BRAIN. Broad Research in Artificial Intelligence and Neuroscience
e-ISSN: 2067-3957 | p-ISSN: 2068-0473
Covered in: Web of Science (ESCI); EBSCO; JERIH PLUS (hkdir.no); IndexCopernicus; Google Scholar; SHERPA/RoMEO; ArticleReach Direct; WorldCat; CrossRef; Peeref; Bridge of Knowledge (mostwiedzy.pl); abcdindex.com; Editage; Ingenta Connect Publication; OALib; scite.ai; Scholar9; Scientific and Technical Information Portal; FID Move; ADVANCED SCIENCES INDEX (European Science Evaluation Center, neredataltics.org); ivySCI; exaly.com; Journal Selector Tool (letpub.com); Citefactor.org; fatcat!; ZDB catalogue; Catalogue SUDOC (abes.fr); OpenAlex; Wikidata; The ISSN Portal; Socolar; KVK-Volltitel (kit.edu)
2025, Volume 16, Special Issue 1 (April 2025), pages: 415-426.
Special Issue 1: *Neuroscience, Artificial Intelligence, and Innovation in Education*
Submitted: January 27th, 2025 | *Accepted for publication:* March 24th, 2025

Anxiety in the Age of AI: Constructing a Tool to Assess Public Perceptions

Adrian Hatos
Doctoral School of Sociology, Faculty of Social Sciences, University of Oradea, Romania.
ahatos@gmail.com
https://orcid.org/0000-0003-4197-6950

Abstract: *The rapid proliferation of artificial intelligence (AI) technologies has sparked widespread debate about their societal implications, prompting a need to understand public attitudes, particularly anxiety, toward AI. This study aimed to develop and validate a scale to measure AI-related anxiety, exploring its correlates across demographic groups. Using an online survey of 708 Romanian adults conducted in October 2024, we constructed a 14-item scale with a 5-point Likert format, balancing positive and negative statements. Psychometric validation, including structural equation modelling to address method effects, confirmed the scale's reliability (Cronbach's alpha > 0,7) and fit (CFI = 0,963, RMSEA = 0,053). Results revealed that AI anxiety varies by education, occupation, income, and region, with lower anxiety among the highly educated, self-employed, and high-income individuals. Convergent validity was supported by correlations with technological readiness (-0,411) and a summated AI anxiety score (0,698). These findings align with prior research on AI perceptions and underscore the role of information access and experience in shaping attitudes. Despite this scale offers a robust tool for assessing AI anxiety, with implications for tailoring AI adoption strategies to diverse populations. Future research should pursue longitudinal and qualitative approaches to deepen understanding of this evolving phenomenon.*

Keywords: *artificial intelligence; AI anxiety; scale development; technology attitudes.*

How to cite: Hatos, A. (2025). Anxiety in the age of AI: Constructing a tool to assess public perceptions. *BRAIN. Broad Research in Artificial Intelligence and Neuroscience, 16(*Sup 1), 415-426. https://doi.org/10.70594/brain/16.S1/32

1. Introduction

The recent emergence of tools based on artificial intelligence (AI) algorithms and the debates regarding their utility, but especially the risks associated with the use of AI in various fields of human life, as well as the firm positions that have appeared in public opinion on this topic, have generated several efforts among social science specialists to measure a construct titled, in various forms, as a variant of "attitudes towards artificial intelligence”, more precisely the anxiety towards AI.

Due to the recent generalisation of AI-based tools and the speed with which this field is transforming, the attitudes of the population towards digital technology and, in particular, towards the use of AI-based tools in everyday life are still insufficiently known. Although there is a considerable amount of research (Baptista & Oliveira, 2015; Gupta & Arora, 2017; Williams, Rana & Dwivedi, 2015; Zhao, Ni & Zhou, 2018) on the adaptation of new digital technologies in general, studies on attitudes towards the uses of AI in the world of work, in commercially acquired services, in the domestic environment, or various leisure activities are limited and do not benefit from sufficiently in-depth measurement tools, descriptions, or explanatory investigations. Such knowledge can be useful for programs introducing AI-based tools in various fields of human activity.

This study, therefore, aimed at the following objectives: 1) testing and applying a scale of anxiety towards AI; 2) exploring the correlates of attitudes towards AI. This article is organised as follows. First, the Literature Review section outlines key studies and theoretical perspectives on AI-related anxiety and its measurement. Next, the Methodology section details the development of the scale, the data collection process, and the statistical techniques employed—particularly structural equation modeling to address method effects. The Results section then presents the psychometric properties of the scale, along with analyses of its convergent validity and differences across demographic groups. Finally, the Discussion and Conclusions sections interpret these findings in the context of existing research and discuss practical implications, limitations, and directions for future inquiry.

