

The relationship between generative artificial intelligence and cybersecurity

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ABSTRACT

This research paper investigates the adoption of generative artificial intelligence by citizens using the Technology Adoption Propensity (TAP) index. The study aims to explore the influence of cybersecurity factors on the acceptance of generative artificial intelligence technologies. The data for the research will be collected through a questionnaire survey that seeks to understand respondents' attitudes, expectations and concerns towards generative artificial intelligence technologies. The research will use a mixed-methods approach to analyse the data, including quantitative such as descriptive statistics, cross-tabulation analysis, cluster analysis. The expected outcomes of this study include a better understanding of the factors that influence the adoption of generative artificial intelligence technologies by citizens and the development of strategies to address any concerns that citizens may have.

CCS CONCEPTS

• **Applied computing** → Law, social and behavioral sciences; Sociology; • **Theory of computation** → Theory and algorithms for application domains; Machine learning theory; • **Security and privacy** → Human and societal aspects of security and privacy; Usability in security and privacy.

KEYWORDS

Cybersecurity, Technology Adoption Propensity Index, Survey

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1 INTRODUCTION

In recent years, the concept of Artificial Intelligence (AI) has captured the attention of a wide range of stakeholders, from the general public to researchers, and has been further propelled into the public

consciousness following the outbreak of the new type of coronavirus. As a result, there has been a surge of interest in the subject, with a plethora of publications and media reports featuring experts discussing the topic on a daily basis. The rapid pace of technological advancement has often outstripped society's ability to adapt to a changing landscape, leading to a sense of disorientation and uncertainty.

The current century has ushered in noteworthy transformations in various aspects of human existence compared to preceding eras. With the emergence of the information society, marked by swift technological advancement, there has been a substantial revolution in how we interact, learn, and engage in work-related activities. This era is distinguished by an unparalleled velocity of information dissemination, enabled by the proliferation of digital technologies, which have rendered knowledge more accessible than ever before. The ubiquitous presence of the internet has engendered a global network that is catalyzing innovation and engendering social and economic transformations. In contemporary times, the use of artificial intelligence has become increasingly ubiquitous across diverse domains of human activity. John McCarthy, a seminal figure in the field, characterizes AI as the scientific endeavor to create intelligent machines, with a particular emphasis on intelligent computer programs. McCarthy envisions AI as an avenue for comprehending human intelligence through computational means.[3] Following the debut of the Open AI ChatGPT in November of 2022, there has been a notable surge in the utilization of this technology in the realm of security, particularly in the context of influence and cybercrime. The widespread adoption of AI technologies in various domains has facilitated the acceleration of workflows, enhanced precision, automated processes, and streamlined the production of innovative content. The proliferation of AI platforms has contributed to the expansion of businesses and organizations employing these technologies. As the technology continues to evolve, AI is poised to become an integral component of industry transformation, heightening decision-making efficiency and catalyzing innovation. The interplay between technological progress and information dissemination is shaping a future in which AI can play a pivotal role in addressing complex societal issues that are both significant and indispensable. The swift pace of AI development underscores the need for adapting to emerging technologies and comprehending their societal implications. Post-2020, artificial intelligence is poised to become increasingly commercialized and accessible across diverse platforms. The hastening pace of AI development has engendered a pervasive integration of this technology in increasingly intricate workflows across various industries. The escalating automation and optimization of tasks portend new vistas for enhancing work

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and learning efficiency in both corporate and private settings. The growing recognition of generative AI, a constituent of the Large Language Model, is anticipated to play a pivotal role in this trend after 2022. Looking ahead, the potential impact of AI on our daily lives in the coming decades is vast and varied, with numerous areas poised for transformation. The inaugural extended scholarly book chapter on generative artificial intelligence was published in 2013. In that chapter, the authors underscored the presence of deficiencies that impede the progress of AI, notably the deployment of closed-source AI systems, which constrain the capacity to develop and implement this technology.[12] Artificial intelligence (AI) pertains to models, processes, and systems that simulate human intelligence in solving specific tasks. Machine learning, a subset of AI, employs algorithms that utilize preexisting data to accomplish a given task and can employ this data to produce predictions, discern data patterns, and create novel content. Deep learning, identified as a sophisticated component of machine learning, involves networks that emulate neural pathways in the brain, enhancing the algorithm's capacity to recognize, process, and replicate objects, animate entities, and sounds, among other inputs.[2] Within deep learning, generative artificial intelligence (GenAI) constitutes a specialized subfield, which resides within the overarching Large Language Models (LLM). GenAI demonstrates the capacity to produce diverse content, including text and images, based on input data. LLM represents a model that has undergone training on a considerable corpus of data, thereby allowing it to acquire knowledge, identify, and discern mathematical relationships among words. The model conducts statistical analyses on the data it receives, enabling it to recognize intricate relationships and generate novel content.[6] Historically, machine learning has been restricted to predictive models that observe and categorize data patterns. Generative artificial intelligence (GenAI) has emerged as a transformative breakthrough, owing to its remarkable efficacy in not only recognizing, categorizing, and classifying input data, but also generating novel content on demand.

