# Illusions about AI in marketing: a qualitative and quantitative study of two perspectives

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## ABSTRACT
Artificial intelligence (AI) is a concept of increasing importance that is applied in various fields, one of them being marketing. As it involves the participation of many people, notably individual and business customers, it is of paramount importance to maintain the transparency behind the implementation of AI in marketing. This is particularly hard to do for two reasons – the complexity of AI itself, and more importantly, the false beliefs associated with the subject, referred to as illusions. This research aims to investigate the differences in perception of AI between end-users (receivers) and company representatives (implementors), so to present and explain the reasons behind AI implementation, and using this context to discuss the topic of illusion. To capture the viewpoints of receivers and implementors, the research is based on a two-step methodology: a case study of Amazon's AI-driven dynamic pricing, including the ethical implications associated with it, and a quantitative analysis of data measuring the attitude of individual end-users towards the subject. The main outcomes of the research are that receivers' attitude towards AI significantly affects individual susceptibility to both favorable and unfavorable illusions about the concept, and that Amazon implements AI as a profit maximization tool. Ultimately, the research's contribution would be raising awareness on the issue with the emergence and spread of illusions about AI, thus laying the ground for further research.

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## Keywords
Artificial intelligence, illusion, perception, attitude, digital literacy, dynamic pricing, ethics

# 1. INTRODUCTION

Artificial intelligence (AI) can be defined in the following simple way – a collection of technologies that can be used to imitate or even outperform tasks performed by humans using machines (Bollegala, 2016). Despite the fact that they represent a next-level version of human knowledge, thus determining the level of technological advancement and, consequently, shaping the future state of the world, the role of machines and the logic behind their learning process is precisely the factor that sparks controversy about artificial intelligence among modern society (Hearst & Hirsh, 2000). In the end, machine knowledge originates from human knowledge. This means the former is influenced by human traits. What if developers of artificial intelligence are subordinate to malicious intentions? AI can be extremely dangerous in such cases. As per UNICRI & UNCCT (2021), the main cause of concern within senior business leaders and academics was AI falling into the wrong hands. Two key factors for this concern are the "democratization" of AI (its increasing availability and ease of use to everyone) and the growing societal dependency on data and technology (UNICRI & UNCCT, 2021).

Another crucial issue are the "hidden and unchecked biases of algorithms used in advertising, hiring, lending, risk assessment etc." and the lack of responsibility obligation for developers and users of algorithms (Martin, 2019). This basically leaves the distribution and implementation of biased algorithms without consequences, which goes against the ethical principles of AI development. However, the EU has been actively addressing this problem in terms of numerous approaches and legislations towards responsible AI (European Commission, 2022). In addition, subjective algorithms may be used as a benchmark only because they yield proper results, even in the case of non-malicious intentions. Therefore, as more and more algorithms are based on subjectivity, biases would become increasingly difficult, if not impossible, to be found and eliminated.

These issues represent the dark side of AI, which, along with the lack of clarity about AI development and implementation, leads to the emergence of controversial, unproven statements regarding the topic that in many cases turn out to be false. In the context of this research, these statements, also known as misconceptions and myths, will be referred to as illusions. Their impact on individual end-users, referred to as receivers, is crucial for the future development of AI, as its perception by the public will determine its popularity and success. The bigger the number of receivers, the bigger the impact, therefore the research will focus on AI implementation in marketing, as it is a field revolving around a vast multitude of end-users and creating value for them by designing, communicating, delivering, and exchanging offerings (American Marketing Association, 2017). The use of AI in this context involves collecting and analyzing customer and market data, which are processes that should be carried out in accordance with certain ethical principles such as data protection. Therefore, a key problem is ensuring AI implementation is aligned with organizational goals while maintaining a consistent and transparent ethical approach. This problem is addressed in the current study by focusing on a specific example – Amazon and its implementation of AI-driven dynamic pricing. The following section discusses the research objective and the way towards achieving it.

## 1.1 Research objective

There have been many debates about the implementation of AI and the validity of algorithms used for its development. They have generated a variety of opinions on the subject from experts as well as independent individuals. They usually span from "the development of full artificial intelligence could spell the end of the human race" (Hawking, 2014) to "AI makes life easier" (Modern Diplomacy, 2019). Both these opinions have been supported by valid arguments and, undoubtedly, everyone is free to maintain their stance. The real problem comes when one forcefully tries to impose their point of view, or uses it to create propaganda suiting their narrative. Especially due to the assumption that paranoia is a common reaction of human intelligence to artificial intelligence (Brooks, 2017), it is relatively easy to manipulate society into the illusion that AI is "evil".

Taking this under account, the core goal of this research is to introduce the topic of illusion into the context of AI implementation in marketing. This involves discussing the differences in perception of AI between people that make personal use of AI-based technologies (receivers) and people that integrate AI in business operations (implementors). In further detail, the research will include a case study of Amazon's AI-driven dynamic pricing with an emphasis on marketing and business ethics, as well as a quantitative analysis of data collected from a sample of end-users via online survey about their attitude towards AI. The idea behind this two-part structure is to analyze and compare two different points of view – the one of a company, or more precisely company representatives, and the one of an individual person. This approach would give insights into the differences between the way of thinking of business-minded people and regular individuals, which would consequently explain differences in attitude. This leads to the formulation of the research questions presented in *Table 1*.

**Table 1. Research questions (RQ) and approach.**

| | |
|---|---|
| RQ1. What is the motivation for Amazon to implement AI-driven dynamic pricing? | Case study (section 4) |
| RQ2. Which factors determine individual attitude towards AI? | Literature review + quantitative data analysis (sections 2.4 & 5.2-5.4) |
| RQ3. What are the differences between receivers' and implementors' perception of AI? | Literature review + quantitative data analysis (sections 2.4, 4 & 5.5) |
| RQ4. What are the most common illusions about AI? | Literature review + quantitative data analysis (section 5.5) |

It would be fair to assume there are differences in perception of AI between companies implementing it, particularly company representatives, and end-users. The former are supposed to be more knowledgeable of the topic as they use AI as part of company operations or directly as a profit-making vehicle. On the other hand, many ordinary people are not tech savvy or simply are not aware of AI, how it works and what is it used for. In figures, approximately 58 percent of CIOs understand the benefits of AI in the workplace (Wharton Online Blog, 2022), while according to Kats (2017), 38 percent of internet users worldwide know very little about this concept or nothing at all. Therefore, it can be assumed a common perception of AI by end-users is that of an unknown piece of technology that may be even a cyber threat.

This paper is structured as follows. A literature review introduces the main topics of study and the components of the quantitative research. Then, the research methodology is outlined. It is followed by the qualitative study of Amazon and the quantitative data analysis. Next, a discussion including a summary of the findings as well as the academic and practical relevance of the paper. Then, a conclusion, including the study's limitations and suggestions for further research, will be presented. The paper will finish with an acknowledgement for those involved in this research, and the references and appendix sections.

# 2. LITERATURE REVIEW

## 2.1 Artificial intelligence (AI)

### *2.1.1 Definition*

As mentioned in the opening sentence of the introduction, artificial intelligence is basically a collection of technologies used to educate machines to perform human tasks. Burns, Laskowski and Tucci define it as "the simulation of human intelligence processes by machines, especially computer systems". The common denominator is *machines*, underlining the role of automation in AI development. The typical pathway of operation of AI systems consists of absorbing training data, analyzing it for patterns and correlations, and using these patterns to predict future states (Burns et al., 2019). In order to go through this process, an intelligent agent – the autonomous entity perceiving AI environment and taking AI-evoked actions (Wikipedia, n.d.) – must be programmed. This programming procedure involves three particular cognitive skills (Burns, Laskowski & Tucci, 2019):

- **Learning** – focuses on acquiring data and creating rules for transforming it into actionable information. The rules are known as algorithms and provide step-by-step instructions on how to complete a task.
- **Reasoning** – focuses on the selection of the right algorithm for achieving a desired outcome.
- **Self-correction** – focuses on continuous fine-tune of algorithms for the sake of producing results of maximum accuracy possible.

In addition, artificial intelligence can be classified in two types, according to IBM Cloud Education (2020): *weak AI*, which is limited to the function of completing specific tasks, thus enabling robust applications and autonomous vehicles; and *strong AI* – a more complex structure involving two additional concepts: *Artificial General Intelligence (AGI)* and *Artificial Super Intelligence (ASI)*. AGI is based on the idea that machines and humans have the same level of intelligence, suggesting a machine has a self-aware consciousness. ASI goes beyond this limit and implies that machine intelligence surpasses the abilities of human brain.

### *2.1.2 Application*

Artificial intelligence has found an application in a myriad of areas and industries. The earliest recorded use of AI was in 1951 when Christopher Strachey, a researcher from the University of Oxford, wrote an AI program whose function was playing a game of checkers (Encyclopedia Britannica, n.d.). Since then, the boom of technology has led to the development of videogame bots that nowadays form an integral part of the gaming industry.

In addition, AI finds use in Internet and e-commerce (Google search engine, Amazon Alexa virtual assistant), media industry (AI-driven photo editing, music composition, storytelling, visual art production), environmental monitoring [1], agriculture (autonomous robots and drones for planting and harvesting), education (AI tutors and learning environments), and so on (Wikipedia, n.d.). Nevertheless, AI is not only implemented in usable products, but more importantly, in businesses and their operations. 35 percent of the companies all around the world have reported the use of AI in their business (IBM, 2022). One of them is Amazon, whose implementation of AI-driven dynamic pricing will be explored in section 4.

To sum up, artificial intelligence can be found practically anywhere in humans' everyday life. This wide variety of applications is a prerequisite for increasing concerns over privacy and control, which are sensitive topics for modern society.

### *2.1.3 Advantages and disadvantages*

The underlying idea of artificial intelligence is mechanizing human thought (Wikipedia, n.d.). This leads to the assumption that the motivation for developing AI is doubling intelligence so that more tasks and processes are able to be executed in a less error-prone way, thus making human life easier. Reducing human error is also the number one advantage of AI (Soken-Huberty, 2022). She proceeds to name further benefits of AI, from which the ability to help with repetitive and/or dangerous jobs stands out. This essentially contributes to reducing human error and also improving safety, therefore ensuring better working conditions. Another advantage associated with labor is that AI and automation create a lot of jobs, with 58 million vacancies expected to open up (Hanspal, 2021). In the end, the wide application of AI not only opens new niches that generate more human-performed tasks, but also increases working efficiency, helping workers to achieve better results. This supposes more personal benefits for them.

Downsides are also applicable to artificial intelligence. The first thing that comes to mind is the complexity associated with developing an intelligent agent and leading it through the programming process required for the existence of fully functional AI. For this to happen, deep technical expertise is needed (Burns et al., 2019). Currently, there is a shortage of workers possessing the necessary skills and experience, potentially stalling progress for both the development of AI as a whole as well as its particular implementor (Financial Times, 2021). In addition, there are issues related to AI essence itself, for example understanding only what it is taught, id est, capturing specific cues around which it bases its whole reasoning. AI does not understand emotion, which means there are limitations in its intelligence compared to humans.

