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Barriers of Human and Nonhuman Agents' Integration in Positive Hybrid Systems: The Relationship Between the Anthropocentrism, Artificial Intelligence Anxiety, and Attitudes Towards Humanoid Robots

ABSTRACT

The article focuses on the analysis of subjective conditions for the integration of humans with humanoid robots. By interacting with each other, these units create hybrid systems that deserve to be called positive, as interactions with technological artifacts contribute to increasing the optimal functioning of users. An online survey-based study with 364 respondents was conducted that tested the relationship between anthropocentric beliefs of individuals, attitudes towards, and interactions with humanoid robots. It was found that this relationship is positive and is mediated by the aspects of fear of artificial intelligence

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(AI) related to the perception of AI-driven agents as scary and intimidating and by anxiety caused by the fear of their strong expansion (e.g., in the labor market). The significant strength of the relationship is an important clue for people designing hybrid systems (e.g., in the workplace), especially in conservative societies whose representatives are sensitive to the position humans in the hierarchy of entities.

KEYWORDS: positive hybrid systems; human-computer interaction; artificial intelligence anxiety; attitudes toward robots; flourishing.

INTRODUCTION

The process of digitalization as the core of the digital revolution focuses on the psychological aspects of integrating interacting agents endowed with natural (human) and artificial (artifacts controlled by artificial intelligence, AI) cognitive systems. The aforementioned entities spontaneously or intentionally create hybrid systems. These systems are examples of human–machine interaction characterized by a set of collaborating agents that are clearly distinguishable and yet still autonomous (Hubig, 2008). They are oriented to achieve different types of goals, e.g., workplace teams or multi-agent systems implemented in business organizations support production, sales and customer service, school education, diagnostic processes, treatment in healthcare units, etc. The integration of humans with artificial agents within hybrid systems is identical to the process of cyborgization of life (see: Fuller, 2021). Traditionally, a cyborg is defined as an organism (not only human) having a technological element that enhances their abilities in a particular environment (Carvalko, 2012). However, cyborgization does not necessarily mean the fusion of artificial systems with the human body and nervous system. When humans and artificial systems interact and interdepend on each other without physical fusion, then one can speak of "soft cyborgization" (e.g., the use of computers, smartphones, or car navigation; Kamieński, 2014). The desired outcome of hybrid systems should be the well-being or optimal functioning of individuals. If this happens, they gain the attribute of having a positive impact (Fortuna, 2021).

Concerning the debate over business organizations, based on two criteria: agent (human vs. artificial) and characteristics (anthropic vs. computronic), Gladden (2016) identified four categories of entities that can enter the boundaries of hybrid systems: (1) natural human beings (human and anthropic; e.g., employees, customers); (2) cyborgs (human and computronic; e.g., neuroprosthetically augmented human employees); (3) computers (artificial and computronic; e.g., artificial intelligence driven software, expert systems); and (4) bioroids (artificial and anthropic; social robots, humanoid robots). In this article, we focus on the last category following the International Organization for Standardization, which distinguishes robots from other machines as automatic control, programmability, multitasking, having manipulative or locomotor properties (ISO 8373:1994). Humanoid social robots are embodied systems that can be perceived as a social entity with the capability of communicating with the user via social interface, able to generate verbal and/or non-verbal signals (see: Broekens et al., 2009). They occupy a special place among units that can enter the boundaries of positive hybrid systems.

The market for these agents is growing seven times faster than the market for production robots. It reached $5.4 billion at the end of 2017 and is expected to grow to $14.9 billion by 2023 (Business Wire, 2017). Interactions with social robots are considered from the perspective of forming relationships with them (Fox & Gambino, 2022), affective reactions (Kislev, 2022), perceived human-likeness (Ruijten et al., 2019), perception of the mind (Lukaszewicz & Fortuna, 2022), and moral status (Fortuna et al., submitted). Humanoid robots are protagonists in numerous pop culture narratives presented mainly in the form of high-budget film productions (e.g., I Robot), which include "...portrayals of any machines (or hybrids, such as cyborgs) to which intelligence has been ascribed, which can include representations under terms such as robots, androids or automata" (Cave et al., 2018, p. 5). Moreover, robots often appear in media messages that emphasize their almost equal status with humans. For example, in 2017, the fembot Sophia received the status of a citizen in Saudi Arabia (Griffin, 2017), and less than a week later, Japan granted the resident status to a chatbot named Mirai (McCall, 2017).

