

Fearing the Robot Apocalypse

Correlates of AI Anxiety

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Abstract—This study examines the relationship between individuals' beliefs about AI (Artificial Intelligence) and levels of anxiety with respect to their technology readiness level. In this cross-sectional study, we surveyed 65 students at a southwestern US college. Using partial least squares analysis, we found that technology readiness contributors were significantly and positively related to only one AI anxiety factor: socio-technical illiteracy. In contrast, all four links between technology readiness inhibitors and AI anxiety factors were significant with medium effect sizes. Technology readiness inhibitors are positively related to learning, fears of job replacement, socio-technical illiteracy, and particular AI configurations. Thus, we conclude that AI anxiety runs through a spectrum. It is influenced by real, practical consequences of immediate effects of increased automatization but also by popular representations and discussions of the negative consequences of artificial general intelligence and killer robots and addressing technology readiness is unlikely to mitigate effects of AI anxiety.

Keywords—Artificial intelligence, anxiety, technology readiness contributors, technology readiness inhibitors, technology dispositions.

1 Introduction

A quick search shows that people are generally ambivalent about the advent of artificial intelligence (AI). On the one hand, individuals perceive advantages afforded by AI applications such as recent advances in image and voice recognition. On the other, they are cognizant of attendant negative consequences of increased automation such as job displacement and erosion of human rights to privacy, liberty, and agency. Popular representations of killer robots and the enslavement of humanity to technology contribute to the general distrust. Present controversies over social media technol-

ogy's stewardship of privacy and public discourse and government supervision of its citizens render notions of technological utopianism naive at best and harmful at worst. AI anxiety is an increasingly recognized phenomenon as individuals grapple with a changing present and an uncertain future [1]. To address AI anxiety, it is important to examine the correlates of AI anxiety to identify mechanisms that can mitigate distress and better manage individuals' emotions and perceptions.

Johnson and Verdicchio [1] have argued that much of AI anxiety is overblown and can be attributed to three factors: an exclusive focus on AI programs that leaves humans out of the picture, confusion about autonomy in computational entities and in humans, and an inaccurate conception of technological development. They conclude there are good reasons to worry about AI but not for the reasons advanced by AI alarmists.

In *an Anthropology of Robots and AI: Annihilation Anxiety and Machines*, Richardson [2] discussed the existential fears ("annihilation anxieties") that another intelligence poses to humans as represented by popular fiction. The author argued that there is a resonant relationship between our fiction of robots and our "lived realities of robotic practices" that feedback into each other influencing our experiences of both. As our fears often reflect ourselves more than anything else, perhaps our AI anxiety stems from our primal nature, motivated by dominance and our own history of genocide, subjugation, and intolerance of others. But also, the fear of being made redundant, replaced, or erased. As Richardson [2] writes about R.U.R. (Rossum's Universal Robots) by Karel Capek, the first play to feature a robot: "The robot [...] is a device to explore the fears of terminus in human existence brought about by mechanization, political ideologies and high modernism, and it speaks to the theme of humanity's end" (p. 2). Discussions of AI and robots inevitably are faced with the dehumanizing effects of technology, as has been a prevailing theme of fiction in the modern, industrial era.

Faced with contemporary realities of job loss and economic insecurity brought upon workers worldwide from increasingly automated, globe-spanning production chains, it is not surprising that many might be skeptical about the benefits of AI and question to whom those benefits might accrue. Contemporary debates about technology and high-profile critics [3, 4] stoking fears of an inevitable robot apocalypse—if artificial general intelligence were ever created—contribute to the distrust and the malaise. Privately funded AI research labs with little governmental oversight and publicly funded surveillance do not instill trust either, especially when new research continues to make huge progress on tasks that were once believed to be the exclusive remit of humans and are now mastered by machines. However, the end of humanity could be much more mundane, as reported by Achenbach [3] in the *The Washington Post*:

"The world's spookiest philosopher is Nick Bostrom [...] in his mind, human extinction could be just the beginning. Bostrom's favorite apocalyptic hypothetical involves a machine that has been programmed to make paper clips. This machine keeps getting smarter and more powerful, but never develops human values. It achieves "superintelligence." It begins to convert all kinds of ordinary materials into paper clips. Eventually it decides to turn eve-

rything on Earth — including the human race (!!!) — into paper clips. Then it goes interstellar.”

