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Empirical Assessment of Artificial Intelligence Anxiety, Associated Factors among University Employees in Nasarawa, Nigeria

Yakubu Ibrahim Itse[1,]*, Isah Yahaya[2], Tobechi Larry Uzoigwe[2]

[1] Plateau State Univerity, Bokkos, Nigeria; yakubuibrahimitse4@gmail.com.

[2] Department of Psychology, Nasarawa State University, Keffi, Nigeria; isah4unmi@gmail.com; Uzoigwetobechi@gmail.com.

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Abstract

While prior research has explored Artificial Intelligence Anxiety (AIA) in various countries, limited research has examined its predictors within Nigerian universities. This study examines the relationship between Counterproductive Work Behaviour (CWB), Persecutory Ideation (PI) , and AIA among staff at Nasarawa State University, Keffi. A cross-sectional survey was employed to gather data from a representative sample of 291 participants, comprising 59.21% aged 25-34, 51.2% male, and 47.8% female. The majority were single (57.4%), with 44.7% senior staff and 55.3% junior staff. Data were collected using a demographic questionnaire, Persecutory Ideation Questionnaire (PIQ), condensed form of the CWB checklist, and Fear of Autonomous Robots and Artificial Intelligence (FARAI) scale. The results showed a significant influence of PI on AI anxiety ($t = -2.90$, $p < .05$), with high PI linked to lower AI anxiety scores. Conversely, high CWB also predicted higher AI anxiety scores ($t = 3.00$, $p < .05$). Furthermore, a gradual increase in AI anxiety scores was observed with increasing age ($F(3, 291) = 19.02$; $p < .05$), with the youngest group reporting the lowest scores. The findings support the hypotheses that CWB and PI play crucial roles in shaping individuals' anxiety towards AI. The study highlights the need to address these factors to reduce AI anxiety and promote smoother AI adoption in Nigerian universities.

Keywords: Counterproductive work behavior, Persecutory ideation, Artificial intelligence anxiety, Organizational behavior, Technology adoption.

1 | Introduction

As Artificial Intelligence (AI) becomes more present, businesses are being reshaped in various ways, from accelerating the pace of innovation to transforming job roles and required skills. Traditional business models are being challenged, and companies are discovering the need to rethink their organizational structures. This shift requires developing AI literacy, which many countries are prioritizing in their curricula [1], equipping individuals with critical thinking and collaboration skills. AI adoption increases globally, Africa must develop

Corresponding Author:

its own unique AI solutions that cater to its specific needs and context. However, most AI applications in Africa are often imported from outside, lacking local relevance due to cultural and infrastructure differences. To address this, ongoing research aims to develop tailored AI solutions that are crucial for Africa's AI success [2]. By leveraging these solutions, Africa can revolutionize education with AI, personalizing learning experiences, enhancing access, and bridging the digital divide. Furthermore, these innovative solutions have the potential to empower educators, enabling them to focus on high-value tasks while AI handles routine administrative tasks.

Furthermore, while some hope that AI will improve education and make it more equal for all students, others worry that it will replace teachers and lead to higher unemployment rates [3]. sparking widespread anxiety among educators who worry about the potential loss of job security and autonomy. The introduction of technology often brings unusual feelings, including anxiety, as educators struggle to adapt to the uncertainty of their roles in an increasingly automated education landscape.

The term "AI anxiety" describes emotions of dread or unease regarding AI that are out of control [4]. Excessive fear stemming from issues resulting from changes brought about by AI technologies in one's social or personal life is also known as Artificial Intelligence Anxiety (AIA) [5]. It encompasses worries about job security, privacy concerns, and the ethical implications of AI. Three main factors have been identified as the causes of AI anxiety. Misunderstandings about computational entities and humans, the exclusion of humans from the use of AI, and inaccurate conceptions of technological development [4]. Meanwhile, four dimensions of AI anxiety were defined by Wang et al. [6] as follows: job replacement anxiety, which is the fear of how AI will affect business life; sociotechnical blindness, which is the fear of not understanding how AI depends on humans; AI configuration anxiety, which is the fear of humanoid AI; and AI learning anxiety, which is the fear of learning AI technologies. One of the primary sources of AI anxiety is the potential for AI to be used for malicious purposes, such as creating deepfakes, which raises serious ethical questions about the potential misuse of AI technology. As these concerns imply the need for careful consideration of the ethical implications of AI development, Li and Huang [7] have given the phenomenon of AI anxiety new dimensions, including privacy, transparency, bias, and ethics. For this study, AIA is defined as the overall affective response of anxiety or fear that inhibits an individual from interacting with AI.

As AI continues to transform industries and jobs, an analysis of the European labour market shows that 54% of jobs in the EU are at risk of computerization on average [8]. Frey and Osborne [9] expand on this prediction by estimating that 47% of American workers face the possibility of losing their jobs as a result of computerization, including robotics and AI. This projection has raised concerns about the potential impact on individuals, with many already feeling anxious about the risks associated with AI. Notably, public opinion on AI development is divided, with Dafoe [10] finding that 41% of Americans support AI development, while 22% oppose it. Africa is no different, as African countries have low scores on the Government Artificial Intelligence Readiness Index [11], [12].

AI anxiety can negatively impact behavioural intention, making individuals less likely to adopt AI technology. This is consistent with the Technology Acceptance model, which links perceived usefulness and ease of use to behavioural intention [13]. High levels of anxiety can negatively impact both perceived usefulness and ease of use, leading individuals to have lower behavioural intentions towards adopting AI technology.

Any employee behaviour that is meant to cause harm to the organization or its members is referred to as Counterproductive Work Behaviour (CWB) [14]. This can include actions such as theft, sabotage, and aggression towards others. CWB can be divided into two categories: interpersonal deviance and organizational deviance [15]. Interpersonal deviance refers to behaviours that harm other individuals in the organization, while organizational deviance refers to behaviours that harm the organization as a whole [15].

University staff who engage in workplace deviance may feel threatened by AI's ability to track performance and monitor productivity [16]. When employees know AI monitors their behaviour, including detecting cyberbullying [17], it can heighten anxiety, especially among those who engage in such acts. Fear of detection and punishment may lead to apprehension towards AI adoption, as individuals worry about being caught and penalized. Since CWB can be fueled by exploiting loopholes and manipulating existing systems, the introduction of artificial anxiety might create distrust in this set of people due to a lack of understanding of how to manipulate new technology for personal gain.

Persecutory Ideation (PI) is the experience of having persistent thoughts that someone is deliberately trying to harm you. This thought often manifests as exaggerated apprehension, suspicion, or mistrust, leading to significant distress and impairment in daily functioning. Researchers have proposed that hypervigilant cognitive processes [18] may contribute to the maintenance of AIA. However, their focus on human threats and conspiracies may overshadow concerns about AI. While AI may seem emotionally flat, its predictable nature can be surprisingly appealing for university employees with PI. This is because AI doesn't require the same level of emotional investment and interpersonal sensitivity as social interactions, which can be overwhelming at times for a paranoid person [19]. Furthermore, AI's rules-based behaviour is often comforting because it is less prone to misinterpretation, allowing for more efficient and straightforward communication. The absence of perceived "malice" in AI's actions, driven by programming rather than human intent, can be a relief for those with PI, who are less likely to attribute malicious intent to machines.

Previous studies have investigated AIA in Western countries and various occupations [5], [20]. However, only one study has examined the predictors of AIA among tertiary education staff in Nigeria [21], focusing on factors such as resistance to change, resilience, and organizational ethical climate. These studies have not explored the combined prediction of CWB and PI on AIA in Nigeria. This research gap is particularly noteworthy, given the importance of understanding the factors that influence university personnel's attitudes towards AI. In light of this, the current study sought to determine the prediction of CWB and PI on AIA among staff at Nasarawa State University, Keffi.

The research questions guiding this study were:

I. What is the significant prediction of PI on AIA.

II. What is the significant prediction of CWB on AIA.

III. How does ageing affect anxiety about AI?

Hypotheses 1. For the purpose of the investigation, the following hypotheses were developed and put to the test:

I. There'll be a significant prediction of PI on AIA.

II. There will be a significant prediction of CWB on AIA.

III. There'll be a notable age gap in AIA.

2 | Literature Review

2.1 | Counterproductive Work Behaviour

CWB refers to voluntary behaviours that harm the organization and its members [22]. Sackett and DeVore [23] describe CWB-O as harmful and dysfunctional behaviours that are not aligned with the organization's interests. Robinson and Bennett [24] voluntary behaviour (of employees) that violates significant organizational norms and, in so doing, threatens the well-being of an organization; its members categorize CWB into two types: CWB-O (harming the organization) and CWB-I (harming others within the organization). Gruys and Sackett [25] developed a model with 11 categories of CWB, including theft, property destruction, information misuse, time and resource abuse, unsafe behaviour, low attendance, subpar work, drug and alcohol use, inappropriate speech, and inappropriate physical behaviour. Spector et al. [26] proposed a five-facet model of CWB, including abuse, production deviance, sabotage, theft, and withdrawal.

3 | Counterproductive Work Behaviour and Artificial Intelligence Anxiety

Oss Aversion theory, proposed by Tversky and Kahneman [27], describes loss aversion as a cognitive bias where the pain of losing is psychologically twice as powerful as the pleasure of gaining, suggesting that people fear losses more than they value gains. This implies that individuals may be more motivated to avoid losses than to pursue gains. This may be particularly relevant for individuals who engage in deviant work behaviour and have developed a sense of comfort with exploiting loopholes and manipulating systems for personal gain. The introduction of AI disrupts this system, making it harder to engage in these behaviours. Uncertainty about how AI algorithms work or how they'll affect their deviant acts creates anxiety and mistrust, as individuals are likely to perceive the potential loss of control over their deviant behaviours as a more significant threat than the potential gain of improved efficiency or productivity. The perceived loss of control and benefits from their deviant behaviours can trigger feelings of frustration, anger, and resentment towards AI.

Moreover, as the study by Tasgit [28] reveals, employees' attitudes towards AI have a significant impact on their work performance. Positive AI attitudes boost task and contextual performance, while negative attitudes are linked to CWB. Conversely, negative AI attitudes hinder task and contextual performance yet promote counterproductive behaviour. ([28]) highlights the importance of understanding and addressing employee AI anxiety, as negative attitudes can lead to decreased productivity and increased deviant behaviour.

4 | Persecutory Ideation

PI refers to thoughts that an individual will come to harm due to others' deliberate intentions [18]. When these beliefs are sustained despite others' opinions, they become persecutory delusions [29]. A wide range of delusions, including suspiciousness and persecutory delusions, have been categorized under the term "paranoia" [18]. The term " PI " [30] will be used to describe a variety of nonclinical and clinical experiences in this work. Ideations of persecution may result in emotional distress, hospitalization, and social disengagement [31]. They are often considered a symptom of schizophrenia [29].

PI is a mental health phenomenon that can affect university staff, where they may believe they are being unfairly targeted, harmed, or persecuted by colleagues, supervisors, or administrators. This can manifest in various ways, including delusional thinking, paranoia, an exaggerated sense of vulnerability, lack of insight, fear and anxiety, avoidance behaviours, and lack of emotional regulation [32]. Persecutory delusions can lead to emotional distress, impact job performance, and affect overall well-being. Paranoid individuals may have an unfounded suspicion that others intend to cause harm, leading to difficulties in social interactions and communication with colleagues [19].

5 | Persecutory Ideation and AI Anxiety

People with PI may be more concerned about the potential misuse of AI by humans, such as surveillance or manipulation, rather than the technology itself. This fear can be amplified by media portrayals and popular culture depictions that emphasize the negative aspects of AI. PI has been linked to conspiracy beliefs [33]. Individuals with PI tend to harbour a profound distrust of AI, driven by conspiracy theories fueled by a fear of government manipulation and nationalist fervour. Concerns about foreign high technology further exacerbate this scepticism, disturbing allegations of AI development and sensational claims of government control over fertility rates used to control minds, suppress dissenting opinions, or facilitate a new world order [34]. This can lead to increased anxiety levels related to AI adoption and may even cause them to avoid or reject AI-based tools altogether. When individuals with PI encounter AI-related changes, they may approach these developments with caution and suspicion. Their tendency to interpret ambiguous information as confirming their fears can result in a distorted perception of AI technologies. For example, a minor glitch in an AI system may be perceived as deliberate sabotage or surveillance.