GenAI-based applications have gained widespread popularity among everyday users, given their capacity to produce diverse images, sounds, videos, and text based on specific instructions or prompts. In the case of high language models, the prompt issued to the application is of paramount importance in ensuring optimal outputs. Currently, Prompt Engineer training courses have emerged as a ubiquitous offering across numerous global learning platforms, such as Udemy and Coursera, which can be completed remotely. A prompt engineer, a language expert, is tasked with communicating with large language models to achieve the desired outcome (content creation) in the most effective manner possible. Certain predictions suggest that this occupation may emerge as an emerging profession within the AI domain in the near future.[11]

Generative artificial intelligence (AI) has the potential to improve efficiency in various aspects of our lives, including cybersecurity. Its positive use in cybersecurity can be identified in several areas, such as cybersecurity consulting. However, caution is necessary when using chatbots in cybersecurity consulting since it is challenging to verify the information source. Generative AI can also be helpful in vulnerability testing, which is a significant challenge in cybersecurity. Understanding the workings of vulnerabilities, how they can be exploited by malware creators, and how to identify and detect their use in code is a major challenge. While AI may not fully

understand the context of vulnerabilities, it can provide additional information, which can help in detecting the use of vulnerabilities in code. ChatGPT, in particular, can comprehend user requests and remain in context while providing explanations on how to exploit vulnerabilities. Additionally, the program's ability to package information and modify it according to user requests is a significant advantage. For instance, when the answer to a question is too complicated, ChatGPT can simplify it to the level of a five-year-old. This advantage of ChatGPT also presents a significant risk: it enables anyone without prior knowledge to produce malicious content. ChatGPT can guide users, even a five-year-old, step by step on how to write programs in Python, including downloading the program, opening the tool, and typing the programs written. As a result, anyone can design malicious code, including malicious websites, using generative AI without prior knowledge. This technology is a serious enabler for the production of phishing content, allowing for the formulation of phishing emails with professional grammar in the language of choice and the production of accompanying malicious code. Additionally, generative AI can pose a significant challenge in the production of disinformation content, using image, video, and sound generation to design complex fake news campaigns. Moreover, professional voice generation can play a prominent role in a variety of voice-based phishing schemes, which are used to scam family members. The potential harm that malicious users can cause through generative AI can have a significant impact on the technology's use and further development. If fears about generative AI's misuse predominate, this can slow further innovation in the field.

In contemporary times, diverse technological innovations are being introduced into users' daily lives, with varying degrees of success. The Gartner Hype Cycle is a periodic examination of the trajectory by which a technology progresses from a "technological breakthrough" to a "productivity plateau." The Hype Cycle posits that technology adoption undergoes five distinct phases, beginning with the release of a technology and culminating in its incorporation into everyday use. However, it should be noted that not every technological breakthrough undergoes all of these stages. Additionally, the cycle denotes the pace of development, which can vary considerably among different technologies. Throughout recent decades, numerous innovative technologies have failed to gain traction, such as 3D television, as users have been reluctant to embrace them for various reasons. Models of technology adoption examine the multifaceted factors that contribute to the diffusion of technologies and their uptake in everyday usage. Based on Gartner's 2023 analysis, generative artificial intelligence (genAI) currently occupies the "Peak of Heightened Expectations" on the Hype Cycle, and is projected to reach the "Plateau of Productivity" in approximately 5-10 years.[1]

A wide array of international models are at disposal to monitor the technology adoption process. These models can be broadly classified into five distinct types, each characterized by a unique set of dependent and independent variables, as well as advantages and disadvantages. The suitability of a given model in a research project depends on these factors. The five international models are as follows:

- The Technology Acceptance Model (TAM1) is a widely-known and frequently-utilized model that serves as the foundation for several other models. The central aspects of TAM1 include the triad of attitude, demand, and actual usage. However, the model has been criticized for not considering individual factors, such as demographics (e.g., age, education, etc.), which may impact the technology adoption process.[14] [7]
- The Technology Acceptance Model 2 (TAM2) offers more detailed insights into the adoption process compared to Model 1. A critical aspect of TAM2 is the incorporation of external factors that affect perceived usefulness. Additionally, the model includes a moderating variable, which highlights the conditions under which the relationship between the dependent and independent variables may change. [9]
- The Technology Acceptance Model 3 (TAM3) represents a sophisticated model that, relative to its antecedents, considers factors that impact perceived ease of use, with a particular focus on an individual's prior experience. However, a potential drawback of Model 3 is that, consistent with its predecessors, it does not account for individual factors.
- The Unified Theory of Acceptance and Use of Technology (UTAUT) consolidates eight preceding theories of technology acceptance, including the Theory of Reasoned Action, the Theory of Planned Behavior, the Technology Acceptance Model, the model resulting from the combination of the latter two theories, the Motivational Model, the Model of Personal Computer Use, Rogers' Diffusion Theory, and the Social Cognitive Theory. The integration of these theories enabled the development of a model that, unlike its precursors, takes into account individual factors. UTAUT aims to provide managers and executives with insights into the potential success of a new technology in their specific context.[10] The Unified Theory of Acceptance and Use of Technology (UTAUT) consolidates eight preceding theories of technology acceptance, including the Theory of Reasoned Action, the Theory of Planned Behavior, the Technology Acceptance Model, the model resulting from the combination of the latter two theories, the Motivational Model, the Model of Personal Computer Use, Rogers' Diffusion Theory, and the Social Cognitive Theory. The integration of these theories enabled the development of a model that, unlike its precursors, takes into account individual factors. UTAUT aims to provide managers and executives with insights into the potential success of a new technology in their specific context.[10]
- The Unified Theory of Acceptance and Use of Technology (UTAUT2), the enhanced version of UTAUT aims to assess the willingness of everyday customers and users to adopt technology. To capture aspects of everyday use and motivation, the model incorporates three new factors: hedonic motivation (the pleasure derived from technology use), value for money (the extent to which customers perceive the cost to outweigh the benefits), and habit (users' past experience with the technology). The inclusion of these factors enables the measurement of attitudes towards technologies that are part of everyday life.[8]

The evolution of technology acceptance models continues unabated, as researchers endeavor to adapt the models to meet the demands posed by emerging innovations. Among the various technology acceptance models, we have selected the Technology Adoption Propensity Model created by Ratchford and Barnhart as the most appropriate model for our research, given the superior design of their questionnaire for measuring the likelihood of adopting state-of-the-art technologies.[5]

However, alongside the promise of a more efficient and sustainable future, the proliferation of AI has also given rise to a range of concerns, primarily pertaining to privacy and ethics. To ensure that AI is appropriately regulated from legal and ethical perspectives, it is essential to address these concerns proactively. In sum, AI holds the potential to engender a more sustainable future, albeit with the caveat that care must be taken to prevent the disproportionate collection of data, the erosion of privacy, and the establishment of a comprehensive digital surveillance state. With this in mind, the European Union (EU) promulgated the Artificial Intelligence Act in March of 2024, with the stated objective of forestalling the emergence of these dystopian scenarios.[13]

The primary aim of our research is to conduct an empirical investigation into the social acceptance of generative artificial intelligence technology, with a specific focus on its vulnerability. Our hypotheses in this regard are as follows:

- H1. The respondents are distrustful of generative artificial intelligence technology.
- H2. Individuals with a minimum of a bachelor's degree are more likely to integrate generative artificial intelligence services into their daily routine.
- H3. Individuals with at least a bachelor's degree perceive themselves to be less vulnerable to the impact of generative artificial intelligence technology.

2 METHODOLOGY

In our research, we replicated the questionnaire developed by Ratchford and Barnhart, with the modification of replacing the term "technology" with "generative artificial intelligence". The TAP model comprises four distinct factors. The optimism component encompasses four questions that aim to gauge the respondent's positive or negative attitude towards generative artificial intelligence in terms of increased control, efficiency, and freedom. The proficiency theme, consisting of four questions, evaluates the extent to which the participants perceive the use of generative artificial intelligence platforms as challenging. The dependency segment, comprised of three questions, endeavors to explore the level of dependence and possible addiction to the technology. Lastly, the vulnerability component, consisting of three questions, assesses the respondent's level of skepticism or distrust towards the technology. In addition to the core questions of the Technology Adoption Propensity index, our questionnaire incorporated general inquiries regarding tool usage and questions related to generative AI. The responses were subjected to analysis using the IBM SPSS software package, which facilitated the application of descriptive statistics, cross-tabulation analysis and cluster analysis. In the initial stage of the research, the responses to the Technology Adoption Propensity factors were

subject to evaluation using descriptive statistics, which entailed analyzing the mean score, overall deviation from the mean score, skewness, and kurtosis of the distribution. The scores of the responses to the questions related to the TAP factors were subsequently averaged and examined to determine which of the four factors dominated among the respondents, following the technology acceptance model. Subsequently, the questions related to generative artificial intelligence use were evaluated using cross-tabulation analysis, employing the chi-square test to determine whether the questions on generative artificial intelligence knowledge exhibited a significant association with educational attainment of the respondents. In the final phase of our research, we proceeded with a cluster analysis of the three questions pertaining to the vulnerability of the TAP model. Our objective was to categorize respondents into two or three distinct groups based on their perceived vulnerability towards generative AI. We compared the clusters formed from our analysis with various education levels. The purpose of cluster analysis is to identify coherent elements based on specific criteria and segregate them as a separate group along that criterion. In this analysis, the elements that are most similar to each other are grouped together. Firstly, we performed a hierarchical cluster analysis (using the nearest neighbor method) to identify any outliers in the sample. The hierarchical cluster analysis is a method to arrange certain elements into groups. The clustering of each element is crucial, and in this case, we used the nearest neighbor method to ensure that similar elements are grouped together. A dendrogram was used to show the hierarchical relationships between values and to determine the number of clusters to divide the sample into based on technical interpretability. Based on the dendrogram, we removed three items from the sample ($N=161$) that we identified as outliers. Then, we performed a cluster analysis on the cleaned sample ($N=158$) using Ward's method. Ward's method is a commonly used method that calculates the mean and the Euclidean distance for each element and sorts the units into different or identical clusters. The Euclidean distance helps to identify the distance between two elements, if they are moving in a straight line. This method ensures that the elements closest to each other in space are in the same cluster. The dendrogram produced using this method no longer contained any outliers, so we could clearly distinguish clusters based on the responses. We determined the correct number of clusters by querying item count, standard deviation, and mean. We named the clusters based on their characteristics and performed cross-tabulation analysis to compare them with education and examine whether other factors influenced membership of each cluster.

The questionnaire was made available for completion between 13 November 2023 and 15 March 2024, and it was shared on Facebook. It is important to note that the results of the questionnaire cannot be considered representative and should only be interpreted in the context of the respondents. This is because the sample was not randomly selected, and the respondents were not evenly distributed across different demographic groups. For instance, respondents with at least a bachelor's or an academic degree were over-represented among the sample. Out of the 172 respondents who completed the questionnaire during the four-month interval, 11 respondents were excluded during the data cleaning process, and 161 responses were analyzed further.

The reasons for excluding these respondents were as follows: one respondent was only 15 years old, and their response could not be considered due to the lack of parental consent and data protection reasons. Another respondent provided a non-binary response to the question on gender, which caused issues in the cross-tabulation analysis on gender. Since the expected frequency in each cell should be at least 5, this condition could not be met due to the presence of one non-binary respondent. For similar reasons, the low number of 'Don't know' responses to the questions on generative AI use (only three in total) justified their exclusion from further analyses.

3 RESULTS

The gender distribution of the respondents was nearly equal, with 85 women and 75 men providing responses to the questionnaire. In analyzing the age distribution, the responses were categorized by generation based on the age of the respondents. Out of the 161 responses analyzed, 10 respondents belonged to the Baby Boomer generation, 60 respondents to Generation X, 63 respondents to Generation Y, and 28 respondents to Generation Z. It is worth noting that there is a preponderance of respondents from Generation X and Generation Y. The questionnaire provided seven categories for respondents to indicate their highest level of education. However, due to the low frequency of some categories (e.g., only one respondent reported completing primary education), it was not possible to conduct certain analyses. Therefore, before carrying out the analyses, the responses were divided into two groups based on the attainment of a bachelor's degree or higher. In this case, 115 people indicated that they had at least a bachelor's degree.

In the preliminary phase of our research, we employed cross-tabulation analysis to investigate the impact of higher education on responses to three questions pertaining to the use of generative artificial intelligence. The questions included whether the respondent had prior knowledge of the technology, had utilized it in the past, and incorporated it into their daily lives. The analysis was conducted on a sample of 161 respondents to determine whether higher education affects the likelihood of answering affirmatively or negatively to the aforementioned questions related to generative artificial intelligence. Following the completion of the cross-tabulation analysis, we conducted a Chi-square test to determine the significance of the relationship between the two observed variables. Cramer's V index was then utilized to gauge the strength of the relationship.

Our findings indicate that a relationship exists between the variables of "Have you heard of GenAI before?" and "Have you used GenAI before?" in the higher education questionnaire. However, a low correlation coefficient, as indicated by a Cramer's V value close to 0, suggests a weak relationship. This implies that, for the respondents, whether they have heard of generative artificial intelligence and whether they have used it, displays a weak link with their possession of a tertiary education.

Subsequently, we analyzed the mean scores obtained concerning the assessment of the TAP factors. Our findings reveal that the vulnerability factor garnered the highest mean scores. The skewness and kurtosis of the vulnerability factor were examined, with negative values indicating that the mean is smaller than the median

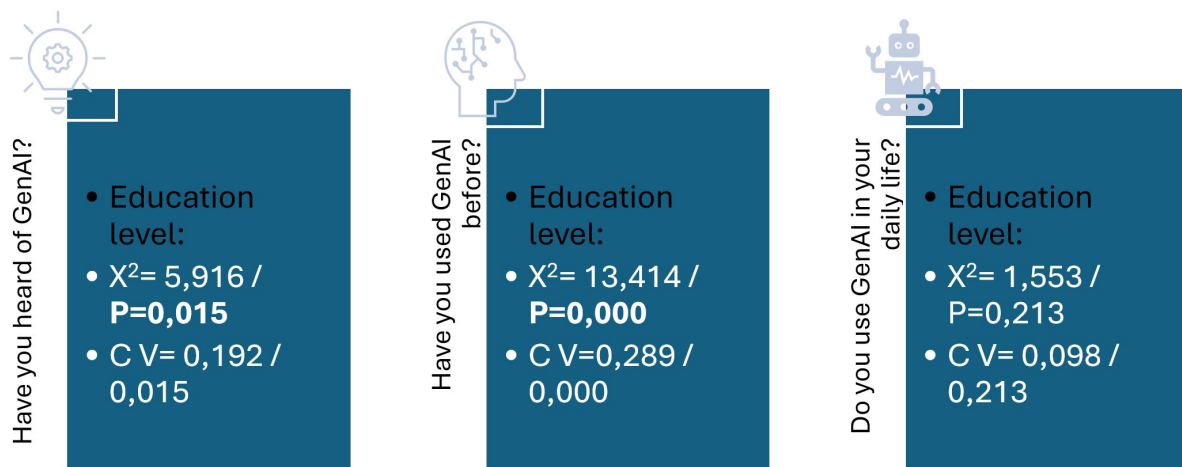


Figure 1: Correlation between knowledge and use of genAI and tertiary education (own edited, N=161)

Table 1: Descriptive statistics for responses to TAP factors (own edited, N=161)

