From Anxiety to Resistance: A Dual-nature Perspective on AI Adoption Intentions

Yvonne O' Connor[1] and Grace Fox[2]
[1]Department of Business Information Systems, Cork University Business School, University College Cork, Ireland
[2]School of Modeling, Simulation and Training, College of Engineering and Computer Science, University of Central Florida, Orlando, FL, USA

y.oconnor@ucc.ie
grace.fox@ucf.edu

Abstract: In recent years, Artificial Intelligence (AI) has become increasingly integrated into everyday life, from assistants such as Siri and Alexa to advanced Generative AI (GenAI) systems like ChatGPT, Claude, and Gemini. These technologies are rapidly expanding across personal and professional contexts and are expected to transform industries and daily activities. Despite their benefits, AI systems may also generate psychological concerns that influence users' perceptions, behaviours, and intentions toward adoption. However, empirical research examining how psychological factors shape AI-related behaviours remains limited. This study addresses this gap by examining AI anxiety through two dimensions: long-term trait anxiety and temporary state anxiety experienced in AI-related situations. The study investigates how these forms of anxiety influence resistance to AI and intentions to adopt AI systems. The conceptual model incorporates perceptual and behavioural constructs relevant to AI acceptance. Survey data were collected from 122 respondents across multiple countries, representing diverse age groups and levels of technological experience. Data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS. Results showed that trait anxiety, measured through technology readiness, significantly influenced state anxiety. Positive relationships were identified with self-efficacy for change, value congruence, and AI awareness, while perceived threats showed a negative relationship. Trait anxiety did not directly affect intentions to use AI. State anxiety constructs subsequently influenced resistance behaviours toward AI. Active opposition was negatively influenced by value congruence and perceived threat, while passive avoidance was negatively influenced by value congruence, perceived threat, self-efficacy for change, and AI awareness. Intentions to adopt AI were negatively affected by both active opposition and passive avoidance, which mediated the effects of state anxiety. Overall, the findings demonstrate that enduring beliefs associated with trait anxiety shape state anxiety in AI contexts, which then drive active and passive resistance behaviours that reduce intentions to use AI. The model explained 62% of the variance in AI use intentions and contributes to AI research by clarifying mechanisms influencing acceptance of emerging intelligent technologies across diverse cultural and organisational environments globally.

Keywords: Artificial intelligence (AI), AI anxiety, State and trait anxiety, Conceptual model, Resistance, Active opposition, Passive avoidance, AI adoption

1. Introduction

By 2030, Artificial Intelligence (AI) is envisioned to significantly disrupt several areas of daily life from transportation, healthcare, education, public safety and security to employment and the workplace, and entertainment (Verma et al., 2021). While lots of research has been conducted around the internal workings of AI in terms of transparency and decision-making processes (de Fine Licht & de Fine Licht, 2020), ethical implications underpinning AI (Siau & Wang, 2020), and regulations to monitor and manage how AI is operationalized (Schuett, 2023), the long-term impacts of AI on society are unknown. As with most technological disruptions, some systems disappear while new ones emerge and thrive (Arthur, 2009), thus contributing to individuals' anxiety. Generally, AI anxiety can be defined as *"excessive fear arising from problems originating from changes formed by AI technologies in personal or social life"* (Kaya et al., 2024, p. 499). Individuals' perceptions of AI and their anxiety are less accounted for (Lemay et al., 2020). This is important to explore as Miceli & Castelfranchi (2005) argue that anxiety amongst a population will remain if the epistemic goal of technology (i.e., AI, in this study) is unknown and not fully appreciated. That is, anxiety is likely to persist, underpinned by an enduring and unfulfilled need for certainty and prediction. While the concept of AI anxiety has grown in popularity in recent times (Russo et al., 2025), it is often examined as a single entity. However, according to Saviola et al. (2020) anxiety in general has a dual nature (Trait and State), observed as a relatively enduring characteristic or as a transitory experience (Roberts & Pomerantz, 2004). Trait anxiety is stable over time and consistent across different situations, but not necessarily permanent while state anxiety is temporary, short-lived, or passing (Spielberger, 1966). The impact of AI anxiety on resistance and intentions to adopt AI, from a state and trait perspective to date has neither been richly theorized nor explored in depth. The objective of research, therefore, is to explore how intentions to adopt AI are influenced by the presence of two distinct

types of resistance and two distinct types of AI anxiety. To achieve this, the following research question is examined: (1) To what extent does AI Anxiety impact resistance to and Behavioural intentions to adopt AI?

2. Literature Review

Reis et al. (2020) found that an AI project failed due to user resistance, highlighting the importance of understanding its "root causes" (p. 279). User resistance broadly refers to opposition to technology-related change (Kim & Kankanhalli, 2009) and may be functional, by signalling system issues, or dysfunctional when it causes disruption (Rivard & Lapointe, 2012). This study adopts Joshi's (1991) perspective of active resistance, involving deliberate and visible opposition, and passive resistance, where users withdraw cooperation and resistance is less visible and harder to detect (Ali et al., 2016).

AI resistance research spans macro-level issues including ethical concerns, bias, dystopian narratives and regulation (Hutson & Plate, 2024; Werder et al., 2025), and meso-level factors such as organisational culture and inertia, implementation challenges and contextual concerns (Albannai & Raziq, 2025; Reis et al., 2020). Although micro-level resistance has also received considerable attention (Yuniawan et al., 2025), AI anxiety warrants further examination given its growing societal relevance. Understanding such anxiety may help identify social concerns triggered by AI and inform its future governance (Rahwan et al., 2019).

Importantly, perceptions of AI have shifted following ChatGPT's public release in November 2022. Earlier studies largely examined AI when exposure was indirect, whereas generative AI has made interaction more visible and accessible, intensifying concerns around trust, accuracy and human oversight (van Dis et al., 2023) with US adults reporting greater concern than excitement about AI increasing from 38% in December 2022 to 52% by August 2023 (Tyson & Kikuchi, 2023).

3. Conceptual Model and Hypotheses

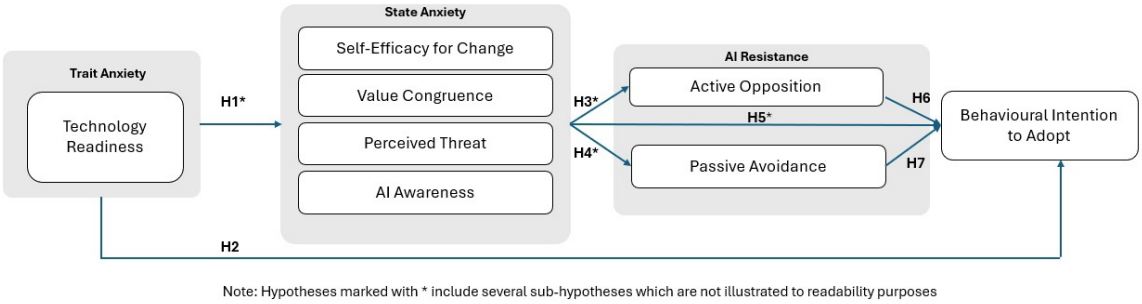

Figure 1: Conceptual Model and Hypotheses

Figure 1 presents the study's conceptual model with several hypotheses. The model primarily comprises reflective first-order constructs. However, *Technology Readiness* is a formative-formative higher-order construct. It is formative of its dimensions (*Inhibitors* and *Motivators*) with each dimension being formative in nature. Conversely, *Perceived Threat*, is a reflective-reflective higher-order construct meaning it is reflective of its dimensions (*Identity Threat* and *Realistic Threat*) with each dimension being reflective in nature.