An inspiring perspective for the analysis of hybrid systems is a concept of Systems Informed Positive Psychology (SIPP; Kern et al., 2020). Its principles are derived from systems theory (Bertalanffy, 1968) and facilitate the identification of important directions for analyzing the problem of integrating individuals. One of these is factor identification, which favors the system organization, including the individuals' beliefs critical to effective functioning within them. The constructors of artificial agents, marketing specialists, and pop culture narratives present them as equal to, or superior to, humans in some respects. In consequence, the humanoid nature of those artificial agents disrupts the hierarchical relationship between human and artifact, to which those with strong anthropocentric beliefs should be sensitive (Chandler & Dreger, 1993).

Anthropocentrism, as a psychological construct, is understood as a comprising set of beliefs about human as a superior life form on the planet, resulting in the view that the nonhuman world exists only as raw material for human purposes (Washington et al, 2021). Research indicates that anthropocentrism is negatively related to attitudes toward and interactions with humanoid robots (Fortuna et al., 2021). However, little is known about the interrelationship between these variables. The goal of the current research is exploring this phenomenon with the mediating role AI anxiety. Research shows that knowledge of technology users about AI is deficient (Maison, 2019; Davies, 2020), and perceptions mainly shaped by pop culture narratives are mostly catastrophic

(Cave et al., 2018). A number of publications highlight a possible negative impact of AI on human well-being (Kaplan, 2016). For example, Müller and Bostrom (2016) predict that AI will perform most of the duties carried out today in human occupations, at least as well as humans. It is anticipated that it will happen by 2050 with 50% and by 2070 with 90% probability. On the other hand, techno-optimists in the field of machine consciousness would welcome the possibility of the emergence of conscious AI, whose mental life is richer and more complex than that of humans (see: Schneider, 2019). Such visions translate into concerns revealed in the studies regarding the threatened loss of subjectivity, dependence on technology, and unemployment (Pruś et al., 2020).

The structure of the article is as follows: firstly, we introduce the process of forming positive hybrid systems. Secondly, we illustrate the link between anthropocentric beliefs and attitudes toward humanoid robots and the importance of artificial intelligence anxiety as a potentially mediating variable. The obtained results with discussion along the limitations and directions for the future research are the last part of the article.

LITERATURE OVERVIEW AND DEVELOPMENT OF HYPOTHESES

Forming positive hybrid systems

The AI and robotics development will be a successful direction for humans only if these innovations support humans in achieving worthwhile goals (which is not certain with regard to the development of superhuman AI; Tegmark, 2017). According to the suggestions formulated within the framework of positive psychology, it is those goals that maximize optimal functioning or flourishing (Donaldson et al., 2015). Both concepts assume positive personal experiences, but the boundaries between them are blurred. Optimal functioning refers to those psychological processes and peoples' activities that ensure that they are effective given their own needs and the environmental demands (Trzebińska, 2008). On the other hand, human flourishing emphasizes the subjective, transactional, and dynamic nature of good life, stressing the interdependence of its biological, psychological, and social dimensions (physical health and positive relationships with the environment) and development aimed at realizing potentials and responding constructively to challenges (Keyes & Haidt, 2003). Human flourishing, in addition to maximization of efficiency/optimization/profit, and social control is one of the possible purposes of AI (Stahl, 2021). Referring to the classic distinction pathways to happiness (Riva et al., 2012), robots that contribute to improving optimal functioning, which can be referred to as *hedonic technology* when they transform "human-computer interaction" into "human-computer satisfaction" and *eudaimonic technology* when they support the process of self-realization of individuals. However, such labels can only be given after positive effects of interaction within the hybrid system are identified.

Forming favorable human interactions with humanoid robots is a complex process. Robot design is oriented on maximizing positive affect on people by revealing empathy, care, and emotional intelligence (Kislev, 2022). Two paths of innovation are intended to achieve this effect: developmental cybernetics and developmental robotics (Marchetti et al., 2018). Representatives of the first area tend to construct human-like units by simulating human psychological processes and kinesthetic functions. Those who explore the second domain develop neural networks that would allow artificial agents to autonomously acquire sensorimotor and mental abilities of increasing complexity. The successful implementations include the European Union-funded RAMCIP agent, an assistant for daily, in-home care for the elderly and people with mild cognitive impairments, such as those typical of early-stage Alzheimer's disease (Kostavelis et al., 2019). In the field of education, the Socially Interactive Robotic Tutor is being used as a form of verbal encouragement strategy (Brown & Howard, 2013).

Riva and colleagues (2012) proposed a model for shaping positive personal experience through technological enhancement. According to the model, environmental factors such as real-world demands (e.g., assembling things) and use of technology (e.g., robots) lead to the enhancement of new psychological resources and sources of involvement. They are a result of association of tech experience with real life and association of tech effectiveness to personal skills. A prerequisite for the cultivation of optimal experience is an adaptation and technological acceptance, which should be preceded by the formation of an appropriate level of people's readiness for change (Armenakis et al., 1993). Analyzing the process of implementing an artificial system in the role of a supervisor (AI Boss), Fortuna and colleagues (2022) identified three stages of this process: (1) preparation, including necessary antecedents and cognitive, affective, and behavioral readiness; (2) action, including explicit reactions and change outcomes; and (3) acceptance correlated with organizational prosperity, technological functionality, and individual well-being (including job satisfaction). Such dynamics occur at the organizational, technological, and personal human levels, in ways that may reinforce or impede one another. Readiness for the introduction of artificial system is understood as the beliefs, emotions, and intentions of individual employees (within a work group or organization) regarding the extent to which such change is needed, as well as the organizational and technological capacity to successfully undertake such a challenging step (Rafferty et al., 2013).

At this stage, doubts about the need for change, such as fear of artificial systems, as a typical reaction that makes up technostress, should be worked through (Ragu-Nathan et al., 2008). Negative reactions are constantly noted in response to technological innovations. The process of disseminating them (which, by assumption, should improve the quality of life) can be traced by mapping the methods of measuring fears they cause: Computer Anxiety Scale (Heinssen et al., 1987), Internet Anxiety Scale (Chou, 2003), Mobile Computer Anxiety Scale (Wang, 2007) and Artificial Intelligence Anxiety Scale (Wang & Wang, 2019). Distancing oneself from artificial agents is not necessarily a manifestation of technophobia (Khasawneh, 2018). It can be seen as signaling concern about the loss of well-being and as an endorsement of a more thoughtful and cautious integration of artificial entities into already functioning systems than current trends and marketing incentives suggest.

Anthropocentrism and attitudes toward robots

Anthropocentrism, or humanocentrism (Gr. *anthropos* – human being; Lat. *centrum* – middle, center; Lat. *humanus* – human), is understood as a position that regards humans as separate from, and superior to, nature and holds that human life has intrinsic value while other entities (including animals, plants, mineral resources etc.) are resources that may justifiably be exploited for the benefit of humankind (Boslaugh, 2016). Understanding of anthropocentrism as a psychological construct means that it is regarded as a pattern structuring human experience and behavior and as a principle organizing the perception and interpretation of events (Kelly, 1955). In the philosophical tradition, four dimensions of anthropocentrism are distinguished: finalistic, metaphysical, epistemological, and axiological. However, the results of psychological research indicate it as a one-dimensional construct, which combines the indicated aspects (Fortuna et al., 2021).

The analysis of the relationship between anthropocentrism and attitudes toward humanoid robots is relevant to the design of positive hybrid systems, in which the status and role of artificial agents should promote their acceptance. For example, studies conducted in the context of tasks implemented in a museum found that AI is more trustworthy than humans in case of performing statistical analysis and preparation of reports on the visits of exhibitions, while it is less trusted when it acts as an animator or when it arranges an exhibition (Modliński et al., 2022). Consumers who were told that managers had delegated the former tasks to rational agents rated their decisions higher than when they were told that artificial systems performed tasks for which humans were rated as more trustworthy performers. Aversion is observed in case of the agents that perform tasks that seem subjective in nature (based on emotions and intuition; Castelo et al., 2019) and burdened with a high risk of error (Davenport et al., 2020). Delegating such tasks, in instances where humans are perceived as reliable contractors, may lead to human-machine trans role conflict (Modliński et al., 2022), resulting in negative cognitive (e.g., negative assessment of management decisions), emotional (e.g., reduced sense of security) and behavioral (e.g., supporting a consumer boycott of institutions) consumer's reactions. Subsequent research conducted on hybrid systems at the museum examined employees' reactions to the implementation of this type of innovation (Modliński et al., submitted). These reactions were found to be related to AI anxiety and negative attitudes toward robots and interactions with them.

Analyses comparing the results of ninety-seven studies, showed that attitudes toward robots are examined on both affective and cognitive dimensions (Naneva et al., 2020). Measurement was most often made using self-report general attitude (GA), the Negative Attitudes toward Robots Scale (NARS; Nomura et al., 2006): the NARS-S1 (interaction with robots), NARS-S3 (emotions in interaction with robots) subscales to measure affective attitude (AA), while the NARS-S2 subscale (reflecting beliefs about the social influence of robots) to measure cognitive attitude (CA). The original Japanese NARS scale also consists of those three subscales (Nakamura et al., 2006). On the other hand, the Polish adaptation, similarly to the Portuguese one, did not confirm this structure (Pochwatko et al., 2015). In both cases, two factors, instead of three, were identified: (1) The Negative Attitudes toward Interactions with Robots (NATIR), that encompasses reactions to interactions with robots, and (2) The Negative Attitudes toward Robots with Human Traits (NARHT), which captures responses to robots that display human traits like emotions, language, and agency. This modification emphasizes components of an attitude (affective, cognitive) to its object (interaction, display of human traits), which opens a field to new analyses.