TAP factor	Mean Statistic	Std. Deviation Statistic	Skewness Statistic	Kurtosis Statistic
1. ... gives me more control ... (optimism 1)	2,55	1,318	0,138	-1,267
2. ... helps me make ... changes ... (optimism 2)	2,32	1,233	0,354	-1,084
3. ... more easily do ... things ... (optimism 3)	3,19	1,394	-0,434	-1,109
4. ... make my life easier. (optimism 4)	3,35	1,366	-0,532	-0,885
5. I can figure out ... (proficiency 1)	3,06	1,42	-0,219	-1,27
6. ... fewer problems ... making (it) work. (proficiency 2)	2,77	1,437	0,04	-1,343
7. ... people come to me for advice ... (proficiency 3)	2,24	1,482	0,752	-0,937
8. I enjoy figuring out how to use ... (proficiency 4)	2,71	1,494	0,057	-1,519
9. ... controls my life ... (dependence 1)	1,66	0,988	1,401	1,076
10. ... I am overly dependent ... (dependence 2)	1,32	0,747	2,313	4,372
11. ... I become a slave to it. (dependence 3)	1,5	0,943	1,934	3,085
12. ... criminals may ... target me. (vulnerability 1)	3,68	1,33	-0,741	-0,602
13. ... invade my privacy. (vulnerability 2)	3,14	1,325	-0,206	-1,05
14. ... things that we don't really need. (vulnerability 3)	3,28	1,343	-0,304	-1,03

and that there are outliers that pull the mean downwards, leading to a left-skewed distribution. Furthermore, negative kurtosis values imply a flatter than normal distribution, suggesting a significant variance in the sample for these factors.

The descriptive statistics evaluated the scores (Mean Rank) of the responses to the questions related to the factors. The results indicate that the highest scores were for vulnerability, with an average of 3.37. This outcome suggests that respondents are distrustful

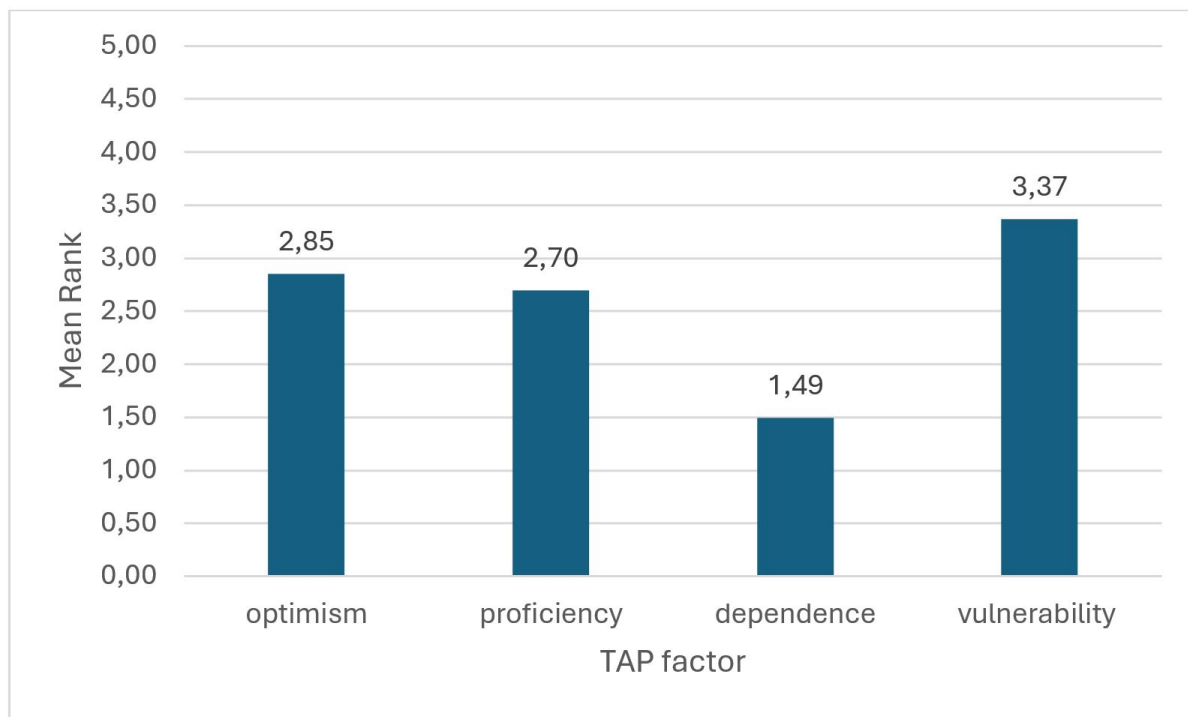


Figure 2: Mean responses to TAP factors (own edited, N=161)

of generative artificial intelligence, harboring concerns about the potential for misuse and excessive influence over their privacy.

In the final phase of our research, we employed a cluster analysis on the questions related to the vulnerability factor, given its high cross-sectional score. Our preliminary hierarchical cluster analysis using the nearest neighbor method identified three values as outliers that could potentially bias the formation of clusters. Therefore, these values were removed from the final analysis, resulting in a sample of N=158. Next, we constructed a dendrogram using Ward's procedure to estimate the clustering, which was used to create three clusters based on the responses to the vulnerability factor. The clustering approach proved suitable for describing the data structure, as the mean values between the clusters exhibited significant differences, reflecting the varying attitudes of the respondents towards vulnerabilities associated with generative artificial intelligence. Moreover, the mean values of the clusters displayed notable differences, sharply demarcating the three groups. Based on the three dimensions (questions), the following three clusters were defined:

- Moderately concerned (averages: vulnerability 1= 3.76, vulnerability 2= 2.71, vulnerability 3= 2.81)
- Totally distrustful (averages: vulnerability 1= 4.66, vulnerability 2= 4.33, vulnerability 3= 4.30)
- Having minimal concerns (averages: vulnerability 1= 1.48, vulnerability 2= 1.34, vulnerability 3= 1.90)

We conducted cross-tabulation analysis to compare the three clusters with the respondents' educational attainment and their use of generative artificial intelligence in their daily lives. However, our

findings reveal that there was no significant relationship between the two variables and the cluster in which a respondent was placed. Therefore, neither their possession of a tertiary education nor their use of generative artificial intelligence influenced the cluster in which respondents were placed.

4 DISCUSSION

The results of our study provided several important insights into public perceptions and the social acceptability of generative artificial intelligence (GenAI) technologies based on the educational background of the respondents. The high level of distrust towards GenAI technologies shows a critical challenge in the integration of these technologies into everyday life. This distrust may stem from various factors, including concerns about privacy, data security, the potential for misuse of technology, but also it may stem from pop cultural aspects, like the rise of the machine.

Interestingly, our study reveals that educational attainment does not significantly influence the likelihood of using GenAI technologies. This contradicts common assumptions that higher educational levels correlate with a greater acceptance and understanding of new technologies.[4] The results suggest that the decision to adopt GenAI may be influenced more by factors such as perceived utility, functionality, ease of use, and cultural attitudes rather than purely educational background.

Furthermore, the finding that there is no significant difference in perceived vulnerability towards GenAI between individuals with a higher education and those without suggests that educational interventions alone may not be sufficient to address the issues of

Table 2: Ward's Method cluster analysis based on responses to vulnerability factor (own edited, N=158)

Ward's Method		vulnerability 1	vulnerability 2	vulnerability 3
1	Mean	3,76	2,71	2,81
	N	62	62	62
	Std. Deviation	,824	,837	1,038
2	Mean	4,66	4,33	4,30
	N	67	67	67
	Std. Deviation	,478	,637	,835
3	Mean	1,48	1,34	1,90
	N	29	29	29
	Std. Deviation	,509	,484	1,081
Total	Mean	3,72	3,15	3,27
	N	158	158	158
	Std. Deviation	1,306	1,325	1,343

trust and security concerns associated with these IT technologies. This could indicate a general concern across different educational backgrounds, possibly driven by broader societal narratives rather than individual knowledge or awareness levels.

The implications of these findings are various. For policymakers and developers of GenAI technologies, there is a clear need to build robust frameworks that enhance transparency and data protection to mitigate the general distrust. Additionally, public engagement strategies should be developed to involve people from all educational backgrounds, providing clear, accessible information about the benefits and risks associated with GenAI. Future research should explore the specific factors that contribute to distrust and reluctance to use GenAI technologies, particularly focusing on qualitative methods to gain deeper insights into individual attitudes and concerns. In conclusion, while GenAI presents significant opportunities for advancement in various sectors, there is a pressing need to address the public's concerns comprehensively to facilitate a smoother integration of these technologies into society.

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