2. Artificial Intelligence Anxiety. Definition and Measurement

AI-related anxiety has emerged as a significant area of inquiry in the context of the increasing integration of AI in various sectors. This paragraph synthesises recent studies that explore the concept of AI anxiety and its measurement, focusing on the sources and implications of these anxieties. Defined broadly, AI-related anxiety refers to the apprehension and unease individuals experience regarding AI technologies, particularly concerning their implications for job security, ethical use, and interpersonal relationships with AI systems.

Xu, Xue, & Zhao (2023) articulate that AI awareness significantly influences employee mental health, wherein individuals' perceptions of AI as a potential threat to their career development contribute to feelings of depression and emotional exhaustion. This suggests that the construct of AI-related anxiety is multifaceted, encompassing fears about job displacement, emotional repercussions, and ethical concerns regarding AI deployment in decision-making contexts (Kong et al., 2021; Xu, Xue, & Zhao, 2023).

Measurement of AI-related anxiety has recently evolved, with studies employing various scales and methodological frameworks to assess this phenomenon. For instance, Elshamly and Gameel utilised Likert-type scales to evaluate AI-induced anxiety levels in educational technology adoption, applying reliability tests such as Cronbach's Alpha to ensure the trustworthiness of their measurement tool (Elshamly & Gameel, 2023). Additionally, Bai et al. (2024) further corroborate the psychological consequences of AI awareness, linking it to counterproductive work behaviours and highlighting the negative psychological impacts stemming from perceptions of AI as a threatening force.

Examples of such recently developed scales are numerous; here are just a few: AIAS (Artificial Intelligence Anxiety Scale) (Wang & Wang, 2022); General Attitudes Towards Artificial Intelligence (Schepman & Rodway, 2020); ATAIS – Attitudes Towards Artificial Intelligence Scale

(Sindermann et al., 2021); The Threats of Artificial Intelligence Scale (TAI) (Kieslich, Lünich, & Marcinkowski, 2021). AI attitude scale (AIAS-4) (Grassini, 2023), Student Attitudes Toward Artificial Intelligence (Suh & Ahn, 2022), patients' views on implementing AI in radiology (Ongena et al., 2019), users' explicit and implicit attitudes toward AI (Fietta et al., 2022), Attitude in Language Learning with AI (Yildiz, 2023), Artificial Intelligence Attitudes Inventory (AIAI) (Krägeloh et al., 2024), AI Attitude Scale (AIAS-4) (Møgelvang & Grassini, 2024).

In sum, the current literature emphasises both the complexity and significance of AI-related anxiety as a psychological construct. Understanding its dimensions—ranging from job security concerns to ethical implications—is crucial for developing standardised measurement tools that can reliably gauge this phenomenon across different contexts.

3. Construction of the Scale of Anxiety Towards AI

The items of our AI acceptance scale were developed considering the complexity of the studied phenomenon (the diversity of positive and negative effects, fears, and hopes associated with AI in public debate), as well as methodological recommendations for developing multiple scales. Thus, we maintained a balance between negatively and positively worded items.

Agreement for each item was measured on a 5-point Likert scale, according to the question: "To what extent do you agree with the following statements regarding the societal and economic effects of using artificial intelligence?"

- Due to AI, many people will lose their jobs.
- AI will become impossible for humans to control.
- The use of AI makes people lazy.
- AI will improve people's lives.
- AI will help people solve the most difficult problems, such as global warming.
- I am concerned that people do not understand how AI makes decisions.
- AI makes people dependent on devices.
- The use of AI will make people less capable of solving problems.
- AI will increase productivity in most jobs.
- AI will turn against humans.
- The widespread use of AI will deepen the gap between the rich and the poor.
- I feel comfortable interacting with AI-powered virtual assistants or robots.
- I believe AI can make more objective decisions than humans.
- I am open to using smart devices in my daily life.
- I believe the development of AI should be strictly regulated by governments.
- I believe the benefits of AI outweigh the potential risks.

Beyond the good face validity of the scale, the included items cover the vast range of life domains affected by AI, as captured in the specialised literature, such as ethical aspects, the use of these tools, and their impact on jobs and productivity. These items encompass a broad spectrum of attitudes and anxieties related to AI, many of which correspond to dimensions found in established AI anxiety and attitude scales. These dimensions include Job Replacement Anxiety, AI Configuration Anxiety, Sociotechnical Blindness, Learning Anxiety, and Positive Attitudes (Grassini, 2023; Terzi, 2020).

4. Data. Sample

The data for this study were collected through an online survey conducted in October 2024, on a commercial sample of online users from Romania.

This sample is not representative of the entire adult population of Romania, being over-represented by certain categories more active online: urban population, young adults, and individuals with higher education. The final sample included 708 participants from the online adult population of Romania.

The structure of the sample by residence, education level, age categories, gender, and occupation is presented in Table 1.

