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User trust in AI and major tech companies in twelve countries

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ABSTRACT
Artificial intelligence (AI) technologies are increasingly present in virtually all life domains, but the trustworthiness of these new technologies and the companies developing them has been a topic of heated public debate. We examined how basic psychological needs in technology use, AI self-efficacy, and positive attitudes toward AI are associated with trust in AI and in major tech companies. Data were collected in 2024 and include 11,259 participants from Africa, Asia, Europe, North and South America, and Oceania. We used linear regression for data analysis. We found that having positive attitudes toward AI and experiencing relatedness in technology use consistently predicted trust in AI and in major tech companies. However, technological autonomy, competence, and self-efficacy in AI use predicted trust only in specific countries. Our findings provide novel insights into the human factors that affect trust in AI and its developers, and as such, they are of relevance for successful AI development, integration, and use. Our study includes culturally diverse perspectives and thus contributes to the debate on establishing fair global AI practices and overcoming the 'AI divide'.

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Artificial intelligence; trust; companies; self-efficacy; self-determination theory; cross-national

1. Introduction

Artificial intelligence (AI) can be broadly understood as technology that exhibits behaviours usually associated with human intelligence, and that operates by relying on and learning from its environment, while demonstrating a degree of autonomy, that is, it operates within limits set by a user or by design (High-Level Expert Group on Artificial Intelligence 2019). Corporations and organisations are seeking ways to benefit from AI, which has resulted in its widespread integration across many domains of our lives (Maslej et al. 2025). For example, customer support chatbots are starting to replace human agents (Li and Zhang 2023a). Social media platforms are flooded with texts and images created by AI that are no longer easy to differentiate from human-made posts. At the same time, generative AI tools such as ChatGPT and Copilot are being exploited for completing all kinds of tasks, from repetitive to creative ones. The increased use of and reliance on AI has made trust in this technology one of the most prevalent issues. Pertinent international organisations such as the European Union are constantly updating guidelines on trustworthy and responsible AI use (e.g. European Commission 2024). Studies show that trust is a crucial factor when it comes to successful AI acceptance (Gillespie, Lockey, and Curtis 2021) and adoption (Bach et al. 2024; Kelly, Kaye, and Oviedo-Trespalacios 2023), while taking into consideration culturally diverse perspectives is crucial for establishing fair global policies (Benk et al. 2024).

The interactivity of AI technologies and their ability to operate autonomously means that they can be more than a tool and instead function as assistants, teammates, or companions in various tasks and spheres of life. Thus, users' perceptions of AI have far-reaching consequences for their behaviour and well-being online. Research on trust in AI indicates that it results in cognitive, affective, and behavioural changes in its users, and this trust is crucial for successful adoption of AI-based tools (Łapińska et al. 2021; Montag et al. 2023; Yang and Wibowo 2022). Kaplan et al. (2023) identified that research on trust in AI revolves around three key factors: (1) the characteristics of a human as trustor; (2) the features of AI as trustee; (3) the context in which the interaction occurs. Saßmannshausen et al. (2023) proposed a fourth factor: *interaction* by arguing that

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trust in AI is dynamic, and it can increase or decrease depending on, for example, AI's performance.

While it is important to understand trust in AI in general, it is also necessary to understand trust in companies developing AI, as well as major social media companies, which rely on AI for key functions such as content moderation and personalised content recommendations (Pan et al. 2025). By demonstrating integrity, especially in the ways user data is handled, companies can gain users' trust (Yang and Wibowo 2022). Yet, in practice, companies do not always follow ethical practices. A good example is the major data breach that happened in 2018 in Facebook, which resulted in users' personal data being transferred to third parties (Landwehr 2019). Such incidents can affect user trust (Ayaburi and Treku 2020) and user behaviour (Ho, Ho-Dac, and Huang 2023). At present, social media companies often use user data to train their AI models. In the European Union, companies are obliged to comply with the General Data Protection Regulation (GDPR) (European Parliament and Council of the European Union 2016). In Brazil, a similar regulation was introduced in 2018 (Senado Federal 2024). This means that, for example, companies need users' consent to use their data for AI training purposes. However, in some countries, there are no regulations that oblige companies to obtain such consent.

The world of AI is currently dominated by U.S. and Chinese AI companies (Maslej et al. 2025). The United Nations has called for global cooperation in overcoming the 'AI divide', a world in which richer countries are capitalising on AI while poorer countries are being left out (Berg, Snene, and Velasco 2024). Our study answers the call for more cross-cultural and human-centric research approaches to trust in AI (Bach et al. 2024; Benk et al. 2024) by providing perspectives from 11,259 participants from 12 countries on six continents. The main aim of including geographically diverse samples in the study is to provide robust evidence and test the generalizability of the findings. This avoids the common problem of studies relating to AI technology often focusing on somewhat homogeneous populations. Our study presents a more global reach and observes emerging technologies in different contexts.

We investigate user trust in AI technology and companies that develop it, as well as social media giants that utilise various AI solutions in their platforms. We are especially interested in how trust in AI technology and tech companies associates with how users perceive their own use of technology and its impact on their well-being and confidence. Namely, our aim is to examine the relationships between user trust, basic psychological needs, AI self-efficacy, and attitudes toward AI. Our study is the first global study conducted from this perspective, and it offers comprehensive insight into the psychological processes underlying modern technology use and its outcomes.

2. Theoretical background and literature review

2.1. Trust in AI

Different definitions of trust exist depending on the context or discipline. The common denominator in many definitions is that trust is associated with interactions that occur in an environment characterised by vulnerability (Lee and See 2004; Mayer, Davis, and Schoorman 1995; Rousseau et al. 1998) or risk and uncertainty (Boon and Holmes 1991; Gefen, Benbasat, and Pavlou 2008). As AI development has progressed, various definitions of trust in AI have emerged. The two definitions most cited in the field are the one of organisational trust offered by Mayer, Davis, and Schoorman (1995) and the one of trust in automation offered by Lee and See (2004) (Saßmannshausen et al. 2023). Mayer, Davis, and Schoorman's (1995) definition implies that when trust is present, there is no need for the trustor to monitor or control the trustee in completing a task that this trustor finds important. Besides vulnerability, Vereschak, Bailly, and Caramiaux (2021) found that trust in the field of human–AI interactions is often seen as an attitude and linked to trustor's positive expectations.

