HIGH SCHOOL EDITION
Journal of Student Research
Volume 13 Issue 4 (2024)

The Effects of Past Experiences, Trust, and Perception on Decisions to Adopt New AI Technology

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ABSTRACT

Artificial Intelligence (AI) offers numerous benefits across various fields, including education, finance, and workplace productivity. However, the factors that prompt the use of new AI technology have yet to be fully explored. This paper explores the neuroscientific origins of decision-making as well as the factors influencing the acceptance and adoption of AI, focusing on the role of past experiences, trust, and perception in decision-making. This study employs a mixed-method approach, combining quantitative surveys and qualitative interviews to provide a comprehensive understanding of the attitudes of participants towards AI. The results reveal that positive past experiences generally enhance trust and willingness to engage with AI, whereas negative ones tend to give rise to skepticism and avoidance. However, while past experiences with AI can influence future decisions, trust and perception play more critical roles in the decision-making process. The findings highlight the importance of trust-building and addressing common misconceptions about AI, suggesting that educational programs and simulations that provide positive initial experiences with AI can help recalibrate risk perceptions and build confidence among potential users. By promoting balanced views of AI's capabilities and limitations, this study contributes to societal progress by using robust evidence to support the integration of AI into various sectors of life.

Introduction

Artificial Intelligence (AI) has made milestone developmental progress in recent years and its usage is being integrated into various fields to provide competitive advantages. AI adoption offers multiple benefits to the workplace such as a boost in productivity and the ease of use of applications (Camarinha-Matos et al., 2023). Furthermore, it was shown that AI adoption improves education by reducing the burdens on teachers to manage administrative tasks and make class material so that they can invest more in teaching, guiding students, and personalizing educational experiences (Ahmad et al., 2022). In finance and the stock market, AI makes it easier for individuals to perform financial predictions and complex calculations (Al-Baity, 2023). Due to the vast amount of benefits AI brings, it is important to understand how an individual makes decisions on adopting new AI technology in order to foster more widespread uses of AI to simplify tasks.

Individuals make decisions consciously or unconsciously throughout their lifespan. Whether they are making simple choices like what to wear for work or impactful ones such as investing in emerging businesses, past experiences significantly shape future decisions and risk perceptions. However, the mechanism of decision-making based on past experiences for potential customers remains elusive despite recent studies. This paper explores the neurological and psychological basis of how decision-making is influenced by various factors in order to lay the foundation for fostering positive social change by exploring the acceptance of AI. As AI continues to integrate into daily life, understanding the factors that influence its acceptance is crucial for professionals like entrepreneurs, educators, and technology developers; with this understanding, businesses can implement strategies to enhance employee acceptance and engagement with AI tools, while communities can better harness the potential of AI to improve productivity, enhance personalized education, and streamline complex tasks.

This paper begins with a brief literature review to examine the biological basis of decision-making, the brain's response to unexpected uncertainty, the role of the frontal cortex in reward-guided learning, risk management when making unknown decisions, and how these factors can influence the acceptance of AI and other new technologies. Then, an independent survey and interview study is presented with data and subsequent analysis. After limitations are discussed and implications regarding past experiences, trust, and perception are drawn from the results, recommendations supported by past literature are given to corporations and communities to foster AI adoption.

Literature Review

To begin with, the neurological and biological basis of physiology informs research on the decision-making process. Dopamine, a key neurotransmitter in the brain, is involved in the reward circuitry and significantly influences how we remember past experiences, especially those with strong emotional components such as extreme happiness or sadness (Schultz, 2016). These emotionally charged memories can strongly impact our future choices, including the acceptance or rejection of new technologies. For instance, a negative experience with AI or stock market investments can leave a lasting impression, making individuals wary of engaging with similar technologies in the future. The concept of dopamine's role in decision-making extends to its effect on maintaining a balance between happiness and sadness. Excessive happiness or sadness is unsustainable, and the brain strives to maintain a relative equilibrium (Berridge & Kringelbach, 2015). This balancing act influences how past experiences are encoded and recalled, thereby shaping future decisions. The implication of raising one's threshold for happiness or sadness means that extreme experiences are more likely to be remembered and influence future behavior (Volkow et al., 2017).