Table 1. Distributions of main demographic variables

Variable	Values	N %
Last school completed	No school, unfinished primary school (less than 8 grades)	0,1
	Primary school (8-10 grades)	3,7
	Vocational or apprenticeship school	4,1
	High school	27,7
	Post-secondary, technical, or master school	12,9
	University, master's, doctorate, long-term university studies	51,6
Current occupation	Retired	25,2
	Student	0,7
	Housewife	8,8
	Unemployed	3,0
	Employed in the public sector	18,7
	Employed in the private sector	38,1
	Self-employed (PFA, owner, freelancer, etc.)	5,4
	Other occupation	0,0
Marital status	Married	61,4
	Single	16,2
	Divorced	10,6
	Widowed	6,1
	Consensual union	5,1
	Don't know/No response	0,6
Net income last month	No income	6,1
	Below 1500 RON	5,6
	Between 1501 - 3000 RON	23,6
	Between 3001 - 5000 RON	29,5
	Between 5001 - 6000 RON	9,7
	Between 6001 - 7000 RON	5,5
	Between 7001 - 8000 RON	4,5
	Above 8000 RON	6,4
	Can't estimate/No response	9,0
Age group (years)	18 - 24	1,4
	25 - 34	9,6
	35 - 44	20,5
	45 - 54	27,4
	55 - 64	25,7
	65+	15,4
Sex	Male	43,2
	Female	56,8
Region	Bucharest-Ilfov	21,5
	Center	10,6
	North-East	15,4
	North-West	10,6
	South-East	11,7
	South Muntenia	15,3
	South-West Oltenia	7,3
	West	7,6
Urbanization	Rural	18,4
	Large urban	40,0
	Medium urban	23,0
	Small urban	18,6
How often do you go to church?	Almost every week	23,6
	Only on major holidays (Easter, Christmas, etc.)	56,8
	Never	8,5
	Not religious	5,8
	Don't know/No response	5,4

While for certain characteristics the distributions are similar to those in the adult population of Romania, for others we can talk about significant distortions, which are partially specific to the structure of the online population: a disproportionate share of individuals with higher education, those from the Bucharest-Ilfov region, women, and the urban population.

5. Results

5.1. Psychometric qualities of the Scale of Anxiety Towards AI

The validation procedures for the 16-item scale included several data interventions. Since the proportion of missing values – lack of response or "don't know/no response" answers – varied between 2.5%-9.5%, with a median of approximately 4% for the 16 items, the missing values were replaced with the mean of each item (Schafer & Graham, 2002; Tabachnick & Fidell, 2001) (Cheema, 2014; Little & Rubin, 2019). Subsequent checks confirmed that this replacement did not significantly affect either the reliability or the summative score of the construct.

The 16-item scale with negatively worded items reversed and non-responses replaced with mean values has a good Cronbach's alpha reliability score (>0,7).

Confirmatory factor analyses, on the other hand, showed that responses were affected by method biases, determined by the negative or positive wording of the items, so the factor score was developed through structural equations, after extracting the latent factors corresponding to the tendency to respond differently to negatively worded items compared to positively worded ones (Marsh & Hocevar, 1988; Podsakoff et al., 2003; Reise, Moore, & Haviland, 2010). Structural Equation Modeling (SEM) is a statistical technique used to analyse complex relationships between observed (measurable) and latent (unmeasured, theoretical) variables — all at once, in a single model and as such it is of conventional use for scale development, in order to assess scale invariance and measurement biases (Bollen, 1989; Hoyle, 2014). The structural equation model with three latent variables led to the elimination of items 13 and 16, which did not have significant loadings with the latent variables. The final model presented an appropriate fit (CFI=0,963, RMSEA=0.053). The values thus obtained are standardised and do not contain the method effects bias; however, they cannot be simply replicated by summing the item values.