## 2.2 Illusions about AI

In the context of this research, illusion refers to a false belief, or misconception, of the essence, purpose and implementation of AI. Usually, misconceptions originate from personal experience, imprecise language, lack of examples and non-examples in concept formation, errors in logic or media representation of phenomena (Betkowski, 1989), but also from superficial understanding (Khalid & Embong, 2020). Consequently, these misconceptions become part of an individual's viewpoint, which is represented in debates over a particular topic. In the case of AI, debates about the validity and applicability of the algorithms that AI employs have been emerging ever since the dawn of technology. Grabiner (1984) outlined four controversies of the $20^{th}$ century associated with the potential of machines to match human thinking, which is one of the bases of AI. The first controversy (Lucas, 1961) questioned the adequacy of mechanical models of the human mind by using mathematical theory to induce that the models work based on an unprovable formula that cannot be reproduced by the machine and is perceived as true by humans, ultimately suggesting that humans can beat machines in intelligence. The second controversy (Dreyfus, 1979) questioned the meaning of "intelligence" when used to describe a machine, stating that AI works under the false assumption that the human mind "works by operating on bits of information, and performs its operation according to formal rules", effectively lacking human qualities such as tolerance of ambiguity and "the ability to distinguish between the essential and the inessential". The third controversy (Searle, 1980) questioned the adequacy of the Turing test – a test of a machine's

[1] https://aiforgood.itu.int/

ability to exhibit intelligent behavior equivalent to that of a human (Wikipedia, n.d.) – arguing that passing it does not mean a machine thinks or understands like humans do. Searle pointed out that the Turing test is "behavioristic and operationalistic" and does not distinguish between simulation and duplication. This implies the test is literal and focuses on a specific instance, which means there is no continuity in the machine's thinking process and therefore no intelligence. The fourth controversy (Weizenbaum, 1976) was again in favor of the "humanistic" point of view, stating that the information-processing model of a human is both "empirically false" and "morally wrong". Weizenbaum highlights the emotional aspect in his theory, arguing that people can do things machines cannot, for instance, understanding natural language in a context of experiences like love and trust, which are atypical for machines.

All of these controversial theories were met with the corresponding objections from other scientifically competent people (Grabiner, 1984), effectively converting the subject into a human versus machine debate, which even nowadays is one of, if not the main topic of discussion about AI. Both advocates and opponents of AI maintain their opinions without necessarily sticking to scientifically proven facts, given the amount of fake news and propaganda surrounding AI and machine learning technologies (Woolley, 2020). Therefore, it can be said the discrepancies between both viewpoints are a major cause of illusions about AI.

## 2.3 Ethics in AI implementation

The OECD.ai Policy Observatory[2] has developed a set of five ethical principles of AI implementation. They are values-based, underlining the role of human beliefs and attitudes towards AI in its future development. The principles concern inclusive growth, sustainable development and well-being, human-centered values and fairness, transparency and explainability, robustness, security and safety, as well as accountability. Furthermore, Hermann (2021) studied the relation between ethics and AI and found out there were five common ethical principles associated with AI implementation – explicability, justice, non-maleficence (no intent to do harm), beneficence (doing good for everyone) and autonomy. The key principle is explicability, which entails intelligibility (understanding how AI works) and accountability (claiming responsibility for AI operations). In terms of importance, it is followed by the principle of autonomy, which is about balancing human and AI agency and decision-making power. It could be said that this principle is the source of many concerns about AI, because fear of being overpowered or replaced by a machine is a common and natural human reaction. In addition, lack of clarity over the roles of humans and intelligent agents in AI implementation is a cause of illusions about AI.

## 2.4 End-users' Attitude towards AI (ATAI)

The variety of opinions and attitudes towards artificial intelligence, from openness to skepticism, called for the creation of "a short and valid measure to assess individual differences in such attitudes", which would also enable future research on human–AI interaction. It was named "Attitude Towards Artificial Intelligence (ATAI) scale" and developed by Sindermann et al. in 2020. It features in English, German and Chinese language for the sake of larger audience and, more importantly, cultural differences in willingness to use particular AI-based products (Sindermann et al., 2020). This measure consists of five short statements to be answered on a Likert scale ranging from "strongly disagree" to "strongly agree". The statements concern people's individual trust (or fear) in AI, as well as their perception of its effect on humanity as a whole (Sindermann et al., 2020). The answers to the statements are also influenced by an introduction and description of five specific AI-based products, which were part of this measuring tool in the developers' original research.

The ATAI scale is to be implemented in this research, albeit without including specific products. This is because the five statements are an accurate compilation of the most basic perceptions of AI – trust and fear, benefits and negatives to humanity – which makes it an ideal measure of individual attitudes at first glance. In other words, these statements are an accurate representation of an individual's attitude towards AI under the assumption of independence. For this reason, the research can investigate the influence of several particular factors on individual attitude towards AI.

### *2.4.1 Digital literacy*

Digital literacy is the first factor to be considered. It is defined as "the ability to navigate our digital world using reading, writing, technical skills, and critical thinking" by means of electronic devices (Microsoft, n.d.).

Nevertheless, digital literacy was perceived as a term with a vague meaning and as such, it was difficult to come up with a measure for it. Driven by the desire to increase focus on in-depth skill measurements, van Deursen and van Dijk (2008) broke down the broad term "digital skills" in four categories: *operational* skills (operating digital media); *formal* skills (handling the structures of digital media); *information* skills (locating information in digital media); and *strategic* skills (employing that information towards personal and professional development). The lack of depth in digital skills-related interpretations forced van Deursen and van Dijk to give further definitions to each of these skill types. Operational skills referred to one's ability to work with an Internet browser, search engines and online forms, and to distinguish between file formats. Formal skills referred to one's ability to recognize different types of web content and to navigate through Internet while maintaining a sense of orientation. Information skills referred to one's ability to organize and conduct a web search for information, while strategic skills referred to the ability to utilize the information found online for the sake of achieving a particular goal.

Similarly to how this framework was implemented to measure the digital skills of the Dutch population (van Deursen & van Dijk, 2008), this research intends to use it in order to measure the digital skills of a population sample with the idea to find out whether and how do these skills affect an individual's attitude towards AI. Researchers have already investigated the influence of digital skills on AI development, pointing out that "firms with stronger digital skills anticipate stronger AI-induced business impacts compared to firms with weaker digital skills" (Brock & von Wangenheim, 2019). Just like that, most of the research on the topic is concentrated on the business and not individual point of view. Therefore, this paper will address the relationship between individual digital skills and AI as well.

### *2.4.2 Perceived usefulness & ease of use*

The Technology Acceptance Model (TAM) is a framework measuring the adoption of a particular technology based on individuals' perception of it. An extension of Fishbein & Ajzen (1975)'s theory of reasoned action (TRA), the TAM was developed by Davis, Bagozzi & Warshaw in 1989 and replaces the TRA's attitude measures with the two technology acceptance measures – *perceived usefulness* and *perceived ease of use.* Davis (1989) defined perceived usefulness as "the degree to which a person believes that using a particular system would enhance

[2] https://oecd.ai/en/

their job performance" and perceived ease of use as "the degree to which a person believes that using a particular system would be free from effort". In order to estimate these two variables, Davis developed a set of statements for which recipients would give an answer ranging from "highly likely" to "highly unlikely", so that a statistically recognized measure is delivered (Hanlon, 2019).

Researchers have been investigating the relationship between technology acceptance and AI. Na et al. (2022) designed a new acceptance model of AI-based technologies in construction firms by applying the TAM in combination with the technology-organization-environment (TOE) framework. Again, existing research mostly focuses on the business perspective. In this paper, the two main components of TAM will be used to investigate individual perception of AI-based technology. More specifically, a case of an AI-driven virtual clothing try-on app will be presented to a population sample, which should estimate the app's usefulness and user-friendliness (see *Appendix A1)*.

### *2.4.3 Public opinion*

Public opinion is defined as "an aggregate of the individual views, attitudes, and beliefs about a particular topic, expressed by a significant proportion of a community" (Encyclopedia Britannica, n.d.) or "the collective opinion on a specific topic or voting intention relevant to a society" (Wikipedia, n.d.).

In practice, public opinion on AI has become an emerging area of study within AI policy. The main reason for this is the role of the public as a major stakeholder in shaping the future of AI, as well as its development and deployment (Zhang, 2021). Most of the research on public opinion was focused on knowledge and trust in AI. Johnson & Tyson (2020) attributed the variance in global opinions to the cultural, gender and educational differences. However, there has not been given enough attention to the influence of public opinion on the individual attitude towards AI. For this reason, it will be addressed in this paper. More precisely, the research shall estimate the influence of different actors' opinions on the subject – experts, influencers and friends – on the individual attitude towards AI. This will be done via self-developed scale containing items measuring the aforementioned influence and its relevance to the particular individual. It would also help to determine whether individuals are more or less prone to manipulation from a group of different people (the public), therefore, to absorbing illusions about AI.

# 3. METHODOLOGY

## 3.1 Research design

This research aims to explore the differences between perceptions of AI by two actors – a company (implementor) that makes use of this technology for business purposes, and individuals (receivers) that observe applications of AI in their everyday life. Essentially, the research uses these two actors as data sources. While the company perspective is only analyzable through available literature, the individual perspective is measurable through data collection and analysis. Hence, it can be said the research connects a theoretical review and empirical data with the idea of putting a social problem – the emergence and spread of illusions about AI – into context, laying the ground for further research and solution. The theoretical part of the research consists of a case study of Amazon's implementation of AI, as well as a literature review introducing various concepts estimated to affect an individual's attitude towards AI. The empirical part represents a data analysis of this attitude. Therefore, the research methodology can be defined as a concurrent mixed-method, allowing the results from the two separate parts to be interpreted together in order to provide a richer and more comprehensive response to the research question (Saunders et al., 2019). In addition, a mixed methodology allows researchers to "explore diverse perspectives and uncover relationships that exist between the intricate layers of multifaceted research questions" (Shorten & Smith, 2017). Therefore, the presence of the two perspectives in this research – company versus individual – makes this method appropriate for the cause.

For the first part, an extensive literature research was conducted. The scientific papers were sought from online databases (Google Scholar, Scopus, ResearchGate). To ensure the material was as relevant to the topic as possible, the article search was mainly based on keywords including parts of the title and the research question. The literature research was about the essence of AI, the way it functions, its areas of application and the benefits and downsides of its implementation. Then, this topic was connected to the other domains of this research. The concept of illusion, as well as its relationship to AI, was introduced first. Afterwards, several concepts related to AI perception were identified and presented. The Amazon case is to be presented in section 4 in the form of a case study. The case is to be put into an ethical context, connecting it with the generally accepted ethical principles of AI development and implementation.

The second part of the research involves the collection and analysis of individual data in the form of an online survey investigating the attitude of individuals towards AI. This method was chosen because online surveys are faster, cheaper and easier to use for both researchers and respondents than the traditional paper questionnaire. By collecting data from individuals, and having already studied the first part, perception of AI from both perspectives – company and individual – can be compared, which would ultimately resolve the research question.

The data analysis is based on operationalizing the factors deemed to affect individual attitude towards AI, introduced in section 2.3. They should be measurable through the survey items and the outcomes analyzable through statistical methods. In accordance with RQ3, each factor, represented as a construct, is shown to have a relationship to individual attitude towards AI (also represented as a construct). In turn, attitude is associated with susceptibility to illusions towards AI. *Figure 1* graphically represents the relationships, which are going to be tested via the following hypotheses:

H1: An individual's high level of operational skills positively affects their attitude towards AI.