According to Parasuraman (2000), *Technology Readiness* (TR) is a trait-like construct reflecting individuals' general propensity to embrace and use new technologies. It captures enduring perceptions of technology and its impact on society. Building on the meta-analysis by Blut & Wang (2020), TR is conceptualised as a two-dimensional construct comprising psychological enablers and inhibitors that jointly influence technology adoption. In this study, TR represents an individual's readiness to adopt technological innovations based on these opposing forces. The *motivating* dimensions of TR, optimism and innovativeness, are associated with favourable attitudes toward technology, greater perceptions of usefulness and efficiency, willingness to experiment, and openness to change (Parasuraman & Colby, 2002). Conversely, the *inhibiting* dimensions, discomfort and insecurity, reduce perceived control, trust, and the benefits associated with technology use (Parasuraman, 2000). Given these influences, TR is expected to shape key perceptions and behaviours related to AI adoption. Therefore, the following hypotheses are proposed: **H1b**: The higher Trait Anxiety, in terms of TR, the higher value congruence with AI; **H1c**: The higher Trait Anxiety, in terms of TR, the lower perceived AI Threat; **H1d**: The higher Trait Anxiety, in terms of TR, the higher AI Awareness; **H2**: The higher Trait Anxiety, in terms of TR, the lower the Behavioural Intentions to Adopt AI.

Unlike trait anxiety, state anxiety is temporary in nature and is triggered by specific situations or experiences with AI. Self-efficacy for change, value congruence, perceived threats, and AI awareness embody state anxiety because they capture transitory experiences for individuals as AI rapidly becomes more commonplace within society. *Self-efficacy for Change* in this study reflects individuals' confidence in their ability to adapt to AI. As a concept, it has been found to be a strong predictor of user resistance in technology adoption studies (Shirish & Batuekueno, 2021). That is, *Self-efficacy for Change* has positive impacts on Behavioural use and lowers resistance. Therefore, it is hypothesized that: **H3a:** The higher self-efficacy for change, the lower active opposition towards AI; **H4a:** The higher self-efficacy for change, the lower passive avoidance towards AI; **H5a:** The higher self-efficacy for change, the higher the Behavioural intentions to adopt.

Value Congruence is the degree to which individuals perceive their personal values align with those embodied by AI (adapted from Rahn, Soutar and Lee, 2023). This definition builds upon the broad desirable goals that motivate people's actions and serve as guiding principles in their lives (Sagiv et al., 2017) and closely aligns with the concept of person-technology fit (Tomer, 2015). AI has been reported to bring about profound opportunities but equally harsh consequences for individuals who use it (Houser, 2020). This conflicting report raises uncertainty around the intentions underlying AI and whether it can uphold and reinforce core moral and ethical behaviours (Bertoncini & Serafim, 2023). This implies that high value alignment often leads to better acceptance of and commitment to AI. Therefore, it is hypothesized that **H3b**: The higher the value congruence, the lower active opposition towards AI; **H4b**: The higher the value congruence, the lower passive avoidance towards AI; **H5d**: The higher the value congruence, the higher the Behavioural intention to adopt.

Perceived Threat reflects people's perceptions of an existential or fictional threat (Huang et al., 2021). Allan, Vonasch and Bartneck, (2022, p. 215) argue that *"machines that are increasingly humanlike and/or highly capable, simultaneously threaten human safety and resources (i.e., realistic threat), as well as human uniqueness and identity (i.e., identity threat)"*. According to the cognitive appraisal theory (Lazarus & Folkman, 1984), once individuals find a stressor (in this case, a machine (AI) which can reproduce the complexity of human cognitive capabilities), they implement feasible strategies to cope with that stressor (e.g. resisting the use and adoption of AI to protect themselves within their workplace/society). Therefore, it is hypothesized that **H3c:** The higher the perceived threat, the higher active opposition towards AI; **H4c:** The higher the perceived threat, the higher passive avoidance towards AI; **H5c:** The higher the perceived threat, the lower the Behavioural intentions to adopt.

Bentley & Evans (2025) defines lack of *AI Awareness* as the extent to which individuals are knowledgeable about AI-based tools, technologies, and their benefits to organisations and society. Dinev & Hu (2007) argue that a lack of awareness/understanding predisposes people to focus on the more negative aspects of technology, thus eroding their trust and confidence (Bentley & Evans, 2025). Therefore, it is hypothesized that **H3d:** The higher the AI Awareness, the lower active opposition towards AI; **H4d:** The higher the AI Awareness, the lower passive avoidance towards AI; **H5c:** The higher the AI Awareness, the higher the Behavioural intentions to adopt.

Kim and Kankanhalli (2009, p. 568) define resistance as *"opposition of a user to change associated with a new IS implementation"* or the natural reaction to anything that upsets the status quo. Resistance can also be observed as active opposition and/or passive avoidance. Active opposition refers to overt, deliberate, and confrontational behaviours actively opposing AI use or implementation (Zhang and Zhu,2024). This is a highly visible action whereby the individual shows explicit expressions of actions. Conversely, passive avoidance is often a covert, less confrontational and more subtle approach of resisting technology (Hong et al., 2025). Research has shown that elevated levels of resistance impact Behavioural intentions to adopt technology (Kim & Kankanhalli, 2009). Thus, it is hypothesized that **H6:** The higher the active opposition, the lower Behavioural intentions to adopt AI; **H7:** The higher the passive avoidance, the lower Behavioural intentions to adopt AI.

4. Methodology

To assess the conceptual model (Figure 1), an online survey was developed using indicators validated in prior research. Data were collected over a two-week period in 2025 from respondents in Ireland, Australia, France, and other countries. Participants were recruited through a multi-channel strategy involving social media posts on Facebook and LinkedIn, with respondents encouraged to share the survey link within their networks. Of the 123 responses received, one participant was under 18 and was excluded, leaving 122 valid responses with no missing data. Data analysis and hypothesis testing were conducted using SmartPLS 4.1.1.5 and Partial Least Squares Structural Equation Modelling (PLS-SEM) (Ringle et al., 2022). Following established approaches for hierarchical second-order constructs (van Riel et al., 2017), the two-stage disjoint approach was applied. Lower-

order constructs were first assessed for reliability (α ≥ 0.70; CR ≥ 0.80) and convergent validity (AVE ≥ 0.50). For formative constructs, VIF values below 3.3 confirmed the absence of collinearity. Higher-order constructs were then evaluated using latent variable scores. After establishing measurement model validity and reliability, the structural model was tested using bootstrapping (5,000 samples, one-tailed, α = 0.05).

5. Results

5.1 Respondent Profile

Of the 122 participants, 48 were male, 72 female, one non-binary and one preferred not to say. Ages ranged from 18–24 (n = 6), 25–34 (n = 19), 34–44 (n = 41), 45–54 (n = 24), 55–64 (n = 26) and 65+ (n = 6). Most participants resided in Ireland (71%, n = 87), followed by Australia (16%, n = 19), the United Kingdom (10%, n = 12), and Canada, Spain, France and Kazakhstan (3%, n = 4). Most respondents (93%) rated their technology proficiency as excellent (n = 21), very good (n = 51) or good (n = 42), while seven rated it fair and one poor.

5.2 Measurement Model Evaluation

Table 1 illustrates that all manifest items are reliable for all reflective constructs, demonstrating internal consistency reliability since all parameters exceed their thresholds (i) Cronbach's Alpha (α) and parameter (all values are above 0.851), (ii) composite reliability (CR) have high values (all values are above 0.9), with the required value being above 0.7 and (iii) Average Variance Extracted (AVE) (all values above 0.769) (Chin, 1998). Note: AO4 was removed as it had a loading value lower than 0.707 (0.622).

