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AI anxiety and fear: A look at perspectives of information science students and professionals towards artificial intelligence

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Abstract
The rapid integration of artificial intelligence (AI) within society and the emergence of the fourth industrial revolution (4IR), has ignited a spectrum of emotions in society, ranging from enthusiasm to anxiety. This study investigates the depths of AI anxiety and fear among a population of information science students and professionals. Utilising a survey of over 200 current students and professionals, this study explores the connections between age, gender identity, ethnicity, geographic location, educational attainment and residence, and the levels of anxiety and fear associated with AI and the 4IR. The findings reveal nuanced relationships, with age, ethnicity, academic achievement and regional context serving as critical differentiators in 4IR and AI anxiety within this population. Students and professionals alike may benefit from seeking further education about this emerging technology.

Keywords
AI anxiety; AI literacy; artificial intelligence; fourth industrial revolution; information professionals; libraries

The rapid advancement of artificial intelligence (AI), especially in the form of generative AI technologies and large language models such as ChatGPT, has been nothing short of remarkable in recent years. Some researchers and professionals have found this emerging technology to be a great democratising force for society – creating a level playing field for innovators who may struggle with language, educational or socioeconomic difficulties [1]. However, the embrace of this technology is far from universal, as some individuals eagerly adopt these innovations while others remain cautious or even resistant. While much scholarly attention has been devoted to understanding AI adoption among early enthusiasts, there is a significant gap in our understanding of the anxieties and fears held by information science students and information professionals regarding the emergence of generative AI technologies. Even Elon Musk, whose funding supported OpenAI, the company behind ChatGPT, warned in 2014 that ‘With artificial intelligence we are summoning the demon’ [2].

This study aims to gain a deeper understanding of feelings of anxiety and fear related to AI among information science students and professionals. To achieve this, we have employed a comprehensive approach that incorporates demographic questions and items adapted from the State-Trait Anxiety Inventory (STAI) and State Fear Inventory to explore information science students and professionals’ perceptions of ‘artificial intelligence’ and the ‘fourth industrial revolution’. By

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utilising various analytical techniques, including correlation, regression and cluster analysis, we intend to examine the connections between demographic factors and anxiety–fear levels. This research seeks to primarily address the research question, 'What are the distinguishing factors that contribute to fears associated with emerging technologies within communities of information science students and professionals?'

1. Definitions

There is considerable disagreement about how the terms 'artificial intelligence' and 'fourth industrial revolution' should be defined, as they have both narrow and broad, general and contextualised understandings among different disciplines and populations [3]. For the purposes of this study, it was critical to clearly define how these terms were used from the outset, so that study participants would firmly grasp what technologies, tools and concepts they were being asked to consider. The following are the definitions of these two terms that were provided to the study's subjects.

AI is the development and use of digital/computer-based intelligence to replicate human abilities, through machine learning and automation, with the goal of enhancing human life by automating tasks and expanding intelligence beyond human capabilities.

The fourth industrial revolution (4IR) is a transformative period marked by the integration of digital technologies into industries, revolutionising processes through digitalisation, automation and emerging technologies, impacting human activities and enhancing information handling and outcomes.

In addition, this research study focuses on the phenomenon of AI anxiety and AI fear, which we define as feelings of discomfort or nervousness when thinking about or interacting with AI tools such as ChatGPT.

2. Literature review

The following literature review is based on existing research relating to generative AI, the 4IR in society, AI anxiety and AI fear. The literature was gathered from relevant Ebsco databases in Spring 2024 and were used to inform the development of this study's primary research question and the study's questionnaire instrument.

AI anxiety is a relatively recent phenomenon, coinciding with the increasing accessibility of AI technology, particularly generative AI technology. In contrast, technology-related anxiety has been a well-documented area of study for some time. Broos observed that females tend to exhibit higher levels of anxiety towards computers than males, with experience and exposure to technology playing a significant role in moderating this anxiety [4]. Hsieh et al. [5] further noted that technology anxiety varies significantly based on factors such as age, gender and 'one's exposure to technology. Similarly, Berner et al. [6] found that older adults who actively engage in digital social participation, belong to younger age groups and have higher educational levels tend to experience lower levels of technology anxiety.