On the one hand, the feeling of being under threat can prompt individuals with higher levels of PI to adopt new technology as a means of protection, whether physical or digital. This might manifest in the adoption of advanced security software, encryption methods, or other digital tools designed to safeguard personal information and online presence. On the other hand, AI can also play a crucial role in detecting and flagging cyber-harassment [35], which can be particularly beneficial for individuals with PI. Moreover, the use of AI in addressing instances of workplace harassment or discrimination can increase positive feelings towards technology among this group. Individuals with PI may view technology as a tool that can help validate their experiences and potentially protect them from further harm, leading to a more favourable attitude towards AI.

PI often stems from the fear of being scrutinized or judged by others. A robot, lacking human perception and judgment, wouldn't be a source of such anxiety. This creates a more relaxed environment where people can focus on the activity without feeling self-conscious. Zhu and Deng [36] found that individuals who experience higher levels of social anxiety are more likely to select robotic training partners as opposed to human ones. In social interactions, individuals with PI may find AI's lack of emotions comforting, as it provides a less overwhelming form of interaction. AI systems are programmed to respond consistently, providing predictable feedback, which can be comforting for those who struggle with social anxiety or fear of rejection. Furthermore, AI systems do not harbour ill intentions, which can reduce anxiety and fear, making it easier for individuals with PI to engage with technology and potentially improve their quality of life.

6 | Methods

This study used a cross-sectional survey design to get information from many respondents at Nasarawa State University Keffi. The participants consisted of 291 participants recommended by the Raosoft sample size calculator. Stratified sampling was used to ensure a fair representative sample from both academic and non-academic staff. A random sample ensured that the majority of participants (59.21%) were between 25 and 34 years old. There were slightly more males (51.2%) than females (47.8%). Most were single (57.4%), while 40.5% were married, and 2.1% were divorced/separated. Senior staff made up 44.7%, while junior staff comprised 55.3%.

6.1 | Instruments

Three instruments were adopted and divided into two sections. Section A was about the demographic characteristics of the participants. The Persecutory Ideation Questionnaire (PIQ) was developed by McKay et al. [37] to measure PI. It uses a 5-point Likert scale and demonstrates excellent convergent validity, reliability, and criterion validity [37]. Internal consistency was recorded in Nigeria as .88 by Oghenekwe et al. [38] and .78 by Tobechi & Monday [39]. The CWB was measured using the short version of the CWB checklist [26]. Participants rated frequency on a Likert scale (1-5). The scale includes 10 items, divided into organizational (5) and interpersonal (5) subscales. To ensure the reliability of the instrument, a pilot study was carried out using seventy-eight (78) staff from Federal University Lafia. Cronbach's alpha was $\alpha = 0.69$. The Fear of Autonomous Robots and Artificial Intelligence (FARAI) scale was developed by Liang and Lee [40] and was used in the second section to measure AIA. Participants responded to 10 questions on a 5-point Likert scale, ranging from "Strongly Disagree" (1) to "Strongly Agree" (5). One question asked: "I am afraid that all jobs performed by humans will be replaced by autonomous robots or AI." Scores ranged from 10 to 50, with higher scores indicating higher levels of anxiety. Three categories were used to group the scores: low (10–23), moderate (24–36), and high (37–50). FARAI has strong internal consistency reliability, with a Cronbach alpha of 0.85. According to the developers, Kenku and Uzoigwe [21] recorded a Cronbach alpha of .79.

The questionnaire was administered using a self-report method, which allows for easy distribution to a large number of people at a low cost. Participants were assured that their responses would be kept confidential and that there was no right or wrong answer. A random sampling technique was used to select participants, reducing researcher bias. The researcher distributed the questionnaires with the help of research assistants. Ethical clearance was obtained from relevant authorities, and participants were informed about their rights, and consent was voluntary. Confidentiality was ensured by not requiring identification and promising that results would not be released individually. Participants were not forced to participate, and those who were unwilling were not disadvantaged.

Data analysis was done using SPSS version 20. Demographic variables were analyzed using descriptive statistics. Hypothesis one and two was analyzed using a t-test, while hypothesis three was analyzed using ANOVA.

7 | Data Analysis and Result

Three research hypotheses were postulated to guide this study. These hypotheses were inferentially tested, and the results are presented in this section.

Hypothesis 2. The first research hypothesis states that there'll be a significant prediction of persecutory on AIA. The results presented in *Table 1*.

Table 1. Summary t-test showing the influence of PI on AIA.

Persecutory Ideation	N	M	SD	t	Sig
High PI	99	17.62	6.81		
Low PI	192	20.36	8.03	-2.90	.004

Table 1 presents the summary results prediction of persecutory on AIA. Those with high PI (M = 17.62, S.D = 6.81) had a lower score on AIA compared to those with low PI (M =20.36, S.D = 8.03). It indicates that there is a statistical influence of PI.

Hypothesis 3. The second research hypothesis states that CWB will significantly influence AIA Keffi. The results presented in *Table 2*.

Table 2. Independent samples T-test summary table showing results on the influence of CWB on AIA.

CWB	N	M	SD	t	df	Sig
High CWB	27	23.63	2.91			
low CWB	264	18.99	7.95	3.00	289	.003

Table 2 presents the summary results of the influence of CWB on AIA among staff of Nasarawa State University Keffi. *Table 2* presents the summary results. Those with high CWB (M = 23.63, S.D = 2.91) had the highest score on AIA compared to those with low PI (M =18.99, S.D = 7.95). It indicates that CWB has a statistical influence on AIA.

Hypothesis 4. This hypothesis stated that age difference significantly influences AIA. This hypothesis was tested using a one-way analysis of variance, and the result is presented in *Table 3*.

Table 3. Summary of one-way analysis of variance showing the influence of age on AIA.

Variable	Types	N	Mean	S.D	Source of Variation	Sum of Squares	df	Mean Square	F	P
Age	25-34	164	17.34	5.57	Between	2880.549	3	960.183		
	35-44	78	19.74	8.84	groups					
	45-54	34	26.88	6.68	Within	14492.613	287	50.497	19.02	0.00
	>55	15	23.67	11.80	groups					
		291	19.42	7.74		17373.162	290			
					Total					

Table 3 reveals a significant age influence on AIA (F(3, 291) = 19.02; $p < .05$). The results show a gradual increase in AIA scores as age increases. Specifically, the youngest group of staff aged 25-34 reported the

lowest AIA scores (mean = 17.34). As age increases, the mean AIA scores also increase, with the highest score observed among staff aged 45-54 (mean = 23.67). Notably, there is a slight decrease in AIA scores among the oldest group of staff (>55 years). These findings support Hypothesis 4, which states that staff age will significantly and positively influence AIA.

8 | Discussion

Based on the first hypothesis's findings, it was discovered that staff with high PI demonstrated lower levels of AIA compared to those with low PI. This finding is consistent with the notion by Zhu and Deng [36] that people who experience greater levels of social anxiety are more likely to select robotic training partners over human ones, suggesting that individuals with PI may find interacting with robotic partners more comfortable and less anxiety-inducing. Notably, this preference for robotic interaction may be driven by a desire for safety and security, leading individuals to adopt advanced security software and digital tools, which in turn contributes to a lower sense of AIA.

The study uncovered a significant correlation between CWB and AIA, confirming our hypothesis. Specifically, highly deviant workers are more likely to experience anxiety about job security, privacy concerns, and the implications of AI. This is because AI technologies are increasingly being used to monitor employee performance, detect anomalies in behaviour, and predict potential misconduct. Deviant employees may perceive AI as a threat to their autonomy and privacy, leading to increased anxiety about the impact of these technologies on their work environment. This finding is consistent with that of Tasgit et al. [28], who found that negative attitudes towards AI among employees can negatively affect task performance and contextual performance while positively supporting CWB.