Table 1: Individual reliability of the indicators

Construct	Item	Description	Loading	α	CR	AVE
AI Awareness (adapted from Wang et al., 2023)	AIA1	I am familiar with the basic concepts of AI.	0.887	0.90	0.93	0.77
	AIA2	I am aware of how AI is being used in everyday technologies.	0.868			
	AIA3	I understand the differences between traditional software and AI.	0.894			
	AIA4	I feel confident in explaining AI to someone else.	0.87			
Active Opposition (adapted from Kim & Kankanhalli, 2009)	AO1	I actively reject using AI in my daily work/life.	0.886	0.85	0.91	0.77
	AO2	I express my negative opinions openly about AI.	0.842			
	AO3	I discourage others from using AI.	0.902			
Passive Avoidance (adapted from Marakas & Homik, 1996)	PA1	I avoid using AI whenever possible.	0.913	0.95	0.96	0.83
	PA2	I delay using the new system (AI) until I have no other choice.	0.927			
	PA3	I tend to procrastinate when asked to use this technology (AI).	0.883			
	PA4	I prefer to continue using old methods rather than adopt the new technology (AI)	0.922			
	PA5	Even though the technology is available, I rarely use it (AI)	0.912			
Self-Efficacy for Change (adapted from Kim & Kankanhalli, 2009)	SE1	Based on my own knowledge, skills and abilities, changing to the new way of working with AI would be easy for me	0.909	0.90	0.93	0.83
	SE2	I can change to the new way of working with AI without the help of others	0.9			
	SE3	I can change to the new way of working with AI reasonably well on my own	0.923			
Value Congruence	V1	My personal values are consistent with the values promoted by AI.	0.923	0.96	0.97	0.90

Construct	Item	Description	Loading	α	CR	AVE
(adapted from Cable & DeRue, 2002; Edwards & Cable, 2009)	V2	I feel that the goals of AI reflect what is important to me.	0.953			
	V3	The principles behind AI resonate with my own beliefs.	0.964			
	V4	I share the same core values as AI.	0.947			
Behavioural Intentions to Adopt	BI1	I am unlikely to adopt AI in the near future.	1	0.96	0.97	0.85

Using the disjoint two-stage approach, CA, CR, and AVE for *Perceived Threat* were calculated from lower-order constructs and latent variable scores. Perceived Threat was modelled as a second-order construct comprising *Identity Threat* and *Realistic Threat*, with higher-order loadings of 0.771 and 0.950, respectively. Lower-order indicator loadings ranged from 0.744–0.849 for Identity Threat and 0.717–0.884 for Realistic Threat, demonstrating acceptable reliability. Internal consistency and convergent validity were supported (CA = 0.697, CR = 0.859, AVE = 0.859). Discriminant validity was confirmed using the Fornell–Larcker criterion and HTMT, with AVE square roots exceeding inter-construct correlations and HTMT values below 0.90. VIF values for all formative constructs (*Technology Readiness*) were below 3.3, indicating no multicollinearity concerns. Bootstrapping (5,000 samples, one-tailed) showed significant effects of *Inhibitor* ($t = 2.852$, $p = .002$) and *Motivator* ($t = 5.542$, $p < .001$) on technology readiness. Redundancy analysis supported convergent validity ($r = 0.76$), confirming the adequacy of the measurement model.