The impact of technology anxiety on individuals is substantial. For example, MacCallum et al. [7] highlighted that anxiety related to information and communication technology (ICT) can lead to a reduced intention to adopt new technologies. Similarly, Donmez-Turan and Kir [8] emphasised that user anxiety regarding technology plays a pivotal role in technology acceptance, potentially hindering adoption even when the perceived usefulness of the technology is high. Failing to embrace new technologies due to anxiety can significantly impact one's quality of life, particularly in an era where computer usage is pervasive in the business world [9]. This reluctance can affect one's ability to effectively carry out work tasks, potentially jeopardising job performance and opportunities for professional growth.

In response to these concerns, several measures of technology anxiety have emerged over recent decades. One influential model, the Computer Anxiety Rating Scale, was proposed by Rosen and Weil [10] during the early years of computers and the Internet. However, as new information technologies such as virtual reality and chatbots have emerged, Redmann and Kotrlik suggest that measures may need to evolve to address these changing modes of interaction [11]. An example of an updated measure is the Abbreviated Technology Anxiety Scale developed by Wilson et al. [12] designed for quick, low-stakes assessments of technology anxiety using a concise set of questions, replacing lengthier and outdated measures.

Several popular theories explore hesitation and adoption behaviour towards technology. Diffusion of Innovations theory, initially proposed by Everett Rogers [13], and the Technology Acceptance Model proposed by Davis [14], are arguably the two most influential. Diffusion of Innovations theory suggests that human behaviour regarding adoption of new innovations/technologies is relatively predictable and that distinct categories of adopters exist, whereby the amount of information received and exposure to the innovation presented may influence adoption [15]. The Technology Acceptance Model suggests that several factors are core to the adoption of technology, including core beliefs and behaviours of the individual, the amount of effort required to utilise the technology, the perceived usefulness of the technology and attitudes towards the technology (including possible fear of the technology) [15,16]. These theories lend a critical dimension to the design of this study, which explores anxiety and fear as factors that may moderate the intention to utilise AI tools.

The emergence of publicly available generative AI technology has shifted societal issues and concerns tremendously. While large language models such as ChatGPT present opportunity for societal growth and improvement of human tasks [17,18], they also pose major risks, particularly in the realms of job replacement, copyright infringement and fabrication of misinformation [19,20]. Given the rapid manifestation of this technology and its associated concerns, it is not surprising that some may develop a fear of the technology [21].

AI anxiety encompasses various concerns related to the lack of personal control over AI technology, including fears of privacy violations, bias, job displacement, learning anxiety and ethical violations [22]. Due to the nature of AI models, involving training on massive datasets that are often not accessible to the general public, the potential for problematic and biased data to influence models' decision-making and outputs is significant [23]. Plagiarism and copyright can similarly prove problematic, as it is difficult to trace what sources a model may be using to help generate outputs [24]. This 'black box' phenomenon in AI naturally leads many to be reluctant to embrace the technology [25].

A few recent studies have explored factors contributing to the phenomenon of AI anxiety and fear. Research by Zhan et al.[26] suggests that synchronicity can generally alleviate AI-related fears, while perceived AI control exacerbates them. Furthermore, Wang et al. [27] and Li and Huang [28] both highlight job replacement as a primary factor contributing to AI anxiety. Kaya et al. [29] found that demographic factors such as computer use, knowledge and personality traits can also influence the intensity of AI anxiety. Despite these concerns, studies by Cugurullo and Acheampong [30] and Hopcan et al. [31] indicate that many individuals are still open to adopting AI technology as it becomes more accessible.

Presently, libraries are experiencing pressure to adapt to emerging AI technologies such as ChatGPT, and many recent articles have discussed the ways in which libraries can integrate these tools to better serve patrons [32,33]. One major way in which libraries have sought to embrace this technology is in the form of AI literacy, or AI-based information literacy, instruction [34,35]. However, a critical aspect of understanding what it takes to be 'literate' in an area such as AI is an understanding of how people currently perceive the technology and potential barriers to its use, such as fear and anxiety. This study endeavours to explore the prevalence of these emotions in relation to AI and considers their significance to the development of AI literacy skills and AI instruction.

3. Methods

This study utilised a survey comprising 29 questions, several of them consisting of multiple parts. These questions collected information about the demographic backgrounds of respondents as well as their levels of anxiety and/or fear relating to AI and the 4IR. The demographic questions included age, gender identity, ethnicity, geographic location and educational attainment. The wording of these questions was refined through a small pilot test, which collected feedback from 14 respondents enrolled in a master's or doctoral programme in information science at the researchers' university.

The survey was distributed electronically to information science students and working information professionals in university-related Facebook groups. A total of 12 different universities in the United States, India and Nigeria were represented, with respondents ranging from information science undergraduate, masters, doctoral students and academic faculty to systems analysts, database managers and academic librarians. It is worth noting that this distribution method inherently introduced a potential skew towards individuals with higher educational attainment, meaning that the results may not be generalisable to the general public, though they should be generally representative of information science students and professionals.

Anxiety levels were assessed using questions adapted from the STAI and the State Fear Inventory. In the initial part of the survey, participants were given the definitions of 'artificial intelligence' and the 'fourth industrial revolution' provided in the definitions section of this article. Subsequently, in the second section of the study, participants were presented with either 'artificial intelligence' or 'fourth industrial revolution' and were asked to rate their emotional responses using a four-point scale. They were asked to indicate the extent to which they associated each of 16 emotions with the respective concept. These emotions included feeling tense, upset, nervous, worried, confused, furious, terrified, irritated, relaxed, calm, confident, content, clear-headed, happy, excited and pleased (with the last eight emotions being inversely scored – that is, less 'relaxed' equals higher score).

After collecting the data, Pearson correlation and multiple linear regression analyses were performed to explore the relationships between the demographic variables and emotional responses related to AI and the 4IR. Regression models were constructed for both the dependent variables of anxiety–fear of AI and the 4IR. K-means cluster analysis was also used to categorise respondents into distinct groups based on their demographic characteristics. An analysis of variance

(ANOVA) was then conducted to assess differences among these clusters regarding anxiety and fear concerning AI and the 4IR. These analyses allowed the researchers to inspect the relationships among variables from multiple angles, identifying any significant findings.

4. Results

A total of 215 valid and complete responses were received from survey participants. These responses can be broken down into several key demographic categories. Regarding age, 26% of respondents were aged 18–29, while 57% fell into the 30–49 age group and 17% were 50 years old or older. In terms of gender identity, 55% identified as female and 45% identified as male. In terms of reported ethnicity, 72% of respondents identified as White, while 28% identified as belonging to a non-White ethnicity, with Black (10%) and Asian (15%) being the most common. Geographically, 70% of participants resided in North America, with the remaining 30% living outside of North America. Educational attainment varied among respondents: 5% had less than a 2-year degree, 9% held a 2-year degree, 44% had completed a 4-year degree and 42% possessed a graduate degree. Approximately 40% of respondents were current information science students, while 60% were information professionals. Finally, with regard to residential location, 13% of respondents lived in rural areas, 18% resided in towns with populations under 10,000, 20% in towns with populations ranging from 10,000 to 50,000, 25% in towns with populations from 50,001 to 250,000 and 24% in cities with populations exceeding 250,000.

Table 1 displays the mean scores for each emotion for AI and 4IR across the 16 feelings attached to anxiety–fear. The final row provides the mean score for all 16 feelings and the percentage that the mean lies between the scores of 1.00 and 4.00 (the four-point scale). For AI, the highest mean score was observed for 'Worried' at 2.37, closely followed by 'Nervous' at 2.34. The lowest mean scores were found for 'Upset' at 2.07 and 'Furious' at 2.12. On the contrary, in the context of the 4IR, the highest mean score was 'Worried' at 2.30, while the lowest was 'Furious' at 2.05. For AI, the mean score on the scale was 2.24, whereas for the 4IR it was just slightly lower at 2.22.