The brain's response to unexpected uncertainty is another critical aspect of decision-making. When facing unexpected outcomes, specific neural circuits are activated to manage and process these surprises (Harrison et al., 2012). This neural mechanism is essential for adapting to new situations and making informed decisions in the face of uncertainty. Reducing unexpected uncertainty in AI interactions can significantly enhance user comfort and adoption rates. Neuroscientific studies have shown that the brain utilizes a network of regions, including the prefrontal cortex and the anterior cingulate cortex, to handle unexpected uncertainty (Behrens et al., 2007). These regions work together to update beliefs and expectations based on new information, allowing for more accurate predictions and better decision-making. By minimizing unexpected uncertainties in AI systems, we can improve user experiences and increase the likelihood of technology adoption (Diederen & Schultz, 2015).

The frontal cortex, particularly regions such as the orbitofrontal cortex and the ventromedial prefrontal cortex, plays a vital role in reward processing and decision-making (Wallis, 2007). These areas are involved in evaluating the value of different options, learning from rewards, and setting goals based on past experiences. Understanding these reward mechanisms can help influence perceptions of new technologies, thereby enhancing their acceptance. Research has demonstrated that the frontal cortex integrates information about past rewards to guide future behavior (Rushworth et al., 2011). This process involves learning from both positive and negative outcomes to make better decisions. By leveraging insights into how the brain processes rewards, strategies can be developed to positively influence attitudes towards new technologies. For example, highlighting the potential rewards and benefits of AI applications can help counteract negative past experiences and promote acceptance (Rangel & Hare, 2010).

Research into such topics may advise the decision-making process in similar fields, such as finance. Traditional financial theories often assume rational behavior, overlooking the complexities of human emotions and cognitive biases (Shiller, 2003). These limitations highlight the need for a more comprehensive perspective that incorporates how our brains process information and makes decisions under uncertainty (Miendlarzewska, Kometer, & Preuschoff, 2017). For instance, psychological factors such as overconfidence, fear, and regret significantly impact financial decisions (Barber & Odean, 2001). Personal experiences and psychological factors can lead to different interpretations of the same information, affecting past experiences on risk-taking and consumer behavior (Camerer, 2005). When individuals encounter positive experiences early on, their perception of risk tends to diminish, leading to more favorable attitudes towards investment opportunities (Kahneman & Tversky, 1979). Conversely, negative initial experiences can heighten risk perception and deter individuals from engaging in similar investments in the future. The continuity of risk perception influences future decisions, as individuals rely on their past experiences to inform their expectations and choices (Loewenstein et al., 2001). For instance, if an individual has experienced significant financial losses, their brain may become more sensitive to potential future risks, leading to more conservative decision-making (Porcelli & Delgado, 2009). Conversely, positive past experiences with risk-taking can enhance an individual's willingness to engage in future risks. In the context of AI adoption, designing positive initial experiences is crucial for encouraging acceptance and recalibrating risk perceptions (Preuschoff, Quartz, & Bossaerts, 2008). Individuals may develop more balanced and informed risk perceptions from participating in educational programs and simulations that provide positive initial experiences with new technologies. These programs can simulate real-world scenarios, allowing users to gain confidence and familiarity with new technologies in a controlled and supportive environment (Hirshleifer, 2001; Li et al., 2023).

In addition, perceived luck and ambiguity aversion are also significant factors influencing decision-making. Those who perceive themselves as lucky are more likely to take risks, while those who view themselves as unlucky may avoid uncertain situations (Kolemba & Maciuszek, 2013). Ambiguity aversion, the tendency to avoid situations with unknown probabilities, is also influenced by past experiences (Camerer & Weber, 1992). Negative experiences with ambiguity can reinforce this aversion, making individuals more cautious in their decision-making. Conversely, positive experiences can mitigate ambiguity aversion and encourage more open-mindedness towards new opportunities. To mitigate negative biases towards new technologies, it is essential to reinforce successful interactions and provide positive experiences (Pulford & Gill, 2014).

In summary, while the literature presented above provides a snapshot of the biological and psychological basis of general decision-making, research that specifically focuses on the decisions to adopt new AI technologies remains scarce. This paper aims to contribute to closing this gap in the knowledge of our understanding of the decision-making process by closely examining the major factors that influence AI adoption decisions.