H2: An individual's high level of formal skills positively affects their attitude towards AI.

H3: An individual's high level of information skills positively affects their attitude towards AI.

H4: An individual's high level of strategic skills positively affects their attitude towards AI.

H5: Perceived usefulness of AI-based technologies positively affects an individual's attitude towards AI.

H6: Perceived ease of use of AI-based technologies positively affects an individual's attitude towards AI.

H7: Prioritization of public opinions about AI positively affects an individual's attitude towards AI.

H8: The more positive an individual's attitude towards AI, the lesser the individual's susceptibility to illusions about AI.

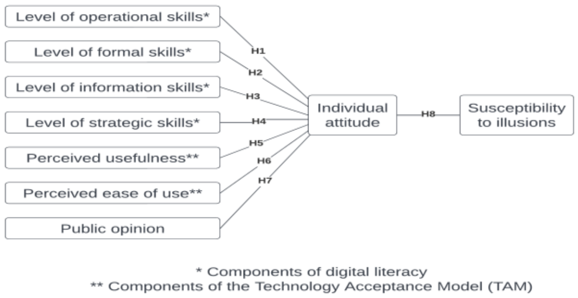


**Figure 1. Relationship model for data analysis.**

## 3.2 Survey design and measurement

The concepts from the literature review, as well as their relationship to AI and illusions about it, served as the basis of the survey that intends to measure individual attitude towards AI. The survey was divided into several sections, including demographic information about respondents. The first one included the five statements of the ATAI scale and the second included statements about AI perception, particularly some of the most common illusions about the topic – without mentioning it in the description – to test respondents' susceptibility to them by indicating the extent to which they agree with the statements. The illusions were sourced from the works of Jordan (2019) and Emmert-Streib et al. (2020). The next section involved statements about the four dimensions of digital skills, developed by van Deursen & van Dijk (2008). Then, statements about perceived usefulness and perceived ease of use, adapted from Davis (1989) and accompanied by a short presentation of an AI-based technology, were presented. The final section involved self-generated statements about the relevance of public opinion. The whole survey, except for the demographic information part, consisted of statements to be answered on a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The survey was created using the Qualtrics XM software.

## 3.3 Survey data collection

A link to the survey was distributed online via social media, the SurveySwap platform and further diffusion by particular respondents. The data collection process started in the last week of July and took approximately a week and a half to complete. There were no restrictions in the sampling process. In total, 69 respondents took part in the survey, but 7 of them did not complete it. The data provided by the remaining 62 respondents will be analyzed in section 5.

# 4. STUDY 1: CASE STUDY OF AMAZON'S DYNAMIC PRICING

As technology and AI keep developing, the demand for algorithmic automation of services keeps growing. The key issue with this is the ambiguity of the algorithms involved (Gómez-Losada et al., 2022). Therefore, researchers have begun to investigate the way in which companies operate with AI in their business. This study will follow these steps, focusing on Amazon and its AI-driven dynamic pricing in order to find the reasons for which this company implements AI in its operations.

## 4.1 The case

Amazon.com Incorporated is a multinational tech company operating in the industries of e-commerce, cloud computing, digital streaming and artificial intelligence (Wikipedia, n.d.). It is a world leader in online retailing, with net sales revenue amounting to nearly $470 billion in 2021. (Coppola, 2021). One of the pillars to Amazon's success is the multi-level sales strategy the company employs. It supports business-to-consumer relationships through its website, digital services and brick-and-mortar stores, business-to-business relationships with its suppliers, and consumer-to-consumer relationships through Amazon Marketplace (Wikipedia, n.d.). This is a platform allowing third-party individuals to sell products on a fixed-price online marketplace. The pricing on the platform is however subject to a strict set of guidelines developed by Amazon, the main one being fairness – the price must be equal to or lower than the price of the same item on other places. There is also a limit to the amount a seller can list an item for. Apart from this, other price-influencing factors include shipping, handling, discounts and Low Price Comparison, a filter for similar items allowing for competitive pricing (Feedvisor, n.d.).

In itself, dynamic pricing is a blanket term for any shopping experience where the price of an item fluctuates based on current market conditions. The main advantage of dynamic pricing is that it ensures fairness on the market. Customers benefit by taking advantage of market dips in order to buy for cheap, while sellers benefit from the ability to adjust prices for profit maximization (Feedvisor, n.d.).

In the Amazon case, dynamic pricing is used by both the company itself and third-party sellers with the goal of product price optimization (Feedvisor, n.d.). As per Guerrero (2021), Amazon makes an average of 2.5 million price changes per day. Such a number suggests that these changes cannot be made manually. In effect, Amazon implements AI-based algorithms weighing a number of metrics to determine the best possible sales price (Kiczek, 2020). These metrics include demand and stock volume, product popularity and day and time of purchase. For instance, if stock units are already low, and continued demand is expected, prices are likely to increase as long as it does not limit purchases for a specific customer segment. In addition, the algorithms make use of cookie data to track which and how many product pages are visited, thus estimating product popularity (Guerrero, 2021). Another function of Amazon's AI algorithms is to monitor prices of competitors, especially for best-selling products, and therefore reduce sales prices for such products. Furthermore, the algorithms are programmed to have clear preference for products offered by the company directly rather than by third-party sellers, as well as products whose shipping is handled by the buyer. Effectively, Amazon lists products on its marketplace based on seller type, popularity, frequency of return and shipping berth (Chen et al., 2016).

Dynamic pricing strategies are also used by third party sellers on Amazon with the intention to "win" the *Buy Box* – the box shown on every product page which contains the price, shipping information, seller name and purchase button. For products sold by multiple sellers, an AI-based algorithm determines which seller's offer is displayed in the *Buy Box*. For this reason, sellers implement the aforementioned strategies in order to get an advantage with respect to being chosen by the algorithm. It was found that Amazon's algorithm does not rank sellers by selling price only, but by other factors. Gómez-Losada et al. (2022) conducted experiments that determined relevant seller characteristics for Amazon's algorithm. User opinions, product rating and price variation were determined to be the most important features when predicting a change in the *Buy Box* occupation, while product recommendation by Amazon and product popularity were found to be the least important. Amazon also distinguishes between new and experienced sellers, prioritizing price variation for the former and user opinions for the latter. Generally applicable factors are price difference and ratio, positive feedback, average seller rating and level of involvement with Amazon (Chen et al., 2016). This last factor has raised suspicions that Amazon may have "tilted the *Buy Box* algorithm in their favor" and has brought forward the subject of Amazon's ethical behavior.

## 4.2 Amazon's ethical behavior

The implementation of AI-driven dynamic pricing has brought success to Amazon, but it has also raised criticism. For instance, the company was accused of debilitating the rest of the retail ecosystem, including sellers, manufacturers, and even its own employees because of its exclusive focus on customers. Furthermore, Amazon has raised concerns over being both owner and seller in the same marketplace, making use of data available in the entire marketplace, which is not accessible to other sellers in it (Wikipedia, n.d.). It is therefore implied that the company performs unfair practices against its own customers, violating the principle of justice.

In 2018, the European Commission sent out formal requests for information to investigate allegations of an anticompetitive conduct by Amazon (Höppner & Westerhoff, 2018). One of the main subjects were the alleged interdependencies between Amazon Marketplace and the company's own retail operations, creating a conflict of interests between business customers (merchants) and individual end-customers (shoppers). Most allegations concern the manner in which Amazon collects and analyzes retailer data to learn which products sell well, and a crucial question is whether Amazon uses the data collected to improve its service for the customers, or uses it for own benefit. The company's market position is a major area of concern for two reasons. Firstly, abuse of dominant market position is prohibited, as it harms competition and encourages monopoly, which would dramatically reduce customers' choice options. Secondly, Amazon's dual position as merchant platform and online retailer allows the company to adjust its own offerings on retail level to the success or failure of other companies selling identical or comparable goods, basically using an unfair advantage to mitigate or completely eliminate the risk of a commercial failure (Höppner & Westerhoff, 2018). The conflict of interests is further expressed by that Amazon's collection and use of the market data gathered through its Marketplace can also be treated as an "exchange of information" amongst competing merchants. In the end, Amazon was found to have breached EU antitrust rules by distorting competition in online retail markets, "systematically relying on non-public business data of independent sellers who sell on its marketplace, to the benefit of Amazon's own retail business, which directly competes with those third party sellers" (European Commission, 2020).

Amazon's corporate code of ethics [3] has various sections concerning the company's pricing and financial policies. The code maintains that "employees may not discuss prices or make any formal or informal agreement with any competitor regarding prices, discounts, business terms, or the market segments and channels in which the Company competes, where the purpose or result of such discussion or agreement would be inconsistent with applicable antitrust law". In other words, employees of Amazon should follow the principles of justice and non-maleficence by acting in a way that is aligned with the local laws enforcing customer protection and fair competition. In addition, the code requires that Amazon's "books, records, accounts and financial statements must be maintained in appropriate detail, must properly reflect the Company's transactions and must conform both to applicable law and to the Company's system of internal controls". This means Amazon gives the necessary attention to transparency, which is one of the most important aspects of maintaining an ethically sound relationship with stakeholders.

In the end, while Amazon's good reputation is intact and the company puts effort in maintaining fairness in its operations, the irregularities and controversies regarding the company's competitive behavior will inevitably contribute to the creation of illusions about the purpose of Amazon's (and customer-centric companies as a whole) implementation of AI.

## 4.3 Amazon's strategy and motivation

Since its beginning, Amazon and its founder Jeff Bezos have prioritized growth over profitability, and the company's business plan included five years without profit (Reimers & Waldfogel, 2017). At that time, the company spent heavily on advertising in order to win customers over and make them comfortable while purchasing from Amazon. This strategy also involved the company charging low prices for its products. Amazon argues that it is "internally driven to improve our services, adding benefits and features, before we have to."

The company's pricing strategy was investigated by Reimers and Waldfogel (2017). The researchers compared Amazon's contemporary pricing on e-books (a relatively new product with complementary costs) with its pricing on physical books (a now-mature product without complementary costs). At the emergence of e-books, Amazon priced them below wholesale cost, which undermined sales of physical books through traditional channels, thus causing competitors to raise prices. The key question was whether these pricing examples were early-stage instances of a dynamic profit maximization strategy. To answer it, Reimers and Waldfogel used observations on prices and sales ranks for the books within a period of one year in conjunction with actual quantity data. The data would then be compared with the expected price figures for static profit maximization (Reimers & Waldfogel, 2017).

These figures are estimated thanks to the different expectations about the pricing of emergent and mature products in relation to the role of profit maximization. Prices on new/emergent products are expected to fall short of the static profit-maximizing levels, as demand and costs for new products cannot be forecasted with precision. On the other hand, prices on mature products are expected to be better described by static models of profit maximization, as demand and costs are already well known. Additionally, pricing also depends on whether products are seen as substitute or complementary goods. Reduction in textbook price stimulates demand for a complement (e-book), therefore pricing for the complement is below the static profit maximizing level (Reimers & Waldfogel, 2017).

There are various reasons to consider low pricing as part of a dynamic profit maximizing strategy (Reimers & Waldfogel, 2017). Firstly, low prices on new products, like e-books, attract customers to Amazon. This can be considered as an investment in customer base. It would repay in the future in the form of the ability to charge higher prices, as customers would prefer to avoid switching costs. Therefore, higher prices for a large customer base maximizes profit. Another reason is that the low price of e-books induces authors and publishers to "join the seller side and give up a share of their revenues to Amazon" in exchange for the advantage of Amazon's large customer base.