5.3 Assessment of Structural Model

First, the model explains Behavioural Intentions to Adopt AI, for which R2 = 0.615. The variance of this construct is explained at close to substantial level according to Chin (1998) criteria. Second, the conceptual model presented nineteen hypotheses for testing. The structural model results indicate that *Technology Readiness* has significant positive effects on *Self-Efficacy for Change* ($\beta = 0.574$, $t = 4.878$, $p < .001$), *Value Congruence* ($\beta = 0.475$, $t = 3.732$, $p < .001$), and *AI Awareness* ($\beta = 0.473$, $t = 4.573$, $p < .001$), and a significant negative effect on perceived threat ($\beta = -0.433$, $t = 3.666$, $p < .001$), supporting H1a, H1b, H1c, and H1d. However, the direct effect of *Technology Readiness* on *Behavioural Intentions to Adopt AI* was not significant ($\beta = -0.027$, $t = 0.320$, $p = .375$), and thus H2 was not supported. Regarding *Active Opposition*, V*alue Congruence* ($\beta = -0.388$, $t = 5.005$, $p < .001$) and *Perceived Threat* ($\beta = 0.291$, $t = 3.923$, $p < .001$) were significant predictors, supporting H3b and H3c. In contrast, *Self-Efficacy for Change* ($\beta = -0.077$, $t = 0.712$, $p = .238$) and *AI Awareness* ($\beta = -0.072$, $t = 0.713$, $p = .238$) did not significantly influence *Active Opposition*, leading to the rejection of H3a and H3d.For *Passive Avoidance*, *Self-Efficacy for Change* ($\beta = -0.388$, $t = 1.933$, $p = .027$), *Value Congruence* ($\beta = -0.368$, $t = 4.500$, $p < .001$), *Perceived Threat* ($\beta = 0.285$, $t = 3.059$, $p = .001$), and *AI Awareness* ($\beta = -0.151$, $t = 1.713$, $p = .043$) all demonstrated significant effects, supporting H4a, H4b, H4c, and H4d. With respect to *Behavioural Intentions to Adopt AI*, *Self-Efficacy for Change* ($\beta = 0.096$, $t = 1.168$, $p = .121$), *Value Congruence* ($\beta = 0.054$, $t = 0.897$, $p = .185$), *Perceived Threat* ($\beta = 0.058$, $t = 0.987$, $p = .162$), and *AI Awareness* ($\beta = 0.029$, $t = 0.319$, $p = .375$) were not significant predictors, resulting in the rejection of H5a, H5b, H5c, and H5d. However, *Passive Avoidance* ($\beta = -0.422$, $t = 3.699$, $p < .001$) and *Active Opposition* ($\beta = -0.361$, $t = 3.441$, $p < .001$) had significant negative effects on *Behavioural Intentions to Adopt*, supporting H6 and H7.

Next, *Technology Readiness* shows the strongest influence in the model, with a large effect on Self-Efficacy for Change ($f^2 = 0.491$) and medium effects on AI Awareness, Perceived Threat, and Value Congruence. Value Congruence also demonstrates medium effects on Active Opposition and Value Congruence, highlighting its theoretical importance. Finally, AI Awareness, Self-Efficacy for Change, and Perceived Threat show mostly small or negligible effects across relationships, indicating weaker predictive relevance in this model. Predictive Relevance was assessed using the PLSpredict procedure (Hair et al., 2021; Shmueli et al., 2019). The results indicated that the constructs Self-Efficacy for Change, Passive Avoidance, AI Awareness, and Value Congruence exhibited Q^2_predict values greater than zero. Behavioural Intentions to Adopt and Active Opposition are predicted less accurately, but still above the relevance threshold (Q^2_predict > 0). The corresponding Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) values (ranging from 0.848 to 0.951 and 0.680 to 0.765, respectively) suggest moderate prediction errors across constructs, supporting the model's satisfactory out-of-sample predictive capability.

