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Public Attitudes Towards Artificial Intelligence: The Impact of Perceived Threats, Potential Benefits vs. Risks, and Trust

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Abstract: - Understanding public attitudes toward artificial intelligence (AI) is crucial for shaping the responsible development and deployment of AI technologies, aligning them with public expectations, and addressing societal concerns and ethical considerations. The goal of this research was to gain a comprehensive understanding of how the public in general as well as customers in exchange process perceive AI and the factors that influence these perceptions. Our research problem based around researching the complex relationships between various aspects of AI, such as perceived threats, societal benefits, trust in AI institutions, and overall attitudes toward AI. We laid the groundwork in the theoretical part by researching existing knowledge about theoretical foundations of attitudes, about AI, and the attitudes of public towards AI. This theoretical background provided essential context for our research into public attitudes toward AI. In the empirical part, we conducted a detailed survey based on stratified sample of adult population of the Republic of Slovenia (n = 205-209) to gather data on how the public feels about AI. This involved asking participants about their views on AI as a potential threat, its societal benefits, the level of trust they have in institutions and companies responsible for AI, and their overall attitudes toward AI. In our study, we found that individuals who perceive AI as a potential threat to their jobs or privacy tend to hold more negative attitudes toward AI. Interestingly, our research revealed that whether people think AI is beneficial for society or poses risks does not have a strong impact on their overall views about AI. Equally surprising, our results suggest that trust in institutions and companies involved in AI development does not appear to be a major factor in shaping public attitudes toward AI. These findings offer a detailed perspective on how the public views AI. They carry significant implications for policymakers, businesses, and AI developers, highlighting the importance of responsible AI development. It is crucial to address personal concerns and work on building trust and confidence in AI technologies among the public.

Keywords: "artificial intelligence", "public attitudes", "perceived threats", "potential benefits vs. risks", "trust".

I. INTRODUCTION

Artificial intelligence (AI) is a field of computer science and engineering that aims to create intelligent machines that can perform tasks that typically require human intelligence, such as visual perception, speech recognition, decision-making, and natural language processing. AI systems are designed to learn from experience and improve over time with algorithms and statistical models (Russell and Norvig, 2010).

It is evident that AI technology has become increasingly prevalent in our daily lives. From voice assistants like Siri and Alexa to personalized content on social media, navigation apps, language models, smart home devices and predictive algorithms, AI technology has the potential to revolutionize many areas of our lives, by improving efficiency, accuracy, and decision-making. In addition to these, AI begins to play a significant role in the exchange processes on the market, i.e. enhances customer engagement through personalized experiences, and increases efficiency (Xu et al., 2021), supports marketing evolution towards automated, data-driven value creation, streamlines operations by automating tasks, improving customer service, and enabling precise marketing strategies (Martinez-Lopez, Casillas, 2013).

However, the adoption of AI technologies has also raised concerns about issues such as privacy, security, and job displacement. As a result, it is important to understand not only customers' but overall public attitudes towards the use of AI.

Public attitudes refer to the overall evaluations, general feelings, or affective states of the general public towards objects, products, services, brands, advertisements, or any other societal stimuli. These attitudes are shaped by various factors such as personal beliefs, experiences, and social influence, and can have significant implications for the adoption and use of emerging technologies (Jowell, 2005).

Public attitudes towards AI can be positive, negative, or neutral and can affect their willingness to use or engage with AI technologies. For example, negative attitudes towards AI may lead to scepticism about the technology's capabilities, concerns about the potential risks and ethical implications of its use, and ultimately, reduced adoption and utilization (Ikkatai, Hartwig, Takanashi, and Yokoyama, 2022).

We believe that individual's attitudes towards AI technologies are a significant factor in their development and implementation. Despite this, there is currently a lack of research exploring the various factors that influence these

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attitudes. To address this gap, our research aims to investigate the relationship between different factors such as perceived threat, benefits vs. risks, and trust of AI on one side, and attitudes towards AI on the other side. The research findings are expected to provide useful insights to policymakers and companies on how to design and market AI-based products and services that address customers' concerns and preferences.

II. CONCEPTS AND THEORETICAL BACKGROUND

2.1 Attitudes

According to Eagly and Chaiken (1993), attitudes are described as "evaluative judgments about objects, people, or events that are expressed by positive or negative affect, cognition, or behaviour". Positive, negative, or neutral attitudes as evaluations can be communicated with affective, cognitive, and behavioural reactions (Fishbein and Ajzen, 1975).

There are a number of factors that affect how attitudes are formed, i.e. personal beliefs, social influence, as well as cognitive processes, such as perception and learning. Personal beliefs refer to an individual's thoughts and convictions about an object or issue. Experiences, socialization, and media exposure can all have an impact on these beliefs (Ajzen and Fishbein, 1980). Social influence refers to the impact that others have on an individual's attitudes and behaviour. It can take many forms, including conformity, social comparison, and persuasion (Cialdini and Goldstein, 2004). In order to make sense of their surroundings, people organize and interpret sensory data through a process known as perception. Contrarily, learning describes the process by which people pick up new facts and understanding about a subject. Both perception and learning can shape an individual's attitudes towards an object or issue (Petty and Cacioppo, 1986).