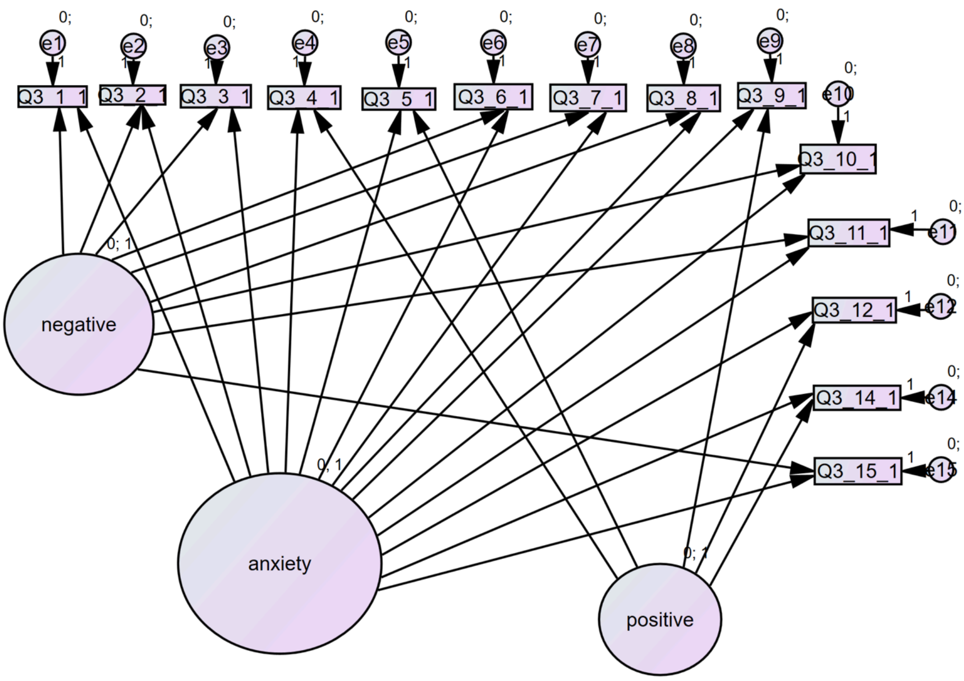

Figure 1. Final SEM with latent variables to eliminate method effects

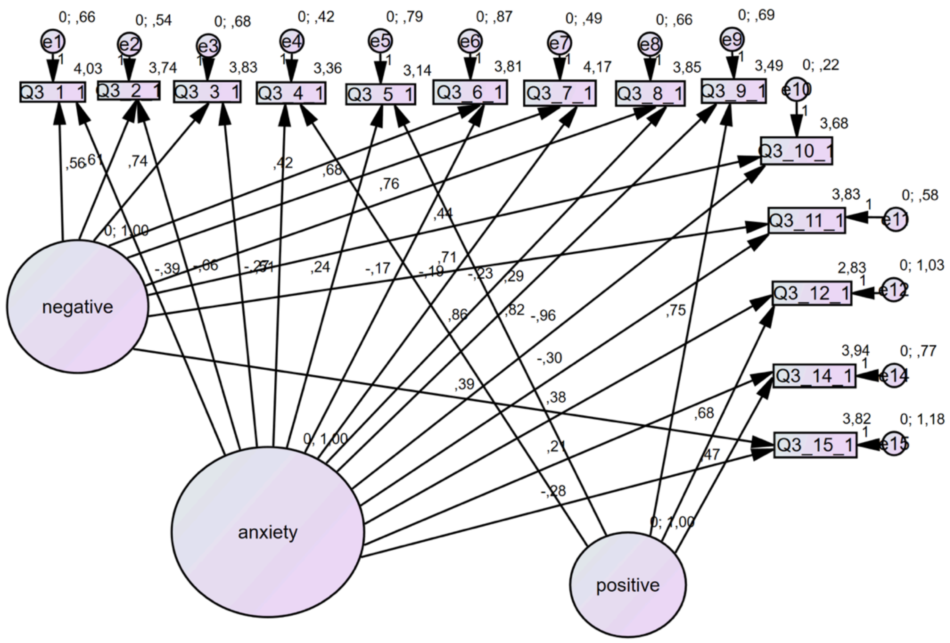

Figure 2. Final SEM with standardized parameters

Table 2. Final SEM model fit measures

Chi-square	186,607, P<0,01, df=63
CFI	0,963
TLI	0,947
RMSEA	High: 0,053 Low: 0,044

*Table 3. Parameter estimates of final SEM model (***=p<0,001)*

Item	Latent variable	Estimate	S.E.	C.R.	P label
Q3_4_1	positive	0,865	0,044	19,872	***
Q3_5_1	positive	0,816	0,046	17,650	***
Q3_9_1	positive	0,752	0,043	17,280	***
Q3_6_1	negative	0,424	0,046	9,301	***
Q3_7_1	negative	0,676	0,042	16,257	***
Q3_8_1	negative	0,755	0,048	15,769	***
Q3_10_1	negative	0,442	0,099	4,470	***
Q3_11_1	negative	0,706	0,048	14,674	***
Q3_15_1	negative	0,386	0,055	6,978	***
Q3_1_1	anxiety	-0,390	0,066	-5,931	***
Q3_2_1	anxiety	-0,656	0,070	-9,408	***
Q3_3_1	anxiety	-0,268	0,083	-3,244	0,001
Q3_4_1	anxiety	0,513	0,057	9,069	***
Q3_5_1	anxiety	0,237	0,054	4,363	***
Q3_6_1	anxiety	-0,165	0,059	-2,797	0,005
Q3_7_1	anxiety	-0,193	0,075	-2,568	0,010
Q3_8_1	anxiety	-0,231	0,084	-2,733	0,006
Q3_9_1	anxiety	0,290	0,052	5,595	***
Q3_10_1	anxiety	-0,955	0,080	-12,000	***
Q3_11_1	anxiety	-0,295	0,078	-3,764	***
Q3_12_1	anxiety	0,377	0,058	6,522	***
Q3_14_1	anxiety	0,211	0,045	4,661	***
Q3_15_1	anxiety	-0,282	0,061	-4,599	***
Q3_14_1	positive	0,469	0,041	11,451	***
Q3_12_1	positive	0,679	0,050	13,510	***
Q3_3_1	negative	0,737	0,049	14,930	***
Q3_2_1	negative	0,607	0,070	8,667	***
Q3_1_1	negative	0,555	0,053	10,519	***