As an additional measure, Reimers and Waldfogel estimated the price elasticities of demand for books at Amazon. In line with expectations, elasticities for e-books were found to be indicative of prices below the static profit maximizing levels, implying a dynamic strategy. More surprisingly, the outcome was the same for the mature product (physical books). This means that Amazon keeps charging low prices for many of its products, regardless of their maturity. This is aligned with what the company refers to as

[3] Amazon Code of Business Conduct and Ethics

an "investment in trust". In the end, Amazon's pricing strategy can be interpreted in multiple ways. More likely, the company may be still in the process of enlarging its customer base. A more ill-minded possibility is that Amazon engages in "predation", or eliminating competition. The third, less likely option, is that Amazon is simply an altruistic company that prioritizes consumer surplus and trust ahead of economic profits (Reimers & Waldfogel, 2017).

# 5. STUDY 2: INDIVIDUAL PERCEPTION OF AI – ANALYSIS & RESULTS

The data analysis was done via the SPSS statistical software. The first part assesses the reliability of the constructs via Cronbach's alpha. Then, factor analysis was implemented to ensure that items are properly related to their respective constructs. Lastly, the hypotheses were tested via multiple regression.

## 5.1 Demographics

The demographic information about the respondents was classified in three categories – age, gender and location. The respondents were of different ages, ranging from 17 to 70 years. Most of them were 22 years old (8 out of 62, 12.9 percent) and 23 years old (7 out of 62, 11.3 percent). The next most frequent age figures were 21, 38 and 49 years old, with five respondents (8 percent) for each. The gender distribution was more or less balanced, with male respondents being 53.2 percent (33 out of 62) and female respondents being 46.8 percent (29 out of 62). Finally, in terms of geographic location, the vast majority of respondents were European (56 out of 62, 90.3 percent). Five respondents were from Asia (8.1 percent) and one was from Africa (1.6 percent). For a graphical scheme, see *Appendix B.*

## 5.2 Reliability analysis

This analysis involved the assessment of the internal reliability of each construct that comprises the quantitative relationship model. Firstly, the scales measuring the four dimensions of digital literacy were shown to be of high internal consistency, with Cronbach's alpha values of 0.82, 0.793, 0.793 and 0.783, respectively. Next, the scales measuring perceived usefulness and perceived ease of use showed even higher consistency, with respective alpha values of 0.834 and 0.913. The self-developed scale measuring public opinion was not so highly consistent, with an alpha value of 0.641.

Moving on to the dependent variables, Sindermann et al. (2020)'s ATAI scale was showed to be relatively consistent, with an alpha value of 0.699. Finally, the self-developed scale measuring AI perception had a similar level of internal consistency, with an alpha value of 0.652.

According to multiple sources, a reliable Cronbach's alpha value should be 0.7 or above (Nunnally, 1978), while values near 0.7 are considered "minimally acceptable". Therefore, some constructs had to be modified in order to yield such a value. The modification consisted of deleting scale item(s). *Table 2* graphically represents the reliability analysis and descriptive statistics, including the modified constructs and the corresponding new values.

**Table 2. Reliability analysis & descriptive statistics.**

| | V1 | V2 | V3 | V4 | V5 | V6 | V7 | V8 | V9 |
|---|---|---|---|---|---|---|---|---|---|
| Cronbach's α | 0.82 | 0.793 | 0.793 | 0.783 | 0.834 | 0.913 | 0.702 | 0.743 | 0.668 |
| No. of items | 9 | 4 | 4 | 4 | 5 | 5 | 8 | 4 | 8 |
| Mean | 4.83 | 4.44 | 4.44 | 4.22 | 3.60 | 4.31 | 3.39 | 3.495 | 3 |
| Std. deviation | 0.32 | 0.746 | 0.65 | 0.67 | 0.77 | 0.645 | 0.64 | 0.81 | 0.64 |

V1 – Operational skills; V2 – Formal skills; V3 – Information skills
V4 – Strategic skills; V5 – Perceived usefulness; V6 – Perceived ease of use
V7 – Public opinion; V8 – Attitude towards AI (ATAI); V9 – Susceptibility to illusions

In the end, all but one construct met the threshold of 0.7. Susceptibility to illusions about AI was not as reliable as the other constructs. This can be explained by the abstract nature of illusions and, correspondingly, the complexity involved in their operationalization and measurement.

## 5.3 Factor analysis (FA)

The FA was implemented in order to determine how strong is the relationship between items and their corresponding constructs, thus ensuring they fit to the model. This is known as confirmatory factor analysis (Wikipedia, n.d.). Before proceeding with the analysis, several tests had to be conducted to make sure the data was appropriate for FA (Watkins, 2018). Firstly, Kaiser-Meyer-Olkin (KMO) test for sampling adequacy was conducted for each construct, along with Bartlett's test for sphericity. The data would be suitable for factor analysis if the KMO values are above 0.5 (Kaiser, 1974) and Bartlett's test significance is below 0.05 (Shrestha, 2021). Since these requirements were met for each construct (see *Table 2*), factor analysis of data was appropriate to implement in this research.

The theory on FA suggests that items with a factor loading less than 0.3 should be suppressed (Field, 2013), while loadings higher than 0.4 are considered stable (Guadagnoli & Velicer, 1988). *Table 3* represents the outcome of the factor analysis.

**Table 3. Factor analysis.**

| Construct | Items | Factor loading |
|---|---|---|
| *Level of operational skills* KMO = .653 Bartlett's test = < .001 | Q11_1 | .744 |
| | Q11_2 | .803 |
| | Q11_3 | .608 |
| | Q11_4 | .736 |
| | Q11_5 | .611 |
| | Q11_6 | .680 |
| | Q11_7 | .738 |
| | Q11_8 | .483 |
| | Q11_9 | .843 |
| *Level of formal skills* KMO = .755 Bartlett's test = < .001 | Q12_1 | .238 |
| | Q12_2 | .965 |
| | Q12_3 | .958 |
| | Q12_4 | .975 |
| *Level of information skills* KMO = .667 Bartlett's test = < .001 | Q13_1 | .793 |
| | Q13_2 | .795 |
| | Q13_3 | .814 |
| | Q13_4 | .755 |
| *Level of strategic skills* KMO = .753 Bartlett's test = < .001 | Q14_1 | .836 |
| | Q14_2 | .901 |
| | Q14_3 | .554 |
| | Q14_4 | .901 |
| *Perceived usefulness* KMO = .808 Bartlett's test = < .001 | Q17_1 | .808 |
| | Q17_2 | .821 |
| | Q17_3 | .741 |
| | Q17_4 | .761 |
| | Q17_5 | .804 |
| *Perceived ease of use* KMO = .868 Bartlett's test = < .001 | Q18_1 | .866 |
| | Q18_2 | .898 |
| | Q18_3 | .794 |
| | Q18_4 | .871 |
| | Q18_5 | .882 |
| *Public opinion* KMO = .667 Bartlett's test = < .001 | Q20_1 | .658 |
| | Q20_2 | .707 |
| | Q20_3 | .602 |
| | Q20_4 | .250 |
| | Q20_5 | .358 |
| | Q20_6 | .684 |
| | Q20_7 | .574 |
| | Q20_8 | .632 |
| *Attitude towards AI (ATAI)* KMO = .694 Bartlett's test = < .001 | Q7_1R | .623 |
| | Q7_2 | .795 |
| | Q7_3R | .806 |
| | Q7_4 | .794 |
| *Susceptibility to illusions* KMO = .582 Bartlett's test = < .001 | Q9_2 | .586 |
| | Q9_3 | .662 |
| | Q9_4 | .533 |
| | Q9_5 | .499 |
| | Q9_6 | .632 |
| | Q9_7 | .356 |
| | Q9_8 | .427 |
| | Q9_9 | .661 |

It can be seen that most of the items were indeed strongly associated with their respective constructs. Only Q12_1 and Q20_4 had a loading smaller than 0.3 and were therefore extracted from the model. In other words, ability to distinguish between hyperlinks (as part of formal digital skills) and the difference in importance between expert and influencers' opinions when it comes to formulating a personal opinion of AI, were shown to be insignificant in the context of this research.

## 5.4 Hypotheses testing

In order to test the hypotheses, two multiple linear regression analyses were conducted – first, the effect of factors on individual attitude was tested, and then the effect of the attitude on susceptibility to illusions. Before that, there were some preparatory activities. Firstly, as a consequence of the factor analysis, the items were organized in new constructs. This was done by calculating the mean of items for each construct, which is one of the preferred methods for summarizing ordinal data. Secondly, a correlation analysis was carried out in order to estimate the strength of the linear relationship between variables. Almost every independent variable was shown to have a positive correlation to attitude towards AI, except for formal skills, which was negatively correlated. However, the relationships were rather weak, with Pearson coefficients ranging from 0.05 to 0.23. Contrary to expectations, attitude towards AI was shown to be positively correlated to susceptibility of illusions (0.316). For more details, see *Appendix C*.

The outcome of the regression analysis was surprising. It appeared that neither of hypotheses 1-7 were supported, with most of the significance values not being even close to 0.05. $H_5$ was the closest to this value, with significance of 0.204. In other words, perceived usefulness of AI-based technologies ($\beta = 0.217$, $t = 1.287$) was the most relevant to attitude towards AI out of the whole set of variables. Nevertheless, $H_8$ had a significance value of 0.016, which is smaller than 0.05, and the hypothesis was therefore accepted. This means that attitude towards AI ($\beta = 0.23$, $t = 2.488$) has a significant positive effect on the susceptibility of illusions, or in other words, the more positive individual attitude towards AI is, the more susceptible to illusions is the individual. In terms of fit, the model explains only 10.1% of the variance in the dependent variable ATAI (see *Appendix D*). *Table 4* represents the regression analysis results and verdict.

**Table 4. Multiple regression analysis.**

| Hypothesis | β | *t* | *p* | Result |
|---|---|---|---|---|
| H1. OpSkills → ATAI | .272 | .932 | **.355** | Rejected |
| H2. FormalSkills → ATAI | −.076 | −.521 | **.605** | Rejected |
| H3. InfoSkills → ATAI | .194 | .746 | **.459** | Rejected |
| H4. StrategicSkills → ATAI | −.129 | −.557 | **.580** | Rejected |
| H5. PU → ATAI | .217 | 1.287 | **.204** | Rejected |
| H6. PEOU → ATAI | −.104 | −.414 | **.680** | Rejected |
| H7. PublicOpinion → ATAI | .152 | .890 | **.377** | Rejected |
| H8. ATAI → SuscToIllusions | .230 | 2.488 | **.016** | Accepted |

## 5.5 Illusions popularity

This step involved carrying out a frequency analysis of the dataset in order to determine the popularity of illusions associated with AI. The illusions were extracted from the works of Jordan (2019) and Emmert-Streib et al. (2020), as well as personal experience. The analysis was conducted by generating the frequency tables for each item from the "susceptibility to illusions" construct and summing the values of the "somewhat agree" and "strongly agree" categories. It was found out that the most common illusion is that progress in AI development is necessary to solve relevant problems, with 33 respondents believing so, or 57.9 percent of the answers for this item being "somewhat" and "strongly" agree. On the other hand, the least popular illusion was that AI is able to properly understand and react to novel (unfamiliar) situations at all times, with only 13 respondents believing so, or 22.8 percent of the answers for the item being in favor of this illusion. The outcome is summed up in *Table 5*.