Discussions on trust in AI should take into consideration that commercial AI-based systems and tools such as ChatGPT, Alexa, or Facebook's recommendation algorithms are developed by private companies that prioritise monetary gain. This is somewhat reflected in past research that differentiates between trust in technology and trust in the organisation providing that technology (Yang and Wibowo 2022). Söllner, Hoffmann, and Leimeister (2016) concluded that user trust in information systems is as important as trust in their providers, which is why companies should make an effort to establish themselves as trustworthy. Another study found that trust in the company providing voice-based digital assistants affects user intention to adopt this technology (Vimalkumar et al. 2021). One common concern related to the use of AI is how these companies treat users' personal data (Hayes et al. 2021; Janssen et al. 2020; Mühlhoff 2023). Considering that major social media companies such as Meta, X, and TikTok have already been involved in unethical practices such as using data for behavioural advertising or user surveillance (Federal Trade Commission 2024), it is reasonable to be wary of their intentions. There is evidence that when people do not trust corporations in general, they tend to have more negative attitudes toward AI (Schepman and Rodway 2022), while people who have trust in corporations are more prone to have trust in AI (Chen and Wen 2021).

Socio-ethical factors such as legal frameworks, AI's technical and design features, as well as users' characteristics (including attitudes and experiences) are all associated with user trust in AI (Bach et al. 2024). After reviewing the literature, Yang and Wibowo (2022) divided factors that impact user trust in AI into two groups: (1) the internal environment, which consists of technology-related and organisational factors; and (2) the external environment, which consists of context-related, social, and user-related factors. Such user-related factors include, for example, users' attitudes toward AI (Montag and Ali 2025) and their cultural backgrounds (Kim, Erdem, and Kim 2024; Rheu et al. 2021).

2.2. Basic psychological needs and AI

Self-determination theory (SDT) posits that autonomy, competence, and relatedness are three main factors that facilitate our motivation, development, and well-being (Ryan et al. 2022). Autonomy refers to a human need to act and make decisions at our own will; competence refers to our need to feel competent and effective in significant life areas; and relatedness refers to our need to establish meaningful connections with others and to experience belonging (Ryan and Deci 2017). When these three basic psychological needs are met, they promote an individual's ability to grow and assimilate, and when they are not met, this ability is hindered (Niemiec and Ryan 2009). Modern AI technologies can, under certain circumstances, promote health and well-being (Li et al. 2023b; Pataranutaporn et al. 2021). However, they can also take away our sense of control and strip us of meaningful experiences and feelings of social connectedness (de Bellis and Venkataramani Johar 2020). Thus, it is important to understand the role of basic psychological needs in the context of human–AI interactions.

Many studies have investigated SDT in the context of learning that includes interacting with AI tools (Annamalai et al. 2025; Chiu et al. 2024; Li, Zhou, and Chiu 2025). For instance, Zhou, Shen, and Chen (2024) determined that when teachers' needs for competence and relatedness are met through interactions with ChatGPT, their teaching competence increases, while this is not the case with autonomy. Shah, Mathur, and Vishnoi (2024) found that ChatGPT use predicted students' perceived autonomy, competence, and relatedness, although these relationships were moderated by their levels of AI literacy. Lu et al. (2023) applied SDT to design a social robot helping adults learn a language. They reported that when the robot supported participants' need to feel connected, they had more motivation to engage in learning (Lu et al. 2023). Nevertheless, more evidence is needed on the associations between trust in AI and basic psychological needs.

2.3. Self-efficacy and AI

Self-efficacy is a concept from social cognitive theory (SCT), and it refers to a person's beliefs in their own ability to complete a specific task in a successful way (Bandura 1977). Despite their differences, both SCT and SDT recognise that competence facilitates human motivation. The role of self-efficacy has been studied, for example, in relation to work performance (Judge et al. 2007; Stajkovic and Luthans 1998), habit building (Stojanovic, Fries, and Grund 2021), general health (Dadipoor et al. 2021), and interactions with technologies (Pan 2020). For example, a study on Chinese undergraduates revealed that students who had higher technology acceptance and technological self-efficacy were more likely to be motivated to engage in learning activities (Pan 2020). Kraus et al. (2020) conducted a study in which participants interacted with an automated driving system and found that those with higher self-efficacy were more prone to trust this automated technology. A few recent studies have specifically addressed technological and AI self-efficacy. For instance, Hong (2022) found that participants who had higher AI self-efficacy were more likely to use and adopt AI technologies. Similarly, Montag and Ali (2025) observed that people with technological self-efficacy were more likely to trust and accept automated systems, and they were less likely to fear AI. Hou, Hou, and Cai (2023) investigated human–AI interactions in the context of online multiplayer games and discovered that self-efficacy in AI use was positively associated with trust in AI teammates and with the intention to interact with them.

2.4. This study

In this study, we adopted a social psychological approach to trust in AI and investigated how basic psychological needs in the context of technology use, AI self-efficacy, and attitudes toward AI relate to it. Since individuals are the end-users of AI technologies, there is a need for empirical evidence on how these technologies influence psychological fulfilment and self-efficacy, thus supporting or hindering technological adoption and usage. We investigated individuals in twelve countries. Hence, this is the first global study to examine how these constructs are related in diverse cultural and technological contexts, and to observe if they replicate across these settings.

We conducted a survey in countries representing six continents: Africa, Asia, Europe, North and South America, and Oceania. Our selection of countries aligned with the cultural areas based on the Inglehart-Welzel's cultural map of the world, including Catholic and Protestant Europe, the English-Speaking world, Confucian Asia, Latin America, and Africa (World Values Survey 7 2023). From Europe, we selected countries representing North (Finland), Central (Germany), West (France and Ireland), South (Italy and Portugal), and East (Poland). From the African continent, we included South Africa, which is home to various ethnic groups, cultures, and languages (Fessha 2011). From Asia, we included Japan, a technologically advanced country with a hybrid cultural model in which original Japanese cultural elements are combined with foreign cultural influences (Starrs 2023). From Latin America, we included Brazil, a multicultural country with populations of different descent, such as African, European, and Native American (de Souza et al. 2019). The study also includes the United States and Australia, which are culturally diverse English-speaking countries.