Methodology

This study uses a mixed-method approach to study how much past experiences influence decision-making regarding AI usage. The methodology combines the quantitative survey study approach and the qualitative interview approach to provide a comprehensive understanding of the attitudes and behaviors of participants. A survey was conducted with 107 participants with a bimodal distribution of ages ranging from under 18 to above 50 with a median age of 31 (Figure 1), recruited with random sampling with both in-person and online methods through various channels such as social media, community groups, academic institutions, and the general public.

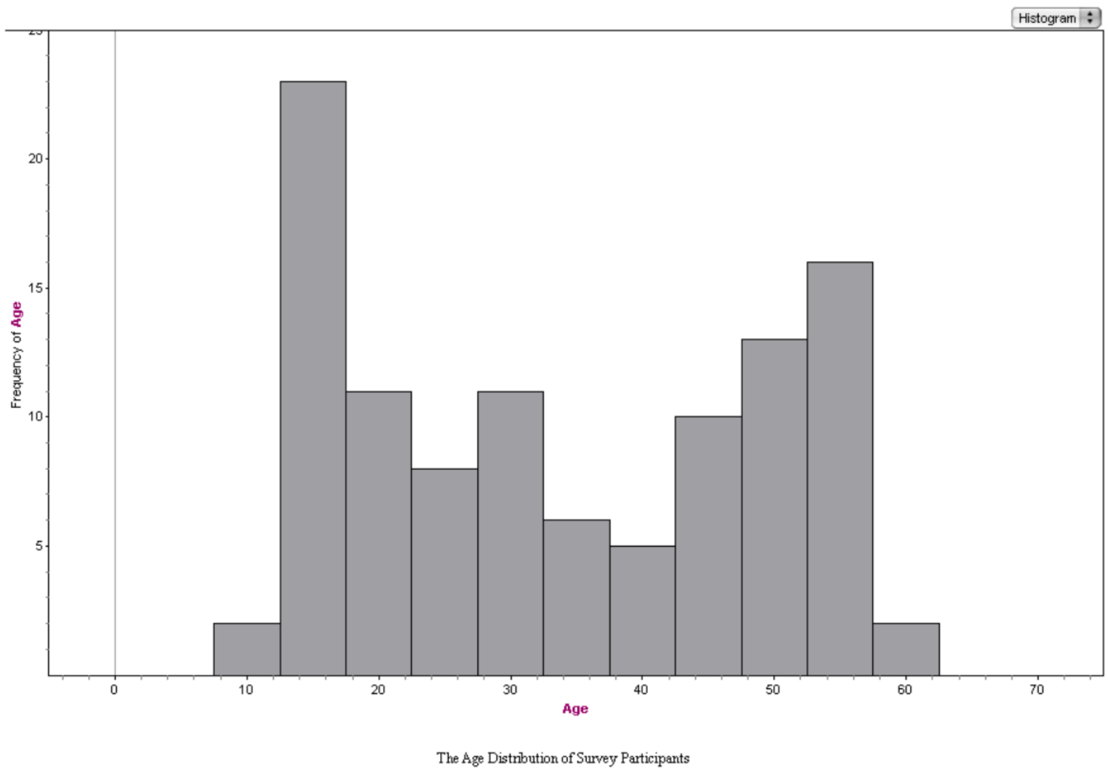

Figure 1. A histogram of the ages of 107 participants in the conducted survey on AI adoption.

Specific in-person questionnaire distribution was conducted in the GTA with select locations like downtown Toronto around the St. George campus of the University of Toronto and the Burlington area and its surrounding regions and neighborhoods not close to city centers. Participants provided details about their age and occupation in the demographics section of the survey to ensure a diverse and representative sample. The survey included questions on AI usage, past experiences with AI, and decision-making patterns which are more specifically outlined in Appendix 1 for further perusal. Questions on AI usage focused on the frequency and types of AI technologies used, while questions about past experiences with AI explored positive or negative encounters and their influence on current usage and perceptions. The survey also assessed decision-making styles and openness to new technologies with a Likert Scale from 1 to 7, with 1 being “Strongly Disagree” and 7 being “Strong Agree” to give a more robust representation of participant experience on a spectrum. Data were collected through online platforms and in-person meetings, and the responses were analyzed using statistical software to identify patterns and correlations between past experiences, AI usage, and decision-making behaviors.

With the aforementioned quantitative data obtained from questionnaires to provide a breadth of statistics for analysis, the qualitative interview method was also used to add depth to this research and provide insight into some of the reasons behind the data obtained. In-depth interviews were conducted with three participants selected from the survey respondents, one with predominantly positive experiences with AI and the others with predominantly negative experiences. The interviews were semi-structured, allowing for flexibility in exploring specific areas of interest while ensuring that key topics were covered. Topics included detailed AI experiences, the impact of these experiences on subsequent decision-making, and overall perceptions of AI. The interviews were conducted online, recorded, and transcribed for analysis. Various statistical methods were used to analyze the data from the survey study, including Pearson’s Correlation Test for R, the Point-Biserial Correlation Test, Pearson’s Correlation Test for Phi Coefficient, and the Chi-Square Test for Independence. Thematic analysis was used to identify common themes and unique insights, providing a nuanced understanding of how past experiences shape AI-related decision-making.

Results

In the analysis using Pearson correlation tests were noteworthy relationships between age and various AI-related factors. To begin with, a moderate negative correlation of -0.39 between age and the number of AIs used was observed, indicating that as age increases, the number of AIs used tends to decrease. Additionally, there was a weak correlation between age and past experience using AI, which holds true when the responses of those who had had no prior experience with AI were excluded as null data points. This suggests only a limited relationship between age and past AI experience.

The Point-Biserial correlation was used to assess relationships between one continuous and one binary variable. There was no correlation between age and trusting AI (0.04), suggesting that age doesn't significantly influence trust in AI. However, a weak positive correlation (0.2) was observed between experience and trusting AI, indicating that positive past experience with AI may slightly increase trust in AI. Similarly, a weak positive correlation (0.1788) was found between experience and the willingness to try out an AI application, suggesting that past experience may have influenced this decision to some extent. In Figure 2, double box plots were created to illustrate the relationship between past experience with AI and two binary variables: trust in AI and willingness to try out an AI application. Figure 2 shows that the majority of participants remain uncertain or neutral about AI, reflecting a wide range of opinions influenced by past experiences. Those who do not trust AI had 2 outliers for their past experiences as well as only an IQR of 1 which shows that there is inconsistency with the answers. However, there are no outliers for individuals who trusted AI as well as an IQR of 2 and a median of 5 meaning that the experience was similar for them as well as majorly positive.

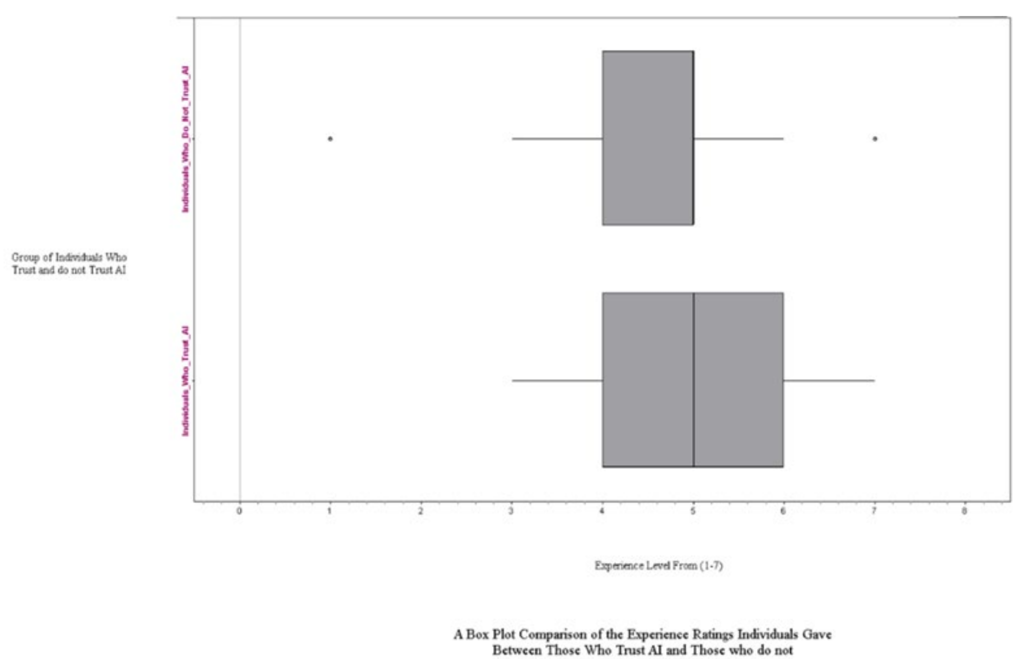

Figure 2. A box plot comparison of the AI experience ratings individuals gave between those who trust AI and those who do not.

Table 1. A two-way table comparison of the correlation coefficient (Phi) for the number of individuals who trust and don't trust AI to whether they would try out an AI application for managing time.

Phi Value	Individuals Who Trust AI	Individuals Who Do Not Trust AI
Individuals Willing to Try AI	0.501286	-0.501286
Individuals Not Willing to Try AI	-0.501286	0.501286

In Figure 3, a comparison is made between the number of individuals who trust and do not trust AI to whether they would try out an AI application for managing time. Phi correlation and Chi-Square tests were conducted to examine relationships between binary variables. There is a strong positive correlation (Phi Coefficient = 0.501286) and a highly significant Chi-Square p-value (1.22722*10^-13) between trusting AI and the willingness to try it. Conversely, there is a strong negative correlation (Phi Coefficient = -0.501286) between not trusting AI and the willingness to try it, underscoring the critical role of trust in the decision to engage with AI. A similarly strong negative correlation (Phi Coefficient = -0.501286) was found between trusting AI and not trying out AI. Finally, a positive correlation (Phi Coefficient = 0.501286) was found between not trusting AI and not trying AI, implying that distrust may lead to avoidance. In Figure 3, 72 individuals trust AI and are willing to try out an AI application, whereas only 5 individuals who trust AI are unwilling to try out the application. This result significantly shows that trust and willingness to try AI out are correlated. For individuals who do not trust AI, it is evenly split into 15 individuals each willing and not willing to try out the AI application. This result indicates that compared to the major factor–trust–contributing to the willingness to try out an AI application, more key factors come into play in decision-making when the person does not trust AI.

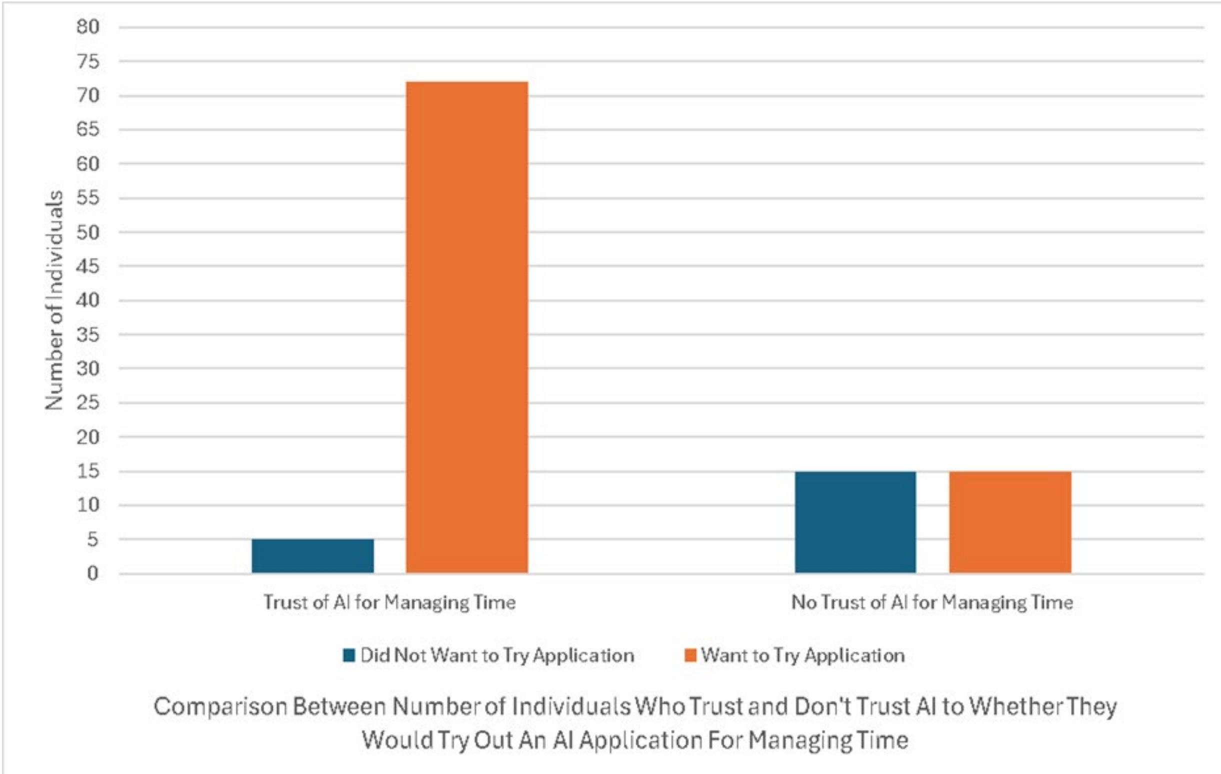

Figure 3. Comparison between the number of individuals who trust and don't trust AI to whether they would try out an AI application for managing time.

The three interviews conducted focused on gathering information from interviewees from three different cohorts of people in the current society. The first interview saw someone in the older population who has had very little prior exposure to AI discuss their perspective on AI. Perception may have played a major role in her distrust of AI since she talked about hearing about AI-generated misinformation from negative publicity in the past and having her opinion influenced by those around her. The second interview involved an interviewee in his late adolescence who has been closely in touch with AI and new technology. He acknowledged the potential misinformation that AI could bring, but proclaimed that his experience using AI played a major role in his perception and acceptance of AI; He posited that the tendency to provide misinformation was branded on all AIs as a package of ignominy, but there are AI models like language and image models that constantly learn and improve from their past iterations. The central idea he conveyed involved a positive feedback loop in which his prior decision to try out AI yielded a generally good experience with AI, which fostered more trust in AI capabilities and thus made him more willing to try out more AI products. Finally, the third interview was conducted with a middle-aged man working in engineering who has a wealth of professional knowledge of AI. Giving examples of how AI works, he stated that he personally believes that AI will be more trustworthy in the future. He posited that since it can be observed that a lot of people have been using AI without realizing it, perception is important in decision-making. A few encounters as the questionnaire survey was conducted provide evidence that corroborates this statement, as there have been instances in which a passerby refused to fill in a questionnaire giving reasons like not being comfortable talking about AI, but immediately went on to ask Siri to call someone for them. A few participants also questioned whether Grammarly is AI and remarked that they have never used AI even though they may actually have used it on a regular basis.

Discussion

Subsequent data analysis reveals an important insight into the relationship between past experiences and decision-making regarding AI usage; our findings indicate that while initial experiences with AI have some bearing on future technology adoption decisions, other factors, most predominantly perception and trust, shape the decision-making process. The nuanced nature of how individuals perceive and adopt new technologies highlights several key factors that influence these processes. First, the Point-Biserial correlation showed a weak positive relationship between past AI experiences and trust in AI, indicating that while past experiences do play a role, other factors are also influential. Positive experiences generally enhance trust and willingness to engage with AI, while negative experiences foster skepticism and avoidance. This aligns with previous research suggesting that emotional responses to past events can shape future behavior (Behrens et al., 2007). Furthermore, the Phi correlation and Chi-Square tests revealed a strong correlation between trust in AI and the willingness to try AI applications, emphasizing trust as a crucial determinant in technology adoption. These results suggest that multiple factors come into play in the decision-making process and it is not past experiences alone but perception, shaped by trust, past experiences, and external influences, that plays a more significant role in decision-making. For example, individuals with predominantly positive experiences may still harbor concerns about AI reliability, particularly in critical tasks like time management or financial decision-making (Kuhnen & Knutson, 2005).

For users and potential customers to harbor a positive prospect about future AI products, educational programs and simulations can provide positive initial experiences with AI to help recalibrate risk perceptions and build confidence in the AI field (Sanusi et al., 2023). Additionally, highlighting the tangible benefits and addressing common misconceptions about AI can mitigate fears and enhance acceptance. For instance, promoting the use of AI in smaller, less critical tasks where it has proven benefits can gradually build trust and familiarity (Horowitz et al., 2023). The broader implications of these findings extend to various sectors of society and the global community. Moreover, promoting a balanced view of AI's capabilities and limitations can help mitigate the spread of misinformation and unrealistic expectations (Pelrine et al., 2023). Individuals need to feel confident and informed about AI's role and functionality to be open to trying out new AIs and integrating them across different disciplines. This approach can ultimately contribute to societal progress by leveraging AI's benefits while minimizing potential risks. In the workplace, for example, AI can boost productivity and streamline operations by assisting with complex tasks in finance, predicting future directions, and making financial management more accessible and efficient. In other areas such as education, AI can reduce the administrative burden on teachers with content creation and review guides for students, allowing them to focus more on personalized instruction and student support. However, the majority of AI applications observed in recent years avoided letting AI manage complex responsibilities or make critical decisions such as legal matters or medical diagnoses, as a single mishap may cause a person harm or even death. By being well-informed of the benefits and risks of incorporating AI into the workplace, individuals and corporations can balance the risk-to-benefit ratio when deciding to try out an AI to avoid excessive negative impact if the risks outweigh the benefits.

Conclusion

In summary, this study explored how past experiences influence decision-making related to AI adoption, emphasizing the importance of perception and trust. Trust and perception were found to play a more significant role than past experiences in shaping decisions about adopting AI technologies. For past experiences, the findings corroborate that positive past experiences with AI enhance trust, whereas negative ones lead to skepticism and avoidance. The research contributes to the broader understanding of the psychological and social factors that influence AI adoption. By integrating insights from neuroscience, psychology, and consumer behavior, the study offers a comprehensive framework for examining the impact of past experiences and trust on technology adoption. It also provides practical recommendations for companies and policymakers on fostering positive perceptions and encouraging the adoption of AI technologies.

For future research, there are several promising directions to explore; to begin with, longitudinal studies that track changes in perception and trust over time could offer valuable insights into how these attitudes evolve with greater exposure to AI. Additionally, exploring the influence of cultural, socioeconomic, and educational factors on attitudes toward AI could provide a more nuanced understanding of the barriers to adoption. These avenues for future research could help develop more targeted strategies for promoting the responsible and widespread adoption of AI technologies.

Implications

The study showed that building trust has emerged as a critical factor in AI adoption. Companies and developers should prioritize transparency, data privacy, and security measures to build trust with users. For example, implementing clear data usage policies and offering features like "incognito mode" can help provide users with a sense of control and security. Moreover, creating positive initial experiences with AI is crucial for mitigating fears and encouraging adoption. Educational programs and hands-on demonstrations can effectively showcase the practical benefits of AI, thereby enhancing user trust and willingness to engage with the technology. Additionally, it is important to demonstrate the versatility of AI applications across various domains, such as healthcare, finance, and education. This broad perspective can help users see the wider potential of AI beyond specific tasks, helping to overcome initial resistance to new technologies (Grassini, 2023). Finally, addressing common misconceptions about AI, such as fears of job displacement or misuse of personal data, is essential. Providing accurate information and highlighting positive case studies can help reshape public perceptions and reduce apprehension.

Limitations

Despite several strengths of this research such as including a diverse range of participants in terms of age and occupation to reflect a variety of perspectives and the use of both in-person and online sampling methods to provide a robust set of data, there are some limitations to this research as discussed below. To begin with, the current sample size and diversity could be further increased to broaden the representativeness and generalizability of the findings; future research may attempt to fully capture the broad spectrum of experiences and perceptions regarding AI across different demographics by including participants with various backgrounds in income statuses, religious believes, and countries of residence.

Additionally, the reliance on self-reported data in surveys and interviews could introduce biases and data stemming from misconceptions. Social desirability or recall biases may result when participants do not accurately remember past experiences or give responses they perceive as socially acceptable instead of recounting what actually happened. In addition, some responses may have been based on misconceptions, which can contribute to the perception differences of every individual and influence how an individual makes decisions as they majorly rely on past decisions. Moreover, while this study focused heavily on perception and trust as key factors in AI adoption, it did not delve deeply into other crucial aspects like accessibility, affordability, and the specific use cases of AI technologies, which could also significantly influence decision-making. Finally, the research lacked longitudinal data, which could have provided how perceptions and trust evolve over time as individuals gain more exposure to AI.

Acknowledgments

I would like to thank my advisor for the valuable insight provided to me on this topic.

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