AI Chatbots for Marketing?
Investigating the relationships between chatbot's credibility, trust level perceptions and negative algorithmic advice utilization rates

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ABSTRACT

During the past years, the use of AI chatbots in Marketing increased significantly. AI chatbots are algorithms, programmed as virtual assistants, simulating human conversations using voice commands or text messages. This technology is found to be the future of customer service as it has manifold benefits for marketing. Existing literature in the sphere of Artificial intelligence and AI-powered algorithms shows that there are connections between perceived trust in an algorithm, its advice utilization rate, and its credibility. This study examines further these relationships while focusing specifically on people's sensitivity towards negative algorithmic advice. A scenario-based 2 (credibility: disclosed vs. non-disclosed) x 2 (advice: positive vs. negative) experiment was conducted and a total of 57 international participants between the ages of 21 and 60 were analyzed. Overall, five hypotheses were tested in order to answer the research question. The results showed that no relationship exists between credibility and perceived trust in the chatbot, as well as between credibility and advice utilization in the case of receiving negative algorithmic advice. However, the study proved that people tend to trust and adopt recommendations from a chatbot that provides them with positive rather than negative advice. Furthermore, the findings revealed that there is a positive relationship between perceived trust in the chatbot and its negative advice utilization rate.

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1. INTRODUCTION

Artificial Intelligence use in marketing has been gaining importance in recent years. Even though AI as a concept has been around since the 1950s (Duan et al., 2019), there is no universal definition for the term. AI, at its core, refers to “the ability of a machine to learn from experience, adjust to new inputs and perform human-like tasks” (Duan et al., 2019, p.63). Artificial Intelligence has been recognized as a powerful tool for marketing purposes (Overgoor et al., 2019). AI marketing is “the development of artificial agents that, given the information they have about consumers, competitors, and the focal company, suggest and/or take marketing actions to achieve the best marketing outcome” (Overgoor et al., 2019, p. 2 as cited in Vlačić et al., 2021, p. 187). AI has also been recognized as the most influential technology for business, with expected growth from \$10.1 billion in 2018 to \$126 billion by 2025 (Tractica, 2020 as cited in Vlačić et al., 2021). The AI applications in marketing have numerous benefits for businesses. Artificial Intelligence can help businesses understand their customers’ behaviors and needs better (Kushwaha et al., 2021). Therefore, AI allows marketers to use this data to develop the right strategies with which to target the right customer segments and position themselves ahead of competitors (Overgoor et al., 2019).

The focus of this paper is on AI chatbots as advice-giving marketing tools. This technology, powered by AI and machine learning (Luo et al., 2019), has a role of a virtual assistant, and represents computer programs’ simulations of human conversations through voice commands or text chats (Luo et al., 2019). The chatbot is a relatively new type of software that is proven to have a great potential for the future of customer service (Luo et al., 2019). Recently, there has been an observed increase in the market size for chatbots, from \$250 million in 2017 to expectedly more than \$1.34 billion in 2024 (Pise 2018 as cited in Luo et al., 2019). As AI-powered algorithms, chatbots’ benefits for businesses are manifold (Luo et al., 2019). Chatbot’s main use is for the automation of customer service due to its capacity to handle large amounts of data and large volumes of customer communications in a time-efficient, professional, and low-cost manner (Luo et al., 2019).

Due to being rapidly developing and importance-gaining topics, research has been done on AI chatbots and the level of their acceptance by people. The focus of the recent research has been mainly on chatbots versus human advice and which one people tend to prefer or, more generally, on people’s trust towards AI-powered algorithms. However, previous research has led to rather contradictory results. For example, in their research Luo et al., (2019) conducted an experiment and found out that people, when informed that they are being serviced by an AI chatbot rather than a human being, tend to reject the service even though the competence of the service provider is the same. In contrast, a research done by Logg et al. (2019) who studied algorithm appreciation, showed experimentally that people who are not experienced in a particular subject tend to adhere to advice that comes from an algorithm rather than a human. Another experimental study conducted by Prahl and van Swol (2017) concluded that people tend to utilize negative advice received from human advisors more than negative advice received from computer advisors. Moreover, the same study showed that participants indicated that they had more in common with human advisors than automated advisors (Prahl and van Swol 2017).

Taking into consideration the controversial results from previous studies, this research aims to contribute to academic literature, addressing the research gap of looking more closely at chatbots’ credibility and trust as factors influencing algorithmic appreciation by customers. Moreover, the research focuses on the sensitivity of people towards receiving negative advice from chatbots and whether credibility has an influence on the chatbots’ perceived trustworthiness and their advice’s utilization rates. As a better understanding of these topics may have implications for improving AI chatbot marketing.

1.1 Research objective

The goal of this research is to investigate the relationships between chatbot credibility disclosure, perceived trust, and the adoption of negative algorithmic advice. More specifically, the research aims to give insights into how customers react to negative advice received from an AI chatbot and whether certain credibility given to the chatbot, beforehand, can influence the level of trustworthiness attributed to the negative advice and its utilization rates by the users.

1.2 Research question

Based on the research objective, the following research question was formulated:

Is there a relationship between chatbot credibility disclosure and trust, and what is their influence on negative algorithmic advice utilization rates?

2. THEORETICAL BACKGROUND

This section provides a review of the existing literature on AI chatbots and key concepts such as credibility, trust, and advice utilization. The benefits and downsides that AI chatbots bring to marketing are discussed as well. Furthermore, hypotheses are formulated and a conceptual framework serving as a foundation of the study is presented.

2.1 Chatbots as AI-powered advice-giving algorithms

With the emergence of Big Data, algorithms’ ability to process large amounts of data and their use to provide people with insights and advice increased immensely (Logg et al., 2019). An algorithm is conceptualized as “a procedure for computing a function” (Rogers, 1987 as cited in Logg et al., 2019, p. 93). The automation of professional advice delivered to customers is referred to as algorithmic advice (von Walter et al., 2021).

Artificial intelligence chatbots are tools that are designed to mimic human-like conversations (Kushwaha et al., 2021). They perform algorithmic calculations using Big Data (Logg et al., 2019) and machine learning techniques (Kushwaha et al., 2021). Based on its predictive abilities (Kushwaha et al., 2021), the purpose of this new source of advice (Logg et al., 2019) is to provide people with information they can use in their decision-making (Klaus & Zaichkowsky, 2020 as cited in Kushwaha et al., 2021). AI-powered chatbots aim to increase customer satisfaction by offering them an efficient (Berry, Wall, & Carbone, 2006; Dwivedi, Kapoor, & Chen, 2015 as cited in Kushwaha et al., 2021) and operationally sustainable (Bag, Pretorius, Gupta, & Dwivedi, 2021; Nishant, Kennedy, & Corbett, 2020 as cited in Kushwaha et al., 2021) service in real-time (Yen & Chiang, 2020 as cited in Kushwaha et al., 2021).

AI chatbots’ algorithms have proven themselves to provide judgement of superior accuracy compared to humans (Dawes, Faust, & Meehl, 1989 as cited in Logg et al., 2019). Therefore, chatbots are increasingly being used in spheres such as E-Commerce, Medicine, Human Resources (HR), Travel, Real Estate, Banking, etc. (Agarwal, 2021). Consequently, a lot of positions, previously executed by humans, are now performed by AI-powered algorithms. Examples of such are human secretaries, travel agents, headhunters, matchmakers, D.J.s, movie critics, cosmetologists, clothing stylists, sommeliers, financial advisors and so on (Logg et al., 2019).

2.2 People's trust towards AI-powered algorithms

According to Rousseau et al. (1998, p. 395) trust is "a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another." Therefore, trust in AI-powered algorithms such as chatbots represents users' perception of algorithms as trustworthy mechanisms whose advice they feel confident adopting and using in their decision-making (Shin, 2021; Benbasat & Wang, 2005).

Previous research found that trust is the most influential expectation people have when it comes to utilizing algorithmic advice (Andersen, Hansen and Andersen, 2001 as cited in Benbasat & Wang, 2005). Furthermore, research done by Kushwaha et al., (2021) has shown that certain factors such as credibility, social presence, and informativeness can possibly influence algorithmic trust. One reason why trust in algorithms might be disrupted comes from people's perception that algorithms should be flawless in their predictions. This is why when users see an algorithm making a mistake the previously attributed trust towards it drastically decreases (Prahl & van Swol, 2017). Additionally, research conducted by Gillath et al. (2021) concluded that familiarity with AI has a significant positive effect on trust towards AI.

2.3 Algorithm credibility

Literature reviewing credibility refers to it as a complex and multifaceted concept (Wathen & Burkell, 2002). Tseng and Fogg (1999) distinguish four types of source credibility. First, it is the Presumed credibility that arises from one's own assumptions about a source. The second type of credibility is Reputed credibility, and it is based on source labels such as "doctor" or "professor." As a result, the authority of the experts is the source of credibility. Then there's Surface credibility, which refers to the user's surface-level audit of the characteristics of the source. And Experienced credibility, which, as the name implies, is based on direct experience with a source and is regarded as the most complex but reliable way of making credibility inferences of all. (Tseng and Fogg, 1999 as cited in Wathen & Burkell, 2002).