In Table 1, we present the selected countries, their AI Vibrancy Ranking (Stanford Institute for Human-Centered AI 2023), and their AI Preparedness Index (AIPI) (International Monetary Fund 2023). The International Monetary Fund (2023) bases countries' AIPI on the following four criteria essential for AI adoption: digital infrastructure, human capital, technological innovation, and legal frameworks. The Stanford Institute for Human-Centered AI (2023) provides Global AI Vibrancy Rankings of 36 countries based on the following criteria: research and development, responsible AI, economy, education, diversity, policy and governance, public opinion, and infrastructure (Fattorini et al. 2024). These rankings suggest that our sample countries are at different levels regarding AI employment and adoption.

Drawing on previous research in the field and the theoretical frameworks of self-efficacy (Bandura 1977) and SDT (Ryan et al. 2022; Ryan and Deci 2017), we set the following research questions:

> RQ1: How is fulfillment of basic psychological needs associated with trust in AI in general, and trust in major technological companies?
>
> RQ2: How is self-efficacy associated with trust in AI in general, and trust in major technological companies?
>
> RQ3: Are positive attitudes toward AI associated with trust in AI?

We tested the generalizability of our findings by repeating the same analyses for each country in our dataset.

3. Method

3.1. Participants

This study utilised survey data collected in autumn 2024 among adult participants aged 18 to 75 years from 12 countries: Australia, Brazil, Finland, France, Germany, Ireland, Italy, Japan, Poland, Portugal, South Africa, and the United States. The final samples used in this article included participants who had user experience in technologies utilising AI (see Table 2). Participants from Finland, France, Germany, Ireland, Italy, and Poland were recruited via the Norstat platform as part of the *Self & Technology* project (PI: Atte Oksanen), and they completed the survey online. The other six countries were added as the global extension of the

Table 1. Global AI vibrancy ranking (Stanford Institute for Human-Centered AI 2023) and AI preparedness index (International Monetary Fund 2023) for each sample country.

Country	Global AI Vibrancy ranking*	AI Preparedness Index**
Australia	28	.73
Brazil	34	.50
Finland	20	.76
France	6	.70
Germany	8	.75
Ireland	30	.69
Italy	22	.62
Japan	9	.73
Poland	24	.60
Portugal	19	.65
South Africa	36	.50
United States	1	.77

Table 2. Sample characteristics of high-end technology users.

	n	*M*, age	*SD*, age	Male (%)
Australia	1,204	44.17	14.92	48.84
Brazil	1,418	39.78	14.34	46.12
Finland	662	49.04	15.70	49.55
France	554	51.44	14.49	48.74
Germany	538	51.82	14.43	54.28
Ireland	366	51.97	14.10	53.83
Italy	763	51.30	13.94	50.98
Japan	1,089	46.74	16.07	52.89
Poland	540	51.01	15.17	52.04
Portugal	1,355	44.98	14.71	49.96
South Africa	1,424	36.94	14.24	49.51
United States	1,346	44.49	15.74	47.62

project. In this case, data collection was conducted by Dynata.

The survey was initially designed in English, and it was then translated into the most widely spoken languages of our target countries. Specifically, the survey was available in English for the participants from Ireland, USA, Australia, and South Africa. In Portugal, the survey language was Portuguese, and in Brazil it was the Brazilian variety of Portuguese. In Japan the survey language was Japanese, in Finland it was Finnish, in Germany it was German, in Italy it was Italian, and in Poland it was Polish. The translation process was executed by professional translators who were native speakers of the target languages, and back-translation procedures were used to ensure the accuracy of the translated items. When available, existing validated pre-translated measures were used.

We asked the participants for their consent, and we informed them about the goals of the study. They had the right to withdraw from the study at any point. This study received the approval of the Ethics Committee of the Tampere region. It was conducted in accordance with the General Data Protection Regulation of the European Union and with the ethical principles and guidelines of the American Psychological Association (2017).

3.2. Measures

The participants were provided with an operational definition of AI before answering any AI-related questions. We clarified that by AI we mean technology that can execute tasks that usually require human intelligence, and that can be embedded into hardware devices such as computers and robots, or other devices that utilise sensors and cameras. We chose this definition because it is widely used in studies utilising the General Attitudes Toward AI Scale (Schepman and Rodway 2022). Additionally, this definition provides a clear and accessible description of AI without imposing too narrow technical interpretation or limiting the concept to a specific application.

3.2.1. Trust

Trust was measured by asking the participants to express how much they trusted the following: (1) AI in general; (2) tech companies developing AI (e.g. OpenAI, Microsoft, Google, IBM); and (3) the social media giants (e.g. Meta [Facebook], Alphabet [Google], X). Each item was treated as a single item with a scale ranging from 1 (*I do not trust at all*) to 7 (*I trust completely*). The specific formulations of the items were designed for this study, but based on previous research on trust. Single-item global assessments are commonly used and shown to have good face validity and predictive utility (Matthews, Pineault, and Hong 2022; Uslaner 2015). For example, cross-national surveys such as the European Social Survey (n.d.), World Values Survey (n.d.), and the Organisation for Economic Co-operation and Development survey (OECD 2024) include measures on social and institutional trust that are measured in a similar way.

3.2.2. Autonomy, competence, relatedness in using new technology

To measure basic psychological needs in technology use, we relied on a scale introduced by Peters, Calvo, and Ryan (2018) that is based on a scale developed by Chen et al. (2015). Autonomy in technology use was measured with four items, including statements such as 'The new technologies end up making me do things I don't want to do'. We included only three autonomy-related statements in our analysis to maintain the reliability of the scale. Specifically, one autonomy-related item was dropped due to low factor loading in the Confirmatory Factor Analysis (CFA). Technological competence and relatedness were measured with three items each, including statements such as 'Using the new technologies has made me feel insecure about my abilities' for competence, and 'Using the new technologies has helped me feel close and connected with other people who are important to me' for relatedness. The scale ranged from 1 (*does not describe me at all*) to 7 (*describes me completely*). We tested reliability with McDonald's omega and confirmatory factor analysis (see Appendix A). Autonomy, competence, and relatedness exhibited good to excellent reliability and adequate convergent validity.

3.2.3. Self-Efficacy in learning to use new AI technologies

We used the AI Learning Readiness Self-Efficacy scale (AILRSE-5) consisting of five items (Oksanen et al. 2026). Respondents rated each item from 1 (*strongly agree*) to 7 (*strongly disagree*). Participants were presented with statements such as 'I'm confident in my ability to understand how new AI technologies work' and 'I'm confident in my ability to learn how to use new AI technologies if necessary'. The full scale is available in Appendix B. We found the measure reliable and valid. The consistency in these metrics, regardless of cultural context, indicated that the self-efficacy scale performed very well (see Appendix A).