While attitudes are generally considered relatively stable and enduring, they are not set in stone and can be changed over time. The process of changing attitudes can be complex and is influenced by a variety of factors i.e.: through persuasion, through direct experience, by social influence, and through cognitive dissonance (Petty and Cacioppo, 1986).

Persuasion involves the use of communication to change a person's attitudes, beliefs, or behaviour (O'Keefe, 2002). It can be accomplished through a variety of means, such as through advertising or interpersonal communication. The effectiveness of persuasion depends on a variety of factors, including the source of the message, the content of the message, and the audience receiving the message (Petty and Cacioppo, 1986).

Exposure to new information or direct experience with a product, service, or situation can changes person's attitudes as well (Zanna and Rempel, 1988). For example, people who have never used a particular technology may have negative attitudes towards it. However, after using it and experiencing its benefits, their attitudes may change to become more positive. Emotions are a fundamental part of human experience, which can influence attitudes by shaping our perceptions, judgments, and beliefs, which in turn affect our evaluations of different objects and events (Petty, Tormala, and Briñol, 2002). Some previous researches have shown that emotions can have a significant impact on attitude formation and change (Zajonc, 1980; Lerner and Keltner, 2000; Tajfel and Turner, 1979).

Social influence is another factor that can play a role in changing attitudes. People's attitudes and actions around them frequently have an impact on them. This can occur through social norms, which are the implicit or explicit rules that govern behaviour within a social group. Particularly, if an individual's peer group has positive attitudes towards a particular product, the individual may be more likely to adopt similar attitudes (Cialdini and Goldstein, 2004).

Cognitive dissonance theory proposes that people experience discomfort or dissonance when their attitudes or beliefs conflict with their behaviour. To reduce this discomfort, they may change their attitudes to be more consistent with their behaviour. (Miller et al., 2015).

Finally, attitudes play a crucial role in decision-making. They influence the evaluation of options and guide behaviour towards a preferred outcome. Research has shown that attitudes can predict behaviour, and decision making is a critical component of behaviour (Ajzen and Fishbein, 1980).

We can argue that changing attitudes is a complex process influenced by various factors. By understanding the mechanisms that underlie attitude change, one can develop effective strategies to promote the adoption of new behaviour or technologies.

2.2 Artificial Intelligence and its market application

The aim of artificial intelligence (AI), is to develop intelligent computers that are capable of carrying out tasks that traditionally require human intelligence, including making decisions, recognition of speech, and language interpretation. AI systems are designed to learn from experience and improve over time with algorithms and

statistical models. It is a rapidly developing field that has attracted a lot of interest recently because of its potential to change many sectors and have an impact on how we live every day (Russell and Norvig, 2010). AI involves creating intelligent systems that can perform tasks that typically require human intelligence, such as learning, reasoning, and problem solving.

There are numerous definitions of AI, however John McCarthy, who first used the phrase "artificial intelligence" in 1956, offers one that is generally recognized. AI is defined by McCarthy as "the science and engineering of creating machines that are intelligent, particularly smart computer programmes" (McCarthy, 1956).

Advances in machine learning drive the development of AI, which is a subset of AI. Algorithms are trained through machine learning to recognize patterns in data, anticipate future events, or take action without being explicitly programmed. There are several machine learning techniques, including supervised learning, unsupervised learning, and reinforcement learning (Sutton and Barto, 2018; Hicham, Nassera and Karim, 2023).

AI has plenty of applications in various fields and industries, i.e. healthcare, finance, retail, transportation, education, and marketing as well (Liao, Liu, Zheng, and Wang, 2019; Cavallo, 2019; Cao, 2022; Bughin, Catlin, Hirt and Willmott, 2018; Bharadiya, 2023; Özüdoğru and Cakir, 2020; Huang and Rust, 2018; Bughin and Hazan, 2019).

The marketing industry has many applications for AI, which can simplify a huge number of activities in the exchange processes on the market, including customer segmentation and personalized advertising (Bughin and Hazan, 2019). AI can analyse customer data to identify patterns in customer behaviour and provide personalized recommendations and advertisements based on their preferences and purchase history (Bughin and Hazan, 2019; Basha, 2023).

Recommendation engines, which use machine learning algorithms to analyse customer data and provide personalized product recommendations, are a common AI application in marketing. These engines are used by e-commerce platforms, streaming services, and social media platforms to improve customer engagement and sales (Huang and Rust, 2018; Yathiraju, Raman, Madala, Patil, Kumar and Ashwin, 2023).

Chatbots are another AI application in marketing that can be programmed to answer customer questions, provide assistance, and even generate leads by engaging with potential customers and collecting their information for follow-up (Bughin and Hazan, 2019).

AI has the potential to revolutionize the marketing industry by providing more personalized and targeted marketing campaigns (Huang and Rust, 2018; Verma, Sharma, Deb and Maitra, 2021).

Artificial Intelligence (AI) is a rapidly developing field that has been identified as a transformative technology that can significantly impact different aspects of human life. However, the deployment of AI raises serious ethical and social implications that require careful consideration (Bostrom and Yudkowsky, 2014).

2.3 Potential benefits vs. risks of AI

According to the majority of researchers, there are four main benefits of AI for society: enhances decision-making and problem solving (Sivarajah et al., 2016; Topol, 2019; Bastani et al., 2021; Chen et al., 2019), increases efficiency and productivity (Deloitte, 2019; Tervo et al., 2020), improves healthcare and medical research (Obermeyer and Emanuel, 2016; Topol, 2019; Wang et al., 2019; Jing et al., 2019), as well as enhances customer experience and satisfaction.

