voice agent	Rhee & Choi, (2020)	Computers in Human Behavior	129
• The dark side of generative artificial intelligence: A critical analysis of controversies and risks of ChatGPT	Wach, et al. (2023)	Entrepreneurial Business and Economics Review	117

Several potential limitations should be considered in interpreting this study. First, the constraints applied during the review and analysis process (including keyword selection, timeframe, and database selection) were based on subjective assessments of their representativeness and sufficiency. Therefore, these choices could be subject to criticism. The review focused specifically on business and customer perspectives, analyzing 216 articles and reviews.

Additionally, the analysis included publications up to August 2021. Given the growing attention to this research area, incorporating more recent publications might provide enriched findings. Furthermore, the research was confined to articles indexed in the Web of Science (WoS) and Scopus databases; consequently, research published in other databases or sources could offer additional insights and potentially yield different results.

2.2. Advice in Human Interactions

Advice plays a crucial role in human communication, helping individuals navigate uncertainty and improve decision-making quality (Eskreis-Winkler et al., 2018). It is defined as a "recommendation concerning what to do, believe, or feel in response to an issue" (M. L. Knapp & Daly, 2011).

Advice typically involves one person (the adviser) offering guidance to another (the advisee), and it can be applied in both personal and professional contexts (Bonaccio & Dalal, 2006; Cheung & Lee, 2012). While advice can foster trust and collaboration in social networks, it is not always received positively. Research has shown that advice can be perceived differently by each individual, with some appreciating it while others may resist due to its face-threatening nature (D. Goldsmith & MacGeorge, 2000).

The study of human responses to advice has a long history, beginning with Meehl's (1954) early work, which noted how individuals react differently to advice based on various factors (Meehl, 1954). However, the recent advancement of AI has allowed machines to take the role of an advisor and give expert advice to users based on their needs. The Computers As Social Actors (CASA) paradigm, introduced by Nass et al. (1994), suggests that people respond to machines in the same social ways they do to humans (Nass et al., 1994). Hence, it is important to explore how advice from a chatbot affects user behavior and decisions, as it may mimic human-to-human advice interactions.

People naturally seek advice to attain useful information that contributes to coping with uncertainty or unclear problems. This, in turn, helps the advisees to improve their decision-making quality. (Eskreis-Winkler, et al., 2018) Advice is a common form of communication in which one person (the adviser, advice-giver, or source) advises another (the recipient or advisee) in both personal and professional relationships, and it can be applied to a wide range of issues. Advice has been conceptualized and examined as a bridge between participants in social and professional networks (Bonaccio & Dalal, 2006) or social support (Cheung & Lee, 2012). In giving advice, the adviser does not try to persuade the advisee to do something for the advisor; rather, it is the advisee who benefits from counsel. When people need guidance on a certain topic, they seek advice (Jenetto & Hanafi, 2019a). The relevance of human preferences for advice has been the topic of research for decades, and the first paper documenting the phenomenon was published almost 60 years ago (Meehl, 1954). Even though advice is a common way of communication among people, the problem is that giving advice is potentially face-threatening. This could be an explanation for why research in the past showed that the information provided by advisors could be perceived differently by each individual. While some might appreciate the advice, others might show negative

reactions to it (D. Goldsmith & MacGeorge, 2000). Therefore, giving advice might not always lead to the desired action by the advisee. On the contrary, s/he might resist or even act the opposite of what is recommended because of the threat that is imposed on the advisees' face. As CASA suggests, people might react to machines the same way they react to other human beings. Hence, in this study, the effect of receiving advice from a Chatbot on the users is investigated.

2.3. Advice-Giving Recommender System Chatbots

Conversational agents (CAs) have revolutionized human-computer interactions by enabling users to engage with AI-powered digital assistants across multiple devices, including smartphones, smart speakers, wearables, vehicles, and home appliances. Consequently, provided the opportunity to do different tasks, such as asking questions and issuing commands to smart assistants, or navigating using CA systems in their cars. Such Conversational AI has been defined as “The study of techniques for constructing software agents that can partake in natural conversations with people” (McTear, 2021).

Currently, there are 2.5 billion devices worldwide that support CAs, including smartphones, smart speakers and computers, wearable technology, cars, and appliances that integrate CAs, reflecting their widespread adoption and expanding functionality (Perez, 2019). CAs vary in their algorithmic structure, capabilities, and interaction modalities**;** the most common type of CAs consists of chatbots that can be either text- or voice-based. Among these, recommender system chatbots stand out as a widely utilized category in business applications. These AI-driven tools not only assist users in identifying relevant products, services, or content but also engage in multi-turn dialogues to refine their recommendations (Jannach et al., 2021).

Hence, understanding how online message attributes affect communication quality in such dialogue-based chatbots is a crucial component of computer-mediated communication (Beattie et al., 2020). According to the speech act theory, a crucial part of pragmatics is speech acts, which are communication activities that convey an intended language function. Speech acts are communicative functions that serve various purposes, such as requests, apologies, suggestions, commands, offers, and advice (*Speech Acts | Foreign Language Teaching Methods: Pragmatics*, 2022). Since recommender chatbots serve an advisory role, their effectiveness depends on how they formulate speech acts to guide users toward desired actions. Thus, examining how different speech act strategies influence user adherence to chatbot advice is critical in designing persuasive and user-friendly AI systems.

The recommender systems can advise on different domains such as movies (Narducci et al., 2020), finding the correct expert (Cerezo et al., 2019), travel and tourism (Argal et al., 2018), etc. As long as any liked products are suggested, a cycle of conversations between the user and the conversational recommender system chatbot is repeated. As a result, these systems seek to enhance not just the recommendations' accuracy, but also the interaction between the user and the chatbot (Narducci et al., 2020). This interaction mirrors expert consultations, where users seek personalized advice to make informed decisions.

Therefore, as could be noticed from the definition and category applications, such CAs' abilities are going beyond just providing information to the customers. They are more than a mere static platform to demonstrate the information; they can be the expert that clients can refer to and receive guidance and advice in many cases, in order to achieve goals or fulfill a purpose. Hence, AI-enabled recommender chatbots provide relevant advice for problem-solving purposes. Despite the growth of the literature in specific domains regarding the general type of CA adoption that leads to advice adherence by the user, the mechanism is still not fully investigated. Specifically, the context of advice is an integral part of communication with recommender system chatbots, which to the best of our knowledge, is still not the subject of enough research. Therefore, this study tries to address this gap by developing a conceptual model for this research.

Addressing this issue can help both scholars and managers understand an effective style of communication in the context of human-computer interactions. The importance of providing human's preferred communication style to improve interaction efficiency in human-agent interactions was emphasized in different environments such as in online teams (Benke et al., 2020; Chien et al., 2020) or offline, trust induced by salesperson behaviors (Swan et al., 1988). Users of bots should evaluate the conversation, similar to when speaking face-to-face with a salesman offline, because customers use social norms and expectations while interacting with computer technology. Hence, the research in this regard can enlighten the impacts and effects on the design of chatbots and help future researchers to investigate more aspects and strategies that might complement our findings.

2.4. Expanding the Role of AI in Advice-Giving

As mentioned before, given their ability to engage users beyond mere information retrieval, AI-enabled recommender chatbots function as digital advisors, offering personalized guidance rather than passive recommendations.

Their role extends from the presentation of static information to interactive problem-solving, in which users actively seek expert-like advice to carry out a particular task or achieve some goal. Although there has been increased application of CAs in various fields, psychological mechanisms behind advice adherence in AI-supported interactions remain understudied. Although existing studies examine general chatbot adoption, research has yet to fully examine how conversational tone, advice alignment, and prompts for interaction influence a user's intention to adhere to chatbot-presented recommendations. Specifically, the AI recommender system's advice-giving setting has not been fully considered. This study tries to close this gap by developing a conceptual model to investigate the impact of different communication styles on advice compliance in chatbot interaction.

Despite the increasing adoption of CAs in various industries, the psychological mechanisms driving advice adherence in AI-driven interactions remain underexplored. While existing literature examines general chatbot adoption, research has yet to fully investigate how conversational style, advice alignment, and interaction cues influence a user's likelihood to follow chatbot-provided recommendations. Specifically, the context of advice-giving within AI recommender systems has not been sufficiently addressed. This study seeks to bridge this gap by developing a conceptual model to examine how different communication styles affect advice adherence in chatbot interactions.

Understanding effective communication strategies in AI-driven recommendations is critical for both scholars and practitioners. Experiments involving virtual teamwork (Benke et al., 2020; Chien et al., 2020) and face-to-face sales interactions (Swan et al., 1988) demonstrate that AI systems which adapt their communication to human nature improve interaction effectiveness and credibility. The research emphasizes the necessity to develop recommender chatbots which deliver precise advice while maintaining socially acceptable behavior to enhance user compliance.

This research investigates these factors to develop enhanced AI-conversational agents while uncovering effective chatbot communication methods that promote user trust and adherence to AI-generated advice. Academic researchers focused on human-AI interaction and business practitioners seeking to enhance chatbot customer engagement strategies will find these findings beneficial.

By addressing these aspects, this research aims to contribute to the design and optimization of AI-driven conversational agents, offering insights into effective chatbot communication strategies that can enhance user trust, engagement, and adherence to AI-generated advice. These findings will be valuable for both academic researchers exploring human-AI interaction and business practitioners seeking to refine chatbot-driven customer engagement strategies.

Advice should be delivered in the context of communication, and effective communication is the essential key to convincing consumers to behave desirably. Communication represents a "human activity that links people together and creates relationships" (Duncan & Moriarty, 1998). People, through communication, discover their part in the world and develop their relations. To do so, they implement different types of communication styles which, in case of failure, could lead to misunderstanding and conflicts. Understanding the characteristics and trends of various communication styles can help us deal with people with different communication styles more effectively. Communication style refers to "the way one verbally or nonverbally interacts to signal how literal meaning should be interpreted, filtered or understood" (Norton, 1978). Hence, relationships can be formed through communication, which can include both verbal and nonverbal indications directed at a person. Businesses also try to find effective communication methods to build effective relationships with their stakeholders, including customers. In order to alleviate clients' uncertainty, anxiety, and psychological distress, communication in commercial service settings exists. Customers, in some cases, have less knowledge than the provider in an interaction, therefore, they implement verbal and nonverbal communication to form opinions (Ben-Sira, 1980). In such cases, Customers often feel insecure and need to consult a qualified source because they often have less technical information and expertise than the service provider. Customers assess the tone and content of service provider communication in order to overcome these psychologically distressing states, which can foster satisfaction and trust (Lang, 2012). Furthermore, when customers resort to providers' advice to make decisions, communication skill plays a significant role in persuading advice adherence. The literature has written extensively about the effect that communication has on adherence, taking into account results such as satisfaction and recall of the details of interactions with service providers (Vermeir et al., 2015). For instance, past studies show that pharmacists should not only have sufficient clinical skills but also high communication skills (McDonough & Mackey, 2006). Also, for the salesforce to be effective, they should have communication and listening skills (Ben Amor, 2019). Haskard Zolnierek & DiMatteo (2009) conducted a meta-analysis of published literature (1949 to 2008), using a random-effects model. Their quantitative study reported that the majority of the physicians rated all communication cues as most important in advice adherence of patients. Moreover, according to a study by Zehir et al. (2011), customers feel high levels of trust and satisfaction.

2.5. Types of Communication

Communication is inherently multimodal, integrating both verbal and nonverbal elements to construct meaning. During interactions, individuals convey messages not only through spoken words but also through body language, facial expressions, tone, posture, and attire. These verbal and nonverbal cues work together to enhance comprehension, establish social connections, and influence behavior.

Traditionally, research on communication has treated verbal and nonverbal communication as separate domains, with early studies in discourse analysis and conversation analysis focusing primarily on speech and linguistic structures. However, later research recognized the interdependence of verbal and nonverbal cues in shaping interactions (S. E. Jones & LeBaron, 2002). Despite the distinction between verbal and nonverbal behavior being centuries old, and the benefits of conducting research in each form and understanding the effects separately, it would be also beneficial to see them in a comparison view to evaluate the effects side by side, even verbal communication can have different aspect to consider that could affect the user's intentions.

For instance, Kendon (1991) differentiates language-focused theories emphasizing speech processing and general language theories centering on auditory and visual integration in meaning-making.

Similarly, Mead (1975) is convinced that nonverbal studies should never be separated from linguistic processes because both forms of communication exist together. Regarding Conversational Agents (CAs), verbal as well as nonverbal cues are significant for user interaction. While chatbots rely primarily on text or speech-based communication, their design typically includes visual as well as identity-related aspects, such as avatars, fonts, and simulated emotional expressions. Understanding the reinforcing role of these verbal and nonverbal components is critical for enhancing chatbot engagement and user acceptance of AI-generated recommendations. This study, therefore, examines how the formality of language, tone, and imagery collaborate to create users' perceptions and enforce compliance with recommendations in CA communication.

2.5.1. Verbal Communication

Understanding how online message attributes affect communication quality is a crucial component of computer-mediated communication (Beattie et al., 2020). While chatbot research has extensively explored functional and technical aspects, there has been comparatively less focus on the impact of verbal cues in shaping user perceptions and behaviors (Babaeva et al., 2020). Given that chatbot interactions primarily rely on text or voice-based exchanges, verbal communication strategies significantly influence user engagement and advice adherence.

One important cue in verbal communication is the speech act theory. A crucial part of pragmatics is speech acts, which are communication activities that convey an intended language function. Speech acts are communicative functions that serve various purposes, such as requests, apologies, suggestions, commands, offers, and advice (*Speech Acts | Foreign Language Teaching Methods: Pragmatics*, 2022)

Verbal communication style can significantly impact how users perceive and respond to chatbot interactions. for instance, Norton (1978) defines nine domains of interpersonal communication to describe verbal and para-verbal interaction styles, including animated, attentive, dominant, dramatic, open, contentious, relaxed, friendly, and impression-leaving ways of communication. Similarly, in advertisements, two types of communication are introduced: Informational (or rational) styles, which display the desired benefits of the product, for instance, the quality or performance, and Emotional styles, which try to evoke negative or positive emotions, like fear or joy. One of the most widely studied verbal communication strategies is the formal vs. informal language distinction, which has been examined across disciplines, including organizational behavior (Saleem & Perveen, 2017), education (Dabbagh & Kitsantas, 2012), and marketing (Lai, 2016). In sales and customer engagement, effective communication requires a balance between formal and informal speech, as research suggests that a mix of both styles enhances trust and information exchange (Maltz & Kohli, 1996). Market-oriented sales professionals adapt various communication styles to connect with clients and increase customer retention (e.g., Yao et al. 2022). McArthur (1992) defines an informal communication style as “common, non-official, familiar, casual, and often colloquial, and contrasts in these senses with formal” contrasting it with formal styles, which convey professionalism and authority (p. 77). In human-machine communication also verbal cues that can create formality or informality in the language have also been pointed out. Liebrecht et al. (2021) provided elements of verbal communication that were found to affect the level of formal vs informal language. In their study, they observed that when participants felt a chatbot had a high level of social presence, its informal communication style had a positive impact on the interaction's quality and brand attitude. However, most studies have not examined the combined effects of verbal and nonverbal cues or how these factors impact post-adoption behaviors, such as continued chatbot usage and advice adherence**.** Given the importance of verbal communication strategies in chatbot interactions, this study explores how formality, speech act strategies, and linguistic tone influence user adherence to chatbot-provided advice. By addressing these factors, this research contributes to understanding the persuasive impact of verbal cues in AI-driven communication, offering insights for businesses, AI developers, and researchers designing conversational agents that maximize user engagement and compliance.

2.5.2. Nonverbal communication

Verbal and nonverbal cues are two major communication cue structures, and they are complementary (Ekman & Friesen, 1972). Nonverbal communication is communicated through non-linguistic methods. And is defined as: “Communication that does not include words but people’s actions or attributes, including their use of objects, sounds, time, and space, that have socially shared significance and stimulate meaning in others.” (Gamble & Gamble, 2013). The purpose of nonverbal communication cues is to communicate emotional messages. It includes all behaviours performed in the presence of others or perceived either consciously or unconsciously. The need for effective nonverbal communication has been recognized in many different contexts such as education (Bambaeeroo & Shokrpour, 2017), management (Singh, 2007), service (Sundaram & Webster, 2000), etc. Furthermore, according to some scholars, nonverbal cues have a stronger effect than verbal and language cues. For instance, Birdwhistell (1952) stated that humans in communication use 65% of nonverbal cues while 35% is verbal. Furthermore, verbal communication has a lower impact if nonverbal communication does not match it (Knapp et al., 2013). In the literature, face-to-face communication using body movements, clothes, personal grooming, and body signs are all known as nonverbal communication (Harrison et al., 1989). Physical appearance as a nonverbal cue represents specific information regarding a person’s grooming and dress codes (Islam & Kirillova, 2020) that could affect the quality of communication and building relationships with others. Therefore, nonverbal communication can supplement or support verbal communication, resulting in improved meaning transfer quality. A single nonverbal cue can elicit a variety of reactions for example, wearing jeans, can be interpreted as simply a relaxed outfit style (Gamble & Gamble, 2013). Hence, choosing the right nonverbal cue can contribute to the meaning transferred and the quality of communication.

There are different categories and styles of nonverbal cues in communication that were considered in past studies. For instance, Gamble and Gamble in their book introduced eight nonverbal message categories including (1) kinesics, (2) paralinguistic (para verbal), (3) proxemics, (4) haptics, (5) olfactics, (6) artifacts and appearance, (7) color, and (8) chronemics.

The importance of these elements has been investigated in services marketing research. In past research, for instance, a few studies have shown that nonverbal communication predicts client satisfaction. In addition, researchers found that non-verbal communication has a significant influence on the customer's evaluation of the service events.

Chatbots, as social actors, can also adopt various nonverbal communication styles to enhance user engagement. Unlike human advisors, AI-driven conversational agents lack physical gestures and facial expressions, but they compensate through avatar design, typography, timing, and voice modulation (Xu et al., 2023). Previous studies have shown that visual elements of chatbots, such as avatars and how the character is dressed, serve as nonverbal cues that impact user experience (Go & Sundar, 2019). Attire (clothing or outfit) plays a symbolic role in communication, influencing how individuals are perceived in terms of credibility, expertise, and approachability. Clothing can communicate status, personality, and intent, affecting interpersonal interactions (Roach-Higgins & Eicher, 1992). Johnson et al. (2014) highlight that clothing not only affects self-perception but also influences the way others respond in social interactions.