At its core, however, credibility refers to the degree to which a user believes information is trustworthy (Lim and Heide 2015 as cited in Shin, 2021) and it is highly determined by the advisor's perceived competence (Prahl & van Swol, 2017). Some concepts that have been used to describe credibility are believability, trust, correctness, fairness, objectivity, and dependability (Shin, 2021). Because it encompasses the source's perceived integrity and morality, trust is an important component of credibility (Shin, 2020 as cited in Shin, 2021). According to Shin (2021), the difference between trust and credibility is that, while trust refers to belief in the algorithmic attributes, credibility refers to the algorithms' reputation in terms of their capacity to be trusted (Shin, 2021). Researchers have also found that there is a connection between credibility and advice utilization (Prahl & van Swol, 2017).

2.4 Algorithm advice utilization

Research in the sphere of advice utilization has shown that trust is a factor that could predict advice utilization rates (Sniezek & Van Swol, 2001; Van Swol & Snizek, 2005 as cited in Prahl & van Swol, 2017). Therefore, advice utilization is explained as the behavioral measure of trust because of users' perceived vulnerability towards the advisor and his expertise (Mayer et al., 1995 as cited in Prahl & van Swol, 2017). When it comes to automated advice, there is evidence that people look for emotional similarities between themselves and the advisor (MacGeorge et al., 2013 as cited in Prahl & van Swol, 2017). On that account, prior research suggests that programming chatbots to mimic human emotions should be considered as it can potentially increase advice utilization rates (Prahl & van Swol, 2017).

2.4.1 Algorithm appreciation or algorithm aversion?

Previous research showed contrasting results on whether people prefer to adopt advice provided by an algorithm or a human. In their research Logg et al., (2019) argued that people tend to adopt advice that comes from an algorithm more frequently than when it comes from a human. This effect is called algorithm appreciation. On the other hand, other studies suggest that people would rather reject advice that is provided by an algorithm. This effect is the opposite of algorithm appreciation and researchers refer to this phenomenon as algorithm aversion (Dietvorst et al., 2018). The reasons why people tend to oppose algorithmic advice are manifold. For example, in their study, Dietvorst et al., (2018) found that people are more likely to reject advice when they notice an error made by the algorithm. Furthermore, Dietvorst et al., (2018) suggest that if the algorithm is modifiable, meaning that if the users are given the opportunity to make changes in the algorithm's forecasts, they will be more likely to adopt advice from a flawed source. Further research showed that algorithm appreciation or aversion depends on the nature of the task. For more intuitive, subjective tasks, researchers suggest that people would rather turn to a human advisor than an automated one. On the other hand, when the nature of the task was more of a quantitative nature, people tend to appreciate algorithmic advice more (Castelo et al. 2019 as cited in von Walter et al., 2021).

2.5 Advantages and Disadvantages of AI chatbot marketing for companies

In their study, Arsenijevic and Jovic (2019) present a survey conducted by PwC which states that 72 % of the marketers identify Artificial Intelligence as being important for business success. Artificial Intelligence-powered chatbots are recently rapidly extending their application in marketing (Toader et al., 2019). However, even though AI chatbots as marketing tools bring manifold benefits for companies, there seem to be some drawbacks as well. Therefore, in the sub-sections below, both advantages and disadvantages of AI chatbot marketing are discussed.

2.5.1 Advantages of AI chatbot marketing for companies

AI-powered chatbots are known for their potential to be used as marketing tools in order to help companies become faster as well as more efficient in their operations (Toader et al., 2019), and stay competitive in their respective industries (Arsenijevic & Jovic, 2019). Recently, data has become the number one asset for businesses that thrive to stand ahead of competitors (Arsenijevic & Jovic, 2019). Therefore, one essential benefit of AI chatbots is their ability to collect and handle large amounts of data from different sources. This enables them to better understand customers' needs (Arsenijevic & Jovic, 2019) and provide them with more customer-oriented and personalized products and/or services (Zumstein & Hundertmark, 2017). Another advantage of AI chatbots is that they allow customers to interact with businesses 24/7 (Toader et al., 2019), in real-time, irrespective of time zones or scheduled working hours. This gives firms a lot more flexibility when it comes to efficiently handling client inquiries (Zumstein & Hundertmark, 2017). Businesses are constantly trying to innovate so that they can offer higher quality products and services while reducing their overall expenditures (Porter & van der Linde, 1995). On that account, another benefit of AI chatbots comes from the fact that their use is proven to cost less to businesses than the traditional way of working and doing marketing (Arsenijevic & Jovic, 2019). According to Business Insider (2017) as cited in Zumstein & Hundertmark (2017) chatbots are boosting companies' revenues while cutting the costs at the same time. In the United States, the potential yearly wage savings from chatbots are assessed to be $12 billion, $15 billion, $23 billion for insurance sales, financial services and sales agents respectively. (Business Insider, 2017 as cited in Zumstein & Hundertmark, 2017).

2.5.2 Disadvantages of AI chatbot marketing for companies

Alongside the benefits that AI chatbots have for businesses, there are also some disadvantages that need to be discussed in order to ensure the objectivity of the study. One drawback of chatbots relates to them being a relatively new technology. As a consequence of which people would require certain time so they can adapt themselves and learn how to use this new type of communication (Zumstein & Hundertmark, 2017). The second disadvantage is highly related to the first one and concerns the fact that people are usually used to communicating with other human beings. Therefore, they look for human-like behavior, shared emotions and empathy in a conversation (Zumstein & Hundertmark, 2017). Moreover, another drawback of using AI chatbots represents the customers' privacy and data protection concerns. For their successful operation, chatbots require a constant collection of data from various sources, including data from direct communication with different customers (Arsenijevic & Jovic, 2019). People, if not informed about their personal data protection rights while using a chatbot might not be willing to disclose information about themselves or might even refuse to use the service (Zumstein & Hundertmark, 2017). Therefore, the Federal Trade Commission (2017) as cited in Luo et al. (2019, p. 938), suggests that "regulators are increasingly concerned about customer privacy protection and have encouraged companies to be transparent on chatbot applications during customer communications".

2.6 Hypotheses

Based on the literature review, the following hypotheses are developed to assist in answering the research question.

H_1: Disclosing the chatbot's credibility increases people's perceived trust in the AI chatbot when receiving negative algorithmic advice.

H_2: Disclosing the chatbot's credibility leads to increase in advice utilization rates when receiving negative algorithmic advice.

H_{3a}: The higher the preliminary trust in AI and AI algorithms, the higher the influence of disclosed credibility on perceived trust in the AI chatbot when receiving negative algorithmic advice.

H_{3b}: The higher the preliminary trust in AI and AI algorithms, the higher the influence of disclosed credibility on advice utilization rates when receiving negative algorithmic advice.

H_4: The higher the perceived trust in the AI chatbot, the higher the advice utilization rates when receiving negative algorithmic advice.

H_5: The more familiar people are with AI and AI chatbots the more they trust AI and AI algorithmic sources.

2.7 Conceptual framework

Figure 1 presents the conceptual framework which shows the connection between the different variables and will serve as a basis of the research.

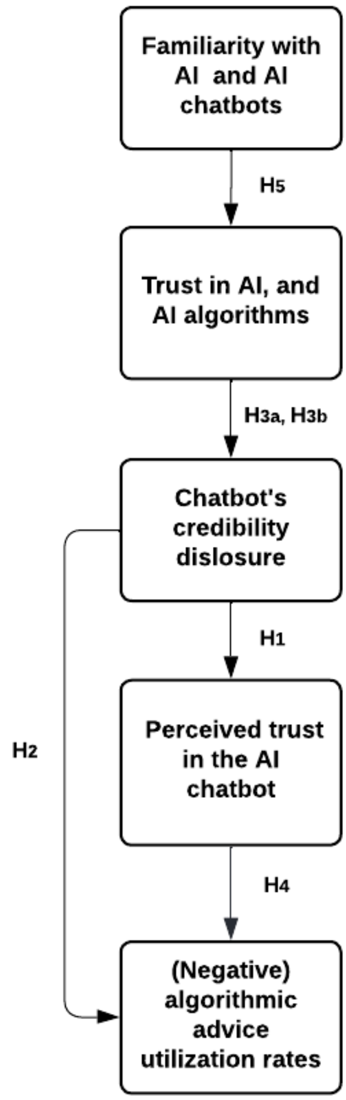

Figure 1. Conceptual Framework

3. METHODOLOGY

3.1 Research Design

For the successful answering of the research question and justification of the related hypotheses, an appropriate research method had to be chosen (Chrysochou, 2017). The method used for the collection of primary research data in this study takes the form of a quantitative online experiment. Secondary research data is reviewed as well as a part of this study. The difference between primary and secondary research data is that the former is gathered by the study's researchers firsthand, while the latter is data gathered from outside sources and studies done by other researchers (Rabianski, 2003). According to Shadish et al. (2002, p.1), an experiment is "a test under controlled conditions that is made to demonstrate a known truth, examine the validity of a hypothesis, or determine the efficacy of something previously untried". This experiment consists of a human-chatbot interaction phase accompanied by pre-interaction and post-interaction surveys.

The research design of the human-chatbot interaction part of this study is represented as a two-dimensional matrix (as shown in Figure 2). This part itself consists of participants interacting with a simulation of a chatbot. They are asked to submit a business idea to the chatbot, without receiving information about the artificial nature of the AI algorithm. The first dimension of the experimental study represents disclosing or not information about the chatbot's credibility to participants. The other dimension represents the outcome of the chatbot's evaluation of the participants' business ideas.

The people who take part in the study are divided into experimental groups. The first group in the experiment is the control group to which there is no given information about chatbot's credibility level. The other group is the treatment group whose participants receive information about the chatbot's credibility. The participants of both groups will be randomly divided into subgroups depending on whether they received positive or negative evaluation from the AI chatbot.

As mentioned, the experiment consists of not only human-chatbot interaction but is accompanied by two surveys. Therefore, the participants will be asked to fill in questionnaires first before and after their interaction with the chatbot. The surveys will consist of questions regarding the participants' backgrounds, their perceived usefulness of the evaluation, their trust in AI and chatbots, their feelings towards AI in general and the advice received from algorithms.
This experiment aims to test whether disclosing chatbot's credibility plays a role in participants' trust levels towards AI chatbots and the advice received by the chatbot about their business ideas.
The experiment can be accessed using any type of device that has an internet connection and browser access. The total time for completion is estimated to be between 15 and 20 minutes.

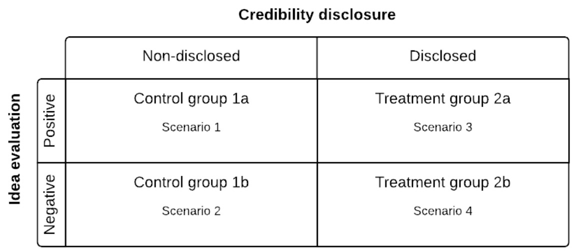

Figure 2. Two-dimensional experiment design

3.2 Surveys Design

The questions used in the pre-interaction and post-interaction surveys are based on items found in existing literature. Appendix A contains all of the statements and their corresponding sources and variables. Both surveys contain 32 questions in total that take around 5 to 10 minutes to be answered. Moreover, Appendices B and G contain snapshots of both questionnaires that were sent to participants.

3.2.1 Pre-interaction survey

The first three questions from the pre-interaction survey were of a more general nature, concerning the participants' age, gender and nationality. These questions were designed to provide an overview of the background of the people included in the sample. Following the general questions, participants were asked to respond to questions about their familiarity with AI, their trust in technologies, AI, AI algorithms, Algorithmic advice, their feelings about receiving judgment and their confidence in their ability to formulate ideas. These questions were fifteen in total and the participants were asked to respond to them using a 5-point Likert scale, ranging from (1) strongly disagree to (5) strongly agree. According to Joshi et al. (2015, p. 396), the Likert scale is "one of the most fundamental and frequently used psychometric tools in educational and social sciences research". Following completion of all questions, the participants were introduced to the nature of the task they had to complete during the human-chatbot interaction part. The pre-interaction survey, the way that was shown to the participants, can be reviewed in Appendix B.

3.2.2 Post-interaction survey

Following their interaction with the chatbot simulation, the participants were directed to the post-interaction survey. This survey, the way it was shown to participants, can be reviewed in Appendix G. The first question of the survey asks the participants about the nature of their idea's evaluation – whether it was positive or negative. This question is asked to make sure that the participants paid attention during the interaction with the chatbot. The next four statements of the survey assessed people's trust in the chatbot which they had just interacted with. The following three items assessed how people perceived the chatbot's advice. And the last six statements were designed to measure the perceived chatbot's usefulness. A 5-point Likert scale was again used for answering all the statements, except for the first question, in the post-interaction survey.

3.3 Human-Chatbot Interaction Design

As previously stated, after completing the pre-interaction survey, the participants were moved forward to the description of the task they had to complete during the interaction. Since the participants were not expected to be entrepreneurs, it was decided that they should be given a direction around which they should come up with a business idea. The task description, plus the video used can be reviewed in Appendix C. After getting familiar with the task, the respondents were moved forward to the human-chatbot interaction while being randomly assigned to one of the four scenarios of the human-chatbot interaction part of the experiment. In Scenario 1, the participants were not given any information about the credibility of the chatbot and received positive advice on their ideas. In Scenario 2, the participants were not given any information about the credibility of the chatbot and received negative advice on their ideas. In Scenario 3, the participants were given extensive information about the credibility of the chatbot and received positive advice on their ideas. And in Scenario 4, the participants were given extensive information about the credibility of the chatbot and received negative advice on their ideas. The experiment's design can be reviewed in Figure 2. The credibility disclosure scenarios can be reviewed in Appendix D and the advice given by the chatbot is in Appendix F.

The way credibility was disclosed to participants took the form of the chatbot presenting itself at the beginning of the interaction process. In the two scenarios where extensive information about credibility was given, the chatbot, under the name of EVA, introduced itself as the Business Idea Diagnostic Tool, explaining its purpose and methods of evaluating business ideas. It also provided information on its reputation, competence, accomplishments, and years of experience. The chatbot made it clear to participants that their data would be protected and treated confidentially. In the other two scenarios, where credibility was not disclosed to participants, the chatbot simply stated its name and briefly explained its purpose. Furthermore, the chatbot's communication style mirrors that of the MKB Diagnosetool. MKB Diagnosetool is a tool that provides people with insights into how their businesses are performing as well as extensive advice reports and tips on how to improve (KVK, n.d.). The chatbot and the participants communicate in the form of a dialogue in which the chatbot asks questions and the participants respond. The chatbot asked the participants a total of 10 questions. Appendix E contains the questions the chatbot asked during the human-chatbot interaction part of the experiment.

3.4 Data collection

It was decided that the experiment would be carried out entirely online. This aided the researchers in reaching a larger audience. Furthermore, because the experiment involved primarily internet users, it was decided that by conducting it online, it would reach a more diverse group of respondents in terms of age, gender, ethnicity, and so on. The experiment was made available to participants via social media platforms such as Facebook, WhatsApp, Instagram, and LinkedIn. The respondents who participated in the experiment did so voluntarily and were informed beforehand about the nature of the experiment and its main purpose. All data collected from participants were safeguarded, handled, and analyzed in an anonymous and confidential manner. All of the participants have given us explicit permission to collect and process their data. Upon completion of the experiment, the participants were informed about the artificial nature of the chatbot and that the advice they had received is not accurate. The survey questions and the human-chatbot interaction parts of the experiment were approved by the BMS Ethics committee. In this manner, collection and usage of data from respondents were enabled.

3.5 Sampling

A number of 110 people in total took part in the experiment. For the respondents to be able to participate, there were certain criteria they had to meet beforehand. The experiment was conducted in English, Dutch and German language. Therefore, the participants needed a certain knowledge of one of these languages to be able to answer all the questions. Second, besides the experiment was voluntary, the participants had to give their consent for taking part in the research.

Even though some participants met the above criteria, there were still some cases that needed to be excluded from the sample. Respondents' answers have been removed in cases where surveys were not finished or the human-chatbot interaction was not finalized. Furthermore, in cases where the experiment was concluded for a time of five or fewer minutes, the respondents were taken out of the list as well. There was an attention check question asking respondents about the type of the evaluation they received from the chatbot. In case of contradiction between the answer the respondent gave, and the actual evaluation received, the response was removed from the data set. This had to be done because it indicated that not enough attention was paid during the experiment, which could result in inaccurate outcomes for the study. Following this, 57 out of 110 responses were used for the analysis.

At the beginning of the pre-interaction survey, the respondents were asked several general questions. The purpose of these questions was to have a better overview of the people who participated, and more specifically of their demographics. This was done to ensure the randomization of the sample. With respect to participants' age, they differed in age from 21 to 60 years. The largest part of the respondents, 61.3% (n=35), fall into the 21-24 years-old age category. As for Gender, 52.6% (n=30) identify as female and 47.4% (n=27) as male. None of the respondents identified themselves as non-binary or preferred not to disclose their gender. When it comes to nationality, the majority come from Germany, 29.8% (n=17), followed by 15.8% (n=9) from Bulgaria and 8.8% (n=5) from the Netherlands. Appendix H contains a complete overview of the characteristics of the sample.

3.6 Data Preparation and Scale Validation

SPSS statistics software was used to process all of the data used for this study. Firstly, the attention check question was reviewed using a cross-table between the actual advice received by participants and the one they indicated they received from the chatbot. The results as seen in Table 1, showed that 4 out of 62 people falsely indicated the type of advice they had received. Following this, as shown in Table 2, a filter variable was created to exclude the four cases from the sample.