The study began by examining the correlation matrix for the constructs under investigation. Interestingly, age exhibited a positive correlation with anxiety and fear related to AI, but the relationship was only significant at a $p < 0.05$ level, not a $p < 0.01$ level. This suggests that, to some extent, older individuals tended to report higher levels of AI-related anxiety. In contrast, gender and political leaning showed no significant correlation with either AI or 4IR anxiety.

Ethnicity and region of origin, on the contrary, played more substantial roles in shaping these anxieties. Individuals from certain ethnic backgrounds and regions displayed notably higher levels of anxiety and fear regarding both AI and the 4IR. The correlations were statistically significant at $p < 0.01$, implying that these factors might be pivotal in understanding the nuances of technological apprehension.

Table 1. Mean scores for 16 feelings associated with anxiety–fear.

Feeling	Artificial intelligence	Fourth industrial revolution
Tense	2.31	2.28
Upset	2.07	2.04
Nervous	2.34	2.29
Worried	2.37	2.30
Confused	2.24	2.25
Furious	2.12	2.05
Terrified	2.15	2.08
Irritated	2.10	2.03
Relaxed	2.31	2.34
Calm	2.22	2.26
Confident	2.25	2.21
Content	2.36	2.40
Clear-headed	2.17	2.18
Happy	2.29	2.24
Excited	2.15	2.28
Pleased	2.33	2.38
Mean	2.24	2.22

Table 2. Correlation coefficients for the AI anxiety/fear and 4IR anxiety/fear.

Variable	Age	Gender	Ethnicity	Region of origin	Academic achievement	Political leaning	Occupation	Urbanicity
AI anxiety/fear	0.154*	0.124	0.263**	0.176**	–0.104	–0.018	0.057	–0.053
4IR anxiety/fear	0.006	0.158*	0.220**	0.242**	–0.137	–0.143	0.167	–0.117

AI: artificial intelligence; 4IR: fourth industrial revolution.
*Significant difference at $p < 0.05$
**Significant difference at $p < 0.01$

Table 3. Regression findings for dependent variable of anxiety/fear of AI.

	Model 1	Model 2
Age	0.017 (0.006)**	0.016 (0.006)**
Gender	0.140 (0.126)	
Ethnicity	0.353 (0.160)*	0.341 (0.148)*
Region of origin	0.009 (0.151)	
Academic achievement	–0.320 (0.075)**	–0.330 (0.073)**
Political leaning	–0.076 (0.075)	
Occupation	0.134 (0.316)	
Urbanicity	–0.091 (0.050)*	–0.102 (0.047)*
R-squared value	0.208, F = 6.78, $p < 0.001$	0.199, F = 13.07, $p < 0.001$

AI: artificial intelligence.
*Significant difference at $p < 0.05$
**Significant difference at $p < 0.01$

Academic achievement, often seen as a marker of knowledge and exposure to these technologies, displayed an intriguing inverse relationship. Lower academic achievement was associated with higher AI- and 4IR-related anxiety, suggesting that a lack of familiarity might breed unease.

Occupation (student versus information professional) and urbanicity, though not significant at a $p < 0.05$ level, hinted at nuanced influences. While occupation showed a slight positive correlation (being an information professional rating higher than a student) with both types of anxiety, urbanicity had a negative correlation with AI-related anxiety, implying that urban dwellers might be somewhat more at ease with the spectre of AI (see Table 2).

Digging deeper, the study conducted regression analyses to unveil the factors that most strongly influenced anxiety and fear towards AI, as shown in Table 3. Model 1 revealed that age, ethnicity and academic achievement were significant predictors. Older individuals, those from specific ethnic backgrounds and those with lower academic achievements reported higher AI-related anxiety. The model accounted for 20.8% of the variance in AI anxiety, underscoring the multifaceted nature of this fear.

Model 2 looked only at the independent variables that were statistically significant from Model 1 (age, ethnicity, academic achievement and urbanicity). While several of these variables were not individually significant in the correlation matrix, they were found to be significant contributors to the regression model. The adjusted R-squared value was 19.9%, providing decent explanatory power, while still reinforcing that there are yet uncharted factors contributing to AI anxieties.