6. Discussion

The research question aims to understand to what extent does AI Anxiety impact resistance to and Behavioural intentions to adopt AI. The findings of this study reveal that 62% of Behavioural intentions to adopt AI are influenced by the factors/constructs presented in this paper. Our work corroborates Endler & Kocovski (2001) interaction model of anxiety which demonstrates that trait anxiety impacts state anxiety. Both state and trait AI anxiety impact individuals' active opposition and passive avoidance of AI. In this context, while state anxiety shapes how users think about resistance, these perceptions appear disconnected from how they behave in terms of their intentions to adopt AI. That is, individual enduring traits and emotional states did not directly alter Behavioural intentions to adopt AI. This corroborates the work of Powell (2013) who did a review of 276 articles on computer anxiety and found it did not influence intent to use. This study extends Reis et al. (2020) a step further by examining why people resist AI even before they consider using it. This could be explained by modern society's relationship with information. Currently, information consumption is undergoing a massive, volatile, and complex transformation, primarily driven by the architecture of the digital world (Kumar et al., 2024). With the global spread of misinformation and/or disinformation (the latter often achieved through highly sophisticated deepfake media) (Lim et al., 2024), individuals' fears, concerns and worries (AI anxiety) are arising from problems originating from changes formed by AI technologies in personal or social life (Kaya et al., 2024). Furthermore, resistance is depicted as passive avoidance or active opposition demonstrating that resistance is more than a single entity reflecting the nuanced nature of resistance (Ali et al., 2016). People can resist change or authority in both subtle and overt ways, depending on their motivations, risks, and perceived control (Mager & Kranz, 2021). As a result, different strategies are needed to resolve resistance (Ashforth & Mael, 2014). It further confirms the work of Markus (1983) who argues that resistance is not just about technology, but about perceptions: threats to power/status, loss of autonomy, and loss of control. This highlights the fact that AI does not exist in a vacuum; its use is shaped by the people expected to engage with it and the context in which it operates (Holton & Boyd, 2021). Additionally, this study contributes to a more nuanced understanding of the psychological mechanisms that shape AI adoption. Therefore, a socio-technical lens must be considered when examining AI.

The study answered the research question posed and achieved its objective however, it is not without its limitations. This study examined AI as a single, general concept. It is recommended that future researchers delve deeper into how AI anxiety impacts specific types of AI. AI can be conversational and/or generative with the former focusing on interaction and dialogue (Kulkarni et al., 2019) while the latter focuses on creation and originality (Sengar et al., 2025). Whilst recent advances are merging these two types of AI together (Bozkurt, 2023), they still possess distinct purposes, focuses and histories (Adamopoulou & Moussiades, 2020). Additionally, according to Sarker (2022), AI can be perceived as a tool (applications and products/services) or a technique (methods and algorithms). These variations in how AI reflect different capabilities, risks, ethical concerns, regulatory needs, and immediate relevance to society (Dwivedi et al., 2023) may generate fluctuations in anxiety levels amongst individuals (Lemay et al., 2020). For example, individuals interacting with virtual assistants or recommendation systems may have lower levels of anxiety and less resistance towards AI compared with higher levels of anxiety associated with the use of autonomous vehicles and AI powered advanced industrial robots (Lemay et al., 2020). Although rich data was obtained from participants in the study to empirically examine the conceptual model, future research could conduct similar empirical work with a larger study population across various geographical locations to get a better understanding of cultural implications impacting anxiety and resistance to AI. Additionally, one potentially relevant dimension not examined in this study is the perceived environmental impact of AI. The substantial energy, water and carbon demands associated with generative AI have become an increasing concern, despite improvements in model and infrastructure efficiency (Crawford, 2024). As this factor was not captured in the present study, future research should examine environmental concerns as a potential inhibitor of AI acceptance and use, particularly as the efficiency and scale of generative AI continue to evolve.

7. Conclusion

This study reflects the importance of considering emotional and societal impacts when developing and deploying advanced AI and implementing responsible guidelines to minimize adverse effects. As AI technology advances, addressing public concerns and regulating its usage is crucial for the benefit of society (de Almeida et al., 2021). To achieve this goal, collaboration between experts, policymakers, and the public is necessary.

Ethics Declaration: Ethical approval was granted by University College Cork, Ireland Social Research Ethics Committee.

AI Declaration: ChatGPT (OpenAI) was used to assist with grammar correction, language refinement, and word-count reduction, with all content reviewed and approved by the authors.

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