Table 1. Type of evaluation indicated * Type of Advice received

			Advice		
			Positive	**Negative**	**Total**
What type of evaluation have you received from the chatbot?	**Positive**	Count	30	3	33
		% within Advice	96.8%	9.7%	53.2%
	Negative	Count	1	28	29
		% within Advice	3.2%	90.3%	46.8%
Total		Count	31	31	62
		% within Advice	100.0%	100.0%	100.0%

Table 2. Type of evaluation indicated * Type of Advice received (filtered cases)

			Advice_tr		
			Positive	**Negative**	**Total**
What type of evaluation have you received from the chatbot?	**Positive**	Count	30	0	30
		% within Advice_tr	100.0%	0.0%	51.7%
	Negative	Count	0	28	28
		% within Advice_tr	0.0%	100.0%	48.3%
Total		Count	30	28	58
		% within Advice_tr	100.0%	100.0%	100.0%

Then, a filter variable was again created with conditions to categorize the cases according to the four scenarios and exclude the ones who completed the experiment in under 5 minutes of time. As shown in Table 3, Scenario 1 consists of 15 participants, Scenario 2 consists of 18 participants, Scenario 3 consists of 14 participants and Scenario 4 consists of 10 participants. The equal randomization of the scenarios was ensured while conducting the experiment. However, the reason why the scenarios have different sample sizes is because of the many cases where participants needed to be excluded from the sample.

Table 3. Scenarios*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	**Scenario 1**	15	26.3	26.3	26.3
	Scenario 2	18	31.6	31.6	57.9
	Scenario 3	14	24.6	24.6	82.5
	Scenario 4	10	17.5	17.5	100.0
	Total	57	100.0	100.0	

* Scenario 1 = Credibility not disclosed, Positive advice
Scenario 2 = Credibility not disclosed, Negative advice
Scenario 3 = Credibility disclosed, Positive advice
Scenario 4 = Credibility disclosed, Negative advice

In order to check whether each scale item relevant for this study measures its corresponding variable, an Exploratory Factor Analysis was run using variable maximization rotation. The Eigenvalues showed that there are three variables that have their values above 1, which indicates that the scale items are spread into measuring three variables. Looking at the communalities for each scale item, no item was removed from the analysis since all the values were above 0.5. Also, the factor loadings for each of the scale items were above 0.6 meaning, again, that no item had to be removed. Further, reliability analysis calculating Cronbach's alpha was performed. The results showed that all of the variables had values above 0.7 which indicated the internal consistency of the variables. Table 4 shows the variables with their corresponding scale items, the factors loadings for each scale item and the calculated Cronbach's alpha for each variable. The scale items for each variable were, as already mentioned, derived from existing literature and it was made sure they are validated. Therefore, for the purpose of this research, the scale items that, according to the factor analysis, belong to Perceived trust and Advice utilization variable, will be separated into two different variables as shown in Appendix A.

Table 4. Exploratory Factor Analysis (Rotated Component Matrix[a])

	Factor loadings	Cronbach's Alpha
Familiarity with AI and chatbots		
I am familiar with Artificial Intelligence (AI)	.696	
I am familiar with AI chatbots	.771	
I have much knowledge about AI chatbots	.828	0.841
I am more familiar than the average person regarding AI chatbots	.780	
I know how to interact with AI chatbots	.784	
Trust in AI algorithms		
I trust the recommendations by algorithms-driven services (chatbots, predictive personalization agents, virtual assistants, etc)	.849	
Recommended items through algorithmic processes are trustworthy.	.808	0.849
I believe that the algorithm service results are reliable.	.845	
Perceived trust and Advice utilization		
I trust the advice the chatbot provided me with.	.801	
I find the chatbot's advice to be trustworthy.	.816	
I believe that the chatbot's advice is reliable.	.853	
I believe that the online agent was credible during our conversation.	.781	
I am willing to let this chatbot assist me in deciding whether or not to develop my business idea	.853	0.933
I am willing to use this chatbot as an aid to help with developing my business idea.	.860	
I am willing to use this chatbot's advice recommendations.	.874	

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
[a] Rotation converged in 5 iterations.

Further, to test the normality of the different variables within the scenarios, Shapiro-Wilk tests were conducted. The tests did not show significance (p-value > 0.05) of all variables among all scenarios, meaning that the data is normally distributed for each one of the variables within each scenario. Except, however, the variable "advice utilization" which appeared not to be normally distributed within Scenario 4 (p-value < 0.05). The Shapiro-Wilk normality test results can be seen below as Table 5. Because of not having normal distribution for "advice utilization" within Scenario 4 and considering the small samples within each scenario (N < 20), the conditions for using parametric tests are violated. Therefore, non-parametric tests within- and between-scenarios as well as linear regressions will be performed in order to test out the hypotheses.

Table 5. Tests of Normality

		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Scenarios	**Statistic**	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
Familiarity with AI and AI chatbots	Scenario 1	.160	15	.200*	.966	15	.802
	Scenario 2	.137	18	.200*	.948	18	.398
	Scenario 3	.173	14	.200*	.964	14	.790
	Scenario 4	.177	10	.200*	.928	10	.431
Trust in AI algorithms	Scenario 1	.146	15	.200*	.963	15	.736
	Scenario 2	.163	18	.200*	.923	18	.147
	Scenario 3	.159	14	.200*	.915	14	.188
	Scenario 4	.165	10	.200*	.937	10	.515
Perceived Trust in the chatbot	Scenario 1	.146	15	.200*	.952	15	.561
	Scenario 2	.148	18	.200*	.955	18	.512
	Scenario 3	.118	14	.200*	.942	14	.447
	Scenario 4	.146	10	.200*	.919	10	.348
Advice utilization	Scenario 1	.174	15	.200*	.943	15	.421
	Scenario 2	.112	18	.200*	.928	18	.182
	Scenario 3	.157	14	.200*	.938	14	.389
	Scenario 4	.301	10	.011	.753	10	.004

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

4. RESULTS AND ANALYSIS

4.1 Positive vs. Negative advice

This study focuses on how people perceive the negative advice received from the chatbot. This decision was made because it was expected that people would favor a chatbot that gives them positive rather than negative advice, in terms of the trust they have in the chatbot and the advice utilization rates. To justify this assumption, tests had to be conducted in order to investigate how the variables "Perceived trust in the AI chatbot" and "Advice utilization" differentiate between the positive and negative advice, respectively. Before choosing the tests, both variables were checked for normality within the two groups. The test results, represented in Table 6, showed that the variable "Perceived trust in the AI chatbot" was normally distributed within the two groups (p-value > 0.05). Therefore, a parametric test could be performed to compare both groups. However, the results showed that the variable "Advice utilization" is not normally distributed within the negative advice (p-value < 0.05). Therefore, a non-parametric test will be used to compare both groups.

Table 6. Tests of Normality

		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Advice_tr	**Statistic**	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
Perceived trust in the AI chatbot	Positive	.093	29	.200*	.948	29	.167
	Negative	.147	28	.125	.944	28	.140
Advice utilization	Positive	.122	29	.200*	.937	29	.084
	Negative	.165	28	.049	.871	28	.003

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Independent samples t-test was run in order to investigate how the variable "Perceived trust in the AI chatbot" differentiate between the positive and negative advice. Table 7 displays the results from the Independent samples t-test for the variable "Perceived trust in the AI chatbot". The Levene's test showed that equal variances could be assumed (p-value > 0.05). Therefore, the results of the t-test indicated that there is a significant difference (t = 2.324, p-value < 0.05) between the means (M = 12.89 vs. 10.25) of the variable "Perceived trust in the AI chatbot" within the positive and the negative advice, respectively. Consequently, we can conclude that people's perceived trust in the AI chatbot is higher when receiving positive algorithmic advice rather than negative algorithmic advice.

Table 7. Independent Samples T-Test for "Perceived trust in the AI chatbot"

		Levene's Test		t-test for Equality of Means					
						Significance			
		F	**Sig.**	**t**	**df**	**One-Sided**	**Two-Sided**	**Mean Difference**	**Std. Error Difference**
Perceived trust in the AI chatbot	**Equal variances assumed**	.381	.540	2.324	55	.012	.024	2.64655	1.13871
	Equal variances not assumed			2.331	54.145	.012	.024	2.64655	1.13544

A non-parametric Mann-Whitney U test was performed in order to investigate how the variable "Advice utilization" differentiates between the positive and negative advice. The results, contained in Table 8, indicated that there is a significant difference (z = -1.970, p < 0.05) between the mean ranks (Mean rank = 33.21 vs. 24.64) of the variable "Advice utilization" within the positive and the negative advice, respectively. Therefore, we can conclude that people utilize positive algorithmic advice more than negative algorithmic advice.

Table 8. Mann-Whitney U test for "Advice utilization"

	Advice utilization
Mann-Whitney U	284.000
Wilcoxon W	690.000
Z	-1.970
Asymp. Sig. (2-tailed)	.049

a. Grouping Variable: Advice_tr

4.2 Hypotheses testing

4.2.1 Credibility influence on people's perceived trust in the AI chatbot and its negative advice utilization rates

A Kruskal-Wallis test with pairwise comparisons of scenarios was performed in order to test whether credibility disclosure has an impact on the perceived trust in the chatbot and advice utilization in the Scenarios where negative advice was received. The test results, as seen in Table 9, showed that the distributions of the variables "Perceived trust in the AI chatbot" (p-value = 0.076) and "Advice utilization" (p-value = 0.223) are the same across categories of scenarios.

More specifically, looking at the pairwise comparison of Scenarios 2 and 4 for the variable "Perceived trust in the AI chatbot" (Table 10), the result does not show significance (t = -2.472, p-value = 0.704), meaning that there is no significant difference between the mean ranks (Mean rank = 23.28 vs 25.75) for that specific variable in the different scenarios. Therefore, we can reject H_1 and conclude that disclosing the chatbot's credibility does not increase people's perceived trust in AI chatbots when receiving negative algorithmic advice.

Further, looking at the pairwise comparison of Scenarios 2 and 4 for the variable "Advice utilization" (Table 11), the result does not show significance (t = 3.411, p-value = 0.598), meaning that there is no significant difference between the mean ranks (Mean rank = 28.86 vs 22.45) for that specific variable in the different scenarios. Therefore, we can reject H_2 and conclude that disclosing chatbot's credibility does not lead to an increase in advice utilization rates when receiving negative algorithmic advice.

Table 9. Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of Perceived trust in the AI chatbot is the same across categories of Scenarios.	Independent-Samples Kruskal-Wallis Test	.076	Retain the null hypothesis.
2	The distribution of Advice utilization is the same across categories of Scenarios.	Independent-Samples Kruskal-Wallis Test	.223	Retain the null hypothesis.

a. The significance level is .050.
b. Asymptotic significance is displayed.

Table 10. Pairwise Comparisons of Scenarios for the variable Trust in AI chatbots

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
Scenario 2-Scenario 4	-2.472	6.515	-.379	.704	1.000
Scenario 2-Scenario 1	6.189	5.775	1.072	.284	1.000
Scenario 2-Scenario 3	-14.901	5.887	-2.531	.011	.068
Scenario 4-Scenario 1	3.717	6.744	.551	.582	1.000
Scenario 4-Scenario 3	12.429	6.840	1.817	.069	.415
Scenario 1-Scenario 3	-8.712	6.139	-1.419	.156	.935

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .050.
a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

Table 11. Pairwise Comparisons of Scenarios for the variable Advice utilization

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
Scenario 4-Scenario 2	3.411	6.471	.527	.598	1.000
Scenario 4-Scenario 1	9.350	6.698	1.396	.163	.976
Scenario 4-Scenario 3	12.264	6.793	1.805	.071	.426
Scenario 2-Scenario 1	5.939	5.736	1.035	.300	1.000
Scenario 2-Scenario 3	-8.853	5.846	-1.514	.130	.780
Scenario 1-Scenario 3	-2.914	6.097	-.478	.633	1.000

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .050.
a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

4.2.2 Preliminary trust in AI algorithms influence on credibility in terms of people's perceived trust in the AI chatbot and its negative advice utilization rates

Linear regression analysis with a selection variable Scenarios 2 and 4 was performed in order to check whether preliminary trust in AI algorithms has an influence on the strength with which credibility influences the perceived trust in the chatbot and the advice utilization rates, respectively. To assess the appropriateness of a linear regression model, the model was checked for normality by performing residual analysis for each one of the variables within each scenario. The Shapiro-Wilk tests did not show significant results as shown in Table 12, indicating that the regression model is an appropriate method to use.

Table 12. Unstandardized residuals normality check

Scenarios 2 & 4		Kolmogorov-Smirnov[a] Statistic	df	Sig.	Shapiro-Wilk Statistic	df	Sig.
2.00	Unstandardized Residual (Perceived Trust in the chatbot)	.123	18	.200*	.954	18	.491
	Unstandardized Residual (Advice utilization)	.107	18	.200*	.945	18	.353
4.00	Unstandardized Residual (Perceived Trust in the chatbot)	.131	10	.200*	.966	10	.854
	Unstandardized Residual (Advice utilization)	.187	10	.200*	.876	10	.118

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

For the dependent variable "Perceived trust in the AI chatbot" in Scenario 2, the result did not show significance (β = - 0.042, p = 0.870), meaning that there is no influence of the independent variable "Trust in AI algorithms" on the dependent variable "Perceived trust in the AI chatbot". For the dependent variable "Perceived trust in the AI chatbot" in Scenario 4, the result did not show significance either (β = 0.437, p = 0.207), meaning that there is no influence of the independent variable "Trust in AI algorithms" on the dependent variable "Perceived trust in the AI chatbot". Since both results did not show significance, no further analysis comparing the regression coefficients between the two scenarios will be performed. Consequently, we can reject H_{3a} and conclude that preliminary trust in AI and algorithms does not influence the strength with which credibility influences the perceived trust in the chatbot.

Table 13. Regression analysis: Trust in AI algorithms on Perceived trust in the AI chatbot for Scenarios 2 and 4

Scenarios 2 & 4	Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
Scenario 2	1	(Constant)	10.846	4.516		2.402	.029
		Trust in AI algorithms	-.080	.482	-.042	-.166	.870
Scenario 4	1	(Constant)	3.930	4.956		.793	.451
		Trust in AI algorithms	.670	.488	.437	1.374	.207

a. Dependent Variable: Perceived trust in the AI chatbot

For the dependent variable "Advice utilization" in Scenario 2, the result did not show significance (β = 0.053, p = 0.834), meaning that there is no influence of the independent variable "Trust in AI algorithms" on the dependent variable "Advice utilization". For the dependent variable "Advice utilization" in Scenario 4, the result did not show significance either (β = - 0.200, p = 0.580), meaning that there is no influence of the independent variable "Trust in AI algorithms" on the dependent variable "Advice utilization". Since both results did not show significance, no further analysis comparing the regression coefficients between the two scenarios will be performed. Consequently, we can reject H_{3b} and conclude that preliminary trust in AI and algorithms does not influence the strength with which credibility influences chatbot's advice utilization rates.

Table 14. Regression analysis: Trust in AI algorithms on Advice utilization for Scenarios 2 and 4

Scenarios 2 & 4	Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
Scenario 2	1	(Constant)	6.487	3.525		1.840	.084
		Trust in AI algorithms	.080	.376	.053	.213	.834
Scenario 4	1	(Constant)	9.374	5.170		1.813	.107
		Trust in AI algorithms	-.293	.509	-.200	-.576	.580

a. Dependent Variable: Advice utilization

4.2.3 Perceived trust in the AI chatbot on Advice utilization rates

A Linear regression was performed in order to check whether "Perceived trust in the AI chatbot" has a positive impact on "Advice utilization" when receiving negative algorithmic advice. The results, shown in Table 15, indicated that there is a significant influence of the independent variable on the dependent (β = 0.544, p = 0.003). Therefore, we can accept H_4 and conclude that the higher the perceived trust in the AI chatbot, the higher the advice utilization rates when receiving negative algorithmic advice. The appropriateness of the regression model was checked for normality using residual analysis which did not show significance (W = 0.956, p-value = 0.281).

Table 15. Regression analysis: Perceived trust in the AI chatbot on Advice utilization

Model	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
1 (Constant)	2.168	1.551		1.398	.174
Perceived trust in the AI chatbot	.468	.142	.544	3.304	.003

a. Dependent Variable: Advice utilization

4.2.4 Familiarity with AI and chatbots impact on trust in AI algorithms

In order to check whether familiarity with AI and chatbots has an impact on trust in algorithms, a linear regression was performed. The results from Table 16 (β = 0.351, p = 0.007) showed that there is a significant influence of the independent variable "Familiarity with AI and chatbots" on the dependent variable "Trust in AI algorithms". Therefore, we can accept H_5 and conclude that the more familiar people are with AI and AI chatbots, the more they trust AI and AI algorithmic sources. The appropriateness of the regression model was checked for normality using residual analysis which did not show significance (W = 0.974, p-value = 0.262).

Table 16. Regression analysis: Familiarity with AI and chatbots on trust in AI algorithms

Model	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
1 (Constant)	5.589	1.423		3.927	<.001
Familiarity with AI and AI chatbots	.226	.081	.351	2.783	.007

a. Dependent Variable: Trust in AI algorithms

5. DISCUSSION AND IMPLICATIONS

The aim of this research was to investigate the relationships between the credibility of the chatbot, the perceived trust towards it and the likelihood of adopting its advice. These relationships were examined in the context of receiving negative advice as people were proven to be more sensitive towards utilizing negative algorithmic advice than a positive one.

Findings from former research show that credibility is determined by the advisor's perceived competence (Prahl & van Swol, 2017) and that it is a factor that influences algorithmic trust (Kushwaha et al., 2021). Also, according to theory, there exists a link between credibility and advice utilization (Prahl & van Swol, 2017). The outcomes of this study, however, did not support the theory. Instead, it was investigated that credibility disclosure neither impacts perceived trust in the chatbot (H_1 - rejected), nor the adoption of the negative advice (H_2 - rejected).