In professional settings, formal attire is associated with competence, trustworthiness, and authority, while casual clothing conveys friendliness and relatability (Peluchette & Karl, 2007). Gledhill et al. (1997) found that patients preferred physicians in formal attire, as it signaled professionalism and expertise. Similarly, in sales and customer service**,** market-oriented professionals strategically use both formal and informal styles to tailor interactions based on customer needs and context (Lai, 2016). Since chatbots are increasingly used in advisory roles, their visual representation and tone of communication should align with user expectations. The choice of chatbot appearance, including avatar formality, may influence user trust and adherence to recommendations. Therefore, this study investigates the effect of chatbot nonverbal cues, particularly visual formality and identity cues, on advice adherence**.**

Attire is defined as “an assemblage of modifications of the body (such as cosmetic use, sun tanning, piercing) and/or supplements to the body (such as accessories, clothing, glasses)” (Roach-Higgins & Eicher, 1992). The social psychology of clothing is concerned with "how a person's attire influences both their behavior and the behavior of others toward them" (Johnson et al., 2014). As an example, Peluchette & Karl's (2007) findings revealed that when wearing formal business attire, employees perceived themselves as the most authoritative, trustworthy, productive, and competent, but when wearing casual or business casual attire, they perceived themselves as the friendliest. A study on a group of patients found that they preferred their physicians to dress formally and wear white coats (Gledhill et al., 1997). Since, as mentioned before, a market-oriented salesperson should use various types of communication (both formal and informal) to transmit information between customers to satisfy customer wants and increase customer retention (e.g., Yao et al. 2022). Given the critical role of nonverbal cues in human interaction, this study examines how chatbots can leverage nonverbal communication elements to enhance user engagement and advice adherence. By understanding how visual and identity-based cues affect user trust and compliance, AI designers can optimize chatbot communication to improve persuasion and interaction quality

2.6. Communication and politeness theory

Politeness is a multidimensional construct that transcends mere word choice, encompassing both verbal and nonverbal elements of communication. Rooted in the seminal work of Brown & Levinson (1987), politeness theory emphasizes the importance of mitigating face-threatening acts, such as giving advice, through linguistic strategies. However, subsequent research has highlighted that verbal strategies alone are insufficient for managing interpersonal dynamics effectively. Nonverbal cues such as tone of voice, facial expressions, attire, and posture significantly influence how politeness is perceived and interpreted in both human-human and human-computer interactions (Ekman & Friesen, 1972; Fukushima, 2004). In fact, nonverbal communication can either reinforce or undermine verbal intentions, thereby shaping users’ reactions and trust in the source (Knapp et al., 2013).

This perspective is particularly salient in human-computer interaction, where users apply social heuristics to digital agents such as chatbots, expecting them to exhibit socially appropriate behavior. The Computers as Social Actors (CASA) paradigm posits that people respond to machines with similar social expectations as they do with humans (Nass et al., 1994). As a result, both the verbal communication style (e.g., formality, speech acts) and nonverbal design features (e.g., visual appearance, avatar attire) of chatbots contribute to perceived politeness and, in turn, influence user responses such as trust, satisfaction, and adherence to advice (Go & Sundar, 2019). Therefore, examining politeness holistically—across verbal and nonverbal channels—is crucial for understanding and designing persuasive, socially attuned chatbot interactions.

2.6.1. Politeness Theory in Advice-Giving Interactions

Advice-giving is inherently a face-threatening act, as it has the potential to challenge an individual's autonomy, competence, or self-image. Drawing on Goffman's (1967) foundational concept of face, defined as the positive social value a person claims during interpersonal encounters, advice can be perceived as either a challenge to one's positive face (the desire to be respected and admired) or negative face (the desire for autonomy and freedom from imposition) (Brown & Levinson, 1987; Metts & Cupach, 2008). Consequently, individuals may resist advice not only when it is unsolicited but even when it is actively sought (Waring, 2007).

Brown and Levinson's Politeness Theory (1987) offers a framework for understanding how communicators mitigate face threats in social interaction. The degree to which advice is perceived as threatening depends on multiple contextual factors, including the social distance between the advisor and advisee, the authority or credibility of the advisor, and the extent to which the recommendation is perceived as limiting personal choice (D. Goldsmith & MacGeorge, 2000). Because advice inherently involves an attempt to influence behavior, its effectiveness often depends on how it is framed—linguistically and socially—to minimize defensiveness and encourage receptivity.

Politeness, described by Foley (1997) as "a battery of social skills whose goal is to ensure that everyone feels affirmed in a social interaction" (p. 270), serves as a crucial strategy in reducing the threat to face.

By employing politeness strategies, advisors can mitigate the imposition, thereby making recommendations more appealing and enhancing the probability of compliance. Although Brown and Levinson's model initially concentrated on sentence-level politeness, subsequent scholars such as Fukushima (2004) and Usami (2006) expanded this framework to encompass discourse-level structures, thereby emphasizing its broader applicability across various conversational contexts. These advancements highlight the pertinence of politeness theory in elucidating communication dynamics not only in human-human interactions but also in AI-mediated exchanges. Politeness strategies are categorized into two primary types: Positive Politeness, which seeks to diminish social distance and foster solidarity, employs techniques such as expressing familiarity, offering encouragement, utilizing inclusive or informal language, and conveying friendliness (Brown & Levinson, 1987). On the other hand, Negative Politeness prioritizes respect for autonomy and personal space, involving the use of indirect language, hedging, and emphasizing user agency (Brown & Levinson, 1987). In human-human interactions, these politeness strategies have been demonstrated to increase trust, compliance, and satisfaction. However, it remains uncertain whether these effects are replicated in AI-driven advice-giving contexts, where interactions are mediated by algorithms rather than human judgment. As artificial intelligence-powered chatbots increasingly assume advisory roles in sectors such as customer service, healthcare, and online shopping, the applicability of politeness theory warrants re-evaluation in light of these emerging dynamics.

According to the Computers as Social Actors (CASA) paradigm (Nass et al., 1994), individuals tend to apply human social rules to interactions with machines. Through a series of experimental studies, Nass and colleagues demonstrated that users respond to computers as though they were social beings, attributing human characteristics to them and engaging with them using socially normative behaviors. This phenomenon suggests that politeness strategies traditionally applied in human communication may have analogous effects in human-computer interaction (HCI).

Recent research reinforces this view. For example, Lee & Park (2022) found that perceived communication quality mediates consumers' parasocial relationships with AI shopping chatbots, significantly predicting continuance usage intentions. Their findings suggest that chatbot communication, when perceived as socially appropriate and effective, can foster deeper user engagement, trust, and behavioral commitment. This implies that politeness strategies, whether through tone, formality, or language structure, are critical for chatbot effectiveness in persuasive communication.

Given that advice challenges autonomy by nature, effective linguistic strategies are essential for mitigating reactance and increasing adherence. In AI-mediated interactions, users often apply unconscious social norms, expecting chatbots to communicate in ways similar to human advisors. Consequently, verbal politeness becomes a central component in the design of persuasive and user-friendly chatbot communication.

This chapter proposes that the formality of chatbot language, as a carrier of either positive or negative politeness, plays a key role in determining how advice is received. While formality can signal respect and competence, informality may convey friendliness and relatability. Therefore, this study investigates whether these verbal politeness strategies, derived from human interaction principles, are equally effective in AI-mediated advice-giving, particularly in influencing advice adherence and user trust.

Understanding the application of politeness theory in AI interactions offers important implications for multiple domains:

AI Design: Integrating politeness strategies into chatbot dialogue systems can help reduce psychological reactance and improve user adherence to advice.

Consumer Behavior: Enhanced communication style can increase trust in AI recommendations and positively shape brand perception.

Human-Computer Interaction Research: Testing the relevance of human communication theories in AI contexts contributes to broader theoretical development and practical design insights.

In sum, politeness theory offers a robust framework for exploring how advice-giving communication strategies can be optimized in AI-driven environments. By investigating how positive and negative politeness influence user adherence, trust, and engagement, this study aims to contribute to the development of more effective, socially intelligent conversational agents.

2.7. Hypothesis Development

2.7.1. Hypotheses 1 and 2 developed for Model 1:

Verbal Communication Cues and Politeness Theory: Both verbal and nonverbal communication cues significantly shape interaction outcomes, particularly in human-computer interactions. How we communicate when offering advice can increase or decrease the threat in the interaction. Like nonverbal cues, the language we use can bring the advisor (chatbot) and the user receiving advice (user) closer or further apart. This is what affects the degree of trust and adherence of the user to the advice. It is hence crucial to investigate the verbal strategies, such as formality or informality of language, in AI advisory systems. Language plays a crucial role in managing interpersonal relationships by either reducing or increasing social distance. It can bring us close and also drive us apart. Individuals are more intimate and relaxed when communicating informally. Informal comm unication reveals warmth, treats everyone equally, and shared-understanding. Brennan (1991) proposed "grounding" in communication. This is sharing common knowledge, beliefs, and ideas to communicate effectively. Informal communication typically enables grounding, meaning it creates a friendly environment where people can share and understand each other better (Di Maro, 2021). Raczaszek-Leonardi et al. (2014) examined how people create and sustain common ground in conversation. They found that shared experience and mutual acquaintance are the prerequisites for effective communication. They have shown through their studies that informal conversation can lead to such shared experience towards more effective, significant interactions (Raczaszek-Leonardi et al., 2014).

Conversely, formal language increases social distance, reinforcing authority and professionalism. Although it may lack the warmth of informal expression, it signals respect and structure, thereby reducing the risk of face-threatening acts. Wierzbicka (1991) notes that formality carries markers of status and distance, while Ide (1989) identifies formal speech as a core feature of negative politeness strategies, intended to show deference and minimize imposition. According to Brown and Levinson (1987), negative politeness serves to protect the listener's autonomy, making the interaction feel less coercive and more respectful of the user's freedom of choice.

In human-computer interaction, language formality directly affects how users perceive a chatbot's effectiveness, credibility, and trustworthiness. Friendly, informal language associated with positive politeness can make a chatbot appear more accessible and interesting, whereas formal, structured language associated with negative politeness can enhance perceptions of professionalism and expertise. However, as literature suggests, the balance is delicate; overly informal chatbots may lack perceived competence, while highly formal ones may be viewed as detached or impersonal. On the basis of these observations, and in accordance with politeness theory, the following hypotheses are formulated as part of Model 1 in the empirical study (see Figure 16 Conceptual Model 1):

Hypothesis H1 and H2 developed for **Model 1**	• **H1:** Informal (vs. formal) language in a chatbot leads to greater feelings of perceived positive politeness. • **H2:** Formal (vs. informal) language in a chatbot leads to greater feelings of perceived negative politeness.

2.7.2. Hypotheses 3 and 4 developed for Model 1:

Nonverbal Communication Cues and Politeness Theory: Nonverbal cues play a critical role in shaping perceptions and interaction outcomes, both in human-human and human-computer communication. In the context of virtual conversational agents, visual elements—such as avatars, interface design, and stylistic choices—substantially influence user engagement, trust, and advice adherence. Among these, one of the most influential nonverbal cues is attire, which helps users infer characteristics about the chatbot, such as expertise, authority, or approachability (Rosenfeld & Plax, 1977).

Empirical findings from service-related contexts highlight the communicative power of attire. Yan et al. (2011) found that consumers form immediate impressions regarding service quality and professionalism based on a salesperson's clothing. Similarly, Forsythe et al. (1985) demonstrated that job candidates dressed in masculine attire received more favorable hiring evaluations, while Kashem, (2019) showed that instructor attire influences students' attitudes and academic outcomes. These findings suggest that clothing functions as a symbolic cue that extends beyond interpersonal encounters to shape human perceptions of digital agents. In chatbot design, avatar clothing or professional branding can impact user trust and willingness to accept recommendations.

Advice-giving inherently involves a degree of face threat, as it may challenge the autonomy or self-image of the advisee. According to Brown and Levinson's (1987) Politeness Theory, visual presentation—including attire—can serve as a nonverbal politeness strategy to reduce this threat. Specifically, informal attire can convey friendliness, familiarity, and reduced social hierarchy, aligning with positive politeness. Studies by Hannover & Kühnen (2002) and Peluchette & Karl (2007) support this view, showing that casual clothing increases relatability and approachability. For instance, a chatbot wearing a T-shirt may appear more personable, making users more comfortable and engaged during interactions.

In contrast, formal attire enhances perceptions of authority, professionalism, and credibility—key indicators of negative politeness. By reinforcing social distance and signaling competence, formal clothing minimizes perceived coercion in advice-giving interactions (Slepian et al., 2015; Stephan et al., 2010). A chatbot represented with a business suit or a medical coat, for example, may inspire trust in domains such as finance or healthcare, where credibility and structure are paramount.

Therefore, attire is not a neutral design element; it plays an active role in managing user perceptions of social presence, credibility, and politeness. In AI-driven conversations, especially those involving advice, the clothing of the chatbot's avatar can significantly influence user attitudes and behavioral responses. Nonverbal communication, particularly visual representation, and avatar attire, serves as an essential mechanism for regulating social distance, which in turn affects the user's receptiveness to chatbot-delivered recommendations.

Building on these insights, and grounded in Politeness Theory and human-computer interaction literature, the following hypotheses are proposed as part of Model 1 in the empirical study 1 (see Figure 16, Conceptual Model 1):

Hypothesis H3 and H4 developed for **Model 1**	• **H3**: Informal (vs. formal) outfit's in a chatbot leads to greater feelings of perceived positive politeness. • **H4**: Formal (vs. informal) avatar's outfit in a chatbot leads to greater feelings of perceived negative politeness.

2.7.3. Hypotheses 5 and 6 developed for Model 1:

Psychological Reactance in Human-Computer Interaction (HCI): Psychological reactance is a motivational state in which individuals feel their freedom is threatened or restricted, prompting a desire to restore autonomy (Rains, 2013). This psychological response has become increasingly relevant in marketing, as firms seek to influence consumer behavior amid highly personalized and, at times, intrusive promotional strategies. Reactance is particularly salient in contexts such as relationship marketing, direct marketing, and online advertising, where perceived intrusiveness can diminish campaign effectiveness (Darpy & Prim-Allaz, 2009; Morimoto & Chang, 2006). When consumers perceive that a marketing message constrains their freedom of choice, they may resist or outright reject the product, campaign, or brand.

Reactance theory has been widely used to explain why consumers often avoid certain forms of advertising, particularly online ads. For example, users may exhibit ad avoidance behavior when they perceive advertisements as intrusive or irrelevant, especially if the ads interrupt primary activities such as video consumption or article reading (Citalada et al., 2022).

Although psychological reactance has been extensively studied in marketing and health communication, its application within Human-Computer Interaction (HCI) is relatively recent. In interactive digital environments, particularly those employing persuasive technologies, multiple factors have been identified as triggers of reactance, including perceived surveillance, coercive prompts, and excessive notifications (Ehrenbrink & Prezenski, 2017). These elements can significantly affect users' acceptance of digital services and technologies.

Psychological reactance is, therefore, a fundamental HCI issue, especially when agents on the internet such as chatbots attempt to direct user decision. Psychological reactance arises when users believe that their freedom is being taken away, typically resulting in resistance against guidance or recommendations by the agent (Ehrenbrink & Möller, 2018; Ehrenbrink & Prezenski, 2017). Reactance thus poses a significant threat to the design and effectiveness of interactive systems, particularly those that are based on persuasive communication and strong social presence, such as virtual assistants and chatbots.

Social cues such as those that enhance perceived social presence or human-likeness play a critical role in modifying psychological reactance in HCI. Findings suggest that agents with high social agency have the ability to induce users to experience higher reactance, especially when tailored language or anthropomorphisms are perceived as manipulative (Roubroeks et al., 2010). Social cues, however, are able to lower reactance if applied appropriately. For instance, in systems using directive or controlling language, reactance can be reduced by carefully balancing authority with warmth and friendliness (Ghazali et al., 2017). In this way, the strategic use of social cues can improve user experience while preserving perceived autonomy.

Interestingly, Ghazali et al. (2018) found that while enhanced social cues can create a sense of familiarity, they may also provoke resistance, particularly when users are focused on a task, if those cues are perceived as infringing upon freedom of action. This emphasizes the importance of understanding psychological reactance in chatbot interactions. In this regard, the present study aims to examine psychological reactance based on a systematic evaluation of user responses in persuasive chatbot interactions.

Psychological Reactance and Politeness Theory: Psychological reactance is a motivational state that arises as a consequence of feeling one's freedom of choice being threatened or restricted, with a concomitant requirement to reassert one's autonomy (Rains, 2013). It is particularly apparent in the areas of consumer behavior and marketing, where companies typically seek to manipulate purchasing decisions through the use of targeted advertising and per-suasive messages. Reactance is highly central in relationship marketing, direct marketing, and online advertisements since the perceived intrusiveness and manipulation may cause consumers to refuse all promotional content completely (Darpy & Prim-Allaz, 2009; Morimoto & Chang, 2006).

In digital environments, reactance theory helps explain why users actively avoid certain types of advertising. For instance, people may resist ads that are perceived as intrusive, irrelevant, or disruptive to their primary activities, such as watching videos or reading articles (Citalada et al., 2022). When consumers perceive a marketing message as limiting their autonomy or manipulating their decision-making, they may not only dismiss the content but also form negative attitudes toward the product or brand associated with it.

Within chatbot interactions, a critical factor influencing psychological reactance is the presence of social cues—features that make digital agents appear more human-like or socially aware. According to Roubroeks et al. (2010), an increase in a chatbot's social presence can heighten the risk of reactance, particularly when users feel manipulated by anthropomorphic characteristics or overly personalized language.

However, recent research suggests that well-calibrated social cues can also mitigate reactance. Ghazali et al. (2017) demonstrate that in systems using directive or controlling language, reactance can be reduced by carefully balancing authority with friendliness. These findings align with Politeness Theory, which proposes that specific communication strategies such as the use of indirect language, the provision of choice, and the reduction of social distance can preserve the user's sense of autonomy and minimize resistance.

Interestingly, Ghazali et al. (2017) also found that while enhanced social cues may improve engagement, they can simultaneously increase reactance if users feel their independence is being compromised. This underscores the need for chatbot designers to manage politeness and social presence with precision, as overly persuasive or socially dominant behavior may backfire and trigger user resistance.

Given the importance of psychological reactance in human-chatbot communication, this study further aims to:
Examine how chatbot communication style (verbal and nonverbal cues) influences user reactance.
Investigate the role of social cues in mitigating or exacerbating resistance to chatbot advice.
Identify effective strategies for designing AI-driven chatbots that enhance user engagement while preserving autonomy.
Building on these insights, the following hypotheses are proposed as part of Model 1 in the empirical study 1 (see Figure 16, Conceptual Model 1):

Hypothesis H5 and H6 developed for **Model 1**	• **H5**: Positive politeness decreases reactance towards the chatbot. • **H6**: Negative politeness decreases reactance towards the chatbot.

2.7.4. Hypothesis 7 developed for Model 1 and Hypothesis 3 for Model 2:

Psychological Reactance and Advice Adherence: Across various disciplines, the behavioral response to receiving advice from recommender systems has garnered increasing scholarly interest. In the context of this study, reactance behavior is defined as a user's resistance or noncompliance with chatbot-provided advice Aljukhadar et al. (2017).