Despite these prognostications of doom, a 2018 Workforce Institute survey of 3,000 individuals found that four out of five employees (82%) saw AI as an opportunity to improve their jobs, while only a third (34%) worried that AI might replace them at work [5]. Whereas a Canadian government policy paper [6] found a correlation between Canadians’ fear of losing jobs due to automation and populist and nativist views, but that Canadians supported traditional government policy solutions such as workforce retraining more than limiting labor mobility.

1.1 Research question

The diversity of reactions to AI and general confusion about the state of AI technological development compelled us to examine the range of antecedent factors that might help mitigate current popular confusion about the state of AI and individual AI anxiety. Thus, we sought to understand the relationship between technology readiness and AI anxiety. We asked two closely related questions:

- a) What are the relationships between technology readiness contributors and AI anxiety?
- b) What are the relationships between technology readiness inhibitors and AI anxiety?

2 Background

Given current debates on AI impact on society for good and for bad, Wang and Wang [7] developed an AI anxiety scale to assess to what degree these uncertainties provoke an existential malaise and anxiety for the future and how to mitigate negative consequences for individuals. Wang and Wang [7] situate AI anxiety with respect to technophobia which they define as an irrational fear of technology characterized by negative attitudes toward technology, anxiety about the future impacts of advancing technology, and self-admonishing beliefs about their ability. They divide AI anxiety in two aspects, computer anxiety [1] and robot anxiety [8]. They term AI anxiety as a distinct and independent variable. They define AI anxiety as “an overall, affective response of anxiety or fear that inhibits an individual from interacting with AI. Thus, AIA may be operationally considered as a general perception or belief with multiple dimensions” (p. 3). Informed by the theory of reasoned action [9], Wang and Wang [7] argue that it is necessary to address negative affect as it is known to negatively affect future performance. The scale is established to measure the degree of motivated learning behavioral intention as anxiety can be a facilitative, motivational factor for proactively addressing anxiety by becoming better informed. Although it can also be an obstacle to action. Hence, we expect a different behavioral profile for divergent reactions to anxiety.

As Haring et al. [8] noted, the research to date has demonstrated the cultural variability of reactions to technology, however, it is precisely the fact of the variability of

social groups' reactions to AI that merits study to aid in determining HR policies for managing workforces worldwide. However, cultural variability alone cannot explain all the remaining variance as Wang and Wang [7] only found low correlation ($r=0.19$) between the AI construct and behavioral intentions. However, such low correlations are very common in the attitude-intention literature [9]. It is likely the case that there are other sources of unaccounted variability that influence individuals' affect and behavior. Such individual differences and social determinants can be modelled and their influences accounted for [10-12].

Wang and Wang [7] found that AI anxiety was facilitative to some extent as it appeared to influence motivated learning behaviors. We wished to determine how enabling and inhibiting determinants might interact to inform a range of behavioral profiles and responses to AI anxiety. Following Khatri, Samuel, and Dennis [13], we sought to determine the extent that an individual's technology-based predispositions (technology readiness contributors and technology readiness inhibitors) might influence their AI anxiety.

3 Method

3.1 Research design

The present exploratory study employs a cross-sectional survey design and partial least squares modeling to assess the influence of technology-based predispositions (technology readiness contributors and technology readiness inhibitors) on AI anxiety.

3.2 Participants and procedure

We drew on data from computer science students enrolled in a southwestern college in the US. In total, 65 students participated in this study. The sample comprised 8 females and 57 males with an average age of 23.86 years ($SD=6.09$). Students were asked to voluntarily participate in the study. No compensation was provided for participation in this study. Students participating in the study were emailed a link to a self-report questionnaire.

3.3 Measure

Along with demographic information, participants responded to statements related to the study measures: AI anxiety scale and Technology Readiness Contributors and Technology Readiness Inhibitors scales.

Scales were gathered from previous literature. AI Anxiety scale [7] was used to evaluate an individual's AI anxiety. The AI anxiety scale contains 21 items measuring the following four factors: Learning; AI Configuration; Job Replacement; and, Sociotechnical Blindness, however we prefer the more neutral term Social-Technical Illiteracy, which we also feel is the more descriptive expression. The items were measured on a 7-point Likert scale (1=*Strongly Disagree*; 7=*Strongly Agree*). To measure

individual’s enabling and inhibiting predispositions, we adapted the Technology Readiness Contributors (TRC) and Technology Readiness Inhibitors (TRI) scales [13]; for each of the items, students responded on a 7-point Likert scale (1=*Strongly Disagree*; 7=*Strongly Agree*).