The comprehensive monitoring capabilities of AI can exacerbate anxiety for deviant workers who fear being caught for their actions. With AI able to track worker activity more thoroughly than traditional methods, the risk of detection becomes even greater. As a result, deviant workers may become increasingly anxious about being monitored and judged by AI-powered systems.

The third hypothesis, that age influences AIA, was accepted. The youngest group (25-34 years) had the lowest AIA scores, likely due to their familiarity with technology and openness to changes brought by AI. This collaborates with the findings by Woodruff et al. [41], who found that. Youthful educators age d groups (18-34) exhibit higher usage of generative AI tools, such as ChatGPT-3, Bard, and Scikit Learn, compared to older age groups (45-64). In contrast, older individuals may be more anxious due to their lack of familiarity with AI and concerns about their skills becoming obsolete. Older staff may worry about being replaced by newer colleagues or AI systems and be resistant to change, leading to increased anxiety. This confirms that the European Agency for Safety and Health at Work (2017) noted that technology can make manual jobs redundant, negatively impacting older workers. The oldest group (>55 years) showed a slight decrease in AIA scores, possibly due to having accepted technological change and focusing on preserving their expertise. They may have developed coping mechanisms or strategies for adapting to new systems and are nearing retirement, reducing their concerns about job security.

9 | Research Contribution

This study breaks new ground in the Nigerian context by investigating AIA and its relationship with psychological factors, which has been understudied until now. One particularly novel finding is the link between PI and lower AIA. This suggests that individuals who hold beliefs that others are out to get them might experience less anxiety when interacting with AI compared to humans. This finding is novel because it challenges the common assumption that individuals with high levels of paranoia or persecutory thoughts would also exhibit heightened anxiety towards AI. The traditional belief would suggest that those who are prone to feelings of persecution or suspicion might be more likely to fear advanced technologies like AI due to concerns about surveillance, control, or malicious intent. Previous research has shown a connection between social anxiety and a preference for robotic interaction. This study extends this concept by suggesting that those with PI might find AI's perceived lack of social judgment or malicious intent to be less anxiety-provoking. This is a fresh perspective within the Nigerian context and highlights the potential role of individual personality traits in shaping AI anxiety.

10 | Implication and Recommendation

This study highlights the importance of considering age-related factors in attitudes towards AI. Older staff members may have distinct perspectives influenced by life experiences and technology exposure. Encouraging collaboration between younger and older employees leverages their strengths for a smoother AI adoption. Transparency in AI decision-making and trust-building by emphasizing its use for improvement, not punishment, may mitigate anxiety. Training programs can clarify how AI complements human work and alleviate replacement fears.

Further research is needed to understand psychological mechanisms and cultural context in Nigeria. Addressing CWB through employee screening, training, and performance management can reduce AI anxiety.

11 | Conclusion

In conclusion, both CWB and PI play crucial roles in shaping individuals' anxiety towards AI. Employees exhibiting CWB tendencies may struggle with the introduction of AI technologies due to heightened stress and fear of consequences, while individuals with PI may welcome AI as a solution to their perceived threat to human harm; the age-related differences in AI anxiety observed in this study highlight the importance of considering individual differences in understanding AI anxiety. Younger staff members may be more likely to adapt to new technologies, including AI, whereas older staff members may be more resistant to change. Understanding these influences is essential for organizations looking to implement AI solutions successfully while addressing employee concerns and promoting a positive attitude towards technological advancements.

Author Contribution

Yakubu Ibrahim Itse and Isah Yahaya: Conceptualized and designed the study, conducted the literature review, and wrote the initial draft of the manuscript.

Tobechi Larry Uzoigwe: Analyzed data, contributed to manuscript revisions, and provided critical insights on this manuscript and ensured adherence to ethical guidelines.

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Conflicts of Interest

No conflicts.

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