Reactance Theory (Brehm, 1966) provides a robust framework for understanding how compliance and advice seeking are influenced by threats to personal freedom. Specifically, psychological reactance is the motivational state to restore a sense of freedom whenever one's freedom to make autonomous choices is perceived to be limited or undermined.
When individuals believe they are being pushed or coerced into accepting advice, they may be likely to resist taking it, even if the advice is logical or consistent with their own interests. This is because advice per se will be seen as limiting personal freedom and so will provoke the recipient to resist in an attempt to regain autonomy. Of special concern, even when the advice is consistent with the advisee's belief or desire, nevertheless, invasions of autonomy will trigger resistance to produce noncompliance.

One of the most well-documented effects of psychological reactance is the boomerang effect, whereby individuals not only reject the advice but even do the opposite of the recommendation (Quick & Kim, 2009). For AI advisory systems, the effect is particularly significant: the users may find chatbot-generated advice over-controlling or intrusive and hence be less engaged, less compliant with

advice, and generally less effective for the conversational agent. Awareness of the role of psychological reactance in chatbot use is therefore central to research as well as practice.
Based on these results, the following hypothesis is included in Model 1 of Empirical Study 1 and Model 2 of Empirical Study 2 (see Figure 16, Conceptual Model 1 and Figure 21, Conceptual Model 2):

Hypothesis H7 developed for **Model 1** And H3 for **Model 2**	• **H7, H3:** Higher reactance leads to lower Advice Adherence intention.

2.7.5. Hypothesis 5 developed for Model 2:

Speech Act in Advice-giving: The choice between direct and indirect speech acts in advising is determined by politeness expectations, cultural norms, and social hierarchy. English-speaking societies, for example, are more accommodating with advice-giving style in that both direct and indirect advice are applied based on situation and relationship between interlocutors (Hinkel, 1997). Japanese society, for example, favors the use of indirect advice because it is perceived as less intrusive and more harmonious (Tanaka, 2022). Ar-abic-speaking contexts are likely to involve straightforward forms of advice, particularly within professional or authoritative contexts, on account of cultural assertiveness and explicitness norms (AL-Khatib & AL-Khanji, 2022).
Where the conversational agents are AI based, the preference for direct versus indirect speech acts can have critical effects on advice compliance and user engagement. Where direct chatbot recommendations are a seeming efficiency as well as compliance, they risk being likely to trigger psychological reactance. Contrastingly, indirectly or hedgily given advice might be the better persuader by allowing the users to infer that they control decisions.
This study examines how word-of-mouth advisory tactics used in chatbot dialogues impact user trust, engagement, and adherence to AI-generated recommendations, contributing to the emerging field of persuasive AI communication.
Speech Act and Advice Adherence: Advice adherence varies significantly depending on the degree of speech act directness. Both direct and indirect advice strategies offer distinct advantages, influencing how recipients interpret, accept, or resist recommendations.

Direct speech acts are clear, explicit, and less likely to be misinterpreted, thus being especially useful in high-stakes or time-sensitive communication contexts. For instance, in COVID-19 health communication, directive advice was widely used and proved to be extremely effective in promoting compliance (Raheem & Nehal, 2021).
However, even though direct advice maximizes clarity, it may further maximize perceived coercion and hence produce reactance. Consequently, direct advice's effectiveness depends on context and users' perception.
Indirect speech acts are usually perceived to be more polite and acceptable, particularly when interacting with strangers, customers, or individuals with social distance (Li, 2016). Indirectness serves to soften face threats, making recommendations less confrontational and softer. In inter-personal relationships, for example, indirect advice facilitates smooth interaction and less conflict. Nevertheless, in professional and structured contexts, indirect communication creates ambiguity and leads to misunderstandings (Yin & Kuo, 2013). This means that while indirect speech acts are socially more favored, they will not necessarily translate into more compliance, particularly in complex decision-making contexts where certainty and clearness are essential. Building on these insights, the following hypothesis is developed as part of Model 2 in the empirical study 2 (see Figure 21, Conceptual Model 2):

Hypothesis H5 developed for **Model 2**	• **H5:** Indirect (vs. Direct) speech act of the advice increases Advice Adherence

2.7.6. Hypothesis 2 developed for Model 2:

Speech Act and Reactance: The way advice is linguistically framed at the sentence level significantly influences user perceptions, emotional reactions, and behavioral adherence. Speech act theory provides a foundational framework for understanding how language functions not only as a vehicle for information exchange but also as a tool for action and influence in interpersonal and digital communication. Yule, (2022) defines speech acts as mechanisms that reflect how speakers and listeners use language interactively. Bach & Harnish (1984) similarly argue that every verbal act conveys an underlying communicative intent, emphasizing that communication is always layered with meaning beyond the literal content. Austin (1975) seminal work further supports this perspective by demonstrating that language performs social actions, such as requesting, commanding, advising, or promising.

In advice-giving contexts, language inherently involves attempts to guide or influence another person's behavior, which can provoke resistance. As D. J. Goldsmith (2000) notes, advising interactions often involve sequences of speech acts that risk threatening the recipient's face, particularly negative face, or the desire to maintain autonomy and avoid imposition (Jenetto & Hanafi, 2019). Advice that is perceived as constraining freedom can therefore trigger psychological reactance, a motivational state in which individuals resist influence in order to reassert control over their decisions (Brehm, 1966).

Hinkel, (1997) classifies advice into direct and indirect speech acts, each eliciting different user responses:

Direct advice includes imperatives and modal constructions such as "You should do this" or "You must try that." These expressions are highly explicit and directive, offering clarity and certainty (Cheatham & Ostrosky, 2013). However, they are also more likely to be perceived as controlling, which can increase reactance and reduce advice adherence (Jenetto & Hanafi, 2019b).

Indirect advice, though, uses hedging, probabilistic language, or conditional grammar. These forms tend to be evaluated as being more respectful and autonomy-supportive.

These forms are generally perceived as more respectful and autonomy-supportive. While they can reduce face threat and encourage receptiveness, they may also introduce ambiguity, particularly in high-stakes or urgent decision-making contexts where directive clarity is valued.

The boomerang effect is a commonly observed side effect of psychological reactance, where individuals not only oppose advice but also behave in opposition to the advice (Fitzsimons & Lehmann, 2004). This is especially relevant in AI systems, where users may experience chatbot-offered advice as too directive or intrusive, thus diminishing trust and usage. André et al. (2019) also discovered that users felt less in control and more frustrated when they were presented with controlling AI-based recommendations. G. Lee & Lee (2009) and Sankaran et al. (2021) also noted that directive chatbot language can decrease perceived agency and increase rejection rates.

Several key factors, including perceived threat to autonomy (Shen, 2014), the use of controlling language, particularly imperatives or modal verbs (Miller et al., 2007), and the intensity of language in AI-generated messages (Bowers, 1963), contribute to reactance in AI-mediated interactions. Miller et al. (2007) also specifically found that imperatives and emphatic adverbs such as "must" or "should" exerted a significant influence on message rejection due to heightened

reactance. Lanceley (1985) further supports this by showing that directive tone in advice-giving communication reduces receptiveness and undermines the relational tone of the interaction.
In the context of chatbot design, these findings emphasize the importance of speech act modulation balancing the clarity of directives with linguistic cues that preserve user autonomy and minimize resistance.
To investigate these effects in AI-driven advice interactions, the following hypothesis is developed as part of Model 2 in Empirical Study 2 (see Figure 21, Conceptual Model 2):

Hypothesis H2 developed for **Model 2**	• **H2:** Direct (vs. Indirect) speech act in an advice-giving chatbot increases the reactance in the user.

2.7.7. Hypothesis 1 developed for Model 2:

Advice Alignment Bias in Advice-Giving: Alignment bias refers to the tendency of advisors to adjust their recommendations to conform with the advisee's pre-existing opinions, preferences, or expectations. This tendency is particularly evident in socially sensitive or interpersonal contexts, where advisors may seek to avoid conflict, preserve rapport, or gain social approval.
Advice-taking behavior is shaped significantly by social dynamics, where the desire for relational harmony and recognition influences both the content and style of advice. For instance, an advisor may downplay their own judgment or defer to the advisee's preferences in order to minimize disagreement (Luo et al., 2024). Consequently, the advice becomes reflective of the advisee's expectations rather than the advisor's independent analysis or expertise.
Extensive research in the fields of judgment and decision-making has examined the emergence and effects of alignment bias. The underlying motivations for alignment bias are often social and reputational in nature. Advisors aim in doing so may be to preserve the relationship or avoid social tension by offering agreeable advice (Yaniv & Kleinberger, 2000). Moreover, a well-received advice can enhance an advisor's credibility and perceived expertise, increasing the likelihood of being consulted again (Harvey & Harries, 2004).
The central challenge of alignment bias lies in balancing objectivity with social rapport. While maintaining friendly and non-confrontational communication is essential in many advice-giving

interactions, overemphasis on alignment risks compromising the integrity and effectiveness of the advice provided.

This issue is particularly salient in the context of AI-driven conversational agents and recommender systems, which are increasingly designed to personalize advice based on users’ preferences, behaviors, and historical data. While personalization can improve perceived relevance and satisfaction, excessive alignment may reinforce filter bubbles and confirmation bias, thereby restricting users’ exposure to novel or corrective information. This raises concerns about the role of AI in promoting narrow, preference-conforming feedback

Advice Alignment and Psychological Reactance: Advice alignment bias refers to the tendency of decision-makers to adjust their judgments to align with received advice, even when that advice may be biased, inaccurate, or unreliable. This phenomenon is especially relevant in organizational and AI-driven decision-making contexts, where individuals frequently rely on external advisors, such as human consultants or algorithmic recommendation systems. Although people attempt to correct for perceived bias in the information they receive, their capacity to do so effectively is often limited (Bonner & Cadman, 2014).

A critical factor influencing advice alignment is psychological reactance—a motivational state that arises when individuals perceive that their autonomy is being threatened. Reactance significantly affects how persuasive messages, including advice, are interpreted and acted upon. In this regard, the relationship between advice alignment and reactance is nuanced and contingent on whether the advice confirms or contradicts the user’s existing beliefs, preferences, or goals.

Empirical research shows that misaligned advice, that is, advice that contradicts the recipient’s expectations or preferences, tends to intensify reactance. For instance, Roubroeks et al. (2010) demonstrated that participants who received advice from a persuasive robot experienced higher levels of psychological reactance when the recommendations conflicted with their pre-existing intentions regarding washing machine usage. This means that even good advice would be rejected when it is perceived as incongruent with personal goals, and this leads to lower advice acceptance. This is a consequence of confirmation bias, the aspect of human perception where individuals favor information that attests to and supports their own existing beliefs over and against contrary information (Rassin, 2008). In practice, aligned advice works better because it minimizes dissonance in cognition and reaffirms one's self-image. Non-aligned advice, while valid, elicits discomfort and leads to rejection. Both confirmation bias and alignment bias involve selective information absorption, favoring preconceived beliefs and discounting or ignoring counter-opinions. In the financial advice industry, Agnew et al. (2019) found that clients' first impressions and value judgments of financial advisors were predictors of their willingness to pay for advice, more influenced by conformity to expectations than by objective performance. Similarly, in AI-mediated interaction, users are more receptive to recommendations that conform to their past choices and less receptive to those that contradict their deep-seated preferences. These findings underscore the key importance of personalization to AI-driven advice systems, where one would suggest that recommendations are aligned to users' preferences but yet founded on objectivity and fairness. Developing systems that acknowledge the importance of alignment can increase trust from users, compliance with advice, and perception of system credibility. Building on these insights, the following hypothesis is developed as part of Model 2 in Empirical Study 2 (see Figure 21, Conceptual Model 2):

Hypothesis H1 developed for **Model 2**	• **H1:** Alignment (vs. Non-alignment) of the advice with user preference decreases the reactance in the user.

2.7.8. Hypothesis 4 developed for Model 2:

Advice Alignment and Advice Adherence: Numerous studies in the domains of recommender systems and driver guidance systems have demonstrated a strong relationship between advice alignment and advice adherence. Research consistently shows that when AI-generated recommendations are misaligned with user preferences, individuals are more likely to reject or disregard the advice.

For example, Chen & Jovanis (2003) investigated real-time en-route navigation systems and found that drivers frequently ignored routing suggestions when they contradicted their preferred travel patterns, such as favoring freeways over local roads. This illustrates how preference misalignment can lead to reduced adherence in AI-supported decision environments, even when the recommendations are objectively reasonable.

The importance of aligning recommendations with user preferences extends far beyond navigation technologies. In the context of online recommender systems, user preferences are often dynamic and influenced by several evolving factors, including: Quality of Service (QoS) metrics and overall system responsiveness (Y. Zhang et al., 2020) past experiences and trust built over repeated interactions and contextual variables, such as time-sensitive goals or situational constraints.

These results support the necessity for adaptive AI-driven systems that are able to learn from user activity and adjust advice strategies in turn. Through embedding real-time feedback and behavioral information, recommender systems can update advice dynamically based on individual factors, thus furthering their usefulness and improving follow-through. While alignment increases acceptance, over-personalization threatens the reinforcement of confirmation bias, with reduced exposure to alternative viewpoints, and potentially more constrained decision-making in the longer term. Advice alignment bias plays a dual role within AI-driven recommendation systems: it can lower psychological reactance and increase advice conformity. As such, achieving an equilibrium between preference-sensitive advice and encountering new information is vital to the development of reflective and autonomous decision-making.

Building on these insights, the following hypothesis is proposed as part of Model 2 in Empirical Study 2 (see Figure 21, Conceptual Model 2):

Hypothesis H4 developed for **Model 2**	• **H4:** Alignment (vs. Non-alignment) of the advice with user preference increases Advice Adherence.

2.7.9. Hypothesis 1 developed for Model 3:

Responsibility Attribution in Advice-giving: Responsibility attribution (RA) is a central component of accountability, concerned with determining who is responsible for specific outcomes in decision-making processes (Triantafyllou et al., 2022). In the case of multi-agents, responsibility attribution entails determining how much each agent is responsible for the outcome of a decision (Triantafyllou & Radanovic, 2023). This dimension has gained popularity in organizational research, particularly in quantifying responsibility assignment and diagnostic models of decision making (Martinko et al., 2018). Two basic components characterize responsibility attribution are culpability, i.e., deciding who is responsible when results are adverse, and causality, i.e., understanding responsibility as a result of the perceived cause of the outcome (Fincham & Jaspars, 1980).

Responsibility is not limited to individual actors. It can also be collective, involving organizations, regulatory agencies, or artificial agents such as AI systems (Lorini et al., 2014). This expansion of responsibility beyond the individual level introduces new complexities, especially in AI-mediated interactions, where the locus of control is often distributed across human and machine agents.

When users receive advice from AI-powered chatbots or recommender systems, and negative consequences ensue, the question that arises is “Who is accountable?”: the user, the developer, or the AI itself? Research suggests that in situations of ambiguity, especially where outcomes are unfavorable, people tend to seek an entity to blame. Particularly when the consequences are perceived as serious or unjust (C. Gu et al., 2024). This phenomenon aligns with the self-serving bias, a cognitive tendency in which individuals claim credit for successful outcomes but deflect blame for failures onto external sources (Moon & Nass, 1998).

In the context of AI-mediated decision support, studies show that users often blame the system for failures, while crediting themselves for successes (Serenko & Detlor, 2004). This attribution dynamic presents a major challenge in designing ethical and trustworthy AI systems.

A key issue emerging from this context is the so-called "responsibility gap" (Matthias, 2004), which arises when AI systems act with minimal human intervention, as in autonomous vehicles, algorithmic trading platforms, or AI diagnostic tools. Unlike chatbots that serve as advisory tools, fully autonomous AI may execute actions without direct oversight, complicating the attribution of moral or legal responsibility. Real-world examples illustrate the difficulty of this problem. In the 2018 Uber self-driving car accident, responsibility was contested among software developers, manufacturers, and regulatory agencies (Taddeo & Floridi, 2018). This situation exemplifies the "problem of many hands" in AI ethics, where accountability is dispersed among numerous stakeholders, making it difficult to assign responsibility to any single actor (van de Poel, 2015).

According to Aristotle's framework of moral responsibility, an agent must Act voluntarily and possess awareness of the consequences (Fischer & Ravizza, 1998). Because AI systems do not act with intentionality or consciousness, they cannot be held morally responsible for their actions (Coeckelbergh, 2010; Floridi & Sanders, 2004). Thus, the ultimate burden of responsibility must fall on the human agents who design, implement, and regulate these technologies.

To ensure ethical and accountable AI deployment, robust frameworks for responsibility attribution must be developed, clarifying how accountability should be shared and upheld in complex human-AI collaborations.

Responsibility Attribution and Advice Alignment: When advice aligns with an individual's pre-existing beliefs or preferences, the advisee is more likely to assume personal responsibility for the outcome. Attribution theory explains how individuals assign causality to events and outcomes, distinguishing between internal attributions (e.g., personal traits, decision-making ability) and external attributions (e.g., situational factors or external agents) (Ross, 1977). A central concept within this theory is the self-serving bias, which refers to the tendency to attribute successes to internal factors such as intelligence, effort, or judgment and failures to external causes such as bad luck, poor advice, or flawed systems (Blackwood et al., 2003; Shepperd et al., 2008).

In the context of AI-mediated decision-making, advice alignment plays a key role in shaping responsibility attribution. When the advice provided by a chatbot aligns with the user's prior beliefs or preferences, the decision is perceived as autonomous and self-directed. In such cases, users are more likely to internalize both the decision and its outcome. Taking ownership of the result, whether it is positive or negative. As Genschow & Lange (2022) argue, aligned advice functions as an affirmation of the user's judgment, thereby reinforcing internal attribution and reducing the likelihood of blame displacement.

This effect is supported by earlier research in decision-making. Frosch & Kaplan (1999) found that individuals are more likely to internalize both positive and negative consequences when decisions align with their preferences. This sense of ownership results in greater perceived autonomy and reduced blame-shifting in the event of failure.

Conversely, when the advice contradicts the user's expectations or preferences, users are more inclined to externalize responsibility, especially in the case of negative outcomes. If the advice leads to an undesirable result, individuals may view the decision as having been imposed or not reflective of their own judgment, making them more likely to blame the AI system or chatbot. This form of external attribution reduces personal accountability and can undermine trust in the system.

Building on these insights, the following hypothesis is proposed as part of Model 3 in Empirical Study 3 (see Figure 24, Conceptual Model 3):

Hypothesis H1 developed for **Model 3**	• **H1:** In case of advice aligned (vs. non-aligned) with the preference of the user they attribute the responsibility of the outcome to themselves (vs. chatbot)

2.7.10. Hypothesis 2 developed for Model 3:

Responsibility Attribution and Advice Success vs. Failure: Research on responsibility attribution has extensively examined its relationship with a range of outcome variables, particularly satisfaction, blame, and post-decision evaluation. Satisfaction is a critical outcome in service interactions, where customers assess who is responsible for success or failure. In online service environments, responsibility attribution becomes even more salient, as service failures are often perceived to occur more frequently than in traditional retail settings (Kuo et al., 2011). When customers experience negative outcomes in online interactions, they are more likely to assign blame to the service provider, which can result in disappointment, dissatisfaction, and diminished loyalty.

Attribution Theory provides a useful framework for understanding these dynamics, suggesting that individuals make causal inferences about events by assigning responsibility either internally (to themselves) or externally (to others or the environment). These attributions have a direct influence on emotional and behavioral responses to outcomes (Valvi & Fragkos, 2012). A key insight from attribution research is that negative outcomes tend to trigger more intense counterfactual thinking than positive ones. For example, studies show individuals are more likely to imagine “what-if” scenarios following undesirable outcomes, speculating about how different choices could have led to better results (Epstude & Roese, 2008). This reflection often strengthens the tendency to attribute blame externally.

Such tendencies are also evident in professional advisory contexts. In a study on tax preparation, Schisler & Galbreath, (2000) found that clients consistently blamed their tax advisors when they were audited, even when the audit was justified and the advice aligned with regulatory standards. This suggests that users may assign responsibility based less on the actual quality of the advice and more on the outcome of the decision-making process. Specifically, when the outcome is positive, users are more likely to attribute success to themselves, reinforcing internal responsibility.

When the outcome is negative, users are more inclined to externalize blame, often to the advisor or system providing the guidance, especially if the advice deviated from their expectations.

These patterns have important implications for AI-driven advisory systems. When users receive AI-generated recommendations that lead to favorable results, they may not actively credit the chatbot or system, and may instead see the outcome as a reflection of their sound judgment. However, when the result is unfavorable, the AI system becomes a convenient target for blame, even if the advice was reasonable or aligned with the user’s preferences. This externalization of responsibility may be especially strong in situations where users feel they had limited agency or were persuaded against their initial judgment.

Understanding this bias is critical for the development of responsible and trustworthy AI systems. If users systematically shift blame to AI in cases of failure—regardless of advice quality—it may undermine long-term engagement, trust, and perceived system credibility. To mitigate these effects, AI systems should emphasize transparency, offering clear explanations of the recommendation logic and highlighting the shared nature of decision-making responsibility.

Building on these insights, the following hypothesis is proposed as part of Model 3 in Empirical Study 3 (see Figure 24, Conceptual Model 3):

Hypothesis H2 developed for **Model 3**	• **H2:** In case of success (vs. failure) of the advice the level of attribution of the responsibility to the user (vs. chatbot) increases.

2.7.11. Hypothesis 3 developed for Model 3:

Responsibility Attribution and Usage Intention: Attribution theory suggests that individuals are naturally motivated to understand and explain events by identifying their underlying causes (Heider, 1958). This cognitive process of assigning causality plays a critical role in how people evaluate products, services, and technologies, particularly in the context of AI-driven systems. In interactions with conversational agents, users form attributions regarding the chatbot's role, capabilities, and effectiveness, which directly influence future levels of trust and their intention to continue using the system.

Attribution theory distinguishes between internal attribution, where outcomes are credited to one's skills, efforts, or decisions and external attribution, where outcomes are linked to external agents or contextual factors (E. E. Jones & Davis, 1965; Kelley & Michela, 1980). In AI-mediated interactions, responsibility attribution functions as a central mechanism shaping users' evaluation of the chatbot. When users perceive that a chatbot played a significant role in delivering a successful outcome, they are more likely to:

- Attribute the result to the chatbot's capabilities and competence.
- Evaluate the chatbot as effective and trustworthy (Song et al., 2025).
- Exhibit a stronger intention to reuse or continue engaging with the chatbot.

Conversely, if users see the chatbot as a passive tool or if its role in the outcome remains opaque, they may attribute success to their efforts and underappreciate the system's contribution, limiting their long-term engagement with the AI system.

Trust is a critical mediating factor between attribution and usage intention. Prior research in technology acceptance has consistently shown that trust in AI, defined as the belief in its reliability, competence, and integrity, is a key predictor of adoption and continued use (Choung et al., 2023). Responsibility attribution reinforces trust: when users believe the chatbot was instrumental in achieving a favorable outcome, their trust in the system increases, thereby enhancing their willingness to rely on it in the future. In contrast, if users blame the chatbot for failure, their confidence in the system declines, reducing subsequent usage intentions.

Insights from corporate social responsibility (CSR) literature further support this relationship. Studies show that consumers respond more positively to companies when their actions are perceived as driven by altruistic or value-based motives rather than self-interest (Foreh & Grier, 2003). Similarly, users who perceive chatbots as competent, agentic, and responsible for successful outcomes are more likely to develop positive evaluations and deeper engagement.

A key distinction in attribution research lies between Egocentric attribution, where users perceive the AI as directly fulfilling their personal goals and needs, leading to enhanced engagement.
Altruistic attribution, more relevant in CSR contexts, where actions are evaluated based on their broader social impact.
In AI-user interactions, egocentric attributions, where users recognize the chatbot's effectiveness in helping them achieve specific outcomes, are especially powerful in reinforcing trust and commitment to future use.
Research on human-AI collaboration further emphasizes the importance of perceived agency. Shank et al. (2019) found that when AI systems are seen as taking a leading role in task execution, users are more likely to credit the system for success, which enhances their evaluations of AI competency and trust. This aligns with findings by Rahwan et al. (2019), who noted that users are more willing to adopt and rely on AI tools when they are perceived as competent, agentic contributors to outcomes.
Together, these insights suggest that responsibility attribution for positive outcomes is a key driver of trust formation and long-term adoption in AI-mediated environments. When users view the chatbot as a meaningful contributor to success, they are more inclined to trust and continue using it.
Based on these insights, the following hypothesis is proposed as part of Model 3 in Empirical Study 3 (see Figure 24, Conceptual Model 3):

Hypothesis H3 developed for **Model 3**	• **H3:** Higher Attribution of the responsibility to chatbot increases the Intention to use it.

2.8. Conclusion

Human communication is multimodal in nature, relying on an active interplay between verbal and nonverbal cues to impact the manner in which messages are sent, received, and responded to. Nonverbal signals—such as facial expressions, gestures, posture, and eye contact, not only walk alongside spoken words but often serve as primary indicators of emotion, intention, and relational positioning (Argyle, 2013; Mehrabian, 2017). In AI-human communication, such cues are equally indispensable in terms of establishing trust, empathy, and engagement.
Conversational AI interfaces increasingly feature nonverbal elements with visual avatars, emotional voice tone, and interactivity tempo in an attempt to simulate human presence and responsiveness. Human-like body language, tone suitability, and tactically timed responses are attributes that

cumulate into impressions of attentiveness, professionalism, and emotional intelligence (Chattaraman et al., 2019; Rhee & Choi, 2020). When well aligned with what users anticipate, these multimodal cues increase the perceived quality of the interaction, enhance trust, and enhance advice taking in decision-supportive contexts (Gambino et al., 2020). Such intergrading holds enormous consequences for AI-driven chatbot development. Developers must move away from purely text-based interfaces and adopt end-to-end communication styles that align with human conventions of communication. This includes the strategic use of avatars, emotive speech patterns, and real-time feedback, all escalated in accordance with user preferences and patterns of communication. In doing so, AI systems are able to produce more natural, intuitive, and engaging interactions, enhancing user trust in the system's suggestions and promoting long-term usage. In summary, integration of verbal and nonverbal communication aspects is essential to the success of conversational AI. Multimodal approaches not only improve message intelligibility and affective impact, but also ensure greater user trust and involvement. With AI systems ever-improving, the communication of humans in a more natural and context-sensitive way will ascertain the effectiveness of these systems across various applications, ranging from customer support to medical guidance and more. Ultimately, incorporating nonverbal cognition in chatbot interactions is called for to build natural, credible, and human-centered AI user interfaces.

Chapter 3: Empirical Studies

3.1. Conceptual Model 1

3.1.1. Moderating Role of Product Type

Hedonic products are “those that provide pleasure, enjoyment, or emotional satisfaction to consumers” while utilitarian products are “primarily functional and serve practical purposes” (Kivetz & Zheng, 2017). Studies have found that the product type (utilitarian vs. hedonic) moderates consumer responses to advertisement communications, which influences attitudes toward advertising appeals and language orientations. Cheng & Jang (2024) found that informational (vs. affective) appeals generated more positive attitudes and purchase intentions for products with higher utilitarian value. In particular, emotive and informal communication better serves hedonic products, and information and formal communication better suit utilitarian products (Drolet et al., 2007). Having been informed of insights, in the present work, it is analyzed whether product category conditions the effects of chatbot style of communication on perceptions of politeness. However, while current research has identified how product type affects consumers' preferences in traditional marketing, its role in human-AI interactions remains poorly investigated. As chatbots are unable to be intrinsically emotionally expressive, it is important to examine whether hedonic and utilitarian product framing modulates chatbot communication style to influence perceived advice following and politeness.

- **H8:** The relationship between Informal (vs. Formal) language is stronger between Informal communication style and Positive Politeness in the case of Hedonic (vs. Utilitarian) Products.
- **H9:** The relationship between Formal (vs. Informal) language is stronger between Formal communication style and Negative Politeness in the case of the Utilitarian (vs. Hedonic) Product.
- **H10:** The relationship between Informal (vs. Formal) Outfit is stronger between Informal communication style and Positive Politeness in the case of Hedonic (vs. Utilitarian) Products.
- **H11:** The relationship between Formal (vs. Informal) Outfit is stronger between Formal communication style and Negative Politeness in the case of the Utilitarian (vs. Hedonic) Product.

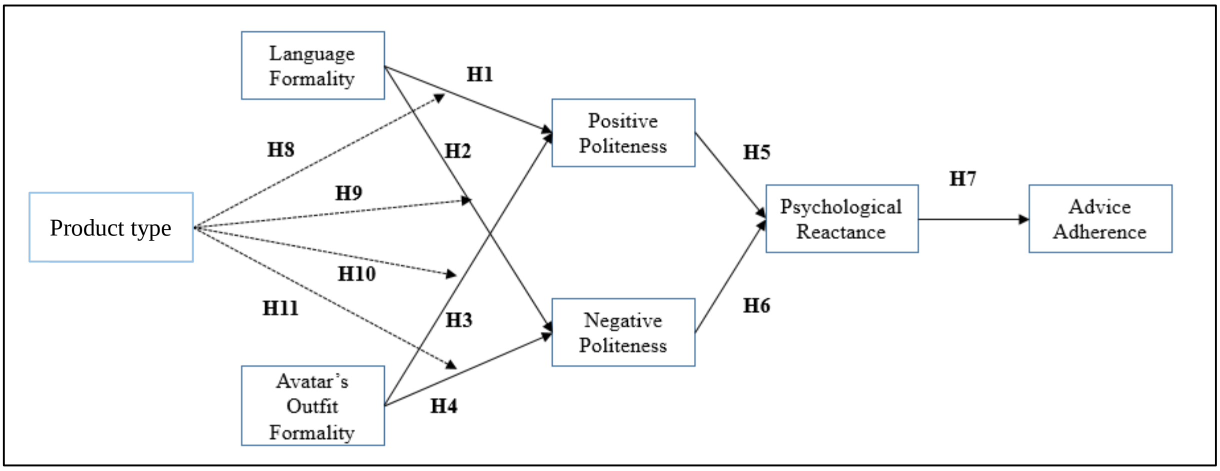
3.1.2. Conceptual Model 1 Overview

This research proposes a model (Figure 16) that examines how visual and verbal communication cues (specifically, clothing and language formality) influence perceptions of politeness (positive or negative), which in turn affect psychological reactance and advice adherence. The model posits that:

- **H1**: Informal (vs. formal) language in a chatbot leads to greater feelings of perceived positive politeness.
- **H2**: Formal (vs. informal) language in a chatbot leads to greater feelings of perceived negative politeness.
- **H3**: Informal (vs. formal) outfits in a chatbot lead to greater feelings of perceived positive politeness.
- **H4**: Formal (vs. informal) avatar's outfit in a chatbot leads to greater feelings of perceived negative politeness.
- **H5**: Positive politeness decreases reactance towards the chatbot.
- **H6**: Negative politeness decreases reactance towards the chatbot.
- **H7:** Higher reactance leads to lower Advice Adherence intention.
- **H8:** The relationship between Informal (vs. Formal) language is stronger between Informal communication style and Positive Politeness in the case of Hedonic (vs. Utilitarian) Products.
- **H9:** The relationship between Formal (vs. Informal) language is stronger between Formal communication style and Negative Politeness in the case of the Utilitarian (vs. Hedonic) Product.
- **H10:** The relationship between Informal (vs. Formal) outfits is stronger between Informal communication style and Positive Politeness in the case of Hedonic (vs. Utilitarian) Products.
- **H11:** The relationship between the Formal (vs. Informal) outfit is stronger between Formal communication style and Negative Politeness in the case of the Utilitarian (vs. Hedonic) Product.

Additionally, this model accounts for psychological reactance as a key mediator, given that language and visual cues influence the perception of imposed authority in chatbot interactions. By integrating product type as a moderating factor, this framework extends previous research by evaluating whether communication preferences in chatbot interactions align with those observed in traditional marketing communications. Figure 16 provides an overview of the proposed relationships.

Figure 15: Conceptual Model 1



3.1.3. Research Design

This study investigates the influence of communication style in chatbots on users' advice adherence intentions in an advice-giving recommender system. Participants were presented with scenarios and asked to complete a questionnaire afterward. To address the research questions and hypotheses, I employed a within-subjects 2 × 2 × 2 factorial design with randomization of participants under different conditions (Shadish, 2002). The independent variables in this design were:

- Communication Style (Formal vs. Informal)
- Outfit (Formal vs. Informal)
- Product Type (Hedonic vs. Utilitarian)

Although multiple factors were included, interaction effects between these factors were not the focus of this study. Instead, each factor was examined independently. Additionally, pre-tests were conducted to ensure the effectiveness of the manipulations (both verbal and visual communication cues).

3.1.4. Method

3.1.4.1. Participants

Participants were 455 users recruited via Prolific, an online platform that facilitates participant recruitment for academic research. Each participant was compensated £0.60 for their time. A participation link was shared with users, inviting them to participate in a study exploring chatbots. Upon clicking the link, participants were randomly assigned to one of the study conditions.

The text-based chatbots used in this study were chosen due to their high prevalence in practical applications. The questionnaire was created and distributed using the Qualtrics platform. Only participants who were native English speakers and resided in the USA or UK were recruited to ensure linguistic consistency.
After data cleaning (removal of respondents who failed at least two out of three attention checks), the final sample size was 452 participants. The demographic breakdown was as follows:

- **Gender**: 36% male, 63% female, 1% non-binary
- **Age**: Participants ranged from 18 to 81 years, with a mean age of 40.11 (SD = 13.27)

To capture a broad understanding of chatbot interactions, participants were recruited from various age groups. This is particularly relevant since older adults (65 and above) are becoming increasingly digitally connected (Chattaraman et al., 2019). A more detailed demographic profile of the participants is provided in Table 17.

Table 17: Demographics Of The Participants In Study1

Gender			Age		
Male	166	36%	18 - 25	59	13%
Female	285	63%	26 - 40	205	45%
Non-binary	3	1%	41 -55	125	27%
Other	1	0%	56 - 70	57	13%
Total	455		above 71	9	2%
Occupation			Total	455	
Management, professional, and related	155	34%	Education		
Service	39	9%	Less than primary	0	0%
Sales and Office	53	11%	Primary	2	0%
Farming, fishing, and forestry	1	0%	Some Secondary	5	1%
Construction, extraction, and maintenance	12	3%	Secondary	74	16%
Production, transaction, and material moving	6	1%	Vocational or Similar	53	12%
Government	24	5%	Some university	45	10%
Retired	25	6%	Bachelor’s degree	166	37%

Student	25	6%
Unemployed	32	7%
Housewife	21	5%
Other	62	14%
Total	455	

Graduate or professional degree	105	23%
Prefer not to say	5	1%
Total	455	

All recruitment and participation adhered to ethical guidelines and privacy regulations. Informed consent was obtained from all participants, who were informed of their right to withdraw from the study at any point. Data were treated with confidentiality and anonymized for analysis.

3.1.4.2. Measurements

All constructs in the study were measured using seven-point Likert scales. The specific scales used are as follows:

- Advice Adherence**:** Measured using 3 items adopted from Camacho et al. (2014).
- Perceived Positive Politeness**:** Measured using 4 items adapted from D. J. Goldsmith (2000).
- Perceived Negative Politeness**:** Measured using 4 items adapted from D. J. Goldsmith (2000).
- Psychological Reactance**:** Measured using 3 items adapted from Drennan & McColl-Kennedy (2003).

The reliability of these measures was tested using factor analysis and Cronbach’s Alpha, and all constructs showed strong reliability, with alpha values exceeding the recommended threshold of 0.7 (Fornell & Larcker, 1981). Detailed reliability statistics are provided in Table 18.
The composite reliability (CR) and the average variance extracted (AVE) were greater than the recommended 0.7 and 0.5 thresholds, respectively (Fornell & Larcker, 1981).

Table 18: Reliability Analysis for Study 1

Measurement	N of Items	Cronbach's Alpha	Average Variance Extracted	Composite Reliability
Advice Adherence	3	0.87	0.74	0.90
Positive Politeness	4	0.92	0.76	0.93
Negative Politeness	4	0.75	0.51	0.80

Reactance	3	0.88	0.76	0.90

3.1.4.3. Procedure

The experiment was based on the Computers Are Social Actors (CASA) paradigm (Nass et al., 1999), where participants were guided through an online scenario simulating an advice-giving interaction with a chatbot. Participants were asked to imagine themselves seeking advice in two distinct contexts: a hedonic (i.e. travel) or utilitarian (i.e. online security) service.

To manipulate the language formality of the chatbot (Figure 17 & 18), I followed suggestions from prior studies (Liebrecht, Sander, et al., 2021) on how to adjust chatbot communication to make it appear formal or informal. A pre-test of this manipulation was conducted to ensure that participants could distinguish between the two levels of formality, with results confirming successful manipulation.

Figure 16: Formal vs. Informal Language Interaction in Online Security Context

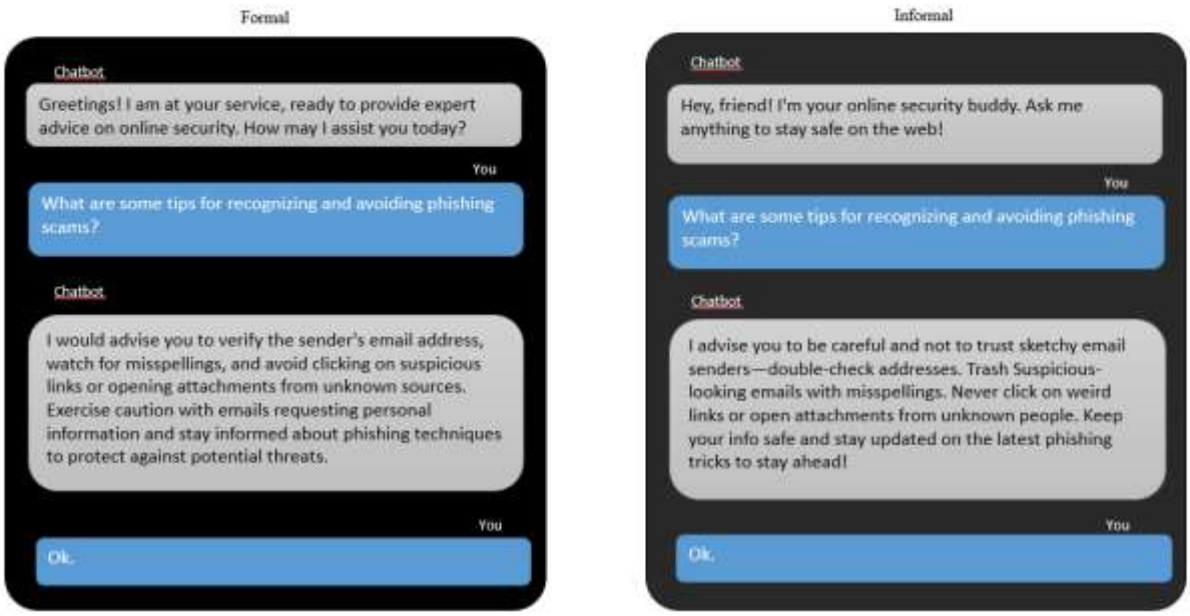
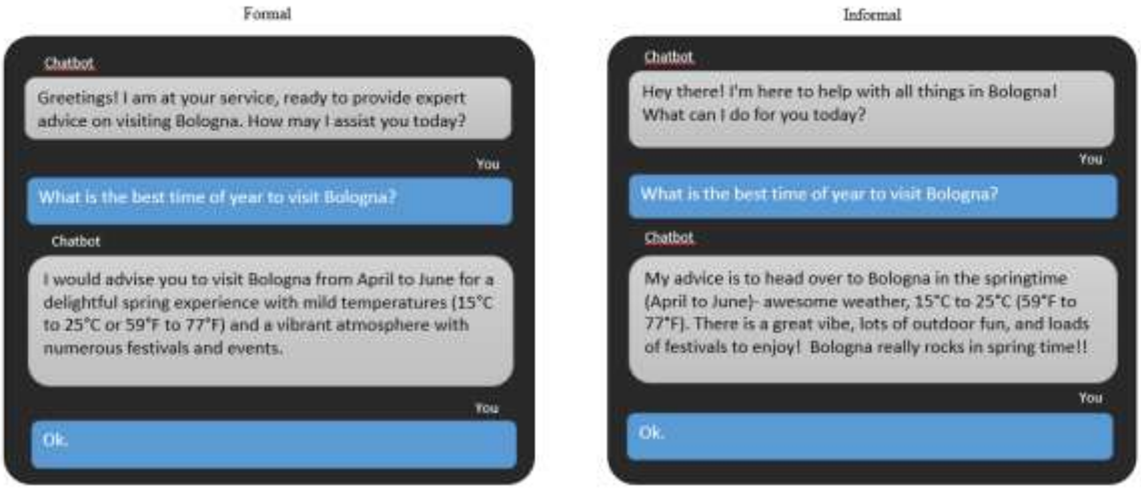


Figure 17: Formal vs. Informal Language Interaction in Travel Destination Context



Similarly, the chatbot's visual appearance (Figure 19) was manipulated by altering its clothing. In the formal condition, the chatbot's avatar wore a suit and tie, while in the informal condition, the avatar wore a hoodie. A pre-test was also conducted to confirm that participants perceived the intended differences in formality. As expected, the results indicated that participants could differentiate between formal and informal clothing conditions.

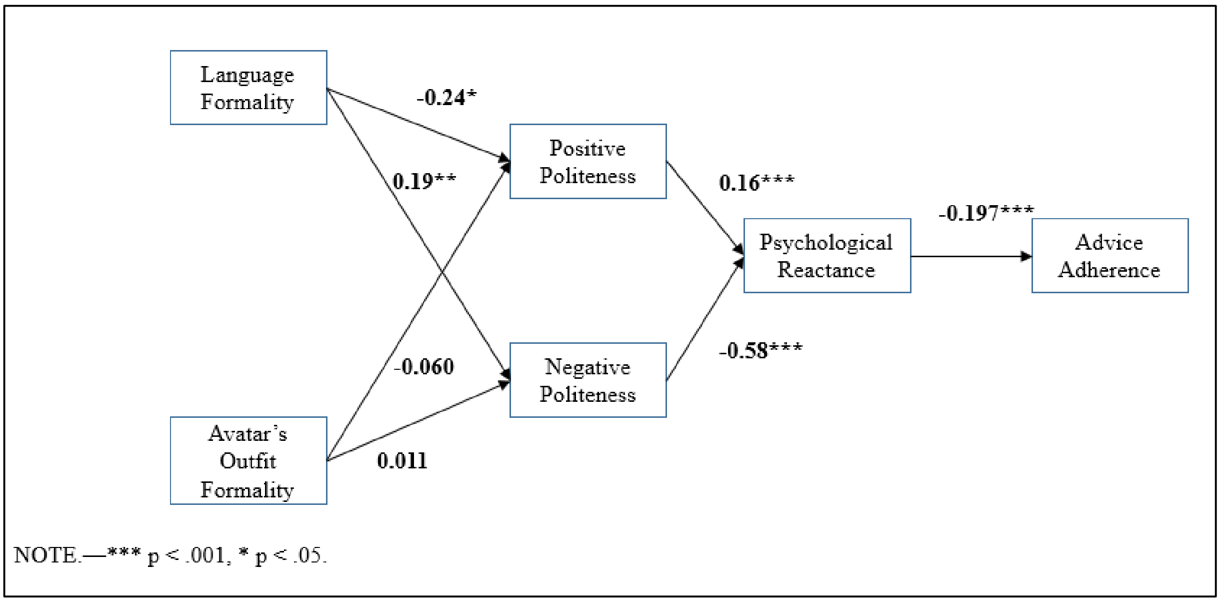
Figure 18: Avatar's Formal vs. Informal Outfit

As a manipulation check, I compared the perception of the chatbot's formality between participants exposed to the Informal (i.e., hoodie) and Formal (i.e., suit and tie) conditions. An independent-sample t-test was conducted. The results for the avatar's outfit indicate a significant difference between the suit and tie (M=3.05, SD=1.589) and hoodie (M=4.79, SD=1.405), [t(450) = 12.305, p = .000 < .05] conditions. The 95% confidence interval of the difference between means ranged from [1.458 to 2.012]. As for the language formality, the results indicate a significant difference between formal language (M=3.84, SD=1.479) and informal language (M=5.67, SD=1.421), [t(450) = 13.412, p = .000 < .05] conditions as well. The 95% confidence interval of the difference between means ranged from [1.561 to 3.098]. Consequently, in both manipulations, I reject the null hypothesis that there is no difference between the sample means. Participants perceived the formal condition as being more formal than the informal and our manipulation was successful.

3.1.5. Results

3.1.5.1. Conceptual Model 1 Analysis

Figure 19: Conceptual Model 1 Analysis



Initially, an evaluation was conducted to determine whether the four conditions had significantly different impacts on the set of investigated dependent variables. A two-way ANOVA was performed to compare the effect of communication style (i.e., Look and Language) on the dependent variable. The analysis revealed the main effect of Language Formality was significant, $F(1, 448) = 18.900$, $p = 0.000$, partial eta squared = 0.040. Therefore, the null hypothesis that there is no effect of Language Formality on Advice Adherence is rejected.

Secondly, the main effect of Avatar's Outfit Formality was not significant: $F(1, 448) = 0.096$, $p = 0.757$, partial eta squared = 0.000. Therefore, the null hypothesis that there is no effect of Avatar's Outfit Formality on Advice Adherence fails to be rejected.

Finally, the interaction of the two variables was not significant: $F(1, 448) = 0.593$, $p = 0.421$, partial eta squared = 0.001. Consequently, the null hypothesis that the effect of Language Formality on Advice Adherence is the same across all levels of Avatar's Outfit Formality fails to be rejected.

The hypothesized effects of Language and Outfit Formality on Advice Adherence through Positive and Negative Politeness were tested using Process Macro in SmartPLS 4.
The analysis from the mediation model (5000 bootstrap samples) yielded the following results (Figure 20):
There is a significant direct effect of Language Formality on Positive Politeness. (Effect = -0.242; p= 0.048; 95% confidence interval [CI] -0.485; -0.002]). H1 is supported.
There is a significant direct effect of Language Formality on Negative Politeness. (Effect = 0.262; p= 0.003; 95% confidence interval [CI] 0.087; 0.435]). H2 is supported.
There is no significant direct effect of Avatar’s Outfit Formality on Positive Politeness. (Effect = -0.559; p= 0.622; 95% confidence interval [CI] -0.305; 0.185]). H3 is not supported.
There is no significant direct effect of Avatar’s Outfit Formality on Negative Politeness. (Effect = 0.053; p= 0.559; 95% confidence interval [CI] -0.125; 0.229]). H4 is not supported.
There is a significant direct effect of Positive Politeness on Reactance. (Effect = 0.104; p= 0.011; 95% confidence interval [CI] 0.024; 0.183]). H5 is supported.
There is a significant direct effect of Negative Politeness on Reactance. (Effect = -0.577; p= 0.000; 95% confidence interval [CI] -0.670; -0.481]). H6 is supported.
There is a significant direct effect of Reactance on Advice Adherence. (Effect = -0.577; p= 0.000; 95% confidence interval [CI] -0.670; -0.481]). H7 is supported.
There is no significant direct effect of Language Formality on Reactance. (Effect = 0.027; p= 0.790; 95% confidence interval [CI] -0.163; 0.218]).
There is a significant direct effect of Avatar’s Outfit Formality on Reactance. (Effect = 0.192; p= 0.039; 95% confidence interval [CI] 0.004; 0.379]).

3.1.5.2. Moderating Role of Product Type

Subsequently, an evaluation of the four conditions was conducted, considering the moderating role of product type and assessing whether the independent and moderating variables had significantly different impacts on the set of investigated dependent variables. A two-way ANOVA was conducted to compare the effect of communication style (i.e., Look and Language) on the dependent variable. The analysis revealed that the main effect of Language Formality was significant, $F(1, 444) = 18.285$, $p = 0.000$, partial eta squared = 0.040. Therefore, the null hypothesis that there is no effect of Language Formality on Advice Adherence is rejected.
Secondly, the main effect of Avatar’s Outfit Formality was not significant, $F(1, 444) = 0.027$, $p = 0.868$, partial eta-squared = 0.000. Therefore, the null hypothesis that there is no effect of Avatar’s Outfit Formality on Advice Adherence fails to be rejected.

Thirdly, the main effect of Product Type was not significant, $F(1, 444) = 2.869$, $p = 0.091$, partial eta-squared = 0.006. Therefore, the null hypothesis that there is no effect of Product Type on Advice Adherence fails to be rejected.

Finally, the interactions between variables were not significant: Language Formality and Look, $F(1, 444) = 1.063$, $p = 0.303$, partial eta squared = 0.002; Language Formality and Product Type, $F(1, 444) = 3.193$, $p = 0.075$, partial eta squared = 0.007; Look and Product Type, $F(1, 444) = 1.573$, $p = 0.216$, partial eta squared = 0.003; Language Formality, Look, and Product Type, $F(1, 444) = 0.17$, $p = 0.702$, partial eta squared = 0.0000. Consequently, the null hypothesis that the effect of each variable on Advice Adherence is the same across all levels fails to be rejected.

The hypothesized effects of Language and Outfit Formality on Advice Adherence through Positive and Negative Politeness were tested using Process Macro in SmartPLS 4.
The analysis of the mediation model, based on 5,000 bootstrap samples, revealed several significant direct effects (see Figure 20). Specifically, Language Formality had a significant negative effect on Positive Politeness (Effect = -0.242; $p = 0.048$; 95% CI [-0.485, -0.002]), supporting Hypothesis 1. In addition, Language Formality exerted a significant positive effect on Negative Politeness (Effect = 0.262; $p = 0.003$; 95% CI [0.087, 0.435]), thereby confirming Hypothesis 2.
In contrast, Avatar’s Outfit Formality did not significantly influence Positive Politeness (Effect = -0.559; $p = 0.622$; 95% CI [-0.305, 0.185]) or Negative Politeness (Effect = 0.053; $p = 0.559$; 95% CI [-0.125, 0.229]), leading to the rejection of Hypotheses 3 and 4.
Positive Politeness was found to significantly increase Reactance (Effect = 0.104; $p = 0.011$; 95% CI [0.024, 0.183]), supporting Hypothesis 5, while Negative Politeness had a significant negative effect on Reactance (Effect = -0.577; $p < 0.001$; 95% CI [-0.670, -0.481]), in line with Hypothesis 6. Reactance, in turn, had a significant negative effect on Advice Adherence (Effect = -0.577; $p < 0.001$; 95% CI [-0.670, -0.481]), supporting Hypothesis 7.
No significant direct effect was found between Language Formality and Reactance (Effect = 0.027; $p = 0.790$; 95% CI [-0.163, 0.218]). However, Avatar’s Outfit Formality was found to significantly increase Reactance (Effect = 0.192; $p = 0.039$; 95% CI [0.004, 0.379]).
Outfit and Negative Politeness (Effect = -0.026; p= 0.883; 95% confidence interval [CI] -0.125; 0.229]), Language Formality and Positive Politeness (Effect = -0.079; p= 0.747; 95% confidence interval [CI] -0.125; 0.229]). H10 and H11 are not supported.

3.1.6. Discussion

The findings from Model 1 shed light on the importance of verbal and visual communication cues in determining advice adherence during chatbot conversations. Our findings showed that the formality of language had a substantial impact on advice adherence, supporting the hypothesis that formal language, which is usually associated with negative politeness, promotes enhanced adherence. This implies that users regard formal language as authoritative and credible, making them more likely to adopt the chatbot's advice.

This is consistent with previous research emphasizing the relevance of formal communication styles in professional and service environments, as such language shows expertise and trustworthiness (Liebrecht et al., 2020).

whereas the formality of the chatbot avatar's outfits had no significant effect on advise adherence. This finding implies that, while visual signals such as outfits may influence initial perceptions of professionalism or approachability, they may be less effective in determining whether users follow the chatbot's advice.

One possible explanation is that in a text-based interaction, consumers favor the content and tone of verbal communication over the avatar's visual appearance when making choices. This finding contradicts previous research, which found that nonverbal cues such as dress influence customer expectations in human-human encounters (Yan et al., 2011).

However, it appears that in human-chatbot interactions, these visual cues may not be as important, particularly when mixed with the chatbot's linguistic cues. Furthermore, the link between the avatar's dress formality and linguistic formality was determined to be insignificant. This stresses that, at least in the context of chatbots that provide advice, verbal communication has a greater influence than visual appearance.

While attire may enhance the initial impression of professionalism, it does not necessarily translate into a higher likelihood of advice adherence. This finding suggests a potential area for future research, where the effect of more dynamic or animated visual cues, such as facial expressions or gestures, could be explored in combination with language formality to better understand the holistic impact of communication style.

The significant effect of language formality on advice adherence highlights the larger importance of politeness theory in chatbot design. As expected, formal language corresponds to negative politeness practices that assist preserve social distance and reduce imposition, making the chatbot's advice appear less intrusive. This decreases user resistance and increases acceptance of the advice. In contrast, informal language, which is associated with positive politeness and social proximity, may reduce resistance in more casual interactions but appears to be less successful in formal decision-making circumstances such as those investigated in this study.

Finally, the results for product type revealed no moderating effects between communication style and advise adherence. This shows that whether the chatbot was recommending hedonic (pleasure-based) or utilitarian (function-based) products, users reacted similarly to the formal and informal communication cues offered. This finding calls into question some assumptions in the literature, which hold that consumers may prefer different communication strategies depending on the sort of product or service being discussed (Kivetz & Zheng, 2017). It raises the issue of whether the impact of communication style is more universally applicable across product categories in chatbot encounters than previously anticipated, or if more adjustments to the experimental design are required to identify more nuanced impacts.

3.2. Conceptual Model 2

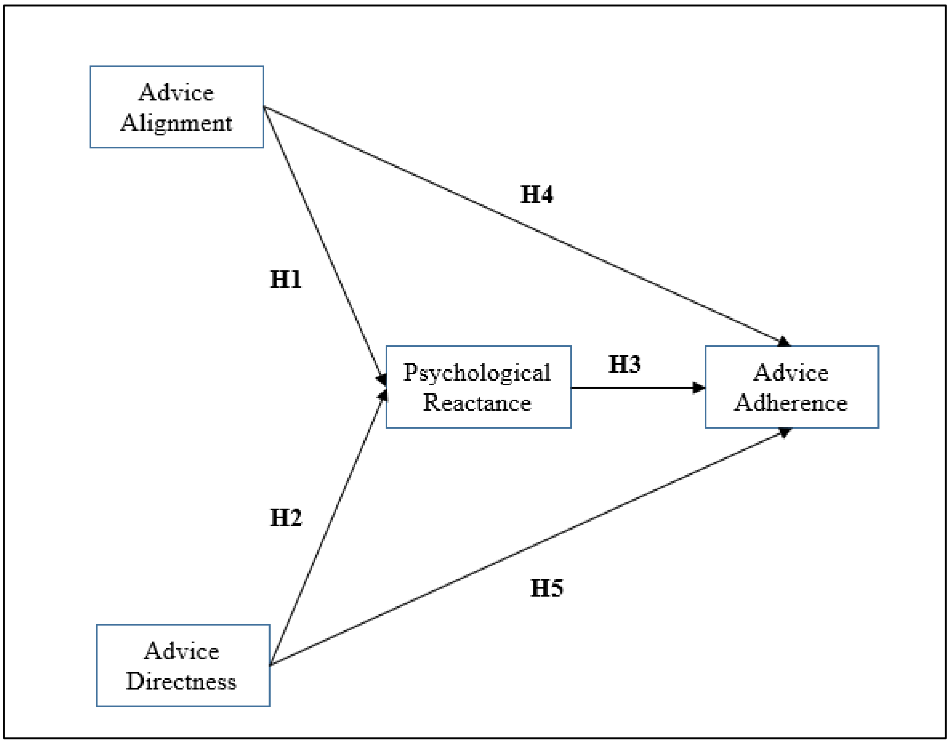
3.2.1. Conceptual Model 2 Overview

Building on the findings from Model 1, where the formality of language was found to significantly impact advice adherence but outfit formality had a marginal effect, Model 2 extends the investigation by examining linguistic characteristics of advice-giving chatbots, specifically advice alignment and advice directness. The objective of this model is to determine how these factors influence psychological reactance and advice adherence.

This model is based on prior research in persuasion and resistance to influence, which suggests that aligned advice (i.e., recommendations that match the user's preferences) reduces reactance, while direct speech acts (explicit recommendations) may provoke resistance due to perceived restriction of choice. Therefore, Model 2 introduces the following hypotheses:

- **H1:** Alignment (vs. Non-alignment) of the advice with user preference decreases the reactance in the user.
- **H2:** Direct (vs. Indirect) speech act in an advice-giving AI-enabled chatbot increases the reactance intention in the user.
- **H3:** Higher reactance leads to lower Advice Adherence intention.
- **H4:** Alignment (vs. Non-alignment) of the advice with user preference increases Advice Adherence.
- **H5:** Direct (vs. Indirect) speech act of the advice increases Advice Adherence.

Figure 20: Conceptual Model 2



3.2.2. Research Design

To address the research questions and hypotheses, a within-subjects 2 × 2 factorial design was employed with randomization of participants under different conditions (Shadish, 2002). The independent variables in this design were:

- Advice Alignment (Aligned vs. Non-Aligned)
- Advice Directness (Direct vs. Indirect)

Several factors informed the selection of a within-subjects design: 1. Control for Individual Differences: By exposing all participants to all conditions, this design eliminates between-subject variability, thereby enhancing statistical power. 2. Focus on Perception Shifts: This approach enables the observation of changes in reactance and adherence within the same individuals, offering clearer causal insights. 3. Efficiency in Data Collection: It reduces the number of participants required while maintaining high validity.

However, to mitigate order effects, we implemented counterbalancing where participants were randomly assigned different sequences of exposure to advice conditions. Future studies may consider between-subjects designs to rule out residual carryover effects.

Although multiple factors were included, interaction effects between these factors were not the focus of this study. Instead, each factor was examined independently. Additionally, pre-tests were conducted to ensure the effectiveness of the manipulations.

3.2.3. Method

3.2.3.1 Participants

Participants were 455 users recruited via Prolific, an online platform that facilitates participant recruitment for academic research. Each participant was compensated £0.60 for their time. A participation link was shared with users, inviting them to participate in a study exploring chatbots. Upon clicking the link, participants were randomly assigned to one of the study conditions.

The text-based chatbots used in this study were chosen due to their high prevalence in practical applications. The questionnaire was created and distributed using the Qualtrics platform. Only participants who were native English speakers and resided in the USA or UK were recruited to ensure linguistic and cultural consistency.

After data cleaning (removal of respondents who failed at least two out of three attention checks), the final sample size was 452 participants. The demographic breakdown was as follows:

- Gender: 36% male, 61% female, 1% non-binary
- Age: Participants ranged from 18 to 81 years, with a mean age of 40.11 (SD = 13.27)

To capture a broad understanding of chatbot interactions, participants were recruited from various age groups. This is particularly relevant since older adults (65 and above) are becoming increasingly digitally connected (Chattaraman, Kwon, Gilbert, & Ross, 2019). A more detailed demographic profile of the participants is provided in Table 19.

All recruitment and participation adhered to ethical guidelines and privacy regulations, with the study approved by a relevant ethics and data protection body. Informed consent was obtained from all participants, who were informed of their right to withdraw from the study at any point. Data were treated with confidentiality and anonymized for analysis.

Table 19: Demographics of the Participants in Study 2

Gender			Age		
Male	49	28%	18 - 25	14	8%
Female	119	68%	26 - 40	81	46%
Non-binary	4	2%	41 -55	68	39%
other	3	2%	56 - 70	10	6%
Total	175		above 71	2	1%

Occupation		
Management, professional, and related	46	26%
Service	18	10%
Sales and Office	13	7%
Farming, fishing, and forestry	1	1%
Construction, extraction, and maintenance	3	2%
Production, transaction, and material moving	4	2%
Government	8	5%
Retired	2	1%
Student	9	5%
Unemployed	16	9%
Housewife	22	13%
Other	33	19%
	175	

	175	
Education		
Less than primary	1	1%
Primary	2	1%
Some Secondary	2	1%
Secondary	25	14%
Vocational or Similar	24	14%
Some university	31	18%
Bachelor’s degree	60	34%
Graduate or professional degree	28	16%
Prefer not to say	2	1%
	175	

3.2.3.2. Measurement

All constructs in the study were measured using seven-point Likert scales. The specific scales used are as follows:

- Advice Adherence: Measured using 3 items adopted from Camacho et al. (2014).
- Psychological Reactance: Measured using 3 items adapted from Drennan & McColl-Kennedy (2003).

The reliability of these measures was tested using factor analysis and Cronbach’s Alpha, and all constructs showed strong reliability, with alpha values exceeding the recommended threshold of 0.7 (Fornell & Larcker, 1981). Detailed reliability statistics are provided in Table 20.
The composite reliability (CR) and the average variance extracted (AVE) were greater than the recommended 0.7 and 0.5 thresholds, respectively (Fornell & Larcker, 1981).

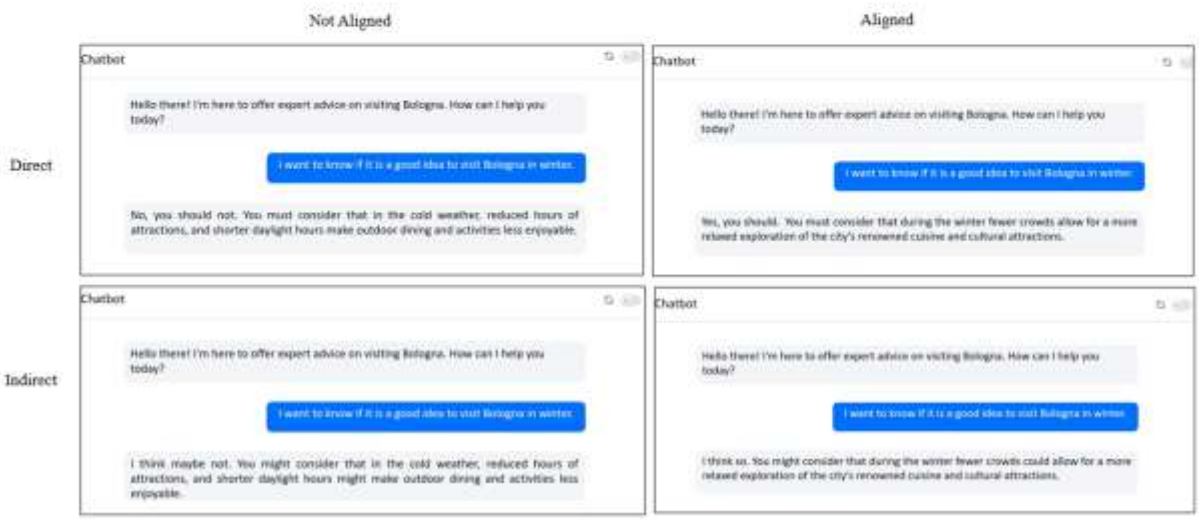
Table 20: Reliability Analysis for Study 2

Measurement	Cronbach’s Alpha	Average Variance Extracted	Composite Reliability
Advice Adherence	0.93	0.81	0.93
Reactance	0.88	0.76	0.90

3.2.3.3. Procedure

The experiment was based on the Computers Are Social Actors (CASA) paradigm (Nass et al., 1999), where participants were guided through an online scenario simulating an advice-giving interaction with a chatbot. Participants were asked to imagine themselves seeking advice in travel services.
the chatbot's Alignment was manipulated by aligning questions and responses (figure 22). In the aligned condition, the chatbot was asked if a season was suitable for visiting a destination, and the answer confirmed it, while in the Non-aligned condition, the chatbot rejected it. A pre-test was also conducted to confirm that participants perceived the intended differences in Alignment. As expected, the results indicated that participants could differentiate between the two conditions.
Similarly, to manipulate the Directness of the chatbot (Figure 22), I followed suggestions from prior studies on how to adjust chatbot communication to make it appear direct or indirect. A pre-test of this manipulation was conducted to ensure that participants could distinguish between the two levels of directness, with results confirming successful manipulation.

Figure 21: Alignment and Directness Manipulation



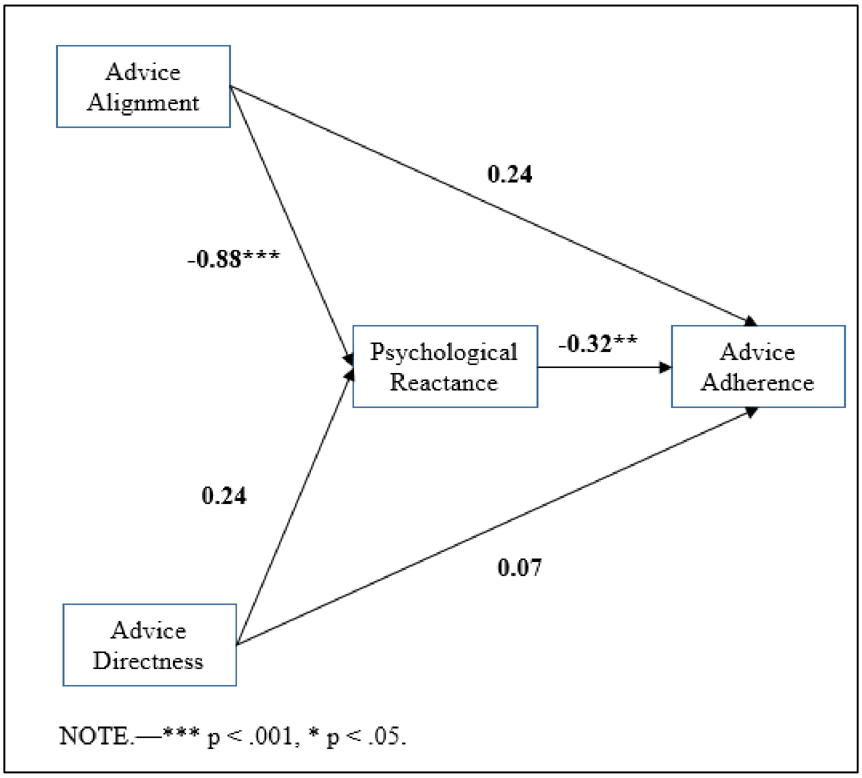
As a manipulation check, the perception of the chatbot's Directness between participants exposed to the Direct and Indirect conditions was compared. An independent-sample t-test was conducted. The results indicate a significant difference between the Aligned (M=5.92, SD=1.402) and Non-aligned (M=1.77, SD=1.467), [t (152) = -17.917, p = .000 < .05] conditions. The 95% confidence interval of the difference between means ranged from [-4.605 to -3.690]. As for the language Directness, the results indicate a significant difference between Direct language (M=3.05, SD=2.043) and Indirect language (M=4.86, SD=1.641), [t(149.128) = 6.098, p = .000 < .05] conditions as well. The 95%

confidence interval of the difference between means ranged from [1.227 to 2.403]. Consequently, in both manipulations, the null hypothesis that there is no difference between the sample means is rejected. Participants perceived the formal condition as being more formal than the informal, confirming that the manipulation was successful.

3.2.3. Results

In this study, it was evaluated whether the four conditions had significantly different impacts on the investigated dependent variable. A two-way ANOVA was conducted to compare the effect of Alignment on the dependent variable. The analysis revealed that the main effect of Language Alignment was significant, $F(1, 150) = 4.998$, $p = 0.027$, partial eta-squared = 0.032. Therefore, the null hypothesis that Language Alignment does not affect Advice Adherence is rejected.
Secondly, the main effect of Directness was not significant, $F(1, 150) = 0.001$, $p = 0.979$, partial eta-squared = 0.000. Therefore, the null hypothesis that there is no effect of Language Directness on Advice Adherence cannot be rejected.
Finally, the interaction between the two variables was not significant, $F(1, 150) = 0.004$, $p = 0.953$, partial eta-squared = 0.000. Consequently, the null hypothesis stating that the effect of Alignment on Advice Adherence is the same across all levels of Language Directness cannot be rejected.
The hypothesized effects of Language Directness and Alignment on Advice Adherence through Reactance were tested using Process Macro in SmartPLS 4.
The mediation model analysis, based on 5,000 bootstrap samples, produced the results presented in Figure 23. Alignment was found to have a significant negative effect on Reactance (Effect = -0.883; $p < 0.001$; 95% CI [-1.185, -0.581]), providing strong support for Hypothesis 1. In contrast, Language Directness did not significantly predict Reactance (Effect = 0.241; $p = 0.114$; 95% CI [-0.060, 0.543]), and thus Hypothesis 2 was not supported.
Reactance significantly and negatively influenced Advice Adherence (Effect = -0.322; $p = 0.013$; 95% CI [-0.583, -0.063]), confirming Hypothesis 3. However, neither Alignment (Effect = 0.241; $p = 0.320$; 95% CI [-0.247, 0.736]) nor Language Directness (Effect = 0.068; $p = 0.750$; 95% CI [-0.374, 0.518]) showed significant direct effects on Advice Adherence, leading to the rejection of Hypotheses 4 and 5, respectively.

Figure 22: Conceptual Model 2 Analysis



3.2.4. Discussion

The outcomes of Model 2 demonstrate the complex relationship between language directness and advice alignment, as well as how these factors affect psychological reactance and advise adherence in chatbot interactions. Users are more inclined to heed chatbot advice when they are in line with their preferences, evidenced by the strong main effect of advise alignment on advice adherence. Given that people are more likely to comply with advice that supports their preconceived notions or expectations, this data supports the hypothesis that alignment bias is a significant factor in advice-taking behavior. Users are more likely to accept and follow advise when it is in line with their preferences because it lessens cognitive dissonance and increases the guidance's perceived legitimacy (Bonner & Cadman, 2014).

Interestingly, language directness did not have a significant effect on advise adherence, calling into question some of the literature's assumptions about direct and indirect speech acts. Previous studies have demonstrated that direct language, by being more authoritative, may result in increased adherence, particularly in advisory environments where explicit instructions are expected (Hinkel, 1997). However, the data show that users may be less sensitive to the directness of the language than they are to the alignment of the advice. One probable explanation is that when users interact with chatbots, they emphasize the advice's content and relevancy over how it is given. This could imply that in human-computer interactions, variables like personalization and relevance are more important than the linguistic style used by the chatbot.

Moreover, the lack of a significant interaction effect between language directness and advice alignment on advise adherence indicates that the two variables have no influence on users' decision-making processes in this case. This could indicate that people consider these factors separately while considering chatbot advice. That is, while alignment of advice has a direct impact on compliance, the style of presentation of the advice (indirect or direct) does not influence the user's decision after alignment is already set. The powerful influence of psychological reactance on compliance with advice is congruent with previous forecasts such as the Reactance Theory, where it's posited that people will resist advice even for their own best when their freedom is seen as being threatened (Brehm, 1966). The discovery that alignment reduces reactance offers support for the assumption that when the user feels the chatbot's recommendation is aligned with what they want, they will be less likely to undergo psychological resistance. Reducing reactance increases the likelihood of accepting the recommendation, and this highlights the relevance of personalization in chatbots. Furthermore, the study's findings highlight the need to consider psychological reactance when the conversational agents are being developed. Conversational agents that provide aligned, customized advice are unlikely to cause reactance, and this increases compliance with advice. The current research has practical implications for chatbot designers, as they must focus on creating systems capable of tailoring advice to suit the desires of the users to reduce resistance and increase user interaction.

Findings from Model 2 provide strong evidence that aligned advice reduces reactance, making users more likely to follow chatbot recommendations. Conversely, direct speech increases resistance, ultimately decreasing adherence. These findings align with prior research on reactance theory and advice-giving resistance (Brehm, 1966; Roubroeks et al., 2010).

Overall, the findings from Model 2 highlight the importance of advice alignment in improving advice adherence, while challenging conventional thinking about the impact of language directness. Chatbots, by lowering psychological reactance through aligned advice, can improve user adherence and contentment, making them more successful tools in e-commerce, healthcare, and customer support.

3.3. Conceptual Model 3

3.3.1. Conceptual Model Overview

Building on the findings from Model 2, which demonstrated the role of linguistic characteristics in advice adherence, Model 3 extends the analysis to examine how advice alignment and the success or failure of the advice outcome influence responsibility attribution and chatbot usage intention. This model is grounded in theories of responsibility attribution and user engagement, which suggest that users' perception of responsibility for an outcome affects their trust and future interactions with AI systems.

This research proposes a model (Figure 24) that examines how advice alignment with previous user preference and the success and failure of the advice outcome influence the attribution of the responsibility of the outcome and intention to use the chatbot. The model posits that:

- **H1:** When advice is aligned (vs. non-aligned) with user preferences, users are more likely to attribute the responsibility of the outcome to themselves (vs. the chatbot).
- **H2:** When advice leads to success (vs. failure), users attribute responsibility more to themselves (vs. the chatbot).
- **H3:** Higher attribution of the responsibility to the chatbot increases the intention to use the chatbot

To address the research questions and hypotheses, a within-subjects 2 × 2 factorial design with randomization of participants under different conditions was employed (Shadish et al., 2002). The independent variables in this design were:

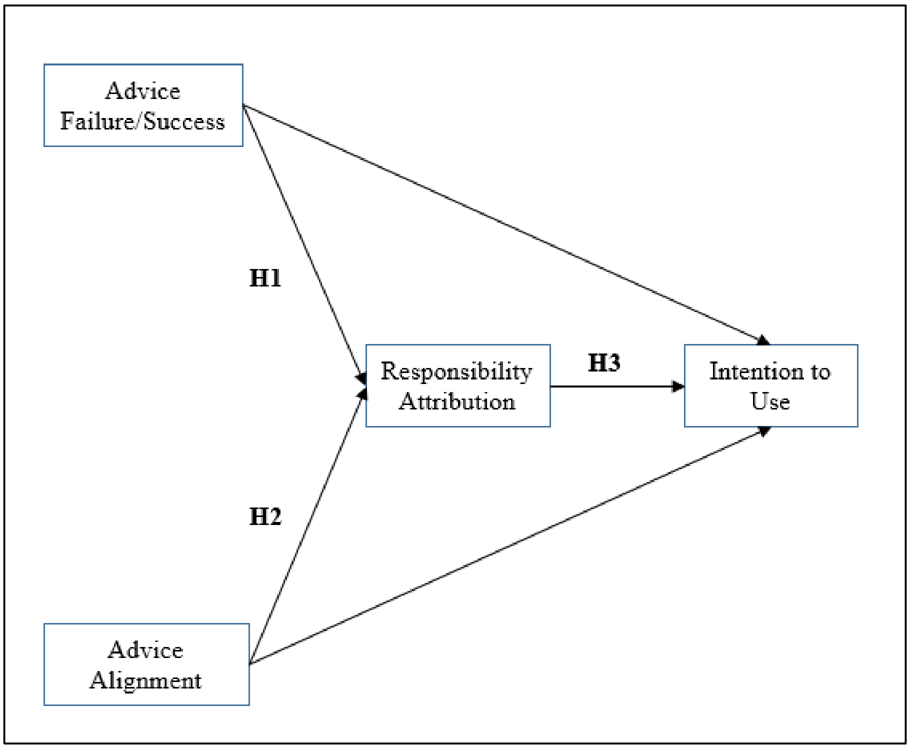
- Advice Success/Failure
- Advice Alignment (Aligned vs. Non-Aligned)

Several factors informed the selection of a within-subjects design: 1. Control for Individual Differences: By exposing all participants to all conditions, this design eliminates between-subject variability, thereby enhancing statistical power. 2. Focus on Perception Shifts: This approach enables the observation of changes in reactance and adherence within the same individuals, offering clearer causal insights. 3. Efficiency in Data Collection: It reduces the number of participants required while maintaining high validity.

However, to control for carryover effects, we implemented counterbalancing so that participants received different sequences of aligned and non-aligned advice. Future studies may explore between-subjects designs to validate these findings further.

Although multiple factors were included, interaction effects between these factors were not the focus of this study. Instead, each factor was examined independently. Additionally, pre-tests were conducted to ensure the effectiveness of the manipulations.

Figure 23: Conceptual Model 3



3.3.2. Method

3.3.2.1. Participants

Participants were 121 users recruited via Prolific, an online platform that facilitates participant recruitment for academic research. Each participant was compensated £0.60 for their time. A participation link was shared with users, inviting them to participate in a study exploring financial investment. Upon clicking the link, participants were randomly assigned to one of the study conditions.

The text-based chatbots used in this study were chosen due to their high prevalence in practical applications. The questionnaire was created and distributed using the Qualtrics platform. Only participants who were native English speakers and resided in the UK were recruited to ensure linguistic and cultural consistency.

After data cleaning (removal of respondents who failed at least two out of three attention checks), the final sample size was 120 participants. The demographic breakdown was as follows:

- Gender: 30% male, 68% female, 1% non-binary, 1% other
- Age: Participants ranged from 18 to 71 years, with a mean age of 38.41 (SD = 13.17)

To capture a broad understanding of chatbot interactions, participants were recruited from various age groups. This is particularly relevant since older adults (65 and above) are becoming increasingly digitally connected (Chattaraman, Kwon, Gilbert, & Ross, 2019). A more detailed demographic profile of the participants is provided in Table 21.

All recruitment and participation adhered to ethical guidelines and privacy regulations, with the study approved by a relevant ethics and data protection body. Informed consent was obtained from all participants, who were informed of their right to withdraw from the study at any point. Data were treated with confidentiality and anonymized for analysis.

Table 21: Demographics of the Participants in Study 3

Gender		
Male	36	30%
Female	82	68%
Non-binary	1	1%
other	1	1%
Total	120	

Age		
18 - 25	18	15%
26 - 40	59	49%
41 -55	28	23%
56 - 70	14	12%
above 71	1	1%
	120	

Occupation		
Management, professional, and related	43	36%
Service	11	9%
Sales and Office	9	8%
Farming, fishing, and forestry	0	0%
Construction, extraction, and maintenance	3	3%
Production, transaction, and material moving	0	0%
Government	5	4%
Retired	6	5%
Student	15	13%
Unemployed	8	7%
Housewife	5	4%
Other	15	13%
	120	

Education		
Less than primary	0	0%
Primary	0	0%
Some Secondary	0	0%
Secondary	11	9%
Vocational or Similar	13	11%
Some university	17	14%
Bachelor’s degree	54	45%
Graduate or professional degree	25	21%
Prefer not to say	0	0%
	120	

3.3.2.2. Measurement

All constructs in the study were measured using **sev**en-point Likert scales. The specific scales used are as follows:

- Intention to use: Measured using 3 items adopted from Zeithaml et al. (1996).
- Responsibility attribution: Measured using 3 items adapted from Botti & McGill (2006).

The reliability of these measures was tested using factor analysis and Cronbach's Alpha, and all constructs showed strong reliability, with alpha values exceeding the recommended threshold of 0.7 (Fornell & Larcker, 1981). Detailed reliability statistics are provided in Table 22.

The composite reliability (CR) and the average variance extracted (AVE) were greater than the recommended 0.7 and 0.5 thresholds, respectively, for intention to use; however, AVE is .65 for Responsibility attribution (Fornell & Larcker, 1981).

Table 22: Reliability Analysis Model 3

Measurement	Cronbach's Alpha	Average Variance Extracted	Composite Reliability
Intention to use	0.94	0.87	0.95
Responsibility attribution	0.74	0.65	0.85

3.3.2.3. Procedure

The experiment was based on the Computers Are Social Actors (CASA) paradigm (Nass et al., 1999), where participants were guided through an online scenario simulating an advice-giving interaction with a chatbot. Participants were asked to imagine themselves seeking advice in financial investment. The chatbot's Alignment was recorded by asking the user's preference between two financial investment options immediately after reading the options and comparing it with the option they chose after reading the chatbot's advice. In the aligned condition, what the user preferred and what the user chose were similar, while in the Non-aligned condition, they were different. A pre-test was also conducted to confirm that participants perceived the intended differences in Alignment. As expected, the results indicated that participants could differentiate between two conditions. Figures 25 & 26 show the advice-giving communication.

Figure 24: Advising Communication Company A

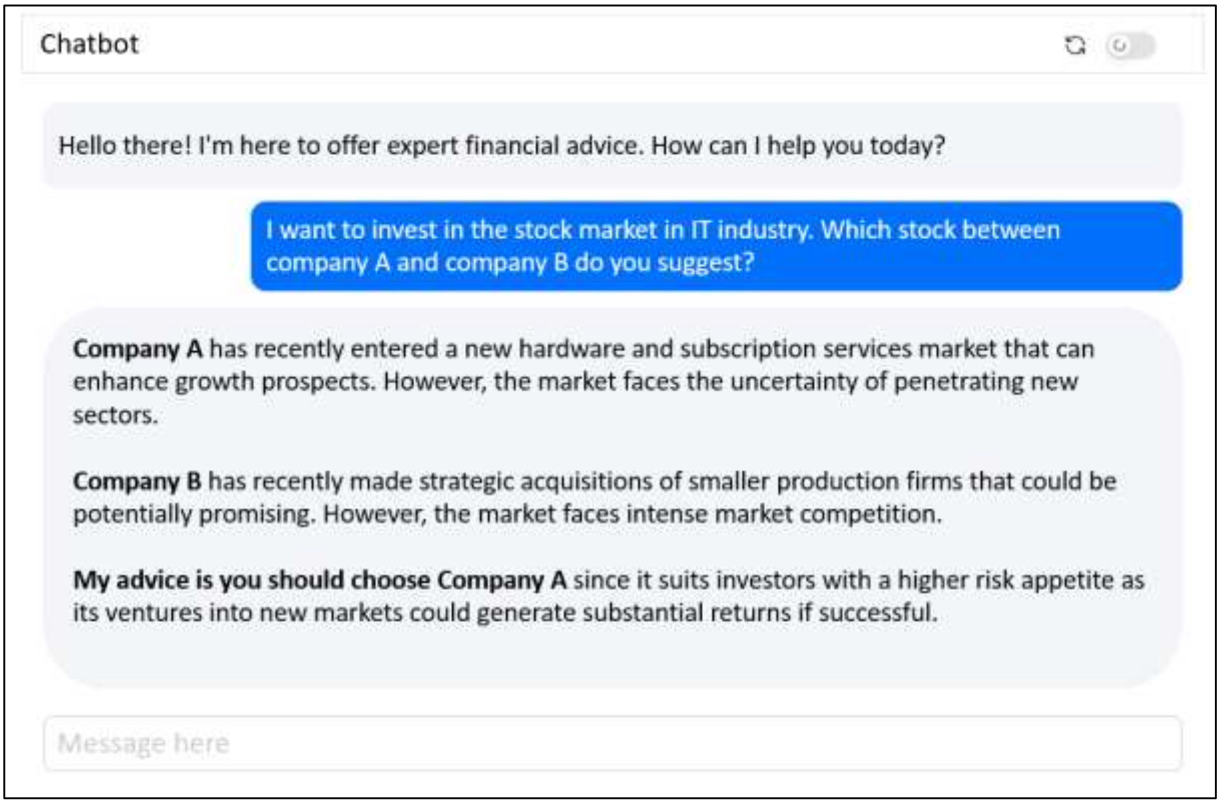
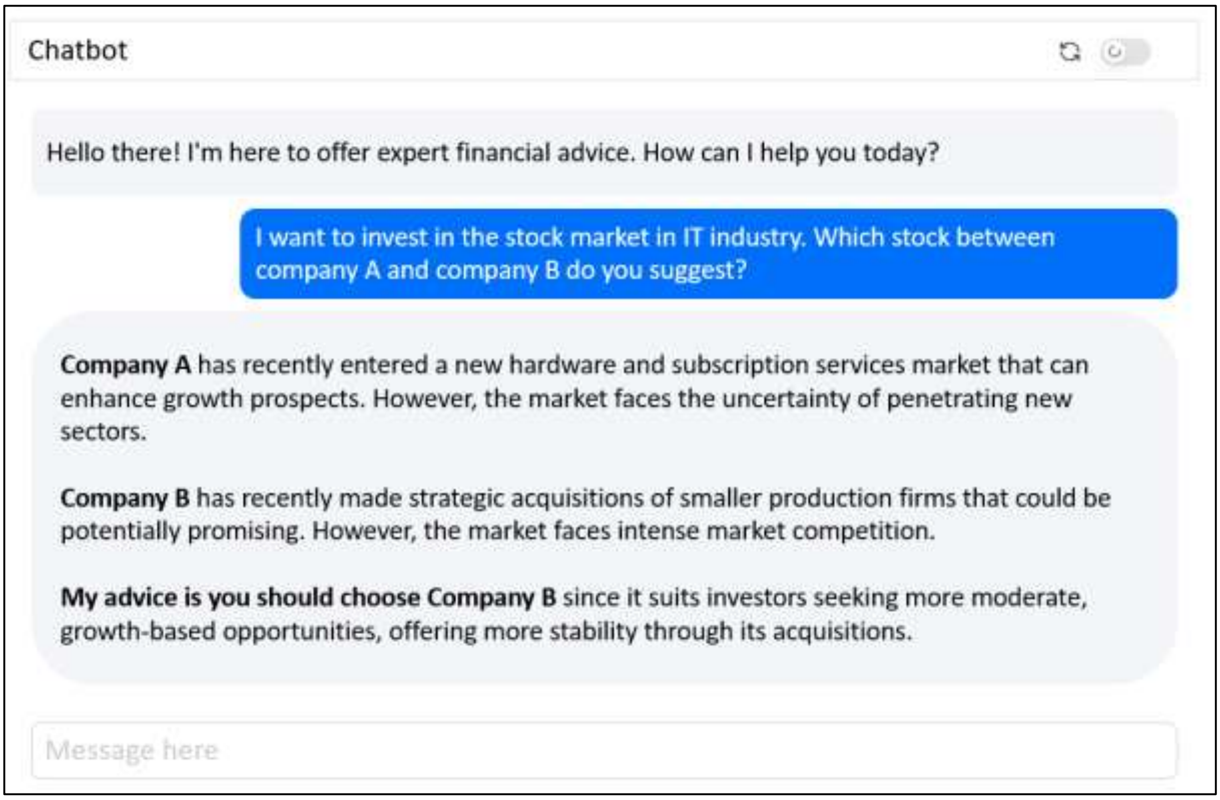


Figure 25: Advising Communication Company B



To manipulate the Success/Failure of the chatbot's advice, results were randomly provided to the user. In the Success condition, the financial investment chosen by the user resulted in a 10% gain, while in the Failure condition, it resulted in a 10% loss.

Figure 26: Advice Success

Here is the result of the investment at the end of the fiscal year:

" You gain 10% of your initial investment (i.e. 1000 £) by following the chatbot advice"

Company A's new hardware and subscription services market entrance was successful and had a positive effect on stock value.

Company	Initial Stock Value	Final Stock Value	Stock Value Change (%)	Total Stock Value Change
A	100	110	10%	10

Company B's acquisitions of smaller production firms failed and had a negative effect on stock value.

Company	Initial Stock Value	Final Stock Value	Stock Value Change (%)	Total Stock Value Change
B	100	90	-10%	-10

Figure 27: Advice Failure

Here is the result of the investment at the end of the fiscal year:

"You lost 10% of your initial investment (i.e. 1000 £) by following your decision"

Company A's new hardware and subscription services market entrance was successful and had a positive effect on stock value.

Company	Initial Stock Value	Final Stock Value	Stock Value Change (%)	Total Stock Value Change
A	100	110	10%	10

Company B's acquisitions of smaller production firms failed and had a negative effect on stock value.

Company	Initial Stock Value	Final Stock Value	Stock Value Change (%)	Total Stock Value Change
B	100	90	-10%	-10

As a manipulation check, the perception of the chatbot's Success/Failure between participants exposed to the two conditions was compared. An independent-sample t-test was conducted. The results indicated a significant difference between the "A success while B fails" ($M=6.44$, $SD=1.218$) and "B success while A fails" ($M=1.66$, $SD=1.422$) conditions [$t(118) = 19.806$, $p = .000 < .05$]. The 95% confidence interval of the difference between means ranged from [4.304 to 5.20]. Consequently, the null hypothesis that there is no difference between the sample means is rejected. Participants correctly perceived the condition, confirming that the manipulation was successful. Regarding Alignment, alignment preference versus non-alignment with choice was manually coded.

3.3.3. Results

In this study, it was evaluated whether the four conditions had significantly different impacts on the investigated dependent variable. A two-way ANOVA was conducted to compare the effect of Success/Failure on the dependent variable. The analysis revealed that the main effect of Success/Failure was significant, $F(1, 115) = 54.014$, $p = 0.000$, partial eta-squared = 0.320. Therefore, the null hypothesis that Success/Failure has no significant effect on Intention to Use is rejected. Secondly, the main effect of Alignment was not significant, $F(1, 115) = 0.035$, $p = 0.853$, partial eta-squared = 0.000. Therefore, the null hypothesis that there is no effect of Alignment on Intention to Use cannot be rejected.

Finally, the interaction effect between the two variables was significant, $F(1, 115) = 4.569$, $p = 0.035$, partial eta-squared = 0.038. Consequently, the null hypothesis stating that the effect of Alignment on Usage Intention is the same across all levels of Success/Failure is rejected.

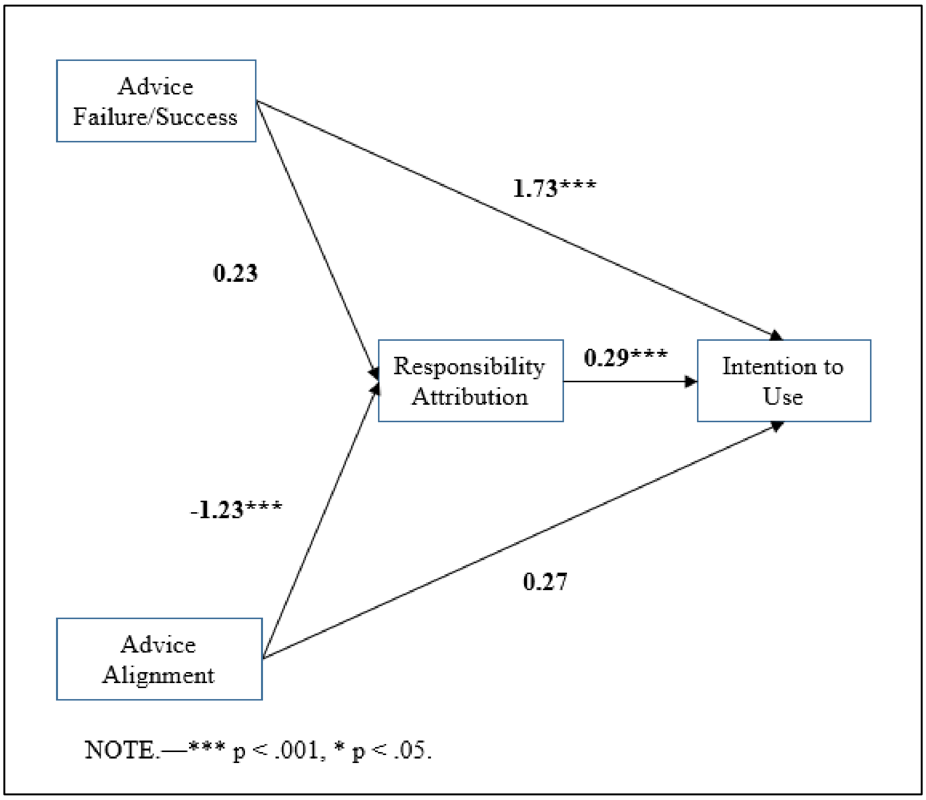
The hypothesized effects of Success/Failure and Alignment on Usage Intention through Responsibility Attribution were tested using Process Macro in SmartPLS 4.

The mediation model analysis, based on 5,000 bootstrap samples, yielded the results summarized in Figure 29. The effect of Success/Failure on Responsibility Attribution was not statistically significant (Effect = 0.227; $p = 0.269$; 95% CI [-0.174, 0.641]), providing no support for Hypothesis 1. However, Success/Failure had a significant positive effect on Intention to Use (Effect = 1.731; $p < 0.001$; 95% CI [1.201, 2.253]).

In line with Hypothesis 2, Alignment had a significant negative effect on Responsibility Attribution (Effect = -1.233; $p < 0.001$; 95% CI [-1.747, -0.744]). On the other hand, its effect on Intention to Use was not significant (Effect = -0.274; $p = 0.328$; 95% CI [-0.291, 0.818]).

Finally, Responsibility Attribution significantly predicted Intention to Use (Effect = 0.285; $p = 0.004$; 95% CI [0.092, 0.473]), thereby supporting Hypothesis 3.

Figure 28: Conceptual Model 3 Analysis



3.3.4. Discussion

The results from Model 3 offer important insights into how the success or failure of advice, alignment, and responsibility attribution affect user intention to follow advice in chatbot interactions.

Findings from Model 3 highlight that responsibility attribution plays a crucial role in determining whether users continue engaging with chatbot advisors. Specifically, users take ownership of advice outcomes when they align with their pre-existing preferences. Also, Successful advice reinforces self-attribution, whereas failed advice increases chatbot blame. And the greater the chatbot is blamed for poor advice, the less likely users are to engage with it in the future.

These results align with Weiner's Attribution Theory (1986) and HCI research on AI credibility (Weiner, 1972). The Model 3 results provide vital insights into how the success or failure of advice, alignment, and responsibility attribution affects user intention to follow advice in chatbot conversations.

The data show a strong main effect of advice success or failure on usage intention, supporting the intuitive notion that users are more likely to follow a chatbot's advice when it results in successful outcomes. This lends credence to the premise that the result of success directly influences user confidence in the chatbot's recommendations, promoting positive impressions and trust (Yaniv, 2004).

In cases where the chatbot's advise failed, users had much lower intentions to follow future guidance, demonstrating that unpleasant experiences can swiftly damage the chatbot's confidence. This is consistent with the broader literature on advice-taking, which shows that the perceived efficacy of counsel greatly predicts future adherence (Sniezek & Van Swol, 2001).

Interestingly, the results demonstrate that alignment did not have a significant main effect on the intention to use the advice, implying that whether or not the advice was aligned with the user's pre-existing preferences had no independent influence on their intention to follow it. This is in contrast to confirmation bias theories, which generally hold that people are more likely to adopt advice that is consistent with their prior ideas or preferences (Nickerson, 1998).

One explanation could be that alignment alone is insufficient to influence decision-making in this setting, especially if the advice results in an undesired consequence. In other words, people may value the actual outcome (success or failure) over how well the advice matches their preferences.

Furthermore, the considerable interaction effect of advice alignment and success or failure on usage intention points to a more complex relationship. Users were more likely to follow advice that was both relevant to their tastes and resulted in success. This conclusion emphasizes the importance of personalization in improving user experience, alignment can increase the beneficial impacts of good guidance, making users feel more in control and satisfied with their choices (D. J. Goldsmith & Fitch, 1997). On the other side, non-aligned advice that leads to failure might further depress consumers, increasing their risk of rejecting future chatbot recommendations.

The analysis of responsibility attribution adds another layer of understanding. The findings show that when the chatbot's advice was tailored to the user's tastes, they were more likely to blame themselves for the outcome, which is consistent with self-serving bias theories (Shepperd et al., 2008). This finding is consistent with attribution theory, which states that people are more likely to accept responsibility for favorable outcomes when the decision is in line with their personal preferences or judgments (Ross, 1977). However, when guidance was not aligned, users were more inclined to attach responsibility to the chatbot, especially in the case of failure, suggesting the tendency to shift blame for unfavorable outcomes to external sources (Kelley, 1973).

This shift in attribution has significant implications for AI system design, implying that users are more forgiving of failures when they believe they played a role in decision-making. Finally, the strong direct effect of responsibility attribution on the intention to follow future advice emphasizes the necessity of creating systems that encourage users to take responsibility for their decisions. Chatbots can increase advice adherence and long-term engagement by making users feel accountable for the outcome, whether through advice alignment or other mechanisms. This research emphasizes the need to incorporate personalization options into chatbot designs to foster a sense of user control and responsibility, which increases trust and usage. Therefore:

- Personalized Alignment Matters: AI systems should tailor recommendations to user preferences to increase perceived self-responsibility and trust.
- Failure Transparency is Key: If advice fails, the chatbot should use transparent messaging to share responsibility rather than be seen as the sole decision-maker.
- Future Research Direction: Should examine whether user personality traits (e.g., locus of control, trust in AI) moderate these attribution effects.

This study confirms that advice alignment and outcome success significantly impact responsibility attribution and chatbot usage intention. Future research should investigate long-term effects on user trust and explore chatbot design strategies that optimize responsibility distribution in AI-human interactions.

Chapter 4: Conclusion

4.1. Theoretical Contributions

AI is influencing businesses in different aspects. Hence, it is important to understand how AI-enabled tools such as CAs could be designed in a way that they would be effective in influencing customers' perceptions and eventually result in the desired behavior. Previous studies show that CAs are being increasingly used by businesses in e-commerce. Moreover, customers are adopting CAs in their everyday lives as well. With Artificial Intelligence (AI) transforming business-customer interactions, it is essential to understand how AI-powered chatbots can be designed for effective advice-giving. This thesis addresses key gaps in the literature by examining how chatbots function as expert advisors and how their communication style influences post-adoption behaviour. In other words, it attempts to address gaps that exist in the literature regarding the design of the chatbots as expert advisors and post-adoption behavior of customers, sheds light on users' needs in their interactions, and investigates the circumstances under which the behavioral outcome of the interactions could be enhanced.

This research builds upon the Computers As Social Actors (CASA) theory to demonstrate that users apply human social norms to chatbot conversations. Specifically, Users attribute social actor responsibility to chatbots, blaming them for advice failure and success in the same way they would blame human counselors. Alignment of advice is a powerful predictor of adherence, suggesting chatbots need to mirror user preferences to increase engagement. Reactance is the essence of chatbot compliance with counsel, revealing psychological mechanisms that could amplify or dampen confidence in AI systems. By integrating politeness theory, reactance theory, and bias harmonization, this study illustrates how chatbots can be adapted to effectively mimic human advisors, influencing customer retention, compliance, and satisfaction in AI-human interactions.

Past research has only studied chatbot adoption and general customer satisfaction, but this work is distinctive in which it demonstrates that advice-giving chatbots trigger reactance responses when messages are overly explicit or off-target from user preferences, confirms that responsibility attribution acts as a moderator of the intention to use a chatbot, providing insight into blame and trust in AI decision-making.

By extending the research of the communication style effect to AI-enabled recommender system chatbot service encounters, I add to the literature firstly by increasing body of research on AI-human interaction, notably from the perspective of the Computers As Social Actors (CASA) paradigm. This underlines the fact that AI-powered chatbots have come to be regarded as social actors, where human advisors tend to be, and where verbal and nonverbal communication cues encompassing formality will influence user trust and obedience. This adds to the literature of bilateral communication between users and AI with respect to providing more details on how AI could actually mimic human conversational approaches to achieve better outcomes in education, health, and business. Therefore, it contributes to bilateral communication and sheds light on the underlying psychological mechanism of the effect. As a result, I also contribute to the body of knowledge about chatbots used for customer service (WilsonNash et al., 2020), contributing to the conversation at hand around how consumers respond to AI utilized for relationship-building and support (Huang and Rust, 2021a, 2021b). Based on this research, I also add to the literature in human-computer interaction, showing that language formality affects advice adherence, indicating that chatbot communication style can considerably affect user behavior. Tailoring the language of AI-enabled chatbots to diverse circumstances can boost user engagement, reduce psychological reactance, and raise the possibility of customers following advice. This has immediate ramifications for companies that rely on automated systems for customer support, such as e-commerce, where chatbot communication could increase customer retention and sales.

This work contributes to the new literature on AI ethics and user experience by offering empirical evidence on the ethical design of persuasive AI, so that chatbots don't manipulate but rather assist in decision-making, training chatbot developers about the balance of directive vs. supportive language so that they avoid reactance while still directing users when necessary, highlighting the significance of personalization to enhance trust, break down resistance, and increase participation in AI-driven services and providing empirical evidence on the ethical design of persuasive AI, ensuring chatbots do not manipulate users but instead support decision-making. These findings have broad implications for AI-human interaction research, chatbot development, and digital customer relationship management across industries such as e-commerce, healthcare, and education. communication style is a crucial topic in business. Moreover, as an important topic in communication, the formality of communication as an important commonly used strategy often has a larger impact on how the hearer comprehends the message than the literal meaning does (Hovy, 1987). The formal-informal dimension has even been referred to as the “most important dimension of variation between styles (of communication)” (Heylighen and Dewaele, 1999). The formality of communication can provide information about the familiarity of the communicators with a person, their perspectives on a subject, and their objectives for an interaction (Hovy, 1987). As a result, the ability to recognize formality is an integral part of dialogue systems and human-computer interaction (Pavlick & Tetreault, 2016). However, chatbot design has been considered more as a language aspect and rarely includes the look of the chatbot. Here, both verbal and nonverbal aspects have been taken into consideration since the matching and mismatching of the language and look can cause ambiguity and disinterest. Even in human-human communication, it is uncommon for both verbal and nonverbal research to be published side by side, let alone to be compared in terms of their underlying assumptions, goals, and possible contributions to communication theory (Denham & Onwuegbuzie, 2013).

Also, this study contributes to the expanding body of information about how AI systems interact with human psychological mechanisms, particularly in the context of advice providing. The study adds credence to the Computers As Social Actors (CASA) theory by demonstrating that users behave towards chatbots in socially appropriate ways, such as rejecting advice that is experienced as too controlling or insensitive to their preferences. These findings can be used to guide the development of subsequent research into how certain features of AI-based advice taking, for instance, cultural variation or emotional tone, are impacted, setting new paths for research into AI-human interaction.

The present research has implications for timely psychological issues in human-computer interaction, including how to control continued human-computer interaction through relational behavior to investigate to which human-machine interaction is able to lead to greater intention to obey a chatbot's advice. Previous studies in human-machine interactions mostly focused on how users' intention to use and satisfaction with the general type of chatbots could be influenced. However, not all chatbots are similar and provoke similar communication expectations during interaction with the user. AI-enabled recommender systems are specifically built to provide options during a dialogue-based interaction and persuade users in an advised direction. Actually, Persuasive technologies such as recommender systems are becoming commonplace. Nowadays, with the advent of open AI, most people are communicating with such kind of chatbots and businesses are providing open AI services for their customers. Furthermore, by illustrating how users might judge and interpret politeness cues from a computer, i.e., chatbot service interaction, which will also contribute to the CASA paradigm, I add to the literature on politeness of machines in communicating with humans.

The findings on the importance of positive and negative politeness methods in minimizing reactance are very pertinent to chatbot development. Businesses can create chatbots that reduce the sense of imposition by maximizing both verbal cues (e.g., professional or informal language) and visual cues (e.g., the avatar's oufit), making people more open to advise. Understanding these psychological dynamics helps bridge the gap between human-to-human and human-machine communication, allowing businesses to imitate the sophisticated social interactions characteristic of human advisors.

Moreover a body of research this study is also comprehending is how users might psychologically react to chatbot which ends in non adherence and non adoption of the service. So the study's findings on psychological reactance emphasize the significance of creating conversational agents that carefully control how direct their counsel is received. The lack of a substantial effect of advise directness implies that limiting language intensity may be less important than ensuring that guidance is well-aligned with user preferences. This shows that practitioners should prioritize establishing individualized systems over focusing only on language style. In the future, this will be of immense importance for health, customer, and education chatbot applications, as reduced reactance may heighten trust and effectiveness. Moreover, people usually have preferred choices beforehand while searching for information online or offline, which influences their preferences. Here in this study, I also considered the effect of advice alignment with the previous preferences of the users, and from the results, it was found to be a significant factor. This supports the personalization design of the chatbots; that is to say, in practice it offers the ability for the businesses using chatbot systems such as ecommerce or travel services, etc. Align the focus and advisement to maximize customer happiness based on user data of their past behaviors and preferences. A tailored, user-based chatbot recommendation reduces the resistance in the customer, making customer assistance more effective because this might improve retained clients and better performance in sales-push scenarios where chatbot recommendations change purchasing decisions. Many websites and businesses offer algorithms that provide product rage based on user preferences. It is essential to understand the influential factors during such interaction since the final goal of these systems is not only providing relevant information but also persuading the customer to make a choice and eventually a purchase decision. Therefore, the importance of delivering the message with a proper communication style should be considered. due to its tight relationship to sales (Williams and Spiro, 1985), intention (Keeling et al., 2010), and customer satisfaction (Van Dolen et al., 2007).
As a result, I add to the expanding literature on the perception of chatbot humanness and follow the recommendations of previous scholars for further research into additional anthropomorphic design cues to increase their influence on user perceptions and intentions. (Adam et al., 2021; Go and Sundar, 2019; Schuetzler et al., 2020).
The findings of this study are expected to contribute to the study of politeness in human-machine interactions. This might also serve as a useful input for practitioners of the dialogues between users and machines. Moreover, to the best of my knowledge, the verbal style of a chatbot has not been considered as a speech act that can use a certain type of language utterance such as advice. However different speech act strategies and how the options are presented are important factors in communication. Here I also contribute to reactance theory by investigating how users might feel

threatened by the speech act and language type I use during interaction which has rarely been the subject of studies in human-computer interaction.
This study provides a theoretical contribution by enhancing the knowledge of how customer participation influences causal attribution and satisfaction after receiving advice from a chatbot. As previous studies determined, dissatisfied customers are more likely to spread negative word-of-mouth after a service failure (Maxham and Netemeyer, 2002). Therefore, I need to explain the conflicting results for advice failure attribution, and if it is the machine to blame or the user. There is limited research regarding how users assign responsibility to specific AI systems in case of either success or failure (Liao et al, 2022). In this research, I respond to this gap by evaluating the responsibility attribution of the advice given by a chatbot and how the consumers' behaviour is based on it.

4.2. Managerial Contributions

The findings of this study offer practical guidelines for businesses, chatbot developers, and AI-driven customer service platforms to enhance chatbot efficiency and user engagement. Personalization emerges as a key driver of increased adherence; chatbots should align advice with user preferences by leveraging past user data and behavioral patterns. Further, adapting the language formality to change based on users' interaction history can significantly enhance the acceptability of advice.
It is also necessary to balance directive and supportive modes of communication. Chatbots should not employ overly controlling or direct language because this can induce psychological reactance and lower compliance. Instead, employing politeness strategies such as indirect language and option-based framing will enhance the effectiveness of persuasion without appearing coercive. To further strengthen trust, transparency in interactions is essential. Users often attribute failure to the chatbot when advice appears misaligned with their previous expectations or unsuccessful. Therefore, providing explanations for chatbot recommendations when they fail and allowing user input in decision-making processes can help mitigate negative perceptions by offering users a sense of control.
Optimizing chatbot avatars and ensuring alignment between visual and verbal cues is not necessarily important. While the visual part seems to be neglected by the user, it is the linguistics that plays th most important role. Businesses should ensure chatbot avatars match the linguistic style and formality desired by the users, as mismatches can decrease credibility and engagement.
Though the visual element seems to be underrated by the user, it is linguistics that contribute most. Businesses ought to ensure that chatbot avatars use the same linguistic style and formality as desired by users, or else they can lose credibility and interaction levels. These results have several implications in real life across fields. For instance, online shopping bots should compare product

recommendations to past purchases while finding a balance between personalization and avoiding reducing perceived choice. Healthcare bots are made possible by empathic tone usage and minimizing direct speech acts to minimize patient reactance, while educational AI tutors should adapt instructional modes based on students' learning styles to minimize resistance. These results will guide organizations to design better chatbots, improve customer retention, and maximize AI-driven decision systems. Managers can also apply these results immediately in designing chatbots. Because chatbots are frequently the initial interface between an organization and customers, developing good chatbot design and language style is critical in creating good first impressions. Tuning chatbot communication capabilities not only boosts customer satisfaction but also results in economically desirable purchasing choices. As today's chatbots more and more serve as service providers and professional consultants, they necessarily create impressions based on their interactive communication, as opposed to providing static information. Therefore, according to the Computers As Social Actors (CASA) paradigm, users naturally think of chatbots as social actors. This study highlights how personalization of chatbot language, for example, formality adjustment, and alignment of advice based on individual user preference, can go a long way in customer engagement. Investment in adaptive chatbot systems allows businesses to offer more relevant advice, enhance user loyalty, and also enhance overall service quality.

Furthermore, since customers expect human-like interactions, every chatbot engagement counts significantly. While chatbots efficiently handle high-volume, routine interactions, managers should ensure seamless handovers to human agents for complex, sensitive, or escalated issues. Personalizing chatbot design balances efficiency with a humanized touch, enhancing both customer experience and trust. Seamless transitions between chatbot and human support address chatbot limitations, ensuring robust and effective customer service.

Moreover, communication with recommender chatbots serves a purpose beyond mere conversational exchange; it guides customers toward relevant choices and final purchase decisions. Therefore, optimizing chatbot design not only enhances user experience but also directly boosts online sales. Managers can thus leverage these insights to strategically optimize chatbots, achieving higher sales with reduced risks and costs compared to traditional offline sales channels.

4.3. Limitations and Future Research

This study has several limitations that offer opportunities for future research. Firstly, it focused on English-speaking participants predominantly from Western countries, potentially limiting the generalizability of findings. Future studies should explore cross-cultural differences in chatbot communication preferences and investigate how varying linguistic and cultural norms influence user reactance and advice adherence.

The research also concentrated primarily on language formality and politeness strategies. Future investigations could expand the range of communication variables considered, such as emotional tone and empathetic framing, speech pace, timing, conversational depth, and the dynamics of multi-turn interactions as they evolve over time.

Furthermore, while this study analyzed text-based chatbot interactions, future research should include voice-based AI platforms such as Alexa or Siri, as well as embodied AI avatars, to better understand how nonverbal cues, tone of voice, and body language influence user perceptions and interactions.

Lastly, the longitudinal effects of AI-driven persuasion warrant further investigation. Important questions remain unanswered, such as whether repeated chatbot interactions enhance or diminish user trust over time, and how users respond when chatbots continuously learn and adapt to their preferences over extended periods. Future studies should particularly explore the potential for habit formation through sustained AI-driven persuasive interactions.

4.4. Conclusion

This study provides a novel understanding of chatbot-human interactions by demonstrating how advice alignment, directness, and responsibility attribution shape user behavior. By integrating the Computers As Social Actors (CASA) paradigm, reactance theory, and AI-driven persuasion models, this research significantly contributes to both theoretical and practical understandings, identifying crucial linguistic and psychological mechanisms driving AI acceptance.

For businesses, these insights offer a practical roadmap for optimizing chatbot interactions. By balancing personalization, politeness, and responsibility attribution, businesses can create more effective, engaging, and persuasive AI-driven customer service experiences. Future research should further expand upon these findings, exploring cultural nuances, multimodal AI interactions, and longitudinal effects of chatbot communication strategies. This continued exploration will help ensure that AI-driven advisors consistently enhance human decision-making rather than hinder it.

This study, however, has some limitations. Firstly, only English-speaking participants from the USA and the UK were included, with participants primarily sourced from online platforms like Prolific. Therefore, results may be less applicable to non-English speakers or different cultural settings where communication styles and attitudes toward politeness may vary. Additionally, given the demographic profile, particularly regarding age and digital literacy, outcomes might not be generalizable to older or less tech-savvy consumers.

Another limitation arises from the study’s controlled, artificial experimental setting. While this design effectively isolates variables, it might not fully represent real-world chatbot interactions, where user goals, urgency, and emotional states could influence responses to chatbot advice. The artificiality of the experimental environment may also alter users' perceptions of interaction stakes, potentially impacting the observed advice adherence behaviors.

Furthermore, the study mainly focused on linguistic formality and politeness strategies. It did not comprehensively explore other important communication attributes like tone, empathy, personalization, and user familiarity with chatbots. Future studies should examine these factors more deeply to enhance the understanding of chatbot communications' impact on user behavior.

Additionally, the lack of significant findings regarding advice directness suggests the need for further research into other communicative factors beyond alignment and directness, such as tone, empathy, context, and subtler interaction elements like timing and frequency of advice delivery. These factors might critically affect how users perceive and respond to AI advice.

Moreover, this research primarily examined text-based interactions, overlooking nonverbal elements such as facial expressions, body language, or chatbot voice in voice-assisted environments. Although visual nonverbal cues like chatbot attire were considered, the absence of other nonverbal cues limits the comprehensive understanding of nonverbal communication’s broader implications, which are vital for realistic applications.

Addressing these limitations in future research, particularly exploring tone, personalization, empathy, and interaction context, will significantly enhance chatbot interfaces' realism and user-friendliness. By examining these elements' interplay, future studies can develop robust, nuanced chatbots suitable for diverse sectors and user needs.

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