4 Analysis and Results

4.1 Analytic plan

The variance based partial least squares structural equation modeling (PLS-SEM) [14] was used to model and analyze the links between the constructs. PLS-SEM can simultaneously estimate both the measurement model and the structural model, and is a widely used estimation method in educational technology research [15-16]. The analysis was conducted via a two-step procedure: first assessing the measurement model and then the structural model. WarpPLS software [17] was used for the analysis of the measurement and structural model.

4.2 Measurement model

Prior to the structural model analysis, we assessed the psychometric properties of the measurement model. We followed the measurement model evaluation guidelines suggested in the literature [14, 18]. In Table 1, we find that the model-fit indices meet the suggested acceptance levels [18].

Table 1. Model Fit Statistics

Measure	Values	Recommended Criterion
Average path coefficient (APC)	0.273, $P=0.005$	Acceptable if $P<0.05$
Average R-squared (ARS)	0.192, $P=0.026$	Acceptable if $P<0.05$
Average adjusted R-squared (AARS)	0.166, $P=0.041$	Acceptable if $P<0.05$
Average block VIF (AVIF)	1.011	Acceptable if ≤ 5
Average full collinearity VIF (AFVIF)	1.748	Acceptable if ≤ 5

The evaluation of the measurement model entailed examining reliability, convergent validity, and discriminant validity [14, 18]. Loadings were greater than or equal to 0.5 (along with p-values less than or equal to 0.5). Internal consistency reliability was established (composite reliability coefficients of the measures were greater than the threshold value of 0.70). All average variance extracted (AVE) values exceeded the recommended threshold value of 0.50. Discriminant validity was also assessed, using the Fornell-Larcker criterion [19]. Table 2 presents the correlation matrix for the Fornell-Larcker criterion. We find that all the diagonal values are greater than the off-diagonal numbers in the corresponding rows and columns, thus, the requirements of the Fornell-Larcker criterion were met and discriminant validity was confirmed. In sum, the constructs were empirically established to be both reliable and valid.

Table 2. Discriminant Validity Test

	TRC	TRI	Learning	Job Replacement	Socio-Technical Illiteracy	AI Configuration
TRC	(0.732)	-0.006	-0.125	0.076	0.235	-0.089
TRI	-0.006	(0.743)	0.426	0.413	0.322	0.265
Learning	-0.125	0.426	(0.856)	0.454	0.482	0.552
Job Replacement	0.076	0.413	0.454	(0.783)	0.589	0.630
Socio-Technical Illiteracy	0.235	0.322	0.482	0.589	(0.747)	0.546
AI Configuration	-0.089	0.265	0.552	0.630	0.546	(0.925)

4.3 Structural model

In the second stage, the relationships between the constructs in the research model were ascertained by evaluating the structural model. Variance Inflation Factors (VIF) values were inspected to check for potential multicollinearity problems. All VIF values were below the suggested threshold of 5, thus, there was no indication of multicollinearity. At the same time, since Q^2 coefficient values were greater than zero, there was an acceptable level of predictive relevance [18].

The structural model was assessed through (see Table 3): path coefficients (β), path coefficients' significance levels (p -value), and effect sizes (f^2). Note that for assessment of f^2 , values of 0.35, 0.15, and 0.02 indicate large, medium, and small effect sizes, respectively [20].

The path coefficients were assessed to determine the significance of the relationships between the constructs. As indicated in Table 3, for the links between TRC and AI anxiety factors, the results show that only TRC was significantly (and positively) related to Socio-Technical Illiteracy ($\beta=0.256$, $p=0.014$), with a small effect size. In contrast, all four links between TRI and AI anxiety factors were significant with medium effect sizes: TRI was significantly (and positively) related to Learning ($\beta=0.474$, $p<0.001$); TRI was significantly (and positively) related to Job Replacement ($\beta=0.404$, $p<0.001$); TRI was significantly (and positively) related to Socio-Technical Illiteracy ($\beta=0.330$, $p=0.002$); and, TRI was significantly (and positively) related to AI Configuration ($\beta=0.345$, $p=0.001$).