The comparative analyses express that attitudes toward robots are influenced by the type of exposure to robots, domain of application, and geographical location. Surprisingly, such characteristics as age and gender turned out to be insignificant, and the fact that studies rarely consider other subjective determinants of attitude formation toward robots, such as anthropocentric beliefs. It was found that general attitude (GA) and cognitive attitude (CA) were more positive in studies where there was no interaction between participants and robots than when there was direct interaction. In direct interaction with robots, negative affect can be aroused by the robots' excessive resemblance to humans, which is referred to as "uncanny valley" (Mori, 1970). It was found that affective attitudes (AA) were more positive toward social robots, intended for companionship or domestic purpose, while CAs were more positive toward robots in educational domains. In addition to this, it was noticed that people living in different parts of the world have different experiences of using AI, which is related to both technological developments and specific legal regulations. For example, GA were more positive in New Zealand than USA, AA were more positive in Italy than in Germany, while CA were more positive in France than in Japan (Naneva et al., 2020).

Emphasizing the importance of cultural and social context for attitudes toward artificial agents highlights the role of anthropocentric beliefs. Research in Poland revealed that this variable is associated with a conservative worldview, right-wing authoritarianism, as well as religious centrality, while negatively correlating with ecocentrism (Fortuna et al. 2021). The belief in occupying the highest position in the hierarchy of entities is also marked regarding new technologies. People with conservative views were more skeptical than liberals about AI (Castelo & Ward, 2016). For example, members of conservatively oriented Catholic families resisted changes involved in the adoption of new technologies, associating them with dehumanization (de Oliveira & Oliveira, 2019). Higher level of religiosity significantly correlated with more negative attitude to self-driving cars than a lower level of this characteristic (Modliński et. al, 2022). Anthropocentric and eco-centric individuals may respect and highly value other entities, but they do so for different reasons. For anthropocentric individuals, utilitarian motive is most important, it is 'ownership' and usefulness to achieve their own goals (Washington et al, 2021). Research conducted in digitalization of medical sector supported these results (Fortuna & Razmus, submitted). It was found that anthropocentric beliefs foster the acceptance of algorithmic agents in the role of a tool, rather than an entity equivalent to a human (doctor).

Regarding the relationship between anthropocentrism and artificial systems, we hypothesize that:
H1a: Anthropocentric beliefs positively correlate with negative attitudes toward humanoid robots.
H1b: Anthropocentric beliefs positively correlate with negative attitudes toward interactions with humanoid robots.

The mediating role of AI anxiety

Artificial systems, especially in the form of general AI, are often presented as a threat to human status (e.g., Tegmark, 2017). According to the 2019 Global Human Capital Trends Report, commissioned by Delloitte (consulting firm), 50% of the Poles believe that automation will eliminate a significant number of jobs. This is an indicative result when one considers that 13% of respondents in the world, where AI anxiety development are also discussed in relation to changes in the labor market, believe similarly (Bernazzani, 2017). A particular example of AI anxiety is algorithm aversion (Dietvorst et al., 2015). Its manifestation is a preference for one's own intuitions and the suggestions of others even when research suggests that algorithms perform better than humans. This is particularly pronounced when pursuing high-risk goals (Davenport et al., 2020), which is why the phenomenon is observed, for example, in the medical field (Longoni et al., 2019).

The AI anxiety is "overall, affective response of anxiety or fear that inhibits an individual from interacting with AI" (Wang & Wang, 2019, p. 3). Wang and Wang (2019) devised The Artificial Intelligence Anxiety Scale (AIAS) to measure anxiety towards AI, which incorporates four components: (1) Learning – fear of special functions, using the AI techniques/products that causes anxiety, as well as interactions with an AI technique/product; (2) Job Replacement – being afraid of AI technique/product make people dependent, lazier and that they may replace humans and take jobs away from people; (3) AI Configuration – finding humanoid AI techniques/products scary and intimidating, and (4) Sociotechnical Blindness – being afraid that AI technique/product may be misused, get out of control and malfunction or may lead to robot autonomy. Developing this standardized tool resulted in research development in this field. For example, Terzi (2020) found that taking gender criterion into account, female teachers were more anxious towards AI than male teachers in Learning, Job Replacement, AI configuration dimensions, and the in total scale. Lemay and co-researchers (2020) found that technology readiness contributors were significantly and positively related to one AI anxiety factor: Sociotechnical Blindness and the inhibitors were positively related to Learning, Job Replacement and AI Configuration. On the other hand, Modliński and colleagues (submitted), studied the relationship between AI anxiety and human-machine trans role conflict in the Polish population. They found that cognitive reactions to perceived conflict were significantly related to the Job Replacement factor, while the behavioral aspect was additionally related to Learning. All the studies confirmed the factor structure of the AIAS as defined by Wang and Wang (2019).