The AI anxiety score was calculated as a factor score according to the structural equation model represented above. Since the calculated score signifies "Acceptance of Artificial Intelligence”, we reversed the AI Acceptance scores to attribute the meaning of anxiety towards AI. The anxiety score calculated based on SEM (Structural Equations Modelling) parameters has a distribution close to normal, with increasing values indicating a growing acceptance of AI-based technology – essentially, it is a measure of AI Acceptance (AIA). Thus, in the following pages, we will refer to AI Anxiety, whose values positively correlate with the rejection of AI-based technologies. Being a standardized variable, the score has a mean of 0 and a standard deviation of 1, with positive values indicating a high level of anxiety towards AI.

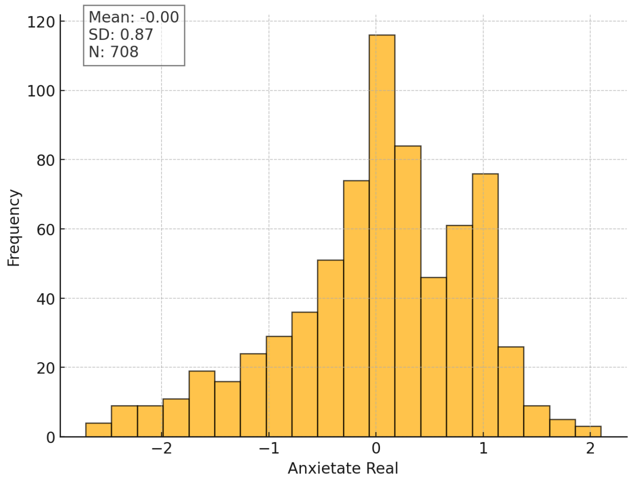

Figure 3. Histogram of AI anxiety

5.2. Convergent Validity of the Score

To measure the convergent validity of the factor score measured as described above, two alternative measures have been employed: 1) a score of technological readiness and 2) the Anxiety about AI computed as the summative score of our items.

5.3. Correlation with the Degree of Technological Readiness

Technological readiness refers to the extent to which an individual, organisation, or society is prepared and willing to adopt and use new technologies. This concept includes the mindset, resources, and infrastructure necessary to embrace technological innovations. It is about the willingness and ability to interact with new technologies, including resources, motivation, and overall preparedness.

In this study, we developed a scale for measuring technological readiness with fewer items than the scales mentioned earlier. The Technology Readiness Index was developed following methodological prescriptions in the field of attitudinal measurement, with each item evaluated on a 5-point Likert scale. This summative scale respects the methodological prescriptions from the specialized literature (Kapuza et al., 2022; Lin et al., 2016; Parasuraman, 2000; Parasuraman & Colby, 2015).

- I am among the first in my circle of friends to adopt new technologies.
- I believe technology significantly improves my daily life.
- I believe technology creates more problems than it solves.
- I feel anxious when I have to use new technology.
- I like to explore and experiment with advanced features of my technological devices.
- I prefer traditional methods over technological ones.
- I believe technology is essential for career success.

The scale has good reliability measured by Cronbach's alpha (alpha>0.7), and the correlation with the AI Anxiety score is -0,411.

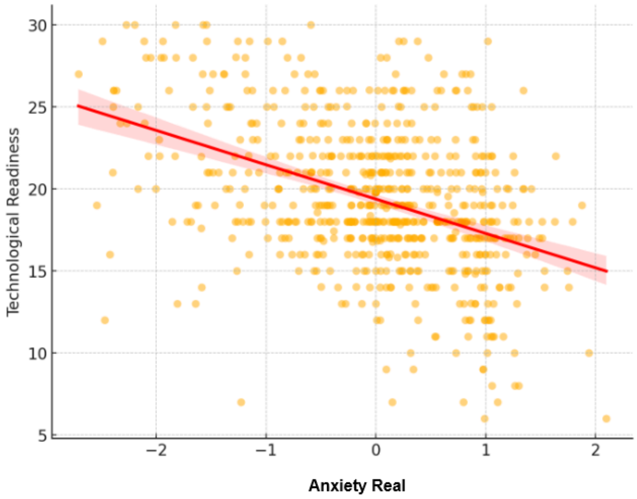

Figure 4. Scatterplot of AI anxiety with technological readiness (r=-0,411)[1]

5.4. Correlation with the Summated Score of Anxiety Towards AI

Based on the results of the SEM, as an alternative, we have also computed the summated measure of the score of Anxiety towards AI, by adding up the values of items 1-15, except 13, with the missing values replaced with averages and with values of negatively worded items reversed. The correlation between the two measures of Anxiety regarding Artificial Intelligence is 0,698. A correlation of 0.698 between the two scoring methods suggests a moderate-to-strong relationship but is not so high that they can be considered interchangeable without caution (Floyd & Widaman, 1995; Hair Jr et al., 2010). While a correlation of 0,698 does not suggest perfect agreement, in many applied settings, researchers do opt for the summated scale given its ease of use. It might be acceptable provided that you acknowledge the potential limitations in terms of variance capture and that further validity checks support its use.

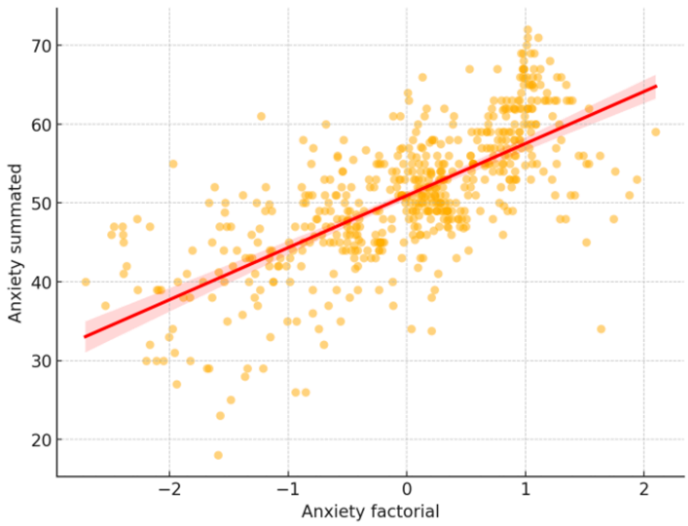

Figure 5. Scatterplot of AI anxiety measured as factor score and AI Anxiety measured as summated score (r=0,698)

[1] In figures 4 and 5 AI Anxiety score scale is labelled as Anxietate Real and Anxietate factorial

5.5. Anxiety about AI by Demographic Categories

The table below presents the average scores of anxiety about AI by demographic variable categories.

Table 4. Average of Anxiety about AI scores by demographic category

Variable	Values	Average of AI Anxiety
Last school completed	No school, unfinished primary school (less than 8 grades)	0,79
	Primary school (8-10 grades)	0,23
	Vocational or apprenticeship school	0,24
	High school	0,17
	Post-secondary, technical, or master school	0,19
	University, master's, doctorate, long-term university studies	-0,18
Current occupation	Retired	0,09
	Student	0,01
	Housewife	-0,05
	Unemployed	0,07
	Employed in the public sector	-0,02
	Employed in the private sector	0,01
	Self-employed (PFA, owner, freelancer, etc.)	-0,34
Marital status	Married	0,01
	Single	-0,05
	Divorced	-0,03
	Widowed	0,04
	Consensual union	0,05
Net income last month	No income	0,01
	Below 1500 RON	-0,05
	Between 1501 - 3000 RON	-0,03
	Between 3001 - 5000 RON	0,04
	Between 5001 - 6000 RON	0,05
	Between 6001 - 7000 RON	0,01
	Between 7001 - 8000 RON	-0,05
	Above 8000 RON	-0,03
	Can't estimate/No response	0,04
Age group (years)	18 - 24	-0,07
	25 - 34	0,02
	35 - 44	0,00
	45 - 54	0,04
	55 - 64	-0,08
	65+	0,06
Sex	Male	0,02
	Female	-0,01
Region	Bucharest-Ilfov	-0,05
	Center	0,01
	North-East	-0,01
	North-West	0,05
	South-East	0,05
	South Muntenia	0,08
	South-West Oltenia	-0,20
	West	0,04
Urbanization	Rural	0,05
	Large urban	-0,03
	Medium urban	0,01
	Small urban	0,01
How often do you go to church?	Almost every week	0,03
	Only on major holidays (Easter, Christmas, etc.)	0,02
	Never	-0,05
	Not religious	-0,35
	Don't know/No response	0,13

Anxiety towards AI is lowest in the case of unmarried or divorced people, those who declare themselves unfaithful, those with higher education, housewives, and, especially, self-employed people. Also, the anxiety felt is lower in people with high incomes (over 7000 lei/month), those in the South-West, and those living in large cities. However, the very high positive average for the Oltenia region is likely the result of sampling distortions.

6. Discussions

After replacing missing values with item means and eliminating two items, the study demonstrated the validity and reliability of a 14-item scale designed to measure anxiety towards AI, highlighted by a Cronbach's alpha coefficient above 0,7, but also the sensitivity of the instrument for measuring attitudes to the formulation of questions, making it necessary to eliminate effects of this type through structural equations, which was also used to measure the latent construct through a structural model (SEM) with good fit indicators (CFI=0,963, RMSEA=0,053). These findings underscore the instrument's sensitivity to item wording, necessitating adjustments to mitigate method effects. Moreover, it is clear that instruments developed simply contain in the scores measurement biases of which the users have to be well aware.