From the marketing point of view, last mentioned benefit of AI, i.e. enhanced customer experience and satisfaction, significantly reshapes exchanging processes by enhancing customer engagement through personalized experiences, interaction and increasing efficiency (Xu et al., 2021). AI technologies such as chatbots, virtual assistants, and predictive analytics are being used by businesses to improve customer engagement, personalization, and support. By analysing customer data, AI can create a detailed profile of each customer and use this information to provide customized recommendations and offers (Kadambi et al., 2018).

Another way AI is enhancing customer experience is through chatbots and virtual assistants. Chatbots are automated software programs that can simulate conversation with human users. They can be used to provide customer support, answer common questions, and provide recommendations. Virtual assistants are similar to chatbots but are designed to provide more personalized assistance to users (Jenkins, 2021).

The use of AI can provide several benefits for businesses, too. By providing personalized experiences, businesses can improve customer satisfaction and loyalty, leading to increased revenue and customer retention. Chatbots and virtual assistants can also reduce the need for human support staff, leading to cost savings for businesses. Predictive analytics can be used to identify trends and patterns in customer behaviour, which can be used to develop targeted marketing campaigns and identify new opportunities for growth (Lee and Kwon, 2019).

In addition to these, AI has the potential to revolutionize education by enhancing teaching and learning experiences. Intelligent tutoring systems can adapt to individual students' learning styles, pace, and progress, providing personalized instruction and feedback (Vanlehn, 2011). AI-powered educational games and simulations can create immersive and engaging learning environments, increasing motivation and retention (Kebritchi, Hirumi, and Bai, 2010). Additionally, AI can assist with grading and assessment, reducing the workload of educators and providing students with immediate and constructive feedback (Pardo and Siemens, 2014).

While AI has the potential to bring significant benefits to society, there is also a risk of potential misuse and abuse. This can occur in a variety of ways, such as the use of AI for malicious purposes (cyberattacks or the spread of misinformation) (Zhu et al., 2019), or the unintended consequences of AI systems (perpetuation of biases or the amplification of harmful behaviours) (O'Neil, 2016). This can lead to discriminatory outcomes, such as biased hiring decisions or the denial of access to services for certain groups of people. AI systems can amplify harmful behaviours, such as the spread of hate speech or the promotion of extremist content, by prioritizing engagement over accuracy or truth (Tufekci, 2018).

One of the most pressing concerns is the potential for AI systems to be used for surveillance and control, which could undermine individual freedoms and civil liberties (Floridi and Taddeo, 2016).

To mitigate the risks of potential misuse and abuse of AI systems, it is important to establish clear ethical and regulatory frameworks for their development and use. This includes ensuring that AI systems are designed with transparency, accountability, and human oversight in mind, to avoid unintended consequences and harmful outcomes. Businesses and governments must work together to establish best practices for the responsible use of AI, such as the development of ethical guidelines and the implementation of robust cybersecurity measures (Bryson et al., 2018).

2.4 Potential threats of AI

The development and implementation of AI have raised concerns about job displacement and economic inequality. AI has the potential to automate many tasks that are currently performed by humans, which may lead to job loss and unemployment. Recent research has suggested that up to 47% of US jobs are at risk of automation in the next few decades (Frey and Osborne, 2017). While some new jobs may be created by the development of AI, the displacement of jobs is likely to have a significant impact on the labour market and may disproportionately affect low-skilled workers and those in industries that are most susceptible to automation, such as manufacturing and transportation (Autor, 2015).

The displacement of jobs can also lead to economic inequality. Those who are most impacted by job loss may not have the skills or resources to adapt to new jobs or industries, which can lead to long-term unemployment and reduced income. This may exacerbate existing economic inequalities and create a widening gap between the rich and poor (Brynjolfsson and McAfee, 2014). In addition, the development of AI may create a new class of "winner-takes-all" industries, where a few companies and individuals benefit greatly from the advances in AI technology, while others are left behind (Brynjolfsson and McAfee, 2014).

As AI technology continues to advance, there are growing concerns about its ethical and legal implications. One of the main ethical concerns surrounding AI is the potential for the technology to be used in ways that violate privacy and human rights. Facial recognition technology has been criticized for its potential use in mass surveillance and tracking of individuals without their consent (Crawford and Calo, 2016).

The possibility for AI to be prejudiced or racist is yet another ethical worry. Because AI systems are trained on historical data, they may learn and perpetuate existing biases and inequalities. This might result in unfairness in the recruiting, financing, and criminal justice systems. In addition, the lack of diversity in the tech industry may contribute to biased AI systems, as the people designing and developing these systems may not represent the diversity of the population they are intended to serve (O'Neil, 2016).

There are also legal concerns surrounding AI, particularly in the area of liability. As AI systems become more autonomous and make decisions that impact human lives, questions arise about who is responsible if something goes wrong (Calo, 2015).

One of the major challenges with AI systems is their lack of transparency and potential for bias. AI systems can be very complex, and it can be difficult to understand how they make decisions. This lack of transparency can make it difficult to identify errors or biases in the system, which can have significant consequences (Jones, 2018).

One way in which bias can manifest in AI systems is through biased data. AI systems learn from the data they are trained on, and if that data is biased, the system can learn to make biased decisions. Specifically, if a facial recognition system is trained on a dataset that is predominantly male and white, the system may not perform as

well on images of women or people with darker skin tones. This can have serious implications for areas such as law enforcement or hiring decisions (Buolamwini and Gebru, 2018).

In addition to biased data, AI systems can also perpetuate and amplify existing social biases. If an AI system is trained on data that reflects existing gender or racial biases, the system may learn to perpetuate these biases in its decisions. This can lead to discrimination and exacerbate existing inequalities (O'Neil, 2016).

To address these issues, it is important to ensure that AI systems are transparent and accountable. This means that the decision-making processes of AI systems should be explainable and understandable to human operators. Additionally, it is important to ensure that AI systems are trained on diverse and representative datasets, and that bias is actively monitored and addressed throughout the development and deployment process (Bender and Friedman, 2018).

2.5 The role of trust in public adoption of AI

Although there is no any universally accepted scholarly definition of this concept, we can define trust as 'a belief by one party in a relationship that the other party will not act against his or her interests, where this belief is held without undue doubt or suspicion and in the absence of detailed information about the actions of the other party' (Tomkins, 2001; Laaksonen, Pajunen, and Kulmala, 2008). One party may trust the other party's benevolence (a belief that on party acts in the interests of the other), honesty (a belief that the other party's word is reliable and credible), and competence (a belief that the other party has the necessary expertise to per-form as required) (Buttle, 2010).

Therefore, trust is a vital aspect of customer behaviour, influencing the attitudes and decision-making processes of customers towards products and services (Rousseau et al., 1998). In the context of AI, trust can be defined as the willingness of individuals to rely on AI systems and accept their recommendations or decisions. Trust in AI can be influenced by various factors, including the perceived reliability, competence, and ethical standards of the system and its operators (Mayer et al., 1995).

As AI technologies are increasingly integrated into various aspects of daily life, such as healthcare, transportation, and finance, the importance of trust in AI is growing (Wang et al., 2019). Trust plays a crucial role in ensuring the safe and effective use of AI, as well as promoting public acceptance of these technologies. Research has shown that customers are more likely to adopt and use new technologies when they trust the technology and its providers (Riegelsberger et al., 2007). On the other hand, lack of trust in technology can lead to resistance and reluctance to use it. Therefore, building and maintaining trust is essential for the successful adoption and integration of AI technologies into society (Komiak and Benbasat, 2006).

However, building trust in AI is not always easy, as AI systems often operate in complex and opaque ways, making it difficult for consumers to understand how decisions are made (Bietti et al., 2021). Additionally, concerns about privacy, security, and bias can erode trust in AI systems (Kaplan and Haenlein, 2019). As a result, there is a need for greater transparency and accountability in AI systems to increase trust and confidence in their use (European Commission, 2020).

Another challenge to building trust in AI is the lack of regulation and standardization in the industry. As AI technologies continue to evolve and develop, there is a need for clear guidelines and standards to ensure the ethical and responsible use of AI. This will not only help build trust among consumers but also promote innovation and growth in the industry (Floridi et al., 2018).

The adoption of new technologies by the public is strongly influenced by the level of trust that individuals have in those technologies (Siau and Wang, 2018). This is especially true for AI technologies, which are often viewed as complex and potentially dangerous. Research has shown that trust is a key factor in the adoption of AI technologies, and that lack of trust can be a significant barrier to adoption (Venkatesh et al., 2003).

One of the main reasons why trust is important for the adoption of new technologies is that it reduces uncertainty and perceived risk. When individuals are uncertain about the potential risks and benefits of a new technology, they may be hesitant to adopt it. Trust helps to reduce this uncertainty by providing individuals with a sense of confidence that the technology will perform as expected and that their personal information will be protected (Morgan and Hunt, 1994).

Another important factor in the role of trust in the adoption of AI technologies is the social influence of trust. People are often influenced by the opinions and behaviours of others when making decisions about new technologies. If individuals perceive that others trust a new technology, they are more likely to adopt it themselves. On the other hand, if there is a lack of trust in a new technology, this can lead to a negative perception and reduced adoption (Luhmann, 1988).

In our opinion, trust plays a crucial role in the public adoption of AI technologies. To promote the adoption of AI, it is important for developers and policymakers to prioritize building trust with the public by addressing concerns related to transparency, ethics, and security. By building trust, AI technologies can be adopted more widely and effectively, leading to their potential benefits being realized.

III. Conceptual Framework And Hypotheses Development

3.1 Conceptual framework

In recent years, the increasing presence of AI technologies in society has sparked significant interest in public attitudes towards AI. Understanding these attitudes is crucial for several reasons, such as constructing effective policies, fostering public trust and acceptance, and addressing ethical concerns.

Several theoretical frameworks have been proposed to explain how individuals form attitudes towards new technologies such as AI. One such framework is the Technology Acceptance Model (TAM) developed by Davis (1989). TAM posits that perceived usefulness and perceived ease of use are the primary determinants of an individual's intention to use a technology. This model has been used to study public attitudes towards a wide range of technologies, including AI (Venkatesh et al., 2003).

Another relevant theoretical framework is the Social Cognitive Theory (SCT) developed by Bandura (1986). According to SCT, individuals learn attitudes and behaviours through observation and modelling of others, as well as through their own experiences (Bandura, 1986). In the context of AI, SCT could be applied to understand how individuals form attitudes towards AI based on their exposure to AI technologies and their perceptions of AI in the media.

The Technology Risk Framework (TRF) developed by Slovic (1999) is another relevant framework. The TRF suggests that public attitudes towards technologies are influenced by three main factors: dread risk, unknown risk, and personal control. Dread risk refers to the perceived potential for a technology to cause catastrophic harm, unknown risk refers to uncertainties surrounding the technology, and personal control refers to the perceived ability of an individual to control the risks associated with the technology (Slovic, 1999).

Several models have been proposed to explain public attitudes towards AI specifically. One such model is the Attitude-Behavioural Intention (ABI) model developed by Moon and Kim (2001). This model suggests that attitudes towards AI are influenced by perceived usefulness, perceived ease of use, and perceived risks associated with AI. These attitudes, in turn, influence an individual's intention to use or not use AI.

Another relevant model is the Cognitive-Affective-Conative (CAC) model proposed by Cacioppo et al. (2007). This model suggests that attitudes towards AI are formed through cognitive (e.g., beliefs about AI), affective (e.g., emotions towards AI), and conative (e.g., intentions to use AI) processes. This model has been used to study public attitudes towards a range of technologies, including AI (Kraus et al., 2017).

While theoretical frameworks and models provide a useful starting point for understanding public attitudes towards AI, empirical studies are necessary to gain a more comprehensive and nuanced understanding of these attitudes. A growing body of research has explored public attitudes towards AI, examining factors such as trust (Hoffman et al., 2018), risk perception (Schwesig, Brich, Buder, Huff, and Said, 2022), as well as benefits and drawbacks (Lewis, 2021).

3.2 Hypotheses development

To our knowledge, empirical studies on public attitudes towards AI have shown that individuals' attitudes towards AI are complex and multifaceted. Because of the lack of research exploring the relationship and impact of factors like threats, benefits, risks and trust on public attitudes towards AI, in order to find out insights for policymakers and businesses to develop AI that aligns with public concerns and preferences, we developed an overall structural research model which is depicted in Fig. 1. It builds on core linkages between main research factors: public attitudes towards AI, perceived public threats, perceived public benefits vs. risks, and trust.

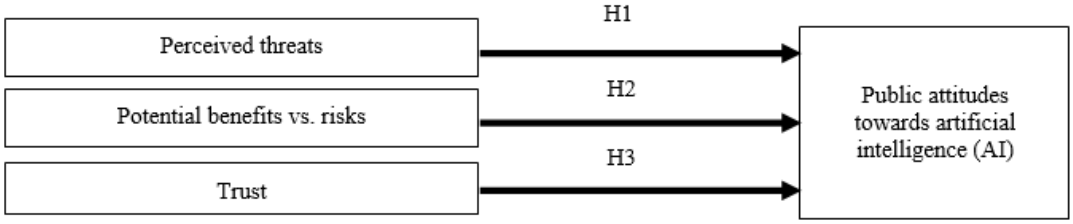

Fig. 1. Structural research model between perceived threats, potential benefits vs. risks, trust, and public attitudes towards AI

Therefore, the following research hypotheses were formulated:

H1: Individuals who perceive AI as a threat to their jobs or privacy will have more negative attitudes towards AI than those who do not perceive such threats.

H2: Individuals who perceive AI as having greater potential benefits for society will have more positive attitudes towards AI than those who perceive the potential risks.

H3: Individuals who have greater trust in the institutions and companies developing and deploying AI will have more positive attitudes towards AI than those who have less trust.

IV. Research Methodology

4.1 Sampling and demographics of respondents

In this study, 258 respondents in Slovenia initially participated in the survey, constituting a stratified sample to ensure that all significant demographic categories of public in Slovenia are included in the final sample. This sampling approach allows us to provide a complete demographic overview, capturing questions related to gender, age, education, status and income of the respondents.

However, during the data analysis process, it became evident that the sample size varied when conducting different analyses. The reason for this variability is attributed to the presence of missing values in some variables. It is important to note that in regression analysis, any response containing even a single variable with a missing value is excluded from the analysis.

As a result, we employed rigorous criteria to ensure the integrity of our analysis. Respondents who did not provide complete and relevant answers, making it impossible to use their responses to research correlations or test our hypotheses, were excluded from the initial data analysis. Such careful selection process led to sample sizes ranging from 205 to 209 respondents in various analyses. Demographic characteristics of the respondents in the final sample (i.e. gender, age, education, employment status and income) are similar to demographic characteristics of the entire adult population of Republic of Slovenia.

4.2 Survey and measures

We obtained data for the research using a Google Forms online survey. We collected them for about 2 months. We distributed the survey to various social media groups to capture as much diversity as possible, to online forums such as Reddit and Quora, and solicited responses through the creation of a mailing list. With the initial question, we measured how familiar the concept of artificial intelligence is to the respondents. This was followed by a combination of open and closed questions with which we measured the importance of individual researched factors (perceived threats, potential benefits vs. risks, trust and attitudes towards AI). All questions except open-ended ones were measured using a 5-point Likert scale as well as 4-point and 5-point other interval scales.

At the end of the questionnaire, demographic questions (gender, age, education, status and income) were asked. The survey was anonymous. The goal of collected surveys was at least 200, and when we collected a sufficient number of completed surveys, we ended the survey and deactivated it.

After collecting the data, we transferred it to the statistical data processing program – SPSS to help verify the hypotheses. We checked all entries and surveys that were not fully completed and excluded them from the analysis using the following methods in data analysis and processing: Pearson correlation coefficient (the most commonly used method of linear association between two variables, the association can be positive or negative and of varying strength) and OLS regression model (a statistical technique used to quantify and analyse the impact between three independent variables (threat, benefits vs. risks and trust) and one dependent variable (public attitudes towards AI) providing coefficients for prediction and hypothesis testing.

V. Data Analysis And Results

5.1 AI familiarity

First of all, we were interested in how the public is familiar with the concept of AI. A familiarity was measured using a 4-point interval scale (1 – not familiar at all; 4 – very familiar). A significant proportion of respondents (55.50%) possess a level of familiarity categorized as "somewhat familiar" with the concept of AI, suggesting a broad recognition without extensive comprehension. A relatively smaller proportion, specifically 29.17%, have a higher level of familiarity, indicating a greater degree of advanced knowledge. In contrast, a collective 15.31% of respondents exhibit either unfamiliarity or possess a little understanding of AI. In general, most respondents possess a certain level of familiarity with AI; nonetheless, there exists potential for further development in terms of attaining a full comprehension of the subject matter.

5.2 AI job security threat perception

Considering that with the development of AI there are also potential dangers, with this question we were interested in public opinion, namely to what extent they believe that AI poses a threat to their job. The question was measured using a 5-point Likert scale (5 – strongly agree; 1 – strongly disagree). The results of the study show a divided opinion on the threat that AI poses to employment: 24.40% of respondents do not agree, suggesting some assurance in continued employment despite AI development. While just 11.48% of respondents strongly disagree, 31.96% agree or believe that AI could be a threat and 7.66% of the respondents strongly agree. 24.40% of people report having no strong view either way, indicating doubt or a lack of knowledge. There is a consensus that AI could be a threat to jobs, although opinions vary widely.

5.3 Analysis of relationship between frequency of AI usage and confidence in potential benefits for society

We were also researching if a higher level of confidence in AI's potential social advantages follow from more frequent usage of the technology in one's daily life. In order to do this, we tested the following null hypothesis: H0: There is a significant influence of the person's belief in AI's potential to benefit society on the frequency of using the AI.

The results and interpretation are presented in table I.

Table I: Analysis of the relationship between frequency of AI usage and confidence in potential benefits for society

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.352[a]	.124	.120	1.29299
a. Predictors: (Constant), AI potential to benefit society				

ANOVAa						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	48.660	1	48.660	29.106	.000b
	Residual	344.398	206	1.672		
	Total	393.058	207			
a. Dependent Variable: Frequency of AI use in daily life						
b. Predictors: (Constant), AI potential to benefit society						

Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.098	.397		2.767	.006
	Q10	.526	.098	.352	5.395	.000
a. Dependent Variable: Frequency of AI use in daily life						

The p-value < 0.05 (0.00) provides evidence to accept the null hypothesis and state that there is a significant influence of the person's belief in AI's potential to benefit society on the frequency of using the AI. The beta coefficient (0.526) is positive, showing a significant positive influence of the person's belief in AI's potential to benefit society on the frequency of using the AI. Various factors may influence this association. For example, those who have witnessed or believe in the favourable effects of AI may exhibit a greater propensity to interact with AI technologies, acknowledging AI's progress and conveniences to contemporary society. Moreover, the regular engagement of individuals with AI technology may strengthen their optimistic perceptions of the potential of AI, establishing a self-perpetuating cycle characterized by heightened trust and increased involvement.

5.4 The impact of demographic factors on attitudes towards AI

In addition, we were interested about the potential influence of demographic factors such as age, gender, education, income, and employment status on attitudes towards AI. The results are outlined in table II.

Table II: Influence of demographic factors on attitudes towards AI analysis

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.323a	.104	.082	.55867
a. Predictors: (Constant), Income, Gender, Education, Employment Status, Age				

ANOVAa						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7.314	5	1.463	4.687	.000b
	Residual	62.735	201	.312		
	Total	70.049	206			
a. Dependent Variable: Attitude towards AI						
b. Predictors: (Constant), Income, Gender, Education, Employment Status, Age						

Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.851	.275		13.994	.000
	Gender	-.057	.076	-.050	-.748	.456
	Age	-.198	.046	-.334	-4.319	.000
	Education	.015	.052	.021	.282	.778
	Employment Status	-.008	.030	-.019	-.260	.795
	Income	-.001	.030	-.001	-.017	.987
a. Dependent Variable: Attitude towards AI						

The p-value of all the variables (gender, education, employment status, and income) except for the age is greater than 0.05. The p-value < 0.05 indicates that age significantly influences the attitude towards AI. The beta value is negative (0.198), which means that age negatively affects the attitude towards AI. This negative relationship can be explained as older population may encounter greater difficulties adapting to emerging technologies or possess limited exposure and comprehension of AI compared to younger population. Consequently, this disparity can result in apprehensions or negative attitudes towards AI. In addition, older population may possess apprehensions regarding privacy, security, and job displacement resulting from AI, factors that may be of less concern or more readily disregarded by younger population who has grown up in the digital era.

5.5 Hypotheses testing

Hypothesis 1: Individuals who perceive AI as a threat to their jobs or privacy will have more negative attitudes towards AI than those who do not perceive such threats.

As it can be seen in table III, the correlation of the AI threats and concerns with the attitudes towards AI is positive but weak (0.265). The results to test the above hypothesis are given in table IV.

Table III: THE correlation of the AI threats and concerns with the attitudes towards AI

Correlations			
		AI Threats and Concerns	Attitudes towards AI
AI Threats and Concerns	Pearson Correlation	1	.265**

Correlations			
	Sig. (2-tailed)		.000
	N	211	204
Attitudes towards AI	Pearson Correlation	.265**	1
	Sig. (2-tailed)	.000	
	N	204	204
**. Correlation is significant at the 0.01 level (2-tailed).			

Table IV: The impact of perceived threat on attitudes towards AI

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.265a	.070	.066	1.10154
a. Predictors: (Constant), AI Threats and Concerns				

ANOVA [a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	18.480	1	18.480	15.230	.000b
	Residual	245.104	202	1.213		
	Total	263.583	203			
a. Dependent Variable: Attitudes towards AI						
b. Predictors: (Constant), AI Threats and Concerns						

Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.285	.219		10.449	.000
	AI Threats and Concerns	.263	.067	.265	3.903	.000
a. Dependent Variable: Attitudes towards AI						

The p-value < 0.05 provides evidence in favor of the hypothesis 1. The variable AI threats and concerns significantly influences the dependent variable attitudes towards AI. The direction of the relationship is direct as the beta value is positive (0.263), indicating that the individual who believes that AI present a threat to their jobs or privacy are more concerned about the potential risk to their privacy posed by the AI. Hence, the first hypothesis is accepted, and we can conclude that individuals who perceive AI as a threat to their jobs or privacy will have more negative attitudes towards AI than those who do not perceive such threats.

Hypothesis 2: Individuals who perceive AI as having greater potential benefits for society will have more positive attitudes towards AI than those who perceive potential risks.

The correlation of the attitude towards AI with both the variable's benefits to society (0.049) and potential risk (-0.024) is weak. However, the correlation is positive with the benefits to society while negative with the potential risk (table V). The results for the second hypothesis are given in table VI.

Table V: THE correlation between potential benefits vs. risks and attitudes towards AI

Correlations				
		Attitude Toward AI	Benefit to the society	Potential Risks
Attitude Toward AI	Pearson Correlation	1	.049	-.024

Correlations				
	Sig. (2-tailed)		.518	.753
	N	195	176	177
Benefit to the society	Pearson Correlation	.049	1	-.014
	Sig. (2-tailed)	.518		.840
	N	176	210	210
Potential Risks	Pearson Correlation	-.024	-.014	1
	Sig. (2-tailed)	.753	.840	
	N	177	210	211

Table VI: The impact of potential benefits vs. risks on attitudes towards AI

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.055a	.003	-.009	.40154
a. Predictors: (Constant), Benefit to the Society, Potential Risks				

ANOVA [a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.084	2	.042	.260	.771b
	Residual	27.893	173	.161		
	Total	27.977	175			
a. Dependent Variable: Attitude Toward AI						
b. Predictors: (Constant), Potential Benefit to the Society, Potential Risks						

Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.932	.174		11.113	.000
	Beliefs and Intentions: Benefit to the Society	.022	.035	.049	.650	.517
	Beliefs and Intentions: Potential Risks	-.009	.028	-.024	-.322	.748
a. Dependent Variable: Potential Benefits of AI						

The beta coefficient of the variable benefit of AI to society is positive (0.022), which means that if a respondent believes that AI benefits society, he will have a positive attitude towards AI. However, the p-value < 0.05 shows that there is no significant impact of the benefit of AI to society on the person's attitude towards AI.

The beta coefficient of the variable potential risk of AI is negative (-0.009), which means that if a person believes that AI poses a potential risk, he will have a negative attitude towards the AI. However, these results are also insignificant. Based on these results, the second hypothesis is not accepted, which states that Individuals who perceive AI as having greater potential benefits for society will have more positive attitudes towards AI than those who perceive potential risks.

Hypothesis 3: Individuals with greater trust in the institutions and companies developing and deploying AI will have more positive attitudes towards AI than those with less trust.

The correlation between trust in AI and attitude towards AI is negative and weak (-0.090) as it can be seen in table VII, while the results for the third hypothesis are given in table VIII.

Table VII: THE correlation between trust in AI and attitude towards AI

Correlations			
		Attitude towards AI	Trust in AI
Attitude towards AI	Pearson Correlation	1	-.090
	Sig. (2-tailed)		.226
	N	210	184
Trust on AI	Pearson Correlation	-.090	1
	Sig. (2-tailed)	.226	
	N	184	203

Table VIII: The impact of trust in AI on public attitudes towards AI

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.090a	.008	.003	.90953
a. Predictors: (Constant), Trust on AI				

ANOVA [a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.219	1	1.219	1.473	.226b
	Residual	150.558	182	.827		
	Total	151.777	183			
a. Dependent Variable: Perceptions of AI Use						
b. Predictors: (Constant), Trust on AI						

Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.798	.190		19.942	.000
	Q6	-.090	.074	-.090	-1.214	.226
a. Dependent Variable: Perceptions of AI Use						

The negative beta value shows a negative association between the dependent and independent variables. However, the p-value > 0.05 does not provide evidence supporting the third hypothesis. Hence, we cannot conclude that individuals with greater trust in institutions and companies developing and deploying AI will have more positive attitudes towards AI than those with less trust.