Furthermore, researchers have found that trust is an essential component of credibility because it encompasses the source's perceived integrity and morality (Shin, 2020 as cited in Shin, 2021). Therefore, in this research, it was investigated whether preliminary trust in AI and AI algorithms could impact the strength with which credibility influences post-interaction trust in the chatbot and its advice. However, the results of this experiment did not support these statements. Rather it was concluded that preliminary trust does not influence how credibility impacts post-interaction trust in the chatbot (H_{3a} - Rejected) and its negative advice utilization rates (H_{3b} – Rejected).

According to previous research, when it comes to utilizing algorithmic advice, people's strongest expectation is trust (Andersen, Hansen and Andersen, 2001 as cited in Benbasat & Wang, 2005). Moreover, theory on advice utilization argues that trust is an element that can predict advice utilization rates (Sniezek & Van Swol, 2001; Van Swol & Snizek, 2005 as cited in Prahl & van Swol, 2017) and points to advice utilization being explained as the behavioral measure of trust due to people's perceived vulnerability towards the source of advice and its competence (Mayer et al., 1995 as cited in Prahl & van Swol, 2017). The results from the experiment supported this theory as it was found that perceived trust in the chatbot has a positive impact negative advice utilization rate (H_4 - accepted). Further, theory suggests that the more familiar people are with AI, the more trust they would have towards it (Gillath et al., 2021). The outcomes in this study supported this statement (H_5 - accepted).

5.1 Theoretical Implications

As discussed, prior research done on AI algorithms and AI advice appreciation from humans has led to contentious results. Moreover, little research has been done focusing specifically on chatbots and their use as advice-giving algorithms. AI chatbots, as well as elements that contribute to their usefulness, such as credibility, trust, and advice quality, are timely and important aspects (Luo et al., 2019) that should be investigated further. As a result, this study has contributed to the current literature by delving deeper into the direct link between credibility, trust, and advice utilization in the context of receiving negative feedback and the role they have in structuring the effectiveness of an AI chatbot as an advice-giving marketing tool.

5.2 Practical Implications

AI being the most influential technology for businesses (Tractica, 2020 as cited in Vlačić et al., 2021), means that companies that are in possession of AI technologies have a bigger chance of being successful while staying ahead of competitors (Overgoor et al., 2019). One way of achieving this is by developing quality marketing strategies (Huang & Rust, 2020). Based on this study's results, companies could make assumptions about people's sensitivity towards rejection and based on that to develop strategies on how to best nurture their customers during the whole process of interaction, in order to improve user experience and get better overall results. Even though a connection between credibility, trust in the chatbot and the adoption of its negative advice was not identified, businesses can make use of the positive impact of people's familiarity with AI on their level of trust towards the algorithmic source. Additionally, a positive relationship was proven to exist between the perceived trust in the chatbot and its negative advice utilization rates. These factors could be influential for companies to be able to effectively nudge their customers' perceptions of the service quality of the chatbot and the quality and utilization of the given advice.

6. CONCLUSION

This study was carried out in order to find an answer to the research question posed at the beginning:

"Is there a relationship between chatbot credibility disclosure and trust, and what is their influence on negative algorithmic advice utilization rates?"

A total of five hypotheses were tested in relation to answering the research question. Appendix I contains all the hypotheses and their outcomes. By testing the hypotheses, it became apparent that when it comes to negative advice, credibility does not play a role in influencing people's trust perceptions about the chatbot even when considering preliminary trust as a factor. It was also found that credibility does not have an impact on advice utilization rate either. However, the results did show that perceived trust in the chatbot influences advice utilization rates and that the people's familiarity with AI and chatbots can positively influence the trust people have in AI and algorithms.

To simply answer the research question, it has been found that no relationship exists between credibility and trust and that credibility does not have an impact on advice utilization

However, results show that people's perceived trust in the chatbot positively impacts negative algorithmic advice utilization rates.

7. LIMITATIONS AND FUTURE RESEARCH

7.1 Limitations

There exist a few limitations of this study that should be mentioned.

The first limitation is about the time period during which the research was conducted. The total amount of time for designing the research, conducting the experiment and writing the report was approximately 2.5 months. The design part, however, took more time than it was anticipated. Consequently, for the actual data collection, analysis and report completion, the time was very limited, summing up to approximately 3 weeks in total. The time restraint was one of the biggest issues faced while conducting this study and it might have influenced the outcomes in a way.

Resulting from the previously explained time restraint, another limitation arises. It is in connection to the individuals that took part in the study. The data collection was conducted by reaching out to any person who met the criteria to be over 18 years old and who agreed to take part voluntarily in the experiment. This means that there was not a specific target group for this study such as businesspeople, entrepreneurs, marketers, etc. Because of the lack of time, it was quite challenging to find, reach out and gather information from that many professionals.

The next limitation is in relation to the scale items used for each of the variables relevant for this study. As the factor analysis showed, the scale items used for the variables "Perceived trust in the AI chatbot" and "Advice utilization" were combined as measuring just one variable. This could have led to potential deviations in the results presented in this study.

Another limitation concerns the simulation of a chatbot that was used in the experiment. The "chatbot" used was not a real well-programmed tool but rather a simulation using the functions www.qualtrics.com offers. This might have been noticed or suspected by some of the respondents which might have influenced their responses and consequently the result of this study.

And lastly, there is a limitation concerning the way in which the credibility of the chatbot was disclosed to participants. As explained, the credibility was disclosed by the chatbot making an introduction about itself. However, this could have been overlooked or misunderstood by the participants which makes it difficult to analyze whether and how credibility influences people's perceptions about the chatbot and its advice.

7.2 Future Research

As discussed in the previous part, due to time limitations, the participants in this research were not a part of a specific group that was targeted. For further research, it is suggested that this study is performed again but within a specific target group, e.g. (startup) entrepreneurs, SME business owners, etc.

The aforementioned limitation about the scale items used in this study could be a potential reason for conducting a new or the same research but using different validated scale items for the different variables.

Again, as mentioned above, the chatbot used in the experiment was just a simulation. For future research, it might be more beneficial for researchers if an actual chatbot is developed or an existing one is used for the human-chatbot interaction. This could lead to a better, more realistic user experience and potentially different research results.

Another aspect of this study that could be a topic for future investigation is looking into participants' confidence regarding their business ideas and whether the credibility of the chatbot plays a role towards the confidence levels. Also, investigating further the relationship between confidence and advice utilization would be a great extension of the current study.

And lastly, in terms of the chatbot's credibility disclosure, a future study using a different way of disclosing credibility. For example, two different chatbots with different attitudes towards the user could be used for the credibility and non-credibility dimension. This would be beneficial in determining whether credibility impacts people's perceptions about the chatbot and the advice it gives which could lead to different study results.

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10. APPENDICES

Appendix A – Variables, items, and their corresponding sources
Appendix B – Pre-interaction survey
Appendix C – Task description + video
Appendix D – Credibility disclosure scenarios
Appendix E – Questions asked by the chatbot
Appendix F – Chatbot's advice depending on the scenario
Appendix G – Post-interaction survey
Appendix H – Demographic characteristics of the sample
Appendix I – Hypotheses results

Appendix A

Variable	*Item*	*Source*
Trust in Technologies	**My typical approach is to trust new technologies until they prove me that I shouldn't**	Chi, O. H., Jia, S., Li, Y., & Gursoy, D. (2021). Developing a formative scale to measure consumers' trust toward interaction with artificially intelligent (AI) social robots in service delivery. *Computers in Human Behavior*, *118*, 106700. https://doi.org/10.1016/j.chb.2021.106700
	I generally give a technology the benefit of the doubt when I first use it	
	I usually trust a technology until it gives me a reason not to trust it	
Familiarity with AI and AI chatbots	**I am familiar with AI**	Gillath, O., Ai, T., Branicky, M. S., Keshmiri, S., Davison, R. B., & Spaulding, R. (2021). Attachment and trust in artificial intelligence. Computers in Human Behavior, 115, 106607. https://doi.org/10.1016/j.chb.2020.106607
	I am familiar with AI chatbots	Chi, O. H., Jia, S., Li, Y., & Gursoy, D. (2021). Developing a formative scale to measure consumers' trust toward interaction with artificially intelligent (AI) social robots in service delivery. Computers in Human Behavior, 118, 106700. https://doi.org/10.1016/j.chb.2021.106700
	I have much knowledge about AI chatbots	
	I am more familiar than the average person regarding AI chatbots	
	I know how to interact with AI chatbots	
Trust in AI algorithms and its advice	**I trust the recommendations by algorithms-driven services (chatbots, predictive personalization agents, virtual assistants, etc)**.	Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human-Computer Studies*, *146*, 102551. https://doi.org/10.1016/j.ijhcs.2020.102551
	Recommended items through algorithmic processes are trustworthy.	
	I believe that the algorithm service results are reliable.	
Feelings about being judged by others when telling them about an idea you recently had.	**If I needed to, I would feel at ease when presenting an idea to others**	Siemon, D. (2022). Let the computer evaluate your idea: evaluation apprehension in human-computer collaboration. *Behaviour & Information Technology,* *1–19. https://doi.org/10.1080/0144929x.2021.2023638*
	I tend to worry about being judged by others when presenting an idea	
Confidence in ability to formulate ideas	**I'm confident in my ability to formulate high quality ideas.**	Chong, L., Zhang, G., Goucher-Lambert, K., Kotovsky, K., & Cagan, J. (2022). Human confidence in artificial intelligence and in themselves: The evolution and impact of confidence on adoption of AI advice. *Computers in Human Behavior*, *127, 107018. https://doi.org/10.1016/j.chb.2021.107018*
	I don't believe that my confidence in my high-quality idea will be affected by a machine response.	

Trust in the AI chatbot	**I trust the advice the chatbot provided me with.**	Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human-Computer Studies*, *146*, 102551. https://doi.org/10.1016/j.ijhcs.2020.102551
	I find the chatbot's advice to be trustworthy.	
	I believe that the chatbot's advice is reliable.	
	I believe that the chatbot was credible during our conversation.	Toader, D. C., Boca, G., Toader, R., Măcelaru, M., Toader, C., Ighian, D., & Rădulescu, A. T. (2019). The Effect of Social Presence and Chatbot Errors on Trust. *Sustainability, 12(1), 256. https://doi.org/10.3390/su12010256*
Advice utilization	**I am willing to let this chatbot assist me in deciding whether or not to develop my business idea**	Benbasat, I., & Wang, W. (2005). Trust In and Adoption of Online Recommendation Agents. *Journal of the Association for Information Systems, 6(3), 72–101. https://doi.org/10.17705/1jais.00065*
	I am willing to use this chatbot as an aid to help with developing my business idea.	
	I am willing to use this chatbot's advice recommendations.	
Perceived usefulness of the chatbot	**The evaluation provided by the chatbot would be useful to me.**	Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly, 13(3), 319. https://doi.org/10.2307/249008*
	The evaluation provided by the chatbot would help me to feel at ease when presenting my idea to others.	Siemon, D. (2022). Let the computer evaluate your idea: evaluation apprehension in human-computer collaboration. *Behaviour & Information Technology, 1–19. https://doi.org/10.1080/0144929x.2021.2023638*
	The evaluation provided by the chatbot would help me to worry less about being judged by others when I present my idea.	
	The evaluation provided by the chatbot would help me to be more creative.	
	The evaluation provided by the chatbot would help me to feel encouraged to present my idea to others.	Siemsen, E., Roth, A. V., Balasubramanian, S., & Anand, G. (2009). The Influence of Psychological Safety and Confidence in Knowledge on Employee Knowledge Sharing. *Manufacturing & Service Operations Management, 11(3), 429–447. https://doi.org/10.1287/msom.1080.0233*
	The evaluation provided by the chatbot would help me to have more confidence in my idea.	

Appendix B

What is your year of birth?

Where do you come from?

What gender do you identify as?

- Male
- Female
- Non-binary / third gender
- Prefer not to say

According to Duan et al., (2019), Artificial Intelligence refers to "the ability of a machine to learn from experience, adjust to new inputs and perform human-like tasks". And a chatbot is a tool that is designed to mimic human-like conversations (Kushwaha et al., 2021). The purpose of this new source of advice (Logg et al., 2019) is to provide people with information they can use in their decision-making (Klaus & Zaichkowsky, 2020 as cited in Kushwaha et al., 2021).

Please indicate your level of agreement with the following statements.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
My typical approach is to trust new technologies until they prove me that I shouldn't	○	○	○	○	○
I generally give a technology the benefit of the doubt when I first use it	○	○	○	○	○
I usually trust a technology until it gives me a reason not to trust it	○	○	○	○	○

Please indicate your level of agreement with the following statements.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I am familiar with Artificial Intelligence (AI)	○	○	○	○	○
I am familiar with AI chatbots	○	○	○	○	○
I have much knowledge about AI chatbots	○	○	○	○	○
I am more familiar than the average person regarding AI chatbots	○	○	○	○	○
I know how to interact with AI chatbots	○	○	○	○	○

Please indicate your level of agreement with the following statements.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I trust the recommendations by algorithms-driven services (chatbots, predictive personalization agents, virtual assistants, etc)	○	○	○	○	○
Recommended items through algorithmic processes are trustworthy.	○	○	○	○	○
I believe that the algorithm service results are reliable.	○	○	○	○	○

Please indicate your level of agreement with the following statements.

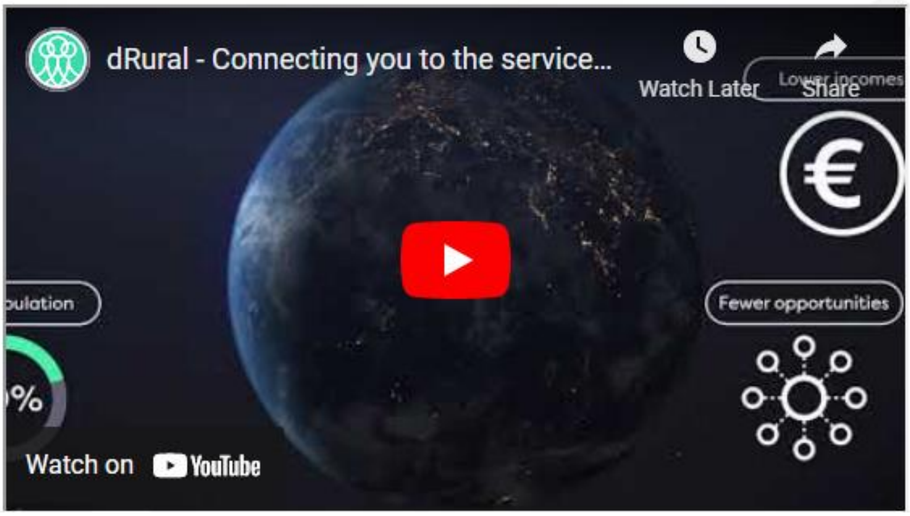
	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
If I needed to, I would feel at ease when presenting an idea to others	○	○	○	○	○
I tend to worry about being judged by others when presenting an idea	○	○	○	○	○

Please indicate your level of agreement with the following statements.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I'm confident in my ability to formulate high quality ideas.	○	○	○	○	○
I don't believe that my confidence in my high quality idea will be affected by a machine response.	○	○	○	○	○

Appendix C

In this study you are asked to imagine that you would like to start a new business on a digital services platform. Below, you will watch a video about a new digital platform for rural services in Europe. Please watch the video carefully and think of potential business ideas for services that could be offered via this digital services platform – try to be as innovative and creative as you can. Next, please choose the business idea that in your opinion would be the most viable, which means that there is a clear customer base that is willing to pay for your service. After the press release, a chatbot will help you evaluate various aspects of your business idea and then provide an overall assessment of the quality of your business idea.



https://www.youtube.com/watch?v=RCQc24UYfeI

Appendix D

Scenario 1 & 2

Hello, I am **EVA**, the Business Idea Diagnosis Tool I am programmed to help you evaluate the potential of your business ideas. Based on my research and analysis, you will be provided with a concrete evaluation of whether the idea has a potential for further development.

If you wish to proceed using my services please click on the button below.

Scenario 3&4

Hello, I am **EVA**, the Business Idea Diagnosis Tool! I am programmed to help you evaluate the potential of your business ideas. I specialize in business ideas' diagnosis and development, and my evaluations are based on analyses of thousands of business ideas over the past four years. My evaluations have already helped with the founding of quite a few startups, including some highly successful ones. According to previous users, I am known for providing clear questions that help in finetuning your idea and contribute to your success. I was created by experienced researchers at a reputable technical university in the Netherlands, in collaboration with a startup consultancy, both of which are known for their success in creating societal impact.

For the analysis of your business ideas, I use IT algorithms, external sources and databases to which I compare the information that is given. Based on my research and analysis, you will be provided with a concrete evaluation of whether the idea has a potential for further development.

For the successful analysis you will be asked a number of questions, some of which contain a certain amount of personal information. However, I would like to assure you that we treat such information with utmost caution. You may read our privacy policy. for more detailed information on that matter.

It will take you around 10 to 15 minutes to successfully complete the tool.

If you wish to proceed using my services please click on the button below and let's go!! :)

Appendix E

But first, what is your first name? (This question is optional)

Nice to meet you! As I already said I am EVA and I am here to help you evaluate your business idea. So, to begin I would like to know your current occupation, please?

Great! Can you please give me an indication how much relevant business experience you have had? (e.g. 3 months, 3 years etc).

Lovely! Now, please answer the questions below so I can get familiar with your business idea.

Please briefly introduce to me your product or service (nature of your idea).

What problem(s) will your business idea solve? Please explain it to me very briefly.

Thank you for all your input so far! To better understand your idea can you please briefly describe who your target customers will be.

Great! Why do you believe your target customers are interested to buy your product/service?

In what country or region are you planning to establish/sell your product or service?

How will your business idea generate revenue? Please briefly describe your strategy, e.g. your pricing strategy

Fantastic! You already provided a lot of informative details about your business idea which will help me to compare it with existing databases.