The results obtained align with previous studies (Xu, Xue, & Zhao, 2023; Kong et al., 2021), which highlights the importance of the perception of risks associated with AI. Similar to the research of Elshamly and Gameel (2023), the present study highlights that both technological and psychosocial aspects influence how individuals perceive the impact of AI. The differences observed across demographic categories – particularly by level of education, occupation, and income – suggest that access to information and direct experience with technology play a key role in how attitudes towards AI are formed.

Research findings on AI anxiety can guide policymakers in developing communication and training strategies specifically tailored to demographic groups with high levels of anxiety. For example, for the self-employed or those with lower incomes, information campaigns can be developed that clarify the benefits of adopting AI and mitigate perceptions of job security risks.

The study has several important limitations. First, the use of an online survey led to an overrepresentation of people from urban areas, with higher education and higher incomes, which may affect the generalisability of the results. Methodological biases are also important: item wording effects (positive vs. negative) required methodological adjustments by modelling response effects, introducing an additional source of variability.

To overcome these limitations, future research directions should include more diverse and representative samples, longitudinal studies that monitor attitudinal changes over time, as well as qualitative investigations (interviews, focus groups) for a deeper understanding of the motivations behind anxiety towards AI.

7. Conclusions

In conclusion, the study succeeded in developing and validating a robust measurement instrument for assessing anxiety towards AI, highlighting the inverse relationship between acceptance of the technology and the level of anxiety experienced. In the author's view, the most important result of this scale development exercise is the fact that it has revealed the impact of measurement biases – in this case of method bias – in the assessment of such simple construct as AI Anxiety, a result that warns against hasty employment and interpretation of such instruments when they are computed using summation for instance. Beyond this methodological insight, the results obtained using AI Anxiety computed as factor scores with SEM suggest that better information and direct experience with technology can reduce fears related to AI, thus facilitating its more harmonious integration into everyday life. The theoretical and practical implications are particularly relevant for the development of implementation strategies that specifically respond to the needs of different demographic segments, thus contributing to a balanced and conscious adoption of emerging technologies. These findings pave the way for further research to expand the analysis on the long-term impact of artificial intelligence on society, underlining the importance of multidisciplinary approaches in assessing the changes brought about by technological innovations.

References

Bai, S., Zhang, X., Yu, D., & Yao, J. (2024). Assist me or replace me? Uncovering the influence of AI awareness on employees' counterproductive work behaviors. *Frontiers in Public Health, 12*. https://doi.org/10.3389/fpubh.2024.1449561

Baptista, G., & Oliveira, T. (2015). Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators. *Computers in Human Behavior, 50*, 418–430. https://doi.org/10.1016/j.chb.2015.04.024

Bollen, K. A. (1989). *Structural equations with latent variables.* John Wiley & Sons. https://doi.org/10.1002/9781118619179

Cheema, J. R. (2014). A review of missing data handling methods in education research. *Review of Educational Research, 84*(4), 487-508. https://doi.org/10.3102/0034654314532697

Elshamly, A., & Gameel, Z. A. A. (2023). AI and BDA impact on stakeholders' responses to education technology adoption. *Migration Letters, 20*(8), 1041–1067. https://doi.org/10.59670/ml.v20i8.5738

Fietta, V., Zecchinato, F., Stasi, B. D., Polato, M., & Monaro, M. (2022). Dissociation between users' explicit and implicit attitudes toward artificial intelligence: An experimental study. *IEEE Transactions on Human-Machine Systems, 52*(3), 481–489. https://doi.org/10.1109/THMS.2021.3125280

Floyd, F. J., & Widaman, K. F. (1995). Factor analysis in the development and refinement of clinical assessment instruments. *Psychological Assessment, 7(3),* 286–299. https://doi.org/10.1037/1040-3590.7.3.286

Grassini, S. (2023). Development and validation of the AI Attitude Scale (AIAS-4): A brief measure of general attitude toward artificial intelligence. *Frontiers in Psychology, 14*. https://doi.org/10.3389/fpsyg.2023.1191628

Gupta, A., & Arora, N. (2017). Understanding determinants and barriers of mobile shopping adoption using behavioral reasoning theory. *Journal of Retailing and Consumer Services, 36*, 1–7. https://doi.org/10.1016/j.jretconser.2016.12.012

Hair Jr, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Pearson.

Hoyle, R. H. (2014). *Handbook of structural equation modeling*. Guilford Publications.

Kapuza, A., Kolygina, D., Khavenson, T., & Koroleva, D. (2022). A time to gather stones–barriers to use technologies before the COVID-19 school closures. *International Journal of Educational Management, 36(6),* 923-936. https://doi.org/10.1108/IJEM-02-2022-0069

Kieslich, K., Lünich, M., & Marcinkowski, F. (2021). The threats of artificial intelligence scale (TAI): Development, measurement, and test over three application domains. *International Journal of Social Robotics, 13*, 1563–1577. https://doi.org/10.1007/s12369-020-00734-w

Kong, H., Yuan, Y., Baruch, Y., Bu, N., Jiang, X., & Wang, K. (2021). Influences of Artificial Intelligence (AI) Awareness on Career Competency and Job Burnout. *International Journal of Contemporary Hospitality Management, 33*(2), 717-734. https://doi.org/10.1108/ijchm-07-2020-0789

Krägeloh, C. U., Melekhov, V., Alyami, M., & Medvedev, O. N. (2024). Artificial Intelligence Attitudes Inventory (AIAI): Development and validation using Rasch methodology. *Research Square*. https://doi.org/10.21203/rs.3.rs-4403120/v1

Lin, H.-H., Lin, S., Yeh, C.-H., & Wang, Y.-S. (2016). Measuring mobile learning readiness: Scale development and validation. *Internet Research, 26(1),* 265-287. https://doi.org/10.1108/IntR-10-2014-0241

Little, R. J., & Rubin, D. B. (2019). *Statistical analysis with missing data* (Vol. 793). John Wiley & Sons. https://doi.org/10.1002/9781119482260

Marsh, H. W., & Hocevar, D. (1988). A new, more powerful approach to multitrait-multimethod analyses: Application of second-order confirmatory factor analysis. *Journal of Applied Psychology, 73*(1), 107. https://doi.org/10.1037/0021-9010.73.1.107

Møgelvang, A., & Grassini, S. (2024). University students' attitude toward AI: A validation of the AI attitude scale (AIAS-4) in a large Norwegian student sample. https://doi.org/10.31219/osf.io/7x5k9

Ongena, Y., Haan, M., Yakar, D., & Kwee, T. C. (2019). Patients' views on the implementation of artificial intelligence in radiology: Development and validation of a standardized questionnaire. European Radiology, 30(2), 1033–1040. https://doi.org/10.1007/s00330-019-06486-0

Parasuraman, A. (2000). Technology Readiness Index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research, 2(4),* 307-320. https://doi.org/10.1177/109467050024001

Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined Technology Readiness Index: TRI 2.0. *Journal of Service Research, 18(1),* 59-74. https://doi.org/10.1177/1094670514539730

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Reise, S. P., Moore, T. M., & Haviland, M. G. (2010). Bifactor models and rotations: Exploring the extent to which multidimensional data yield univocal scale scores. *Journal of Personality Assessment, 92*(6), 544–559. https://doi.org/10.1080/00223891.2010.496477

Schafer, J. L., & Graham, J. W. (2002). Missing data: Our view of the state of the art. *Psychological Methods, 7*(2), 147–177. https://doi.org/10.1037/1082-989X.7.2.147

Schepman, A., & Rodway, P. (2020). Initial validation of the general attitudes towards artificial intelligence scale. *Computers in Human Behavior Reports, 1*, 100014. https://doi.org/10.1016/j.chbr.2020.100014

Sindermann, C., Sha, P., Zhou, M., Wernicke, J., Schmitt, H. S., Li, M., Sariyska, R., Stavrou, M., Becker, B., & Montag, C. (2021). Assessing the attitude towards artificial intelligence: Introduction of a short measure in German, Chinese, and English language. *KI - Künstliche Intelligenz, 35*(1), 109–118. https://doi.org/10.1007/s13218-020-00689-0

Suh, W., & Ahn, S. (2022). Development and validation of a scale measuring student attitudes toward artificial intelligence. *SAGE Open, 12*(2). https://doi.org/10.1177/21582440221100463

Tabachnick, B. G., & Fidell, L. S. (2001). *Using multivariate statistics*. Allyn & Bacon. Needham Heights, MA.

Terzi, R. (2020). An adaptation of the artificial intelligence anxiety scale into Turkish: Reliability and validity study. *International Online Journal of Education and Teaching, 7*(4), 1501–1515.

Wang, Y.-Y., & Wang, Y.-S. (2022). Development and validation of an artificial intelligence anxiety scale: An initial application in predicting motivated learning behavior. *Interactive Learning Environments, 30*(4), 619–634. https://doi.org/10.1080/10494820.2019.1674887

Xu, G., Xue, M., & Zhao, J. (2023). The association between artificial intelligence awareness and employee depression: The mediating role of emotional exhaustion and the moderating role of perceived organizational support. *International Journal of Environmental Research and Public Health, 20*(6), 5147. https://doi.org/10.3390/ijerph20065147

Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): A literature review. *Journal of Enterprise Information Management, 28*(3), 443–488. https://doi.org/10.1108/JEIM-09-2014-0088

Yildiz, T. A. (2023). Measurement of attitude in language learning with AI (MALL:AI). *Participatory Educational Research, 10(4),* 111-126. https://doi.org/10.17275/per.23.62.10.4

Zhao, Y., Ni, Q., & Zhou, R. (2018). What factors influence the mobile health service adoption? A meta-analysis and the moderating role of age. *International Journal of Information Management, 43*, 342–350. https://doi.org/10.1016/j.ijinfomgt.2017.08.006