**Table 5. Illusions popularity.**

| Illusion | Frequency |
|---|---|
| Progress in AI development necessary for problem solving | **33 (57.9%)** |
| Progress in AI development sufficient for problem solving | **26 (45.7%)** |
| Human intelligence is the only benchmark for AI | **23 (40.4%)** |
| AI works similar to the human brain | **23 (40.4%)** |
| AI ensures machines = humans in performance | **23 (40.3%)** |
| Data collection as main purpose of AI | **19 (33.9%)** |
| AI = machine learning | **19 (34%)** |
| Proper adaptation of AI to novel situations at all times | **13 (22.8%)** |

# 6. DISCUSSION

## 6.1 Findings

This study is based on a model connecting individual attitude towards AI and the factors that supposedly influence it, with the susceptibility to illusions associated with the subject. Even though the model was shown to be inadequate, valuable insights were generated. Most importantly, it was proven that end-users' attitude towards AI significantly affects susceptibility to illusions about the concept, even though the effect sign (positive) clashes with the one of the original hypothesis (negative). The logic behind the hypothesis was that as an individual is more favorable of AI, and therefore considered more knowledgeable, it is less likely for them to absorb illusions. However, it turned out the opposite, which also makes sense, as a too favorable opinion may cause excessive trust in AI and therefore easier manipulation.

Just like a negative attitude generates illusions unfavorable of AI, a positive attitude can generate favorable illusions. For instance, nearly half of the respondents (45.7 percent) believe current progress in AI development is sufficient to solve relevant problems, which is something that praises the abilities of AI, but in fact is not true, as many problems require advanced solutions that are out of the range of current human competencies. Therefore, the AI developed by humans lacking the necessary competencies will also be unable to solve such problems. It is implied that the solutions needed involve complex processes of massive data usage and adaptive statistical modeling, which should be addressed in further development of AI (Jordan, 2019). Similarly, a fair portion of respondents (33.9 percent) believe that the main purpose of AI is data collection, which indirectly hints that it is a threat for privacy and security. This is also not true and is therefore an example of an illusion unfavorable of AI. In reality, AI assumes the availability of data which would allow it to study and solve relevant questions or problems (Emmert-Streib et al., 2020). In other words, inflow of data is merely a requirement for the effective operation of AI and not a goal.

People also showed a sense of realism, with only 13 respondents (22.8 percent) being in favor of the illusion that AI is able to properly understand and react to novel situations. The truth is that AI is occasionally not grounded in other modalities of experience, such as video, real-world physical interaction, or human feedback, and thus lacks a large amount of context about the world. Being able to properly adapt to unfamiliar situations is, in fact, a benchmark of genuine intelligence, and true AI will remain an oxymoron until computer algorithms evolve towards mastering this ability (Smith, 2022).

Recurring themes in the Amazon case analysis were algorithmic prioritization and profit maximization. This, as well as relevant trends and statistics showing a steady rise of revenue and share of third-party sellers since the start of dynamic pricing implementation (see *Appendix H*), led to the definition of two main reasons explaining the company's motivation to use AI-driven dynamic pricing ahead of a fixed price formulation strategy. Firstly, Amazon takes advantage of its enormous customer base and brand positioning by creating an image of itself as a leading online retailer offering the best deals. Therefore, counting on customer loyalty, Amazon maximizes its profits by adjusting prices accordingly. The second reason is the company's desire to gain competitive advantage ahead of other mainly physical retailers that do not have the resources to maintain online operations. Therefore, Amazon's perception of AI is that of a profit-making instrument and a vital part of its operations. This is enforced by the fact that the company has managed to cross the ethical border for the sake of profit maximization. Whether Amazon's customers would ignore this out of loyalty to the company is a question which cannot be answered yet.

## 6.2 Academic and practical relevance

The concept of artificial intelligence and its development has been a subject of increased attention and intensive study throughout the years. Researchers have emphasized on the application of AI in various areas and the effects of it on individuals, ecosystems and the society as a whole. This study goes in the opposite direction, investigating not the effects but the causes for AI implementation, as well as its perception. Therefore, gaining insights into the ideas on which AI development is based allowed for shaping a clearer picture of its purpose, and consequently, generating particular expectations of how should AI look like and how should it perform. The research also shines a light on the ethical aspect of AI, thus raising awareness not only of regulators and implementors but on the whole society, paving the way for more research possibilities in the future.

Given the outcome from the comparison between the way individuals and companies see AI, this research offers the possibility for better formulated codes of ethics regarding AI implementation, a more detailed approach to strategic planning and generally a more favorable, responsible attitude towards this topic. The research can serve as an example when companies have to make the decision whether to integrate AI in their operations. Also, regular individuals will have a better idea of how and why their data is processed through AI, thus being fully aware of the advantages and disadvantages of this concept and therefore maintaining an objective point of view towards it, without allowing illusions to cloud their judgement.

# 7. CONCLUSION

Artificial intelligence is a concept yet to be grasped by a large part of modern society, particularly due to its complexity. This results into the creation and distribution of false beliefs, also known as illusions, about the subject, which serve as hurdles for a proper AI development. This study aimed to facilitate this process and shed a light on the topic by investigating the source of illusions. It compared the perception of AI by regular individuals, who are assumingly not in touch with the concept, and a company (Amazon and its representatives), which integrates AI in its operations. The study was based on four research questions which were to be answered via literature review and the development of a quantitative model investigating the effect of individual attitude towards AI, and the relevant factors – digital literacy and its four dimensions (operational, formal, information and strategic skills), perceived usefulness and ease of use of AI-based technologies, and public opinion. Various hypotheses about the relationship between these factors and individual attitude, as well as the relationship between the attitude and individual susceptibility to illusions, were developed and tested. However, it resulted that neither of the aforementioned factors were relevant to individual attitude, while the relationship between the latter and susceptibility to illusions was indeed significant. As for company perception, it was found out that the representatives of Amazon see AI primarily as a way to generate profits, and only secondarily as a concept that should be implemented with significant ethical considerations.

Eventually, only RQ1 and RQ4 had a clear answer. RQ2 and RQ3 were only half-answered, as there is no clear picture of individual attitude towards AI and the factors that determine it. While people believe in illusions both favorable and unfavorable of AI, some also maintain realistic views of it. This should be the driving force behind finding out whether illusions about the topic are fruit of pure ignorance or reasonable concerns.

## 7.1 Limitations

The main limitation of this study was the inadequacy of the quantitative model. Particularly, there were too many variables, some of them unrelated, which resulted into poor fit. Additionally, the sample size was too small given the number of variables. The quantitative analysis is also of dubious significance, as there are no guarantees the surveys were completed truthfully and that it is a representative sample. Finally, this research was focused on a particular application of AI – in the strategic and marketing operations of a company (Amazon), so the findings are not universal across other domains of AI implementation and therefore no general conclusions can be made.

## 7.2 Further research

A general recommendation for further research is to modify and enhance the current model in order to find out which factors really affect an individual's attitude towards AI. Particularly, variables can be combined and better operationalized, and new ones can be added. Their contributions can be presented more clearly via more extensive literature review. Additionally, researchers should think of ways to quantifiably measure company attitude, for example by conducting interviews, surveys or experiments with company representatives. Furthermore, the data sample should be more extensive in order to yield more reliable results. Ultimately, further research could include and align analyses of applications and perceptions of AI in areas other than marketing in order to come up with more widely applicable and significant findings that would consequently facilitate the AI development process, thus doing a favor to society.

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## APPENDIX

A. Survey items

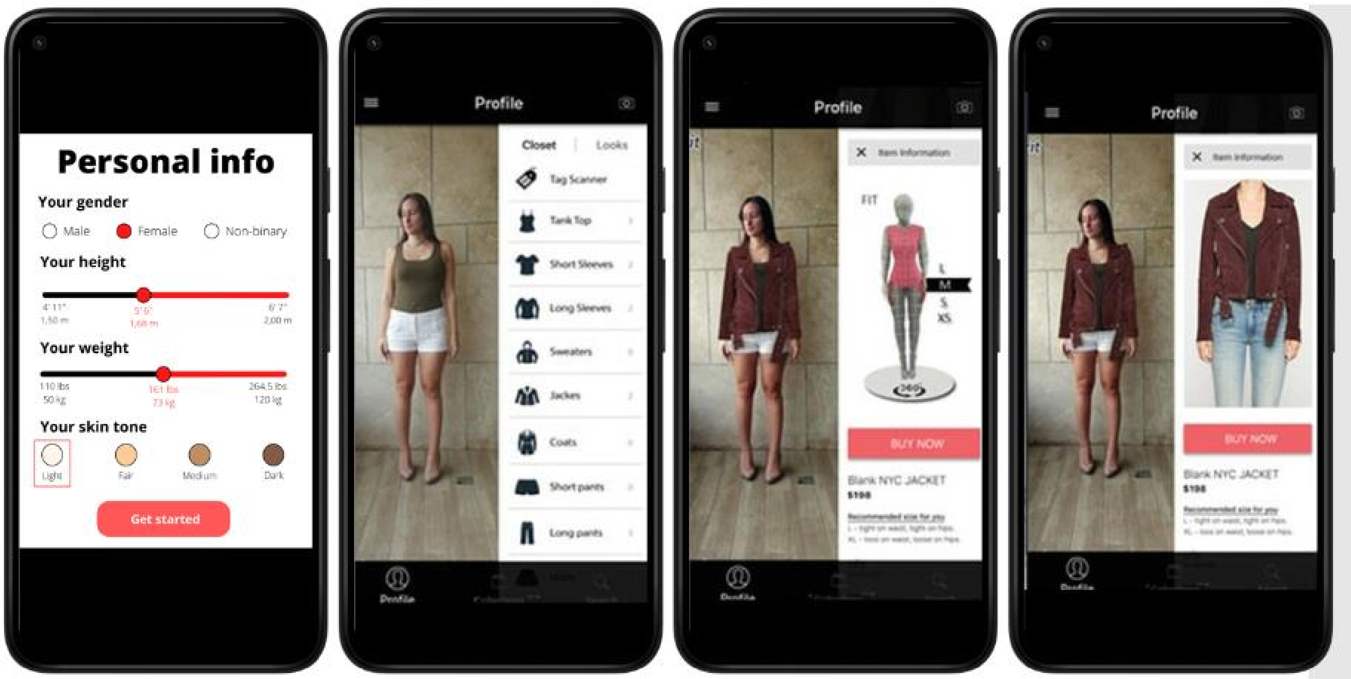
| Items | Statements | Sources |
|---|---|---|
| | CONTROL VARIABLES | |
| Q3 | What is your age? | |
| Q4 | What is your gender? | |
| Q5 | Where are you from? | |
| | ATTITUDE TOWARDS AI (ATAI) | |
| Q7_1* | I fear AI. | Sindermann et al. (2020) |
| Q7_2 | I trust AI. | |
| Q7_3* | I believe AI will destroy humankind. | |
| Q7_4 | I believe AI will benefit humankind. | |
| Q7_5* | I believe AI will cause many job losses. | |
| | SUSCEPTIBILITY TO ILLUSIONS | |
| Q9_1 | I believe AI is a technology. | Jordan (2019) & Emmert-Streib et al. (2020) |
| Q9_2 | I believe AI and machine learning are the same thing. | |
| Q9_3 | I believe the current progress in human-imitative AI is sufficient to solve relevant problems. | |
| Q9_4 | I believe the current progress in human-imitative AI is necessary to solve relevant problems. | |
| Q9_5 | I believe imitating human intelligence as it is, is the only way towards proper AI development. | |
| Q9_6 | I believe AI is data-focused, i.e. its main purpose is data collection. | |
| Q9_7 | I believe AI works similar to the human brain. | |
| Q9_8 | I believe AI can make machines perform at the same level as humans. | |
| Q9_9 | I believe AI properly understands and reacts to novel (unfamiliar) situations at all times. | |
| | OPERATIONAL SKILLS | |
| Q11_1 | I am able to open websites in an Internet browser. | van Deursen & van Dijk (2008) |
| Q11_2 | I am able to surf between webpages. | |
| Q11_3 | I am able to download and save files from the Internet. | |
| Q11_4 | I am able to bookmark webpages. | |
| Q11_5 | I am able to use hyperlinks. | |
| Q11_6 | I am able to change the browser's settings. | |
| Q11_7 | I am able to distinguish and use various file formats. | |
| Q11_8 | I am able to use a search engine. | |
| Q11_9 | I am able to fill in and submit an online form. | |
| | FORMAL SKILLS | |
| Q12_1 | I am able to distinguish hyperlinks in different website layouts. | van Deursen & van Dijk (2008) |
| Q12_2 | I do not get disoriented when surfing within a website. | |
| Q12_3 | I do not get disoriented when surfing between different websites. | |
| Q12_4 | I do not get disoriented when navigating through search results. | |

| | | |
|---|---|---|
| INFORMATION SKILLS | | |
| Q13_1<br>Q13_2<br>Q13_3<br>Q13_4 | I am able to choose a suitable search engine or website to seek information.<br>I am able to formulate a search query.<br>I am able to separate suitable and unsuitable information.<br>I am able to evaluate information sources in terms of quality and reliability. | van Deursen & van Dijk (2008) |
| STRATEGIC SKILLS | | |
| Q14_1<br>Q14_2<br>Q14_3<br>Q14_4 | I take the opportunities offered by the Internet in order to achieve a particular personal goal.<br>I combine various information sources to achieve the best means of reaching the desired goal.<br>I use only the information relevant to the achievement of the desired goal.<br>I recognize the personal, social, professional or educational benefits associated with the achievement of the desired goal. | van Deursen & van Dijk (2008) |
| PERCEIVED USEFULNESS | | |
| Q17_1<br>Q17_2<br>Q17_3<br>Q17_4<br>Q17_5 | I believe this app would represent a more effective way of trying on clothes.<br>I believe this app would be time-saving.<br>I would prefer using this app instead of trying on clothes physically.<br>I believe using this app would enhance my decision making when it comes to buying clothes.<br>I believe this app would be useful. | Davis (1989) |
| PERCEIVED EASE OF USE | | |
| Q18_1<br>Q18_2<br>Q18_3<br>Q18_4<br>Q18_5 | Learning to operate and navigate through the app would be easy for me.<br>I would find it easy to get this app to do what I want it to do.<br>My interaction with this app would be clear and understandable.<br>I believe the functions of this app would provide enough guidance on how to make the best use of it.<br>I believe this app would be easy to use. | Davis (1989) |
| PUBLIC OPINION | | |
| Q20_1<br>Q20_2<br>Q20_3<br>Q20_4<br>Q20_5<br>Q20_6<br>Q20_7<br>Q20_8<br>Q20_9* | I would use an expert's opinion to form my own opinion about AI.<br>I would use an influencer's opinion to form my own opinion about AI.<br>I would use a friend's opinion to form my own opinion about AI.<br>An expert's opinion about AI would be more important to me than an influencer's opinion.<br>An expert's opinion about AI would be more important to me than a friend's opinion.<br>I would consider an expert's opinion about AI even if it clashes with my own.<br>I would consider an influencer's opinion about AI even if it clashes with my own.<br>I would consider a friend's opinion about AI even if it clashes with my own.<br>Public opinion about AI is completely insignificant to me. | |

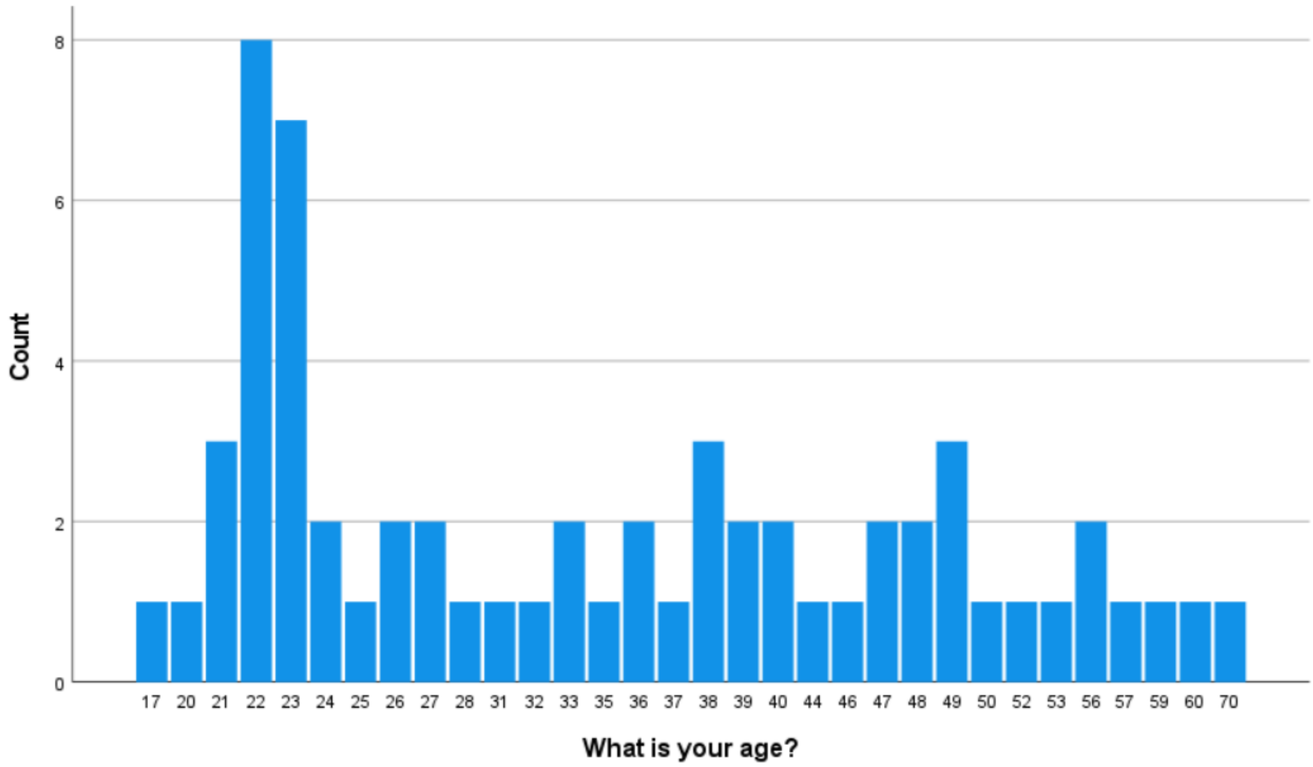
* The item was recoded (reversed) in order to count for the data analysis.

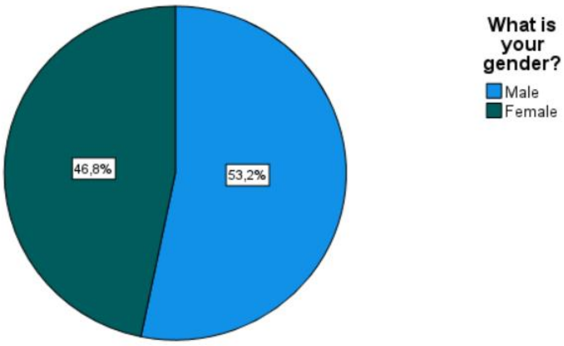
## A1. Case supplement to Q17-Q18

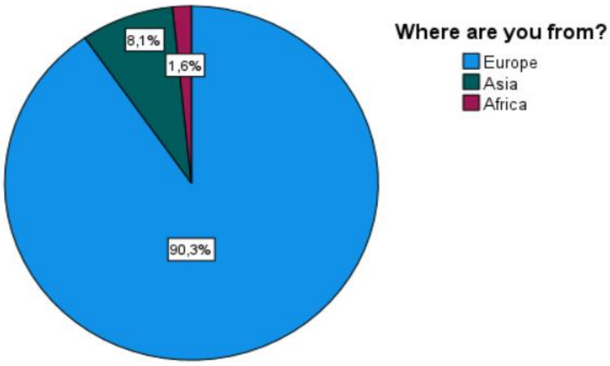
Your preferred clothes brand has released a new app that functions as an AI-driven virtual clothing try-on system. By filling in data about body dimensions, skin tone, fit and size, you can choose a model that fits best these characteristics, i.e. resembles you, in order to see how do clothes look on you. For illustration, see the following screenshots:




## B. Survey demographics






## C. Correlations

**Correlations**

| | | OpSkills | FormalSkills | InfoSkills | StrSkills | PU | PEOU | PublicOpinion | ATAI | SuscTolllusions |
|---|---|---|---|---|---|---|---|---|---|---|
| OpSkills | Pearson Correlation | 1 | ,217 | ,704** | ,628** | ,127 | ,473** | ,001 | ,170 | -,130 |
| | Sig. (2-tailed) | | ,108 | <,001 | <,001 | ,354 | <,001 | ,991 | ,202 | ,339 |
| | N | 58 | 56 | 57 | 57 | 55 | 55 | 55 | 58 | 56 |
| FormalSkills | Pearson Correlation | ,217 | 1 | ,341* | ,350** | -,067 | ,277* | -,257 | -,104 | ,009 |
| | Sig. (2-tailed) | ,108 | | ,010 | ,009 | ,631 | ,045 | ,064 | ,444 | ,947 |
| | N | 56 | 56 | 56 | 55 | 53 | 53 | 53 | 56 | 55 |
| InfoSkills | Pearson Correlation | ,704** | ,341* | 1 | ,635** | -,078 | ,642** | ,003 | ,102 | -,047 |
| | Sig. (2-tailed) | <,001 | ,010 | | <,001 | ,574 | <,001 | ,981 | ,449 | ,732 |
| | N | 57 | 56 | 57 | 56 | 54 | 54 | 54 | 57 | 56 |
| StrSkills | Pearson Correlation | ,628** | ,350** | ,635** | 1 | ,137 | ,460** | -,082 | ,049 | -,120 |
| | Sig. (2-tailed) | <,001 | ,009 | <,001 | | ,320 | <,001 | ,554 | ,719 | ,384 |
| | N | 57 | 55 | 56 | 57 | 55 | 55 | 55 | 57 | 55 |
| PU | Pearson Correlation | ,127 | -,067 | -,078 | ,137 | 1 | ,341* | ,282* | ,234 | ,316* |
| | Sig. (2-tailed) | ,354 | ,631 | ,574 | ,320 | | ,011 | ,037 | ,086 | ,021 |
| | N | 55 | 53 | 54 | 55 | 55 | 55 | 55 | 55 | 53 |
| PEOU | Pearson Correlation | ,473** | ,277* | ,642** | ,460** | ,341* | 1 | ,209 | ,126 | ,141 |
| | Sig. (2-tailed) | <,001 | ,045 | <,001 | <,001 | ,011 | | ,125 | ,360 | ,315 |
| | N | 55 | 53 | 54 | 55 | 55 | 55 | 55 | 55 | 53 |
| PublicOpinion | Pearson Correlation | ,001 | -,257 | ,003 | -,082 | ,282* | ,209 | 1 | ,221 | ,461** |
| | Sig. (2-tailed) | ,991 | ,064 | ,981 | ,554 | ,037 | ,125 | | ,105 | <,001 |
| | N | 55 | 53 | 54 | 55 | 55 | 55 | 55 | 55 | 53 |
| ATAI | Pearson Correlation | ,170 | -,104 | ,102 | ,049 | ,234 | ,126 | ,221 | 1 | ,316* |
| | Sig. (2-tailed) | ,202 | ,444 | ,449 | ,719 | ,086 | ,360 | ,105 | | ,017 |
| | N | 58 | 56 | 57 | 57 | 55 | 55 | 55 | 62 | 57 |
| SuscTolllusions | Pearson Correlation | -,130 | ,009 | -,047 | -,120 | ,316* | ,141 | ,461** | ,316* | 1 |
| | Sig. (2-tailed) | ,339 | ,947 | ,732 | ,384 | ,021 | ,315 | <,001 | ,017 | |
| | N | 56 | 55 | 56 | 55 | 53 | 53 | 53 | 57 | 57 |

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

## D. Multiple regression

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | ,318[a] | ,101 | -,016 | ,82275 |

a. Predictors: (Constant), PublicOpinion, OpSkills, FormalSkills, PU, PEOU, StrSkills, InfoSkills

**Coefficients[a]**

| Model | | Unstandardized Coefficients B | Unstandardized Coefficients Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | 1,321 | 1,305 | | 1,012 | ,316 |
| | OpSkills | ,272 | ,292 | ,165 | ,932 | ,355 |
| | FormalSkills | -,076 | ,145 | -,076 | -,521 | ,605 |
| | InfoSkills | ,194 | ,261 | ,147 | ,746 | ,459 |
| | StrSkills | -,129 | ,232 | -,103 | -,557 | ,580 |
| | PU | ,217 | ,168 | ,196 | 1,287 | ,204 |
| | PEOU | -,104 | ,250 | -,077 | -,414 | ,680 |
| | PublicOpinion | ,152 | ,171 | ,128 | ,890 | ,377 |

a. Dependent Variable: ATAI

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | ,306[a] | ,094 | ,078 | ,58818 |

a. Predictors: (Constant), ATAI

**Coefficients[a]**

| Model | | Unstandardized Coefficients B | Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | 2,200 | ,323 | | 6,811 | <,001 |
| | ATAI | ,230 | ,092 | ,306 | 2,488 | ,016 |

a. Dependent Variable: SuscToIllusions

## E. Initial reliability analysis

**Scale: ATAI scale**

**Reliability Statistics**

| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
|---|---|---|
| ,699 | ,699 | 5 |

**Scale: Illusions**

**Reliability Statistics**

| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
|---|---|---|
| ,652 | ,653 | 9 |

**Scale: OpSkills**

**Reliability Statistics**

| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
|---|---|---|
| ,820 | ,866 | 9 |

**Scale: FormalSkills**

**Reliability Statistics**

| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
|---|---|---|
| ,793 | ,819 | 4 |

**Scale: InfoSkills**

**Reliability Statistics**

| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
|---|---|---|
| ,793 | ,798 | 4 |

**Scale: StrSkills**

**Reliability Statistics**

| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
|---|---|---|
| ,783 | ,814 | 4 |

**Scale: PU**

**Reliability Statistics**

| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
|---|---|---|
| ,834 | ,846 | 5 |

**Scale: PEOU**

**Reliability Statistics**

| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
|---|---|---|
| ,913 | ,914 | 5 |

**Scale: PublicOpinion**

**Reliability Statistics**

| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
|---|---|---|
| ,641 | ,646 | 9 |

## E1. Scale statistics

### ATAI

**Scale Statistics**

| Mean | Variance | Std. Deviation | N of Items |
|---|---|---|---|
| 16,16 | 12,658 | 3,558 | 5 |

### Susceptibility to illusions

**Scale Statistics**

| Mean | Variance | Std. Deviation | N of Items |
|---|---|---|---|
| 28,20 | 29,524 | 5,434 | 9 |

### OpSkills

**Scale Statistics**

| Mean | Variance | Std. Deviation | N of Items |
|---|---|---|---|
| 43,48 | 8,500 | 2,915 | 9 |

### FormalSkills

**Scale Statistics**

| Mean | Variance | Std. Deviation | N of Items |
|---|---|---|---|
| 17,76 | 8,903 | 2,984 | 4 |

### InfoSkills

**Scale Statistics**

| Mean | Variance | Std. Deviation | N of Items |
|---|---|---|---|
| 17,76 | 6,828 | 2,613 | 4 |

### StrSkills

**Scale Statistics**

| Mean | Variance | Std. Deviation | N of Items |
|---|---|---|---|
| 16,89 | 7,284 | 2,699 | 4 |

### PU

**Scale Statistics**

| Mean | Variance | Std. Deviation | N of Items |
|---|---|---|---|
| 18,04 | 14,960 | 3,868 | 5 |

### PEOU

**Scale Statistics**

| Mean | Variance | Std. Deviation | N of Items |
|---|---|---|---|
| 21,56 | 10,403 | 3,225 | 5 |

### PublicOpinion

**Scale Statistics**

| Mean | Variance | Std. Deviation | N of Items |
|---|---|---|---|
| 29,96 | 26,351 | 5,133 | 9 |

**Item-Total Statistics**

| | Scale Mean if Item Deleted | Scale Variance if Item Deleted | Cronbach's Alpha if Item Deleted |
|---|---|---|---|
| Q7_1R | 12,75 | 8,934 | ,698 |
| Q7_2 | 12,93 | 8,476 | ,619 |
| Q7_3R | 12,58 | 6,952 | ,545 |
| Q7_4 | 12,42 | 8,692 | ,604 |
| Q7_5R | 13,98 | 10,500 | ,743 |

**Item-Total Statistics**

| | Scale Mean if Item Deleted | Scale Variance if Item Deleted | Cronbach's Alpha if Item Deleted |
|---|---|---|---|
| Q9_1 | 24,02 | 27,037 | ,673 |
| Q9_2 | 25,39 | 23,789 | ,612 |
| Q9_3 | 25,02 | 24,132 | ,613 |
| Q9_4 | 24,72 | 24,884 | ,626 |
| Q9_5 | 25,06 | 24,733 | ,629 |
| Q9_6 | 25,31 | 23,352 | ,605 |
| Q9_7 | 25,31 | 24,522 | ,643 |
| Q9_8 | 25,24 | 24,073 | ,625 |
| Q9_9 | 25,56 | 22,553 | ,589 |

**Item-Total Statistics**

| | Scale Mean if Item Deleted | Scale Variance if Item Deleted | Cronbach's Alpha if Item Deleted |
|---|---|---|---|
| Q11_1 | 38,58 | 7,187 | ,798 |
| Q11_2 | 38,56 | 7,435 | ,801 |
| Q11_3 | 38,56 | 7,721 | ,813 |
| Q11_4 | 38,62 | 7,057 | ,797 |
| Q11_5 | 38,74 | 6,441 | ,798 |
| Q11_6 | 38,88 | 5,455 | ,823 |
| Q11_7 | 38,60 | 7,184 | ,794 |
| Q11_8 | 38,68 | 6,712 | ,820 |
| Q11_9 | 38,62 | 6,608 | ,780 |

**Item-Total Statistics**

| | Scale Mean if Item Deleted | Scale Variance if Item Deleted | Cronbach's Alpha if Item Deleted |
|---|---|---|---|
| Q12_1 | 13,48 | 6,820 | ,967 |
| Q12_2 | 13,30 | 4,741 | ,629 |
| Q12_3 | 13,24 | 4,865 | ,641 |
| Q12_4 | 13,26 | 4,988 | ,639 |

**Item-Total Statistics**

| | Scale Mean if Item Deleted | Scale Variance if Item Deleted | Cronbach's Alpha if Item Deleted |
|---|---|---|---|
| Q13_1 | 13,30 | 3,835 | ,724 |
| Q13_2 | 13,37 | 3,596 | ,731 |
| Q13_3 | 13,24 | 4,413 | ,736 |
| Q13_4 | 13,37 | 4,577 | ,772 |

**Item-Total Statistics**

| | Scale Mean if Item Deleted | Scale Variance if Item Deleted | Cronbach's Alpha if Item Deleted |
|---|---|---|---|
| Q14_1 | 12,58 | 4,211 | ,717 |
| Q14_2 | 12,49 | 4,366 | ,665 |
| Q14_3 | 12,98 | 4,500 | ,871 |
| Q14_4 | 12,62 | 4,500 | ,664 |

**Item-Total Statistics**

| | Scale Mean if Item Deleted | Scale Variance if Item Deleted | Cronbach's Alpha if Item Deleted |
|---|---|---|---|
| Q17_1 | 14,23 | 9,602 | ,791 |
| Q17_2 | 13,85 | 11,208 | ,800 |
| Q17_3 | 15,40 | 9,244 | ,815 |
| Q17_4 | 14,64 | 9,427 | ,799 |
| Q17_5 | 14,04 | 10,383 | ,797 |

**Item-Total Statistics**

| | Scale Mean if Item Deleted | Scale Variance if Item Deleted | Cronbach's Alpha if Item Deleted |
|---|---|---|---|
| Q18_1 | 17,11 | 6,931 | ,893 |
| Q18_2 | 17,19 | 6,833 | ,884 |
| Q18_3 | 17,26 | 7,215 | ,910 |
| Q18_4 | 17,44 | 6,553 | ,891 |
| Q18_5 | 17,22 | 6,478 | ,889 |

**Item-Total Statistics**

| | Scale Mean if Item Deleted | Scale Variance if Item Deleted | Cronbach's Alpha if Item Deleted |
|---|---|---|---|
| Q20_1 | 26,10 | 20,442 | ,562 |
| Q20_2 | 27,73 | 20,005 | ,579 |
| Q20_3 | 26,69 | 21,668 | ,597 |
| Q20_4 | 25,44 | 24,291 | ,640 |
| Q20_5 | 25,92 | 23,092 | ,634 |
| Q20_6 | 26,12 | 19,594 | ,562 |
| Q20_7 | 27,69 | 20,570 | ,622 |
| Q20_8 | 26,90 | 20,128 | ,589 |
| Q20_9R | 27,10 | 26,010 | ,702 |

## F. Factor analysis

### ATAI

**KMO and Bartlett's Test**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | ,694 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 54,709 |
| | df | 6 |
| | Sig. | <,001 |

**Component Matrix[a]**

| | Component 1 |
|---|---|
| Q7_1R | ,623 |
| Q7_2 | ,795 |
| Q7_3R | ,806 |
| Q7_4 | ,794 |

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

### Susceptibility to illusions

**KMO and Bartlett's Test**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | ,582 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 87,352 |
| | df | 28 |
| | Sig. | <,001 |

**Component Matrix[a]**

| | Component 1 |
|---|---|
| Q9_2 | ,586 |
| Q9_3 | ,662 |
| Q9_4 | ,533 |
| Q9_5 | ,499 |
| Q9_6 | ,632 |
| Q9_7 | ,356 |
| Q9_8 | ,427 |
| Q9_9 | ,661 |

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

### OpSkills

**KMO and Bartlett's Test**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | ,653 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 277,414 |
| | df | 36 |
| | Sig. | <,001 |

**Component Matrix[a]**

| | Component 1 |
|---|---|
| Q11_1 | ,744 |
| Q11_2 | ,803 |
| Q11_3 | ,608 |
| Q11_4 | ,736 |
| Q11_5 | ,611 |
| Q11_6 | ,680 |
| Q11_7 | ,738 |
| Q11_8 | ,483 |
| Q11_9 | ,843 |

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

### FormalSkills

**KMO and Bartlett's Test**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | ,755 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 200,356 |
| | df | 6 |
| | Sig. | <,001 |

**Component Matrix[a]**

| | Component 1 |
|---|---|
| Q12_1 | ,238 |
| Q12_2 | ,965 |
| Q12_3 | ,958 |
| Q12_4 | ,975 |

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

**InfoSkills**

**KMO and Bartlett's Test**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | ,667 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 78,969 |
| | df | 6 |
| | Sig. | <,001 |

**Component Matrix**[a]

| | Component 1 |
|---|---|
| Q13_1 | ,793 |
| Q13_2 | ,795 |
| Q13_3 | ,814 |
| Q13_4 | ,755 |

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

**StrSkills**

**KMO and Bartlett's Test**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | ,753 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 94,980 |
| | df | 6 |
| | Sig. | <,001 |

**Component Matrix**[a]

| | Component 1 |
|---|---|
| Q14_1 | ,836 |
| Q14_2 | ,901 |
| Q14_3 | ,554 |
| Q14_4 | ,901 |

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

**PU**

**KMO and Bartlett's Test**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | ,808 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 101,752 |
| | df | 10 |
| | Sig. | <,001 |

**Component Matrix**[a]

| | Component 1 |
|---|---|
| Q17_1 | ,808 |
| Q17_2 | ,821 |
| Q17_3 | ,741 |
| Q17_4 | ,761 |
| Q17_5 | ,804 |

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

**PEOU**

**KMO and Bartlett's Test**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | ,868 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 178,561 |
| | df | 10 |
| | Sig. | <,001 |

**Component Matrix**[a]

| | Component 1 |
|---|---|
| Q18_1 | ,866 |
| Q18_2 | ,898 |
| Q18_3 | ,794 |
| Q18_4 | ,871 |
| Q18_5 | ,882 |

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

**Public opinion**

**KMO and Bartlett's Test**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | ,667 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 134,930 |
| | df | 28 |
| | Sig. | <,001 |

**Component Matrix**[a]

| | Component 1 |
|---|---|
| Q20_1 | ,658 |
| Q20_2 | ,707 |
| Q20_3 | ,602 |
| Q20_4 | ,250 |
| Q20_5 | ,358 |
| Q20_6 | ,684 |
| Q20_7 | ,574 |
| Q20_8 | ,632 |

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

## G. Illusions frequency tables

**Q9_2**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Strongly disagree | 9 | 14,5 | 16,1 | 16,1 |
| | Somewhat disagree | 14 | 22,6 | 25,0 | 41,1 |
| | Neither agree nor disagree | 14 | 22,6 | 25,0 | 66,1 |
| | Somewhat agree | 17 | 27,4 | 30,4 | 96,4 |
| | Strongly agree | 2 | 3,2 | 3,6 | 100,0 |
| | Total | 56 | 90,3 | 100,0 | |
| Missing | System | 6 | 9,7 | | |
| Total | | 62 | 100,0 | | |

**Q9_3**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Strongly disagree | 6 | 9,7 | 10,5 | 10,5 |
| | Somewhat disagree | 8 | 12,9 | 14,0 | 24,6 |
| | Neither agree nor disagree | 17 | 27,4 | 29,8 | 54,4 |
| | Somewhat agree | 23 | 37,1 | 40,4 | 94,7 |
| | Strongly agree | 3 | 4,8 | 5,3 | 100,0 |
| | Total | 57 | 91,9 | 100,0 | |
| Missing | System | 5 | 8,1 | | |
| Total | | 62 | 100,0 | | |

**Q9_4**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Strongly disagree | 4 | 6,5 | 7,0 | 7,0 |
| | Somewhat disagree | 5 | 8,1 | 8,8 | 15,8 |
| | Neither agree nor disagree | 15 | 24,2 | 26,3 | 42,1 |
| | Somewhat agree | 26 | 41,9 | 45,6 | 87,7 |
| | Strongly agree | 7 | 11,3 | 12,3 | 100,0 |
| | Total | 57 | 91,9 | 100,0 | |
| Missing | System | 5 | 8,1 | | |
| Total | | 62 | 100,0 | | |

**Q9_5**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Strongly disagree | 6 | 9,7 | 10,5 | 10,5 |
| | Somewhat disagree | 9 | 14,5 | 15,8 | 26,3 |
| | Neither agree nor disagree | 19 | 30,6 | 33,3 | 59,6 |
| | Somewhat agree | 18 | 29,0 | 31,6 | 91,2 |
| | Strongly agree | 5 | 8,1 | 8,8 | 100,0 |
| | Total | 57 | 91,9 | 100,0 | |
| Missing | System | 5 | 8,1 | | |
| Total | | 62 | 100,0 | | |

**Q9_6**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Strongly disagree | 7 | 11,3 | 12,5 | 12,5 |
| | Somewhat disagree | 15 | 24,2 | 26,8 | 39,3 |
| | Neither agree nor disagree | 15 | 24,2 | 26,8 | 66,1 |
| | Somewhat agree | 14 | 22,6 | 25,0 | 91,1 |
| | Strongly agree | 5 | 8,1 | 8,9 | 100,0 |
| | Total | 56 | 90,3 | 100,0 | |
| Missing | System | 6 | 9,7 | | |
| Total | | 62 | 100,0 | | |

**Q9_7**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Strongly disagree | 10 | 16,1 | 17,5 | 17,5 |
| | Somewhat disagree | 16 | 25,8 | 28,1 | 45,6 |
| | Neither agree nor disagree | 8 | 12,9 | 14,0 | 59,6 |
| | Somewhat agree | 18 | 29,0 | 31,6 | 91,2 |
| | Strongly agree | 5 | 8,1 | 8,8 | 100,0 |
| | Total | 57 | 91,9 | 100,0 | |
| Missing | System | 5 | 8,1 | | |
| Total | | 62 | 100,0 | | |

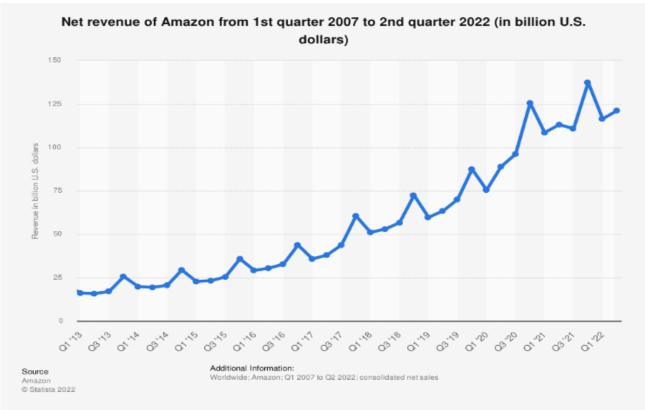
**Q9_8**

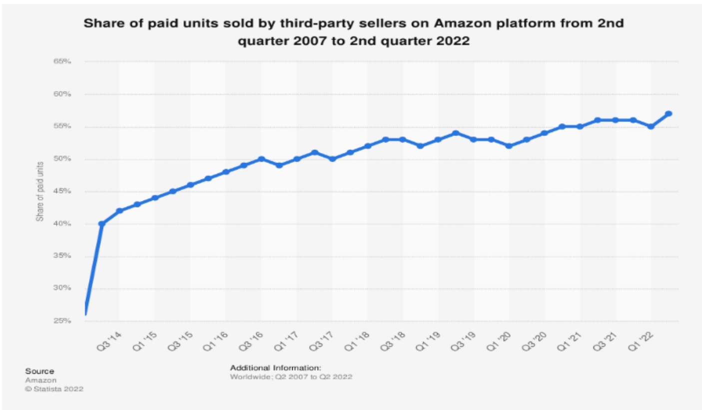
| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Strongly disagree | 10 | 16,1 | 17,5 | 17,5 |
| | Somewhat disagree | 13 | 21,0 | 22,8 | 40,4 |
| | Neither agree nor disagree | 11 | 17,7 | 19,3 | 59,6 |
| | Somewhat agree | 19 | 30,6 | 33,3 | 93,0 |
| | Strongly agree | 4 | 6,5 | 7,0 | 100,0 |
| | Total | 57 | 91,9 | 100,0 | |
| Missing | System | 5 | 8,1 | | |
| Total | | 62 | 100,0 | | |

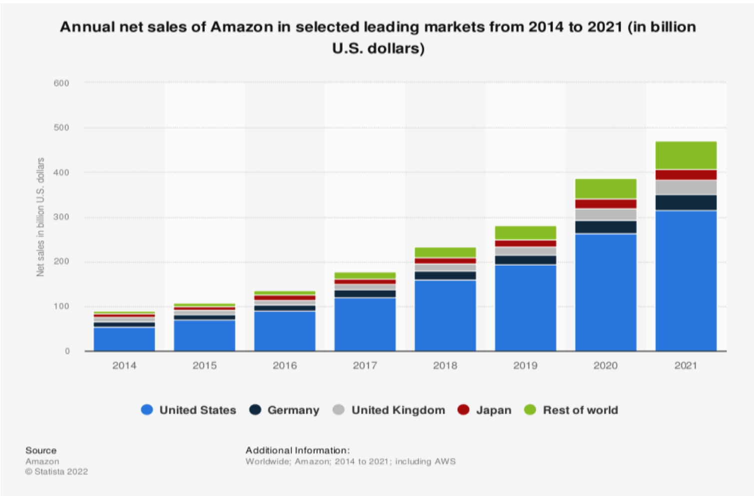
**Q9_9**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Strongly disagree | 12 | 19,4 | 21,1 | 21,1 |
| | Somewhat disagree | 13 | 21,0 | 22,8 | 43,9 |
| | Neither agree nor disagree | 19 | 30,6 | 33,3 | 77,2 |
| | Somewhat agree | 9 | 14,5 | 15,8 | 93,0 |
| | Strongly agree | 4 | 6,5 | 7,0 | 100,0 |
| | Total | 57 | 91,9 | 100,0 | |
| Missing | System | 5 | 8,1 | | |
| Total | | 62 | 100,0 | | |

## H. Amazon statistics & trends




Source: Statista