The aforementioned aspects of fear of AI led us to hypothesize the following:
H2a: The association of anthropocentric beliefs with negative attitudes toward humanoid robots are mediated by AI anxiety.
H2b: The association of anthropocentric beliefs with negative attitudes toward interaction with humanoid robots are mediated by AI anxiety.

METHOD

Statistical data analysis was performed using the SPSS package. Ninety-five per cent confidence interval was used. The validity of AIAS scale construct was verified through an analysis of its factor structure in AMOS 27. Hayes PROCESS macro v3.4 was used to examine the mediation (Model 4; Hayes, 2013). Analyses were based on 10000 bootstrapping samples and 95% bias corrected confidence intervals (CI).

Participants and procedure

Three hundred and sixty-four Polish speaking participants (54.2% of female; $M_{\text{Age}} = 35.92$, $SD_{\text{Age}} = 17.04$;) were recruited via Internet advertisements in social media and Internet interest groups. They varied in education: primary – 9,6%, secondary – 54,8% and university – 35,4%. The study was conducted online. Participants were instructed to respond to each questionnaire item by choosing the response that accurately described their level of agreement. They were also informed that no personal data were collected and that they could withdraw from the study at any stage without any consequences. After accepting these conditions, participants read the short instruction and completed the survey. Finally, they provided information about their sex, age, and education. Prior to data collection, the study was approved by the institutional Ethics Committee.

Measures

Anthropocentric beliefs. The short version of Anthropocentric Beliefs Scale (ABS-4; Fortuna et al., 2021) was used. ABS-4 consisted of 4 items measuring aspects of anthropocentrism represented by separate items (1 = "strongly disagree"; 7 = "strongly agree", α = .84). The items focused on these areas: finalistic ("Man is the final link in the evolution of nature or, from the religious point of view, 'the crown of creation'"), metaphysical ("Man is a unique being, a special one in the Universe"), epistemological ("Only man can get to know the world objectively, as it is"), and axiological ("The good of man is more important than the needs of any other creatures").

Attitudes toward robots. To measure psychological reactions to humanlike and non-humanlike robots The Negative Attitude Toward Robots Scale (NARS) by Nomura, Kanda, and Suzuki (2006) was used. It was translated and adapted to the Polish population by Pochwatko et al. (2015). NARS consist of two subscales: The Negative Attitudes toward Interactions with Robots (NATIR), that encompasses the reactions to interactions with robots (e.g.; "I would feel uneasy if I was given a job where I had to use robots") The Negative Attitudes toward Robots with Human Traits (NARHT) scale, that captures the responses to robots that display human traits like emotions, language, and agency (e.g., "I would hate the idea that robots or artificial intelligences were making judgments about things"). Participants responded to 12 items using a 7-point Likert's scale (1 – strongly agree to 7 – strongly disagree). Both subscales have good internal consistency. Cronbach's alpha coefficients are .81 for NATIR and .78 for NARHT.

The artificial intelligence anxiety. We used the Artificial Intelligence Anxiety Scale (AIAS) by Wang and Wang (2019) to measure anxiety towards AI. The validated 21-item instrument refers to feelings of fear or agitation regarding the out-of-control AI. The AIAS was developed through a rigorous validation procedure and the analyses demonstrated acceptable reliability and criterion-related, convergent, discriminant, and nomological validity of the instrument. The authors of AIAS also point out that further studies require factor analysis (CFA) confirmators, determination of stability of the instrument and testing on other samples. The original version of the AIAS includes four factors: Learning (e.g., "Learning to use AI techniques/products makes me anxious"), Job Replacement (e.g., "I am afraid that an AI technique/product may make us dependent"), AI Configuration (e.g., "I find humanoid AI techniques/products (e.g., humanoid robots) intimidating") and Sociotechnical Blindness (e.g., "I am afraid that an AI technique/product may be misused"). Participants scored items using a 7-point Likert-type response scale.

To investigate how the factor structure of the adapted Polish AIAS matches the theoretical structure of the original scale (Wang, 2019), we performed a confirmatory factor analysis CFA. In accordance with Brown (2006) to assess the model fit, we used the χ^2, Goodness-of-Fit Statistic, the Root Mean Square Error of Approximation (RMSEA), the Standardized Root Mean Square Residual (SRMR), and the Comparative Fit Index (CFI). Moreover, we performed convergent and discriminant validity analyses by calculations Composite Reliability values (CR) and Average Variance Extracted for AVE. We tested four-factor model with following dimensions of the fear of AI: Learning, Job Replacement, Sociotechnical Blindness, and AI Configuration. In the first step, the item F1_7 was removed from the questionnaire due to the low value of the factor loading .37. We received a model with the following parameters (χ^2 = 559.30, $p < .001$; χ^2/df = 3.41; CFI = .92; RMSEA = .075, 95% CI [.069, .082], SRMR = .074,). However convergent and discriminant validity of this model with four scales reveled some problems. Despite the fact that all CR values reached .70, the value of AVE for the Job Replacement scale was smaller than .50. Moreover, the Square Root of the AVE for Job Replacement scale was less than its correlation with Sociotechnical Blindness, and the Square Root of the AVE Sociotechnical Blindness scale was less than its correlation with Job Replacement. These data showed that independent dimensions of these two scales in the Polish version of the questionnaire was not empirically supported, which may be due to the fact that the questions can refer to one common factor. After additional language analyses of the items, we decided to merge those two scales (Job Replacement and Sociotechnical Blindness) into one, which we named AI *Expansiveness*. Having merged Job Replacement and Sociotechnical Blindness scales we tested a model with three factors structure. From the merged scale we removed such items as F2_10, F2_13, F4_18, F4_2, and F4_21 to achieve the average variance extracted (AVE) greater than .50. After such modifications of the scale, we received a model with the following parameters (χ^2 = 278.30, df = 87, p < .001; χ^2/df = 3.19; CFI = .963; RMSEA = .066, 95% CI [.057, .075], SRMR = .051). Convergent validity of the final structure of adapted AIAS are shown in Table 1 and discriminant validity of the final structure of adapted AIAS model with three scales are shown in Table 2.

In essence, convergent and divergent analysis showed the three-thread structure of the Polish version of the tool. After the modifications, the parameters of the model were significantly improved in parameters with respect to the original four-scale model. In the final version of the Polish adaptation of AIAS questionnaire we obtained such scales as Learning, AI Expansiveness, and AI Configuration. The final structure of the questionnaire is shown in Figure 1.

Table 1. Convergent validity of the final structure of adapted AIAS.

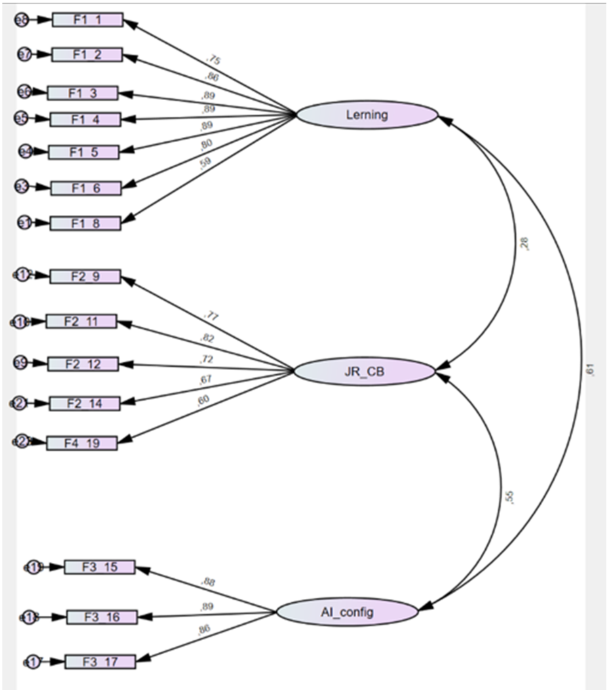
Items	Loadings	CR	AVE
Learning		.930	.665
F1_6	.802		
F1_5	.891		
F1_4	.887		
F1_3	.890		
F1_2	.861		
F1_1	.746		
F1_8	.586		
AI Expansiveness		.842	.519
F2_12	.722		
F2_11	.823		
F2_9	.768		
F2_14	.670		
F4_19	.599		
AI Configuration		.907	.765
F3_17	.857		
F3_16	.890		
F3_15	.877		

Table 2. Discriminant Validity Assessments for Model 2.

Construct	1	2	3
1. Learning	**.665**		
2. AI Expansiveness	.327	**.519**	
3. AI Configuration	.633	.580	**.765**

Note: The diagonal values (in bold) are the AVE, the values below the diagonal are the squared correlations between the scales.

Figure 1. The three-thread structure of the Polish version of the AIAS.



RESULTS

Relationship of anthropocentrism and attitudes toward robots

To verify H1a and H1b, an *r*-Pearson correlation analysis was conducted, the result of which is shown in Table 3. The analyses show that anthropocentric beliefs (ANTHR) positively correlate with NARHT ($r = .22$, $p < .001$), which allows us to accept H1a, and with NATIR ($r = .29$, $p < .001$), which is the basis for accepting H1b.