VI. CONCLUSION

6.1 Research contribution

This research has provided comprehensive insights into the multifaceted landscape of public attitudes towards AI and the many factors that shape these attitudes. The study researched three fundamental hypotheses, providing a deep understanding of the complex relations between AI perceptions of threat, potential benefits vs, risks, trust, and overall attitudes.

The study also identified key findings that significantly contribute to the highly growing field of AI perception. In line with the first hypothesis, it affirmed that individuals who perceive AI as a threat to their jobs or privacy indeed manifest more negative attitudes towards AI. Our research showed a significant positive correlation (0.265) and a direct relationship (beta 0.263) between concerns about AI threats and negative attitudes. This underlines the importance of dealing with individual concerns regarding how AI might affect privacy and job security, as it is essential for encouraging more positive attitude.

However, the second hypothesis, which suggested that people's views about AI's societal benefits and potential risks would have a substantial impact on their attitudes, did not receive empirical validation. The weak correlations in both, the perceived benefits (0.049) and potential risks (-0.024) suggest that individuals' attitudes toward AI are not considerably influenced by these broader societal considerations. While the direction of the correlations was positive for potential benefits and negative for potential risks, the insignificance of the results prompts a deeper exploration of the interplay between public attitudes and societal perceptions of AI.

The third hypothesis explored how much people trust the companies and institutions that develop and use AI. This research did not discover a significant correlation between trust levels and attitudes toward AI. The negative beta coefficient and a p-value exceeding 0.05 imply that trust in AI developers alone does not inherently drive more positive attitudes. These results prompt further research into the all-round nature of trust in the AI domain.

The findings indicate that people's attitudes toward AI are strongly influenced by personal worries, particularly about AI's impact on privacy and job security. In contrast, general views on AI's benefits, risks, or trust in AI developers have little effect. This underscores the importance of addressing individual concerns rather than broader societal considerations. Consequently, AI developers and policymakers should focus on these specific worries and adopt personalized approaches to effectively address them.

In addition to these, the results of our research enable businesses to better understand all three components of the customers' attitude towards AI in the exchange process (i.e. cognitive, affective and behavioural component). Customer experience improved through AI-driven marketing activities can improve effectiveness and efficiency of exchange processes between the businesses and customers. Hence, knowledge about the factors which influence customers' attitude may support the businesses in the process of establishing predictive models of customers' behaviour, defining efficient marketing strategy (product, price, distribution and promotion strategy) (Hicham, Nassera and Karim, 2023; Verma, Sharma, Deb and Maitra, 2021).

6.2 Research limitations

Despite its contributions to understanding public attitudes toward AI, this research has several limitations. Firstly, the study focused on individuals who either use AI-related products or do not, which may introduce sample bias and not fully represent the broader population. The reliability of results depends on respondents providing honest and consistent answers, but self-reported data can be influenced by social desirability bias and limited understanding of AI concepts.

Additionally, the study was conducted over a limited period, affecting the depth of data collection and analysis. A more extensive study with a larger and more diverse sample size could provide deeper insights. Solely relying on surveys might benefit from including other methods like interviews or focus groups to enhance findings. Limited demographic information about respondents may hinder analysis of how factors such as age, gender, education, income, and employment status influence attitudes toward AI. Lastly, the rapidly evolving field of AI means public perceptions may change over time, and this research represents a snapshot of attitudes at a particular moment. These limitations should be considered when interpreting the findings.

6.3 Directions for future research

Considering these limitations, future research in this field can benefit from the following suggestions: longitudinal studies which should track changes in public attitudes over time to identify evolving trends and shifts as AI technology progresses; cross-cultural studies by examining AI attitudes across different cultures can reveal unique concerns and expectations as well as offering a more nuanced understanding of global perceptions; in-depth qualitative research, such as interviews and focus groups in combination with quantitative surveys will help uncover the deeper reasons behind public attitudes that surveys alone might miss; contextual analysis with investigating how various applications and contexts of AI impact public responses can provide insights into specific areas of concern.

Analysing public attitudes toward AI applications in different industries will help address sector-specific concerns (i.e. in healthcare, in education as well as in exchange processes of the businesses in the market).

In addition to these, some ethical considerations should be considered, because research into the ethical aspects of AI, including the development of ethical frameworks, is essential for responsible AI development. Exploring factors that contribute to trust in AI, such as transparency and accountability, can guide the creation of more trustworthy AI systems. As AI technology continues to evolve, understanding and shaping public attitudes remains an ongoing process. Following the suggested areas for future research and addressing individual concerns and ethical issues can help provide clearer and more balanced perspectives on AI. This approach aims to benefit both the industry and society. As AI impacts various aspects of life, establishing a transparent and responsible relationship between AI and the public is crucial. This research offers foundational insights that can guide future developments and improve the integration of AI into society.

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