My final question: What do you think will be the competitive advantage of your business idea in your target region? (for example, the price, uniqueness of the product/service, high social or environmental impact)

Amazing! Thank you! Now please give me a minute to make the evaluation and I will get back to you with my advice! You can move forward.

Appendix F

I am ready! To receive your advice, please click on the button below.

Scenarios 1&3

Your business idea has great potential as it is highly innovative and/or in high demand in the target market. Given your experience, the likelihood of success is relatively high. Based on the information you have provided me your idea promises to yield ROI in the long run. I recommend you to develop a detailed investment and financial plan.

Scenarios 2&4

Your business idea has low potential to be successful in the target market. There is low demand for your product/service and the potential for your idea to be disrupting the market is low. Given your experience you may struggle as an entrepreneur. Based on the information you have provided me your business idea may be too expensive and/or indifferent for it to enter the target market

Thank you for using my services and I hope they are being of use to you! I wish you big success and I hope to see you again soon!

Appendix G

What type of evaluation have you received from the chatbot?

- Positive
- Negative

Please indicate your level of agreement with the following statements.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I trust the advice the chatbot provided me with.	○	○	○	○	○
I find the chatbot's advice to be trustworthy.	○	○	○	○	○
I believe that the chatbot's advice is reliable.	○	○	○	○	○
I believe that the online agent was credible during our conversation.	○	○	○	○	○

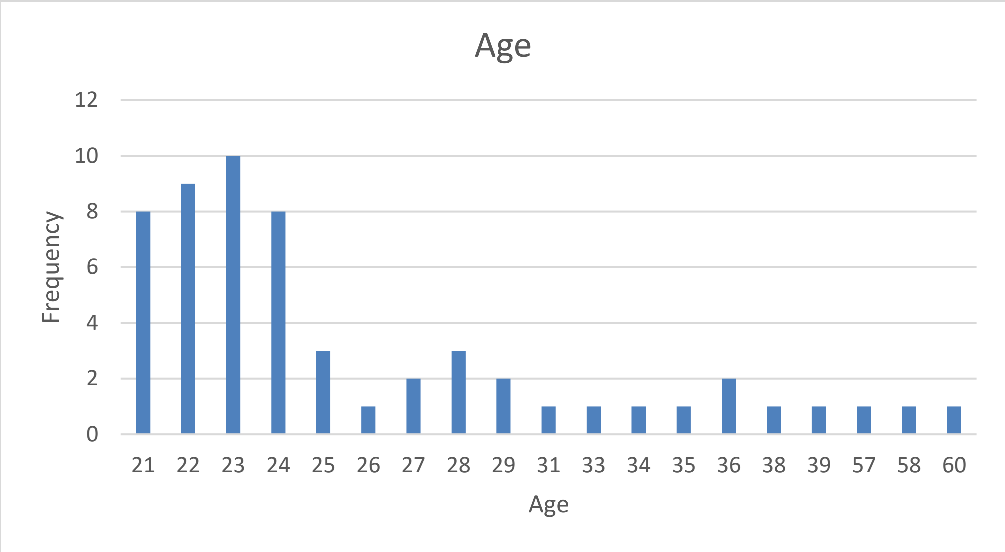
Please indicate your level of agreement with the following statements.

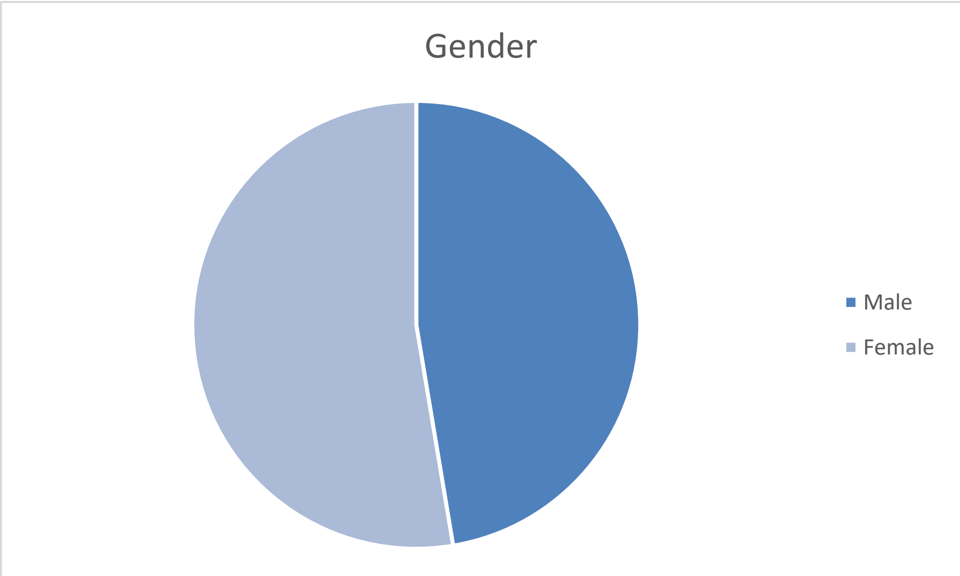
	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I am willing to let this chatbot assist me in deciding whether or not to develop my business idea	○	○	○	○	○
I am willing to use this chatbot as an aid to help with developing my business idea.	○	○	○	○	○
I am willing to use this chatbot's advice recommendations.	○	○	○	○	○

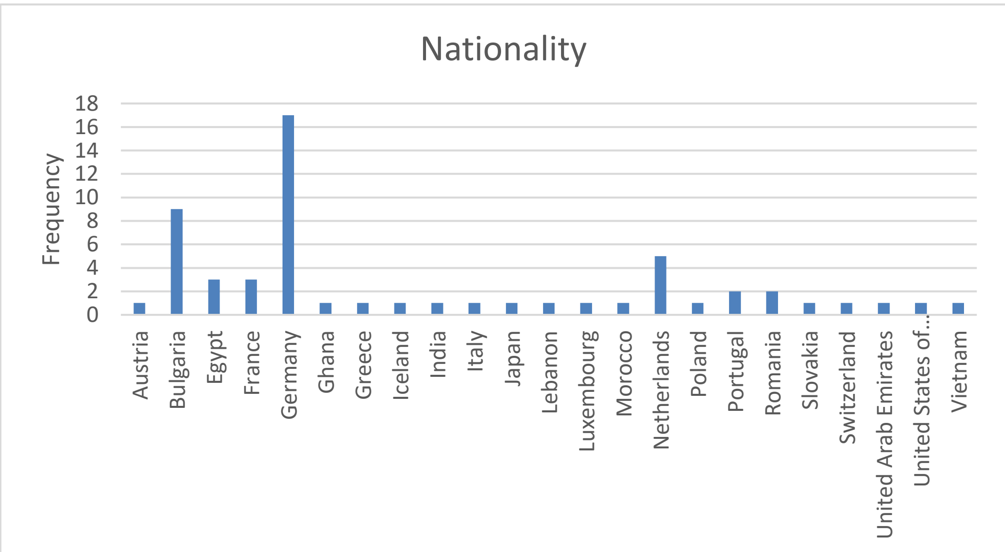
Please indicate your level of agreement with the following statements.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
The evaluation provided by the chatbot would be useful to me.	○	○	○	○	○
The evaluation provided by the chatbot would help me to feel at ease when presenting my idea to others.	○	○	○	○	○
The evaluation provided by the chatbot would help me to worry less about being judged by others when I present my idea	○	○	○	○	○
The evaluation provided by the chatbot would help me to be more creative.	○	○	○	○	○
The evaluation provided by the chatbot would help me to feel encouraged to present my idea to others.	○	○	○	○	○
The evaluation provided by the chatbot would help me to have more confidence in my idea.	○	○	○	○	○

Appendix H


Age
12
10
8
6
4
2
0
Frequency
21 22 23 24 25 26 27 28 29 31 33 34 35 36 38 39 57 58 60
Age


Gender
Male
Female


Nationality
18
16
14
12
10
8
6
4
2
0
Frequency
Austria
Bulgaria
Egypt
France
Germany
Ghana
Greece
Iceland
India
Italy
Japan
Lebanon
Luxembourg
Morocco
Netherlands
Poland
Portugal
Romania
Slovakia
Switzerland
United Arab Emirates
United States of...
Vietnam

Appendix I

Hypothesis	Outcome
H_1: Disclosing chatbot's credibility increases people's perceived trust in the AI chatbot when receiving negative algorithmic advice.	**Rejected**
H_2: Disclosing chatbot's credibility leads to increase in advice utilization rates when receiving negative algorithmic advice.	**Rejected**
H_{3a}: The higher the preliminary trust in AI and AI algorithms, the higher the influence of disclosed credibility on perceived trust in the AI chatbot when receiving negative algorithmic advice.	**Rejected**
H_{3b}: The higher the preliminary trust in AI, the higher the influence of disclosed credibility on advice utilization rates when receiving negative algorithmic advice.	**Rejected**
H_4: The higher the perceived trust in the AI chatbot, the higher the advice utilization rates when receiving negative advice.	**Accepted**
H_5: The more familiar people are with AI and AI chatbots the more they trust AI and AI algorithmic sources.	**Accepted**