Table 3. Descriptive statistics and correlations among the anthropocentrism, NARHT and NATIR.

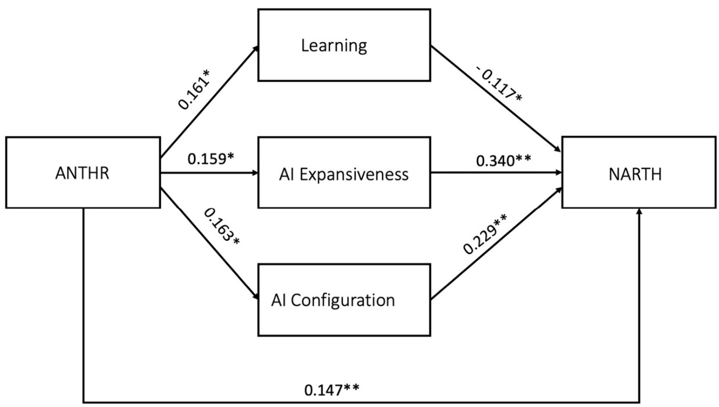
Variables	M	SD	1	2	3
1. ANTHR	4.50	1.19			
2. NARHT	4.83	1.09	0,22**		
3. NATIR	3.95	1.03	0.29**	0.61**	

Note: ** $p < 0.01$

The mediating role of AI anxiety in the relationship between anthropocentrism and negative attitudes toward robots

Mediation analysis was conducted to verify H2a and H2b. Mediation effects were verified by a bootstrap method through confidence intervals; if the intermediate confidence interval contains zero, it means that the mediation effect is not statistically significant. Separate models were made for NARHT (Model 1, see Figure 2) and NATIR (Model 2, see Figure 3), and the predictor variable was anthropocentrism (ANTHR) in both models. The

Figure 2. Standardized regression coefficients for the relationships between anthropocentrism and NARHT as mediated by AIAS subscales: Learning, AI Expansiveness, and AI Configuration. Note: ** $p < .001$.



following AIAS scales (Learning, AI Expansiveness, AI Configuration) were tested as parallel mediators. The use of a parallel mediator model made it possible to examine direct and indirect effects. The results for model 1 are shown in Table 4, and the results for model 2 are shown in Table 5.

Table 4. Mediation estimates for Artificial Intelligence Anxiety (Learning, AI Expansiveness, AI Configuration) in mediating the relationship between the anthropocentrism (ANTHR) and Negative Attitudes toward Robots with Human Traits (NARHT).

Variables	B	SE	LLCI, ULCI	β	Model R^2
Direct effects					
ANTHR – Learning	1.088	0.355	0.391, 1.786	0.161*	0.026
ANTHR – AI Expansiveness	0.754	0.249	0.264, 1.244	0.159*	0.025
ANTHR – AI Configuration	0.588	0.189	0.217, 0.960	0.163*	0.027
Learning – NARHT	-0.016	0.008	-0.031, -0.001	-0.117*	0.250
AI Expansiveness – NARHT	0.066	0.011	0.045, 0.087	0.340**	
AI Configuration – NARHT	0.059	0.016	0.027, 0.091	0.229**	
Anthropocentrism – NARHT	0.137	0.044	3.10.051, 0.223	0.147**	
Indirect effects	Effect	SE	LLCI		ULCI
ANTHR via Learning	-.017	0.012	-0.043	0.002	
ANTHR via AI Expansiveness	0.05	0.020	0.014	0.092	
ANTHR via AI Configuration	0.035	0.015	0.008	0.068	

Note: * *p < .05*, ** *p < .001.*

The bootstrapped total of indirect effect of anthropocentrism NARHT was (IE = 0.085; 95% CI [0.016, 0.118] unstandardized).

The analyses show that two AIAS subscales, AI Expansivness, and AI Configuration, are mediators of the effect of anthropocentrism on negative attitudes toward humanoid robots. At the same time, fear of Learning is not a mediator of the effect of anthropocentrism on general aversion toward robots, and Learning is not a mediator of this relationship. The result obtained allows us to accept H2a.

Figure 3. Standardized regression coefficients for the relationships between anthropocentrism and NATIR as mediated by AIAS subscales: Learning, AI Expansiveness, and AI Configuration. Note: ** $p < .001$.

Table 4. Mediation estimates for Artificial Intelligence Anxiety (Learning, AI Expansiveness, AI Configuration) in mediating the relationship between the anthropocentrism (ANTHR) and Negative Attitudes toward Interactions with Robots (NATIR).