3.2.4. Positive attitudes toward AI

Our questionnaire also included a measure on positive attitudes toward AI. For this purpose, we used the adjusted General Attitudes towards Artificial Intelligence Scale (GAAIS) (Schepman and Rodway 2022). The original scale consists of two subsets, one for positive attitudes with twelve items, and the other for negative attitudes with eight items. Because our study focuses on investigating positive attitudes, we only included the subset that fits the scope of this study. The scale was additionally shortened to four items to reduce respondent fatigue. Before expressing their attitudes, the participants were presented with a short explanation of what AI represents, and it was explained that AI can take different modalities, such as robots, computers, and other hardware devices (Schepman and Rodway 2022). They were then asked to rate statements such as 'There are many beneficial applications of Artificial Intelligence' and 'Much of society will benefit from a future full of Artificial Intelligence'. The scale ranged from 1 (*strongly disagree*) to 7 (*strongly agree*). The Positive AI Attitude measure demonstrated robust reliability and acceptable convergent validity (see Appendix A).

3.2.5. Smart technology use

We asked the participants to express how often they use the following technologies: (a) a mobile robot or another intelligent device (e.g. robot vacuum cleaner, robot lawn mower, assistive robot); (b) virtual assistant via smart speaker, computer, or phone app (e.g. Siri, Alexa); (c) wearable smart technology (e.g. smart watch, smart ring); (d) augmented reality technology; and (e) virtual reality technology. We also asked them about their habits related to the use of the following AI-driven applications: (a) language processing tools (e.g. ChatGPT), (b) text-to-music generators (e.g. MusicLM AI); (c) text-to-image generators (e.g. DALL-E, Midjourney); (d) voice translators (e.g. Vasco Translator); and (e) chatbot friends (e.g. Replica AI, My AI). In both cases, possible answers were: (1) I do not use; (2) less than weekly; (3) daily; and (4) many times a day. We created a dummy variable to select the participants who used at least one of the mentioned technologies daily. Only participants who had experience using AI tools were included in the final dataset ($N = 11{,}259$).

3.2.6. Sociodemographic information

We asked the participants about their age, gender, and economic status.

3.3. Statistical techniques

Stata 17 software was used for statistical analysis of the data. Descriptive statistics, namely mean values and standard deviations, were calculated for all the main study variables. The main analyses were conducted among new technology users and consist of linear regression models with trust in AI technology, companies developing AI, and social media giants as dependent variables in subsequent models. Analyses were conducted for each dependent variable separately across 12 country samples. Main independent variables were autonomy, competence, relatedness, self-efficacy, and positive AI attitudes. Models were adjusted for sociodemographic factors and for using AI at work. No issues with multicollinearity were observed. However, in some models, heteroscedasticity of residuals was detected, and robust standard errors were reported in those cases. We also excluded influential outliers from the regression analyses across all countries to improve model robustness. We report standardised beta-coefficients, and coefficients of determination (R^2) for each model in the tables.

4. Results

Table 3 reports the descriptive statistics for our main variables, and it includes means and standard deviations. The main findings of the study involve trust in AI in general and in technology companies. According to our analyses, relatedness and positive AI attitudes are significant predictors of user trust in AI in general, with a significance of $p < .001$ in all 12 countries. Competence was a predictor of trust in AI in the case of South Africa ($p < .05$), while for other countries it was not significant. Autonomy was a significant predictor of general trust in AI in Ireland ($p < .001$), South Africa ($p < .01$), Finland, and Poland (both $p < .05$). For South Africa, this relationship was negative. When it comes to AI self-efficacy, we found that it is a significant predictor of trust in AI in Australia, Brazil, France, South Africa ($p < .001$), Germany, the United States ($p < .01$), and Italy, Poland, and Portugal ($p < .05$). However, for participants from Finland, Ireland, and Japan, self-efficacy was not found to be a significant predictor of general trust in AI. These results are reported in Table 4.

Table 5 reports our results of linear regression models regarding trust in companies developing AI in the 12 countries. Similar to general trust in AI, relatedness and positive AI attitudes were significant predictors of trust in companies developing AI throughout our sample ($p < .001$), with the exception of Ireland where no association was found between positive AI attitudes

Table 3. Descriptive statistics of main variables of interest, M(SD).

	Trust in AI in general	Trust in companies dev. AI	Trust in social media giants	Autonomy	Competence	Relatedness	Self-efficacy	Positive AI attitude
Australia	3.45(1.53)	3.64(1.55)	3.10(1.55)	14.04(4.42)	14.57(4.83)	10.64(4.81)	22.87(6.56)	18.65(4.72)
Brazil	4.55(1.64)	4.59(1.61)	4.03(1.64)	14.67(4.52)	15.91(5.18)	13.78(5.11)	29.15(5.86)	22.48(4.67)
Finland	3.37(1.31)	3.21(1.30)	2.86(1.23)	16.57(3.63)	17.36(3.77)	7.76(4.20)	23.23(6.40)	19.60(4.62)
France	3.19(1.55)	3.15(1.56)	2.74(1.53)	15.28(4.50)	15.69(4.64)	9.12(4.66)	23.19(6.90)	18.58(4.73)
Germany	3.14(1.51)	3.06(1.49)	2.46(1.34)	16.92(4.25)	17.18(4.40)	7.25(4.49)	24.13(7.06)	18.80(5.14)
Ireland	3.01(1.39)	2.97(1.46)	2.45(1.38)	16.45(4.00)	17.39(4.17)	8.16(4.52)	22.81(6.83)	18.72(4.79)
Italy	3.28(1.57)	3.16(1.54)	2.73(1.45)	15.25(4.29)	15.73(4.63)	10.92(4.65)	23.44(6.73)	19.02(4.84)
Japan	3.81(1.22)	3.93(1.28)	3.45(1.29)	13.18(3.26)	13.75(3.96)	10.98(3.65)	21.11(6.24)	19.25(3.92)
Poland	3.22(1.53)	3.16(1.47)	2.86(1.44)	16.00(4.18)	16.00(4.53)	8.84(4.95)	24.14(6.22)	19.55 (4.63)
Portugal	3.79(1.36)	3.84(1.37)	3.32(1.32)	14.57(3.88)	16.07(4.12)	11.09(4.37)	25.88(5.60)	19.95(4.18)
South Africa	4.45(1.70)	4.37(1.71)	3.76(1.70)	14.08(4.65)	16.10(4.99)	14.22(5.19)	28.68(6.07)	21.36(5.03)
United States	3.42(1.66)	3.44(1.66)	3.02(1.64)	15.30(4.63)	16.13(4.87)	10.04(5.24)	24.10(7.04)	18.61(5.32)

Note: Trust measures on scale 1–7; autonomy, competence, and relatedness on scale 3–21, self-efficacy (AILRSE) on scale 5–35, positive AI attitude (GAAIS) on scale 8–56.

Table 4. Linear regression models predicting general trust in AI among high technology users in twelve country samples.

	Autonomy	Competence	Relatedness	Self-efficacy	Positive AI attitude	Model *n*	Model adj-R^2
Australia	−.02	.00	.30***	.12***	.35***	1,167	.448
Brazil	−.02	−.02	.26***	.20***	.29***	1,267	.425
Finland	.10*	−.02	.24***	.05	.41***	608	.306
France	−.02	.04	.27***	.17***	.35***	523	.445
Germany	.06	.02	.32***	.15**	.40***	504	.419
Ireland	.24***	.04	.33***	.10	.23***	340	.280
Italy	−.04	.05	.19***	.08*	.39***	730	.374
Japan	−.03	.05	.27***	.05	.32***	1,053	.286
Poland	.11*	−.01	.40***	.12*	.21***	506	.312
Portugal	.04	−.02	.22***	.07*	.36***	1,312	.304
South Africa	−.09**	.07*	.31***	.11***	.28***	1,231	.385
United States	.05	−.00	.32***	.07**	.39***	1,269	.495

Note: Tables report standardised beta coefficients. ***$p < .001$, **$p < .01$, *$p < .05$. Models were run separately for each country. All models are adjusted for sociodemographic factors and using AI at work.

Table 5. Linear Regression models predicting general trust in companies developing AI in twelve country samples.

	Autonomy	Competence	Relatedness	Self-efficacy	Positive AI attitude	Model *n*	Model adj-R^2
Australia	−.03	.00	.33***	.07	.26***	1,167	.310
Brazil	.03	−.07	.34***	.14***	.20***	1,267	.369
Finland	.16**	−.07	.23***	.02	.29***	608	.175
France	−.01	.03	.30***	.06	.26***	523	.270
Germany	.16*	−.07	.39***	.06	.30***	504	.278
Ireland	.21**	−.01	.32***	.06	.06	340	.110
Italy	−.03	.00	.21***	.05	.27***	730	.225
Japan	−.02	.03	.17***	.06	.35***	1,053	.264
Poland	.08	.01	.40***	.04	.14**	506	.220
Portugal	.04	−.02	.20***	.09*	.26***	1,312	.184
South Africa	−.03	.02	.35***	.11**	.18***	1,231	.297
United States	.00	−.04	.36***	.00	.28***	1,269	.336

Note: Tables report standardised beta coefficients. ***$p < .001$, **$p < .01$, *$p < .05$. Models were run separately for each country. All models are adjusted for sociodemographic factors and using AI at work.

and trust in AI-developing companies. Autonomy was associated with trust in companies developing AI only for Finland, Ireland ($p < .01$), and Germany ($p < .05$), while competence was not significant in any of the countries. AI self-efficacy was significantly linked to trust only in Brazil ($p < .001$), South Africa ($p < .01$), and Portugal ($p < .05$).

Lastly, in Table 6, we report our findings based on the linear regression models considering trust in social media giants. As is visible in the table, the most consistent predictor of trust in social media giants in all 12 countries was relatedness. Positive attitudes toward AI yielded mixed results. In Australia, Brazil, France, Italy, Japan, South Africa, and the United States ($p < .001$), and Poland ($p < .01$), positive attitudes toward AI were associated with trust in social media companies, while in the rest of our sample countries, no link was identified. AI self-efficacy was not associated with trust

Table 6. Linear regression models predicting general trust in social media giants in twelve country samples.

	Autonomy	Competence	Relatedness	Self-efficacy	Positive AI attitude	Model *n*	Model adj-R^2
Australia	−.10*	−.05	.35***	.04	.11***	1,167	.326
Brazil	−.05	−.07	.37***	.02	.19***	1,267	.330
Finland	.08	.01	.28***	−.02	.08	608	.078
France	−.01	−.06	.26***	−.03	.23***	523	.196
Germany	.13	−.09	.42***	.03	.09	504	.167
Ireland	.18*	−.14	.30***	−.03	.00	340	.079
Italy	−.11	−.04	.12**	.04	.19***	730	.125
Japan	−.07	.02	.27***	.03	.22***	1,053	.222
Poland	.07	−.11*	.36***	.02	.13**	506	.194
Portugal	−.00	−.06	.28***	.00	.05	1,312	.112
South Africa	−.06	−.03	.37***	.02	.18***	1,231	.276
United States	−.04	−.06	.41***	.00	.18***	1,269	.328

Note: Tables report standardised beta coefficients. ***$p < .001$, **$p < .01$, *$p < .05$. Models were run separately for each country. All models are adjusted for sociodemographic factors and using AI at work.

in social media companies in any of the countries, while in the case of competence, a significant relationship was seen only for Poland ($p < .05$). In this case, competence was negatively related to trust. Autonomy was negatively associated with trust in social media companies for Australia and positively associated for Ireland, with a significance of $p < .05$ for both countries.

5. Discussion

5.1. Overview of main findings

This large-scale study across twelve countries investigated trust in AI technology and in major tech companies. The investigation was grounded in positive attitudes toward AI and the social psychological constructs of self-efficacy and basic psychological needs. In the study, experiencing a sense of relatedness through technology use and positive attitudes toward AI were consistently associated with higher trust in AI, while we obtained mixed results when it comes to competence, autonomy, and AI self-efficacy.

Our findings suggest that the use of AI is a group phenomenon, where a sense of belonging with other users may create a safe environment and a feeling of support, which in turn fosters trust in the technology itself. To our best knowledge, this is the first study to identify such associations between technological relatedness and trust in AI. Technological autonomy and especially technological competence did not show such consistency in predicting trust in AI. For example, technological autonomy was a significant predictor of trust in all three entities only in Ireland. Interestingly, we also identified a significant negative relationship between technological autonomy and general trust in AI in South Africa. Similarly, a negative relationship was observed between technological autonomy and trust in social media companies in Australia. Regarding competence, we found a positive link with trust in AI only in the case of South Africa, while a negative link was identified regarding trust in social media companies among Polish respondents.

In other words, our results imply that when AI technologies enable a feeling of belonging, people tend to trust them more, while acting at one's own volition and feeling competent are only important for trust in certain cultural contexts. These findings are aligned with studies reporting that trust in AI differs from trust in other technologies (Kaplan et al. 2023; Yang and Wibowo 2022) and with studies that show trust differs depending on cultural context (Kim, Erdem, and Kim 2024; Rheu et al. 2021). The countries in our sample are at different levels of AI employment, which might explain some of the differences in our findings. Similarly, having autonomy and competence might be valued differently depending on the country, which might be the reason for, for instance, negative links between autonomy and general trust in AI in South Africa, or with trust in social media companies in Australia.

However, there might be an alternative explanation for our findings. Literature suggests that AI and social media affect people's cognitive load, for example, they impact our memory, attention span, perception, decision-making, and learning (Shanmugasundaram and Tamilarasu 2023). It is possible that people are willing to give up some autonomy when interacting with AI because we receive too much information from this technology. In other words, trying to take control over every single decision algorithms make daily on our behalf would create excessive information load that one could simply not process. Similarly, because AI is quite autonomous and easy to use, it is possible that people do not prioritise competence when interacting with it. These might be the reasons people prioritise a feeling of belonging when interacting with AI, over feelings of autonomy and competence. Nevertheless, this is a gap in knowledge that future studies should address.

Regarding self-efficacy, we determined that when people feel confident in their ability to learn how to use AI tools, they are more prone to trust AI in general and companies developing AI, but this was only true for specific countries in our sample. Our results are aligned with studies that discerned a positive link between technological self-efficacy and trust in specific AI tools, such as ChatGPT (Montag and Ali 2025) and AI teammates (Hou, Hou, and Cai 2023). AI self-efficacy was found to be associated with trust in companies developing AI in only three countries: Brazil, Portugal, and South Africa. However, AI self-efficacy was not a predictor of trust in major social media companies.

Our study uncovered that when people have positive attitudes toward AI, they are more likely to trust AI in general, as well as companies developing AI – except for Ireland, where the latter association was not found. Positive attitudes toward AI predicted trust in social media companies in eight countries excluding Finland, Germany, Ireland, and Portugal. Our findings are aligned with previous studies concluding that positive attitudes toward AI are associated with trust in this technology (Bach et al. 2024; Montag and Ali 2025), although differences exist depending on the specific cultural context as in previous examples.

5.2. Contextual and cultural considerations

The ways people perceive and behave in relation to smart technologies can be influenced by different factors, such as cultural values (Jan, Alshare, and Lane 2024). According to the Inglehart-Welzel's Cultural Values Map (World Values Survey 7 2023), countries can be divided based on their preference for traditional or secular-rational values, and based on whether they prioritise survival or self-expression. Survival values are more common for societies experiencing hardship and insecurity and are characterised by lower levels of interpersonal trust and subjective wellbeing, while self-expression values have to do with individual autonomy, subjective wellbeing, and higher levels of interpersonal trust (World Values Survey n.d.). The countries included in this study differ not only based on their commonly held cultural values but also based on their readiness to adopt AI and their current AI activities (Table 1). Therefore, it is worth examining our findings from this viewpoint as well.

For instance, Ireland was the only country in our sample where technological autonomy was a significant predictor of trust in all three cases, and the only country for which positive attitudes toward AI were not a predictor of trust in companies developing AI. In the World Values Survey (n.d.), Ireland is highlighted as a country that scores high in traditional and self-expression values. When tracking the changes in the live cultural map, one can notice an increase in Ireland's self-expression value scores from the 1980s until 2015. Inglehart and Welzel (2005) argue that when values shift from survival to more self-expression oriented, levels of tolerance and trust in society tend to increase. This might explain our finding that the fulfilment of technological autonomy among the Irish participants predicted trust in AI and major tech companies. It is also interesting to consider that Ireland scores relatively low in the Global AI Vibrancy ranking, but above average in the AI Preparedness Index, compared to other included countries (Table 1). This suggests that while Ireland might be prepared for AI deployment in terms of regulations or infrastructure, actual AI activities are at an early stage. This might also partly account for how people perceive AI technologies in Ireland.

South Africa was the only country in which we found fulfilment of technological competence predicting general trust in AI and technological autonomy being negatively associated with general trust in AI. As presented in Table 1, South Africa had the lowest scores in both AI vibrancy and preparedness to adopt AI among the included countries. This implies that criteria such as legal frameworks, infrastructure, human capital, research and development might not yet be aligned with AI adoption and deployment. Therefore, it is possible that people have less exposure to AI from professional or educational contexts, and are more exposed to AI through media and leisure activities. For that reason, people might perceive AI as a tool for which they need higher technological competence, or as a tool that can perform efficiently without human oversight, which could explain why higher autonomy would lead to less trust in AI. As it comes to the Cultural Values Map (World Values Survey 7 2023), South Africa is positioned quite central, although leaning more toward traditional and self-expression values.

Nevertheless, when interpreting the results of a cross-national study, one should refrain from attributing a certain finding to a single factor because cultural, historic, economic, and other factors interact with each other forming complex interwoven realities. In other words, while two countries can share certain characteristics, for example, ranking high (e.g. United States and Japan) or ranking low (e.g. South Africa and Brazil) on the AI vibrancy and readiness to adopt AI scales, these overlapping characteristics do not guarantee that participants from these countries will share similar perceptions of AI. Therefore, it is important to avoid oversimplifying interpretations and instead maintain the stance that the interplay of different factors shapes people's behaviours and attitudes in each country.

5.3. Theoretical and practical implications

Trust is a key element for successful interactions between humans and advanced technologies (Saßmannshausen et al. 2023). Literature shows that human-related factors have a significant influence on trust in AI (Bach et al. 2024; Kaplan et al. 2023; Saßmannshausen et al. 2023; Yang and Wibowo 2022). Our study extends knowledge on trust in AI by providing new insights on user-related antecedents of trust. Specifically, we provide new information on the associations between user trust in AI and basic psychological needs in technology use, AI self-efficacy, and attitudes toward AI. We also extend knowledge on SDT and self-efficacy and their role in interactions with technology. In addition, prior research identified two components of trust in relation to AI: (1) trust in technology, and (2) trust in the organisation providing that technology (Yang and Wibowo 2022). Our results are in line with the notion that trust in technology itself differs from trust in technology providers (Söllner, Hoffmann, and Leimeister 2016; Yang and Wibowo 2022). Yet, our study identifies a third component: trust in companies that rely on AI for different purposes (such as social media companies) but that are not developers of that technology per se.

Interactions with AI can hinder or improve users' well-being (Cramarenco, Burcă-Voicu, and Dabija 2023; Inkster, Kadaba, and Subramanian 2023; Stamate, Sauvé, and Denis 2021). Because AI is starting to have a central place in our lives, it is essential to develop it in a way that is beneficial and safe for users. SDT posits that the fulfilment of basic psychological needs has a positive impact on people's well-being and flourishing (Deci and Ryan 2000; Ryan et al. 2022; Ryan and Deci 2017). Our study provides new insights on associations between basic psychological needs and user trust in AI and major tech companies. Because trust is a key factor that drives AI user behaviour, namely AI acceptance (Gillespie, Lockey, and Curtis 2021) and AI adoption (Bach et al. 2024; Kelly, Kaye, and Oviedo-Trespalacios 2023), our results are of relevance for parties developing and utilising AI. In other words, by developing AI technologies that foster basic psychological needs – especially relatedness – companies can increase user trust, which will likely result in better AI adoption and acceptance. At the same time, this will positively affect users' well-being.

There are concrete examples of how basic psychological needs can be integrated into technology design. One example is the Motivation, Engagement and Thriving in User Experience (METUX) model proposed by Peters, Calvo, and Ryan (2018). Burnell et al. (2023) relied on the METUX model to explore how people evaluate Facebook, TikTok, Blackboard, and Moodle and confirmed a link between the evaluations of these technologies and basic needs fulfilment. Burnell et al. (2023) argued that designing technologies that satisfy users' basic needs is also beneficial for companies because when users are satisfied, they are more likely to recommend these technologies to others. Another specific example of how SDT can be integrated into technology design was proposed by Janssen and Schadenberg (2024), who created directions for a social robot design by relying on the METUX model.

Our findings imply that enhancing people's confidence in learning how to use AI tools can positively impact their trust in AI in general and in companies developing AI, but only in some cultural contexts. According to Bandura (1977), self-efficacy develops through personal mastery experiences, vicarious experience, verbal persuasion, and physiological states. Based on this, users' AI self-efficacy could be improved by giving users a chance to practice using AI tools, fostering their motivation, or providing training and tutorials that enhance their confidence in using AI tools. Similar to the previous example with basic psychological needs, increasing a user's AI self-efficacy can lead to increased trust, which then might lead to better AI acceptance and adoption. Nevertheless, cultural differences must always be taken into account.

Attitudes toward AI can affect people's behaviour regarding AI, such as willingness to use (Schwesig et al. 2023) and accept AI (Gerlich 2023). As previously discussed, companies can influence attitudes toward AI by incorporating practices that show integrity (Yang and Wibowo 2022), for example, by complying with GDPR (European Parliament and Council of the European Union 2016) and similar regulations across the globe. Our findings imply that improving attitudes toward AI can have a positive impact on trust in AI in general and in companies developing AI, but as previously laid out, tech companies should always take into consideration the cultural context in which AI is used.

Nevertheless, in the current context of extensive AI integration into everyday life, it is important to consider not only the factors that foster appropriate trust in AI but also the risks associated with over-trust and overreliance. Prior work in HCI and HRI has shown that in certain situations people tend to trust intelligent systems more than their own judgement. In sensitive or high-risk contexts, such as taking recommendations from a healthcare robot (Wang et al. 2025) or making a life-or-death decision while interacting with an intelligent agent (Holbrook et al. 2024), overreliance and overtrust can lead to dangerous consequences. Other examples are outlined in the European Union's AI Act (European Commission 2024), which already classifies AI systems according to their potential risk to individuals and society, where inappropriate levels of trust may lead to particularly serious consequences. However, even in contexts not classified as moderate- or high-risk, there remains the potential for excessive trust in AI to have negative consequences. For instance, overreliance on outputs AI produces was found to have a negative impact on students' cognitive abilities (Zhai, Wibowo, and Li 2024). Therefore, when designing AI tools, it is important to also consider strategies that contribute to better calibration of trust (Lee et al. 2025; Lee and See 2004). In addition, AI literacy is increasingly important, helping individuals differentiate high-quality content from large volumes of generated material (Chee, Ahn, and Lee 2024).

Lastly, uneven adoption of AI is deepening inequalities in the world, such as quality of life, income levels, and access to opportunities (Berg, Snene, and Velasco 2024). To overcome the 'AI divide', countries must engage in international collaboration that embraces diverse perspectives and includes human-centered AI policies (Berg, Snene, and Velasco 2024). Our study contributes to the debate on how to close the 'AI divide' by including culturally diverse perspectives from 12 countries that are on different levels regarding AI employment and adoption (Table 1). Our study is also significant because it highlights the relevance of giving human needs a central spot in technology design.

6. Limitations and future research

Our study provides novel insights into trust in AI by examining it through social psychological lenses. The findings are based on a large dataset collected from participants on six continents. Nevertheless, our study has limitations that must be addressed. To begin with, we relied on a questionnaire, so our findings are based on self-reported data. Although we included a working definition of AI and an explanation on the modalities AI could take in our questionnaire (e.g. computer, robot, chatbot), it is still possible that participants had different understandings of what AI represents, which might have affected their responses.

Additionally, it is possible that users do not equally trust all tech companies, and that trust is affected by factors such as the solutions offered by the company, their public profile, or image. Thus, future studies could investigate trust in specific tech companies or social media platforms separately. Moreover, using multi-item, detailed measures of trust can provide more insights into users' attitudes and experiences (Beltrão, Sousa, and Lamas 2025; Kohn et al. 2021). Further, future research should extend the findings of this study by relying on other methods, such as focus groups or even diary studies as proposed by von Terzi et al. (2021). Although we included countries that are culturally diverse and at different developmental stages regarding AI, future studies should consider including countries that score even lower on AI adoption scales and that are in a more disadvantaged position than countries in our sample. This would be an important step toward fairer and more equal AI development and employment. Lastly, future studies should look into the reasons why technological relatedness predicts trust more consistently than autonomy, competence, and AI self-efficacy.

7. Conclusions

AI systems are increasingly integrated into all domains of our lives, which highlights the need to understand the human factors that shape trust in these technologies and their creators. Building trust in AI is not only a technical challenge but a social and psychological one as well. This large, cross-national study offers valuable initial insights into how trust in AI technology and major tech companies relates to basic psychological needs, AI self-efficacy, and attitudes of technology users. Integrating basic psychological needs perspectives into technology design and development can foster trust in AI and its developers. Doing so can further promote well-being and coherence in a world where major technological companies have significant economic and social power.

Author contributions

CRediT: **Anica Cvetkovic:** Conceptualization, Formal analysis, Methodology, Writing – original draft, Writing – review & editing; **Iina Savolainen:** Conceptualization, Data curation, Writing – original draft, Writing – review & editing; **Magdalena Celuch:** Conceptualization, Writing – original draft, Writing – review & editing; **Moona Heiskari:** Conceptualization, Writing – original draft, Writing – review & editing; **Eerik Soares Ruokosuo:** Conceptualization, Writing – original draft, Writing – review & editing; **Patrícia Arriaga:** Conceptualization, Writing – original draft, Writing – review & editing; **Mayu Koike:** Conceptualization, Writing – original draft, Writing – review & editing; **Atte Oksanen:** Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Supervision, Funding acquisition, Investigation, Project administration.

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Ethics approval

All study procedures were carried out in accordance with relevant laws and institutional guidelines of Tampere University. The Academic Ethics Committee of the Tampere region in Finland reviewed the study protocol before data collection and stated that the study does not include any ethical issues (statement 115/2022).

Data availability statement

The data that support the findings of this study are available upon reasonable request.

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APPENDIX A

McDonald's Omega Reliability (ω) and average variance extracted (AVE) of the study variables.

	Autonomy		Competence		Relatedness		Self-efficacy		Positive AI attitude	
	ω	AVE	ω	AVE	ω	AVE	ω	AVE	ω	AVE
Australia	.83	.63	.93	.82	.92	.79	.95	.81	.87	.66
Brazil	.77	.55	.91	.77	.88	.71	.88	.75	.93	.57
Finland	.83	.58	.91	.79	.90	.77	.95	.79	.88	.64
France	.88	.63	.92	.75	.90	.79	.96	.82	.86	.60
Germany	.89	.66	.91	.78	.92	.78	.96	.83	.87	.63
Ireland	.87	.59	.94	.84	.92	.81	.95	.79	.87	.62
Italy	.87	.65	.92	.80	.91	.80	.96	.82	.87	.63
Japan	.72	.48	.88	.72	.84	.65	.96	.84	.86	.61
Poland	.86	.63	.93	.83	.95	.87	.94	.77	.84	.56
Portugal	.80	.59	.92	.80	.88	.71	.95	.82	.84	.59
South Africa	.76	.52	.89	.74	.90	.75	.93	.76	.82	.56
United States	.85	.65	.93	.82	.92	.79	.95	.80	.88	.65

APPENDIX B

Trust.
How much do you trust the following?
The social media giants (e.g. Meta [Facebook], Alphabet [Google], X)
Tech companies developing AI (e.g. OpenAI, Microsoft, Google, IBM)
AI in general
1 I do not trust at all
2
3
4
5
6
7 I trust completely

Autonomy, relatedness, and competence in new technology use.
Rate the following statements about how using the technologies has affected your life.
Now that I use the new technologies, I feel pressured to use those more often than I'd like.*
I spend more time on the new technologies than I feel I should.
The new technologies end up making me do things I don't want to do.
The new technologies intrude in my life.
Using the new technologies has made me feel insecure about my abilities.
Using the new technologies has made me feel less capable in my life.
Using the new technologies has lowered my confidence.
Using the new technologies has helped me feel a greater sense of belonging to a larger community.
Using the new technologies has helped me feel close and connected with other people who are important to me.
Because of these new technologies, I feel closer to some others.
1 Does not describe me at all
2
3
4
5
6
7 Describes me completely
Note: We used the Technology Effects on Need Satisfaction in Life Scale (TENS-Life) that was developed by Peters, Calvo, and Ryan (2018) and it was based on the validated Basic Psychological Need Satisfaction and Frustration Scale (Chen et al. 2015).
*Item 1 was dropped due to weaker CFA.

AI Learning Readiness Self-Efficacy scale (AILRSE-5) (Oksanen et al. 2026).
In the following, we are interested in your confidence in learning to use new AI technologies. Please rate the following statements.
I'm confident in my ability to understand how new AI technologies work.
I'm confident in my ability to learn how to use new AI technologies if necessary.

I'm confident in my ability to learn how to apply new AI technologies in my daily life.
I'm confident in my ability to learn how to use new AI technologies to solve a problem.
I'm confident in my ability to learn how to use new AI technologies independently.
1 Strongly disagree
2
3
4
5
6
7 Strongly agree

Positive attitudes toward AI.
We are interested in your attitudes towards artificial intelligence. By artificial intelligence (AI) we mean technology that can perform tasks that would usually require human intelligence. Please note that AI technology can be integrated into computers, robots or other hardware devices, or other devices that utilise sensors, cameras etc. Please complete the following scale, indicating your response to each item.
Artificial Intelligence can provide new economic opportunities for this country.
Artificial Intelligence can have positive impacts on people's wellbeing.
There are many beneficial applications of Artificial Intelligence.
Much of society will benefit from a future full of Artificial Intelligence.
1 Strongly disagree
2
3
4
5
6
7 Strongly agree
Note: We used the adjusted General Attitudes Toward AI Scale (GAAIS) developed by Schepman and Rodway (2022).

Smart Technology Use.
How often do you use the following technologies?
Mobile robot or another intelligent device (e.g. robot vacuum cleaner, robot lawn mower, assistive robot)
Virtual assistant via smart speaker, computer, or phone app (e.g. Siri, Alexa)
Wearable smart technology (e.g. smart watch, smart ring)
Augmented reality technology (AR)
Virtual reality technology (VR)
I do not use
Less than weekly
Weekly
Daily
Many times a day
How often do you use the following AI driven applications?
Language processing tools (e.g. ChatGPT)
Text-to-music generators (e.g. MusicLM AI)
Text-to-image generators (e.g. DALL-E, Midjourney)
Voice translators (e.g. Vasco Translator)
Chatbot friends (e.g. Replica AI, My AI)
I do not use
Less than weekly
Weekly
Daily
Many times a day
Note: The questionnaire was always administered in the official or most commonly used language of each country.