Shifting the focus to anxiety and fear surrounding the 4IR, Model 1 initially showed age, ethnicity and occupation as potential contributors. While age displayed a positive coefficient, ethnicity and occupation exhibited significant relationships. The region of origin (United States versus International) and specific occupations (student versus librarianship versus information science and technology positions) seemed more susceptible to 4IR-related anxiety, explaining 15.1% of the variance in AI fear. In Model 2, only the variables that were significant in Model 1 were evaluated. The resulting model explains only 7.5% of the variance in AI fear, but does produce a greater F statistic, indicating a significant influence of these two variables (see Table 4).

Using k-means cluster analysis, four groups were found in the data based on the demographic variables. Group 1, containing 56 of the 215 responses, included respondents who lived in medium-density urban or suburban areas and had a high level of educational attainment. Group 2, containing 82 responses, included respondents who were in low-density

Table 4. Regression findings for dependent variable of anxiety/fear of 4IR.

	Model 1	Model 2
Age	0.088 (0.054)	
Gender	0.122 (0.076)	
Ethnicity	0.152 (0.100)	
Region of origin	0.241 (0.091)**	0.288 (0.086)**
Academic achievement	–0.032 (0.045)	
Political leaning	–0.039 (0.045)	
Occupation	0.346 (0.191)*	0.397 (0.200)*
Urbanicity	–0.033 (0.030)	
R-squared value	0.151, F = 4.57, $p < 0.001$	0.075, F = 8.89, $p < 0.001$

*Significant difference at $p < 0.05$
**Significant difference at $p < 0.01$

urban or rural areas and had a high level of educational attainment. Group 3, including 68 responses, were high urbanicity and high educational attainment. Finally, Group 4, with nine responses, included responses with low levels of urbanicity and low levels of educational attainment.

To investigate differences among these groups, we conducted an ANOVA with the dependent variables of AI anxiety–fear and 4IR anxiety–fear. No difference was found for AI, with F = 1.541, p = 0.205. However, a statistically significant difference was found for 4IR, with F = 3.36, p = 0.02. A Tukey post hoc analysis indicates that the difference emerges between Groups 1 and 3, the medium-density urban and high education group and the high urbanicity and high education group, while no significant difference was found with the low urbanicity group and medium urbanicity group. This suggests a jump from suburban or small urban to large urban community may correspond with a reduction in anxiety–fear of the 4IR.

5. Discussion

The findings from our study provide valuable insights into the distinct factors that influence anxiety and fear concerning AI in general and the 4IR, particularly its implications for employment and jobs. This discussion section will delve into the reasons behind the differences in predictors for these two domains of technological apprehension, aligning with the primary research question for this study.

5.1. Age as a differential predictor

One of the notable distinctions lies in the role of age as a predictor. While age exhibited a positive relationship with AI-related anxiety in both the correlation and regression analyses, suggesting that older individuals tend to report higher levels of fear in the face of AI advancements, this relationship did not hold for 4IR anxiety. A key reason behind this distinction might be the diverse ways in which AI and the 4IR impact individuals of varying age groups.

AI is perceived as an overarching and potentially disruptive force in various aspects of life, including personal interactions, decision-making processes and the workforce. Older individuals, who may have less exposure to these technologies during their formative years, could perceive AI as more intimidating compared with young generations, as is often the case with emerging technologies [36,37]. In contrast, the 4IR's implications for employment and jobs might be perceived with heightened anxiety across all age groups. Younger generations, who are probably more deeply integrated into the rapidly changing job landscape, may harbour unique anxieties related to the 4IR's influence on their career prospects that match the anxieties of older populations.

5.2. Ethnicity and region of origin: universal versus contextual concerns

Ethnicity and region of origin emerged as significant predictors for both AI- and 4IR-related anxieties, albeit with varying degrees of influence. The question arises as to why these demographic factors play such pivotal roles in shaping technological apprehensions.

For AI-related anxiety, the universal nature of AI's impact might explain the significance of ethnicity and region of origin. AI has the potential to disrupt various aspects of life across the globe, but its consequences might be felt differently in different cultural and regional contexts. Individuals from specific ethnic backgrounds or regions might have distinct cultural or economic ties to AI-related technologies, influencing their perceptions and anxieties [38]. In addition, access to information and education about AI could vary based on one's geographical location or cultural background, especially in developing countries, further contributing to these differences [20].

Conversely, when it comes to 4IR anxiety, the focus on employment and jobs in a specific regional or industrial context could be the key differentiator. The 4IR's impact on employment is probably localised, with certain regions or industries experiencing more pronounced disruptions than others [39]. This localised impact could explain why region of origin becomes a significant predictor for 4IR-related anxiety. Specific ethnic backgrounds might also be associated with particular industries or job sectors that are more vulnerable to 4IR-related changes.

5.3. Academic achievement and exposure to technology

The inverse relationship between academic achievement and AI-related anxiety is another intriguing finding. Academic achievement is often considered a marker of knowledge and exposure to technology. This study's results support this belief by suggesting that individuals with lower academic achievements report higher levels of anxiety. Those with lower academic achievements may perceive these technologies as threatening their livelihoods and competencies, leading to higher anxiety levels. In contrast, individuals with higher academic achievements may more probably see these technologies as opportunities for innovation and adaptation, thereby mitigating their anxieties. Indeed, a 2023 study by Pew Research found that those professions requiring the greatest knowledge and exposure to AI tend to have a more positive outlook than jobs in areas such as accommodation and food services [40].

5.4. Occupation and urbanicity: nuanced influences

Occupation and urbanicity provide nuanced insights. The positive relationship between occupation and anxiety in both domains suggests that individuals in information professionals might be more attuned to the potential impacts of AI and the 4IR on their work compared with information science students. Similarly, the negative correlation between urbanicity and AI-related anxiety hints at urban dwellers' potentially higher exposure to and comfort with technological advancements. The findings of the cluster analysis and ANOVA test lends further support to this potential and suggests that the distinction between medium urbanicity and high urbanicity is much more significant than between low urbanicity and medium urbanicity. These findings align with existing understandings of various urban–rural and occupational divides, such as in the areas of politics and religion [41].

5.5. Further implications for theory and practice

The findings of this study convey several important implications for theory and practice. This study found several demographic factors that correlate with AI anxiety and fear, which may be crucial to understanding how these anxieties emerge and manifest in different populations. However, the findings also suggest that these anxieties are multi-faceted constructs, not easily explained by any one single or group of variables. We may grow in our understanding of some factors contributing to AI anxiety and fear, while recognising that there are yet many others that we have not identified or explained.

These results further suggest that targeted educational interventions to introduce these technologies to current and future information professionals may increase the likelihood that they embrace the technology, especially if they are members of a group that may be more apprehensive about AI. If AI anxiety were to be reduced among the population of information professionals, these professionals could, in turn, be fundamental in educating the public about AI in order to reduce misplaced concerns. Several recent studies, such as those by James and Filgo [34] and Lund [42], suggest paths for information professionals seeking to embrace these new AI training roles.

5.6. Limitations and future research

There are several limitations to note for this study, some of which also provide opportunities for further research. As noted in the Methods section, there is a skew towards participants with higher educational attainment than the general public, which limits the generalisability of the study's findings. Future research could expand the participant sample to include more individuals with lower educational attainment. In addition, the geographic distribution was limited to only three countries, making generalisability outside of these regions problematic as well. Finally, this survey relied on self-reported data, which can be impacted by several biases, including social desirability, recall and inaccuracies in selfassessment towards emotions. Future studies could include additional measures and questions to assess the expression of AI anxiety and fear.

6. Conclusion

This study provides critical insights into the factors influencing anxiety and fear surrounding AI and the 4IR with a specific emphasis on their implications for employment and jobs within information science. Age, ethnicity, geographic origin and educational attainment all proved to be significant factors to some extent. The backgrounds of information science students and professionals may help to shape how they view the prospect of AI, and the 4IR as a whole, integrating into their lives. For individuals and groups that are particularly inclined towards high levels of anxiety or fear towards AI, greater education and exposure to the technology may prove beneficial.

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