Variables	B	SE	LLCI, ULCI	β	Model R^2
Direct effects					
ANTHR – Learning	1.149	0.352	0.457, 1.842	0.170**	0.029
Anthropocentrism – AI Expansiveness	0.756	0.245	0.275, 1.237	0.161**	0.026
Anthropocentrism – AI Configuration	0.637	0.187	0.269, 1.005	0.177**	0.031
Learning – NATIR	0.015	0.007	0.002, 0.027	0.115*	0.403
AI Expansiveness – NATIR	0.043	0.009	0.025, 0.060	0.231**	
AI Configuration – NATIR	0.083	0.014	0.056, 0.110	0.346**	
Anthropocentrism – NATIR	0.149	0.036	0.077, 0.220	0.172**	
Indirect effects	Effect	SE	LLCI		ULCI
ANTHR via Learning	0.017	0.012	-0.001		0.045
ANTHR via AI Expansiveness	0.032	0.013	0.009		0.059
ANTHR via AI Configuration	0.053	0.019	0.019		0.095

The bootstrapped total indirect effect of anthropocentrism on NATIR was IE = 0.102; 95% CI [0.050, 0.116] unstandardized. The analyses show that the dimensions illustrating fear of AI, as AI Expansiveness and AI Configuration, are mediators of the influence of anthropocentrism on negative attitudes toward interaction with humanoid robots, while Learning is not a mediator of this relationship. Based on the results, H2b can be accepted.

DISCUSSION

The purpose of the presented research was to explore the relationship between anthropocentric beliefs and attitudes toward humanoid robots and interaction with them. As expected, the variables were negatively correlated, confirming the results of previous studies (Fortuna et al., 2021). The mediating effect of AI anxiety was also confirmed. A mediating role is played by an array of concerns about the loss of human subjective status in the face of the development of AI. This is feared to make humans dependent on it and lose their jobs, subject to the control of systems that gain autonomy, which intensifies the negative affect towards this type of innovation. Although the relationship between anthropocentric beliefs and the aforementioned aspects of AI anxiety is not strong although significant. It indicates that this variable should not be ignored in the debate on the integration between humans and humanoid robots in positive hybrid systems. Importantly, the link between anthropocentric beliefs and the need to learn special functions related to the use of AI was not recognized. This should be taken as a confirmation that anthropocentrism displays particular sensitivity to aspects of technology that threaten the position of humans in the hierarchy of entities. Metaphorically speaking, a human being looking at technological innovations through anthropocentric glasses primarily focuses on those signals that are relevant to his or her status.

Two observations are particularly noteworthy. The first concerns the AIAS scale; its four-factor structure was not confirmed, and three factors were considered in the analyses instead: Learning, AI Expansion, and AI Configuration. The AI Expansion factor combines the original Job Replacement and Sociotechnical Blindness scales. This result indicates a close connection between concerns about the misuse of AI and the replacement of humans by artificial systems. This result corresponds with research findings that one of the main concerns about AI development is job loss (e.g., Pruś, 2020). Thus, current study confirmed that concern for job stability is one of the most sensitive aspects that filters the incoming information on AI progression. This is significant mainly regarding to the possibility of the emergence of superhuman AI. Experts agree that no one in the world is able to determine whether, and if so when, this is possible (e.g., Tegmark, 2019). Nonetheless, the elements of the debate that permeate pop culture should be given appropriate commentary. Fear-mongering naive theories about AI's autonomy hinder the formation of positive hybrid systems, increasing aversion to systems that can gain independence and take control of humans in ways that are difficult to understand.

LIMITATIONS AND CONCLUSIONS

The presented research has several limitations. First, it was conducted on a Polish sample, who represent a conservative society with low knowledge of AI, where contact with humanoid robots is mainly mediated by information available through media. The participants were not presented with a stimulus example of a humanoid robot, so data obtained are based on the subjects' generalized knowledge of such agents. In the future, it would be worth monitoring the relationship between anthropocentric beliefs and attitudes toward specific artificial entities within particular positive hybrid systems designed for that purpose to make the participants' experience better informed. Finally, the research was conducted online, which means weaker control of participants' responses. This form of research was necessitated by the COVID-19 pandemic. It is also difficult to determine a real, disruptive impact of the pandemic situation on subjects' reactions (anxiety), which is another incentive to replicate this research. The development of hybrid systems that support humans in achieving optimal functioning is a matter of time, which adds to the importance of carrying out research in this field.

Current research draws a crucial conclusion for the design of positive hybrid systems. The process of their implementation, and therefore the adoption of artificial agents, requires subjective factors such as the anthropocentric beliefs of their human individuals, to be considered. Akin postulates are formulated within the framework of system concepts such as SIPP (Kern et al., 2020). This means that a humanoid and usability of the systems alone, which is in the focus of attention of designers and UX specialists, are insufficient to predict success in shaping positive interactions with humans. Consequently, it makes it difficult to forecast their integration for optimal functioning in the fields of education, medicine, business, or entertainment.

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