Table 3. Path Testing Results

Path	Path coefficient (β)	P value	Effect size (f^2)	Result
TRC→Learning	-0.184	$P=0.059$	0.035	Not Significant
TRC→Job Replacement	0.059	$P=0.314$	0.008	Not Significant
TRC→Socio-Technical Illiteracy	0.256	$P=0.014$	0.073	Significant
TRC→AI Configuration	-0.130	$P=0.139$	0.020	Not Significant
TRI→Learning	0.474	$P<0.001$	0.225	Significant
TRI→Job Replacement	0.404	$P<0.001$	0.167	Significant
TRI→Socio-Technical Illiteracy	0.330	$P=0.002$	0.116	Significant
TRI→AI Configuration	0.345	$P=0.001$	0.122	Significant

5 Discussion

This study examined the relationship between individuals' beliefs about AI (Artificial Intelligence) and levels of anxiety with respect to their technology-based predispositions (technology readiness contributors and technology readiness inhibitors). We surveyed 65 students at a southwestern US college and found that TRC were significantly and positively related to socio-technical illiteracy. In contrast, all four links between TRI and AI anxiety factors were significant with medium effect sizes: TRI was positively related to learning, fears of job replacement, socio-technical illiteracy, and specific AI configurations. Thus, we conclude that AI anxiety runs through a spectrum and is influenced by real, practical consequences of immediate effects of increased automatization but also influenced by popular representations and discussions of the negative consequences of artificial general intelligence and killer robots. Both TRC and TRI influenced socio-technical illiteracy. This could potentially be explained by a mediating influence; however, we did not include mediators in the present study. Learning appeared to mitigate TRI but not TRC. This is not surprising since assessing the limits of technology is expected to lessen AI anxiety whereas discussing its potential can actually increase fears. In fact, our results tend to indicate however counterintuitively that discussions of technology readiness contributors and inhibitors can actually increase AI anxiety and fears of job replacement and the actual diversity of AI configurations. Thus, our results are contrary to Johnson and Verdicchio's [1] contention that clarification of the true status of artificial intelligence would allay fears and AI anxiety would recede. It would appear that the actual state of AI and the wide diversity of current AI applications—that AI is actually 'eating the world'—is concerning for individuals in general. Our results tend to support Wang and Wang's [7] findings that AI anxiety can have a facilitative effect and support motivated learning. However, the results do not show the expected beneficial effects from motivated learning, as socio-technical illiteracy is related to both TRC and TRI.

Whereas Khatri, Samuel, and Dennis [13] have argued in favor of a two-system behavioral model in technology acceptance research, where individuals are both in conscious, deliberative (system 2) thinking and unconscious, automatic (system 1) behavior. They argue that our default mode is unconscious, or automatic (system 1) and is influenced by past experience and individual preferences and beliefs; system 2 can influence system 1 through effortful practice. Coming from a more social perspective, automatic behavior that characterizes system 1 behavior is not simply unreflective autonomic behavior (we are not ready to countenance zombie computer users devoid of consciousness or agency/will); c.f. [21]. Rather, an important proportion of system 1 behavior can be seen as socially learned, influenced by customs, values, and other social imperatives that dictate appropriate and expected reactions. A more social perspective would term such behavior as "transparent" to conscious [22-23], cognitive processes, because they are not individually determined but socially learned through reflexive activity [24]. Thus, it ought not appear to be a matter of preference alone. The argument inherent in addressing AI anxiety through motivated learning is that an individual's predispositions can be changed by increasing awareness and rational deliberation. Such behavior and perceptions are not automatic in the mode of auto-

onomic physiological processes; perceptions can be apprehended and responses adapted. Their constructed nature suggests that inhibitors and enablers might reveal hidden dimensionality beyond individual self-perceptions that are the focus of Khatri, Samuel, and Dennis's [13] two-system approach.

5.1 Limitations

This study is limited by design. As a cross-sectional study, we are limited to examining correlational relationships, no causal relationships can be inferred from these findings. The study is also limited in the number of explanatory variables. A socially-oriented study of technology perceptions and beliefs [15] may suggest other enabling and inhibiting variables that could explain the variance in beliefs of AI anxiety.

5.2 Future directions

Future studies may employ experimental designs to infer causality, and may employ different statistical learning approaches to build models that account for the hidden dimensionality in enabling and discouraging variables influencing technology readiness and AI anxiety.

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