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Self-determination and attitudes toward artificial intelligence: Cross-national and longitudinal perspectives

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ABSTRACT

Artificial intelligence (AI) is becoming increasingly important in all domains of life. Therefore, it is crucial to understand individuals' attitudes towards AI. This article investigated attitudes toward AI through two studies that are based on the self-determination theory and basic psychological needs (autonomy, competence, and relatedness). Study 1 used cross-sectional samples of adult populations aged 18–75 from Finland ($N = 1{,}541$), France ($N = 1{,}561$), Germany ($N = 1{,}529$), Ireland ($N = 1{,}112$), Italy ($N = 1{,}530$), and Poland ($N = 1{,}533$). Study 2 was based on a longitudinal two-wave sample of adults aged 18–80 from Finland ($N = 828$). Based on the robust regression analyses, Study 1 found that fulfillment of basic psychological needs was associated with higher AI positivity and lower AI negativity across Europe. According to the Study 2 results, based on hybrid multilevel regression models, autonomy and relatedness increased AI positivity and decreased AI negativity over time. The results provide robust evidence on the role of self-determination in attitudes towards AI. Self-determination is an important factor in AI acceptance and is becoming increasingly important considering the rapid development and adoption of AI solutions.

1. Introduction

Artificial intelligence (AI) is becoming increasingly important and influential in all domains of life. The prevalence and continuous development of AI make it almost impossible to avoid it. Most of the devices, systems, and technologies we use every day utilize AI (Makridakis, 2017; Olhede and Wolfe, 2018; Reinhart, 2018; Schepman and Rodway, 2020). With the spread and wide use of AI, it has become important to investigate people's attitudes towards it. Attitudes affect people's acceptance and adoption of new tools, and how widely they spread in society (Marangunić and Granić, 2015; Schepman and Rodway, 2020). Therefore, AI is unilaterally shaping our reality, while our attitudes towards AI affect the development, implementation, and acceptability of new solutions that utilize AI (Schepman and Rodway, 2020). Attitudes towards AI vary greatly (e.g., Neudert et al., 2020). Some have questioned the security of programs and applications using AI, and fears around AI are common, including concerns that AI will replace the human workforce and extending to the notion that AI could be taking over human civilizations (Challen et al., 2019; CNBC, 2017; Johnson and Verdicchio, 2017; Lichtenthaler, 2020; Sanders and Schneier, 2023). At the same time, the possibilities of AI fascinate people and elicit curiosity

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(Rhee and Rhee, 2019). A better understanding of different attitudes towards AI can lead to more efficient implementation and usage of these technologies (Kelly et al., 2023; Schepman and Rodway, 2020; Schepman and Rodway, 2022).

Thus far, research has shown that attitudes towards AI differ from traditional technology acceptance (Schepman and Rodway, 2020). It is commonly said that technological evolution gives individuals the ability to decide which solutions to adopt. However, AI can also be adopted and implemented into people's daily lives based on the decisions of governments or large corporations. Consequently, the end user does not always have freedom of choice when it comes to implementing AI into their lives (Brownsword and Harel, 2019; Chen and Wen, 2021; Jones et al., 2018; Kelly et al., 2023; Misra et al., 2020; Schepman and Rodway, 2020). AI may carry different benefits and risks than previous technologies. Some psychological factors may correlate more specifically with AI attitudes than with attitudes towards other technology (Park and Woo, 2022; Schepman and Rodway, 2022; Zhang and Dafoe, 2019). Due to the generalization and continuous development of AI, it is particularly important to understand what factors influence people's attitudes towards it. Previous studies have stated that people's general attitudes toward AI are linked to their acceptance and use of AI in their daily lives (Choung et al., 2023; Gillespie et al., 2021; Kelly et al., 2023; Lancelot Miltgen et al., 2013; Schepman and Rodway, 2020; Schepman and Rodway, 2022). Without up-to-date research on AI-related attitudes and acceptance, end-users' opinion regarding implementation and usability cannot be taken into proper consideration when developing solutions that utilize AI.

Attitudes toward AI have not previously been studied through the dimensions of the social psychological self-determination theory (SDT; Ryan and Deci, 2017). Along with research on the affective component of AI attitudes, more research focusing on cognitive constructs is needed (Park and Woo, 2022). The SDT is grounded on the principle of humans' fundamental psychological needs for autonomy, competence, and relatedness. According to the SDT, the well-being of individuals increases when these needs are met. The potential of SDT to explain AI attitudes has been discussed, but there is a lack of research on the matter (Cascio and Montealegre, 2016).

This article offers longitudinal and cross-national perspectives on attitudes towards AI while focusing on the central social psychological factors that may be at play. We base our research on the theoretical framework of the SDT (Ryan and Deci, 2017). Our aim is to investigate how basic psychological needs (i.e., autonomy, competence, and relatedness) are connected to attitudes towards AI. Alongside the SDT dimensions, we examine how daily technology use, demographic factors, and personality are connected to AI attitudes. This article is based on a cross-national 6-country study and a longitudinal study. The two studies in this paper fill the existing gaps in cross-national and longitudinal research on this area.

1.1. Background factors of attitudes towards AI

By studying people's attitudes, we can better explain the decision-making and behavior of both individuals and communities (Cao et al., 2021; Edison and Geissler, 2003). Factors that influence AI attitudes have been studied from demographic, personality, anxiety, and trust perspectives (Kaya et al., 2022; Park and Woo, 2022; Schepman and Rodway, 2020; Schepman and Rodway, 2022). In many studies, men have reported more positive attitudes towards AI (Liang and Lee, 2017; Schepman and Rodway, 2022; Sindermann et al., 2022). Regarding age and AI attitudes, the research results are contradictory (Kaya et al., 2022). However, most of the literature states that younger age is connected to more positive attitudes towards AI (Gillespie et al., 2021; Schepman and Rodway, 2022). Higher education has also been shown to be connected with positive AI attitudes (European Commission, & Directorate-General for Communications Networks, Content and Technology, 2017; Neudert et al., 2020; Zhang and Dafoe, 2019).

Kelly et al. (2023) conducted a systematic review that focused on factors that affect AI adoption. Based on the review, perceived usefulness, performance expectancy, and effort expectancy can predict behavioral intention, eagerness, and utilization of AI. Furthermore, trust and attitudes are seen to be equally important in the formation of user acceptance. Gillespie et al.'s (2021) research results support this conclusion. Park and Woo (2022) investigated the effect of both psychological and technological factors on the adoption of applications that use AI. They discovered that certain psychological factors were linked to the adoption of AI applications, including inner motivation, confidence, voluntariness, and expected accomplishments. Moreover, technological factors such as practicality, usability, technological complexity, and comparative advantage were found to be connected to adoption of AI-based applications (Park and Woo, 2022).

Research has suggested that personality traits may predict attitudes towards various phenomena, including technology (Davis, 1989; Milfont and Sibley, 2012). Possible links between personality traits and attitudes towards AI have been examined in past research (e.g., Kaya et al., 2022; Park and Woo, 2022; Schepman and Rodway, 2022). Schepman and Rodway (2022) tested whether psychological factors, namely the Big Five personality traits (openness, conscientiousness, extraversion, agreeableness, and neuroticism) predict attitudes towards AI. They used their previously developed General Attitudes towards Artificial Intelligence Scale (GAAIS; Schepman and Rodway, 2020; Schepman and Rodway, 2022) and discovered that introverts had more positive attitudes toward AI overall. Park and Woo (2022) classified attitudes into four dimensions by considering affective components such as positive and negative emotions, as well as cognitive components such as sociality and functionality. Schepman and Rodway's (2022) study showed that introverts tend to have more positive attitudes toward AI, leading Park and Woo (2022) to conclude that extraversion was associated with more negative emotions towards AI. Kaya et al. (2022) study showed weak correlations with extraversion and both subscales of the GAAIS, but they were not remarkable predictors of either subscale of the GAAIS. In Park and Woo's (2022) study, neurotic people were more negative toward AI. Openness was positively related to functionality, but when other proximal predictors were included, it did not connect to other attitudes.

In general, expressing one's attitude towards AI can be challenging. The image offered by the media can influence attitudes, especially if it only provides a limited view of the subject (Schepman and Rodway, 2020). Moreover, not all that is AI and the ways in which it is used are understood and the user may not always be aware of the AI technology being used in applications and devices. This can also affect the measurement of general attitudes (Kelly et al., 2023; Liang and Lee, 2017). According to previous research, the factors that explain attitudes towards AI can vary depending on what kind of attitude is being studied. Thus, are we interested in AI acceptance, usability, or general attitudes.

1.2. SDT and attitudes toward technologies

SDT is a widely used and validated theory that describes human's basic psychological needs to experience autonomy, competence, and relatedness (Ryan and Deci, 2017). Autonomy is a person's experience with free decision-making power over their own actions, which generates internal motivation. Competence refers to an individual's perception of their ability to perform tasks effectively and achieve desired outcomes. Relatedness refers to a person's experience with caring for and connecting with other people. Basic psychological needs are one of STD's mini-theories and contribute to the division of intrinsic and extrinsic motivation. According to SDT, when these basic psychological needs are met, autonomous (intrinsic) motivation increases, which is considered the driving force of an individual (i.e., the ultimate reason for an individual's actions; Deci and Ryan, 2000; Ryan and Deci, 2017; Ryan, 2023). In recent years, SDT has been applied to many areas, including education, healthcare, work life (e.g., Buck et al., 2022; Van den Broeck et al., 2016; Ryan, 2023; Xia et al., 2022), and technology use (Peters et al. 2018).

SDT also provides a useful framework for understanding human attitudes. Previous studies have suggested that individuals who feel a sense of autonomy tend to develop more positive attitudes because autonomy provides a sense of control over one's thoughts and behaviors in relation to a particular object or event (Deci et al., 2017; Ryan, 2023). Moreover, competence is potentially associated with positive attitudes towards new phenomena because it elevates an individual's self-confidence, belief in their own skills, and sense of understanding (Ryan, 2023). If an individual's need for relatedness is met, they may have more positive attitudes towards an object or event because they feel a sense of belonging and connection with others who, for instance, use the same technology (Ryan 2023; Sahin and Sahin, 2022).

Regarding attitudes toward technology, previous studies suggest that individuals who feel more competent and autonomous in their use of technology are more likely to have positive attitudes toward it (Kaya et al., 2022; Lu et al., 2019; Sahin and Sahin, 2022). The fulfillment of basic psychological needs has also been associated with individuals' motivation to use technology (Lu et al., 2019; Moradbakhti et al., 2022. Based on the literature review by Marangunić and Granić (2015), attitudes towards technology play a crucial role in user acceptance and behavior change. Integrating basic psychological needs with the Technology Acceptance Model (TAM), studies have shown that autonomy, competence, and relatedness significantly influence users' intention to use technology, perceived ease of use, and perceived usefulness (Lu et al., 2019; Sahin and Sahin, 2022). Only limited research exists on the connection between AI and basic psychological needs so far. De Vreede et al., (2021) found that users who experienced higher levels of autonomy, competence, and relatedness reported increased satisfaction and engagement with chatbots. Similarly, Moradbakhti et al., (2022) discovered a relationship between autonomy, competence, and attitudes towards AI assistants in the context of personal banking.

Technology can both facilitate and hinder individuals' basic psychological needs (Peters et al., 2018). For instance, using social media can provide a sense of relatedness by enabling individuals to connect with others, but it can also be influenced by social comparison and lead to negative effects (Lin, 2016; Sheldon et al., 2011; Yang, 2016). Prioritizing technology over human interaction may also result in social isolation and reduced connectedness among individuals (Muhammad et al., 2019). Moreover, there are concerns about the advancement of AI and its potential effects on human competence, including the risk of machines surpassing human intelligence and undermining human autonomy (Johnson and Verdicchio, 2017; Lichtenthaler, 2020; Sanders and Schneier, 2023).

SDT further posits that environments that support autonomy, competence, and relatedness are more likely to foster intrinsic motivation and well-being (Deci and Ryan, 2000; Ryan and Deci, 2017; Ryan, 2023). The rise of technology and AI has enhanced individuals' autonomy, for instance through remote work, enabled by communication and collaboration technologies (Ferrara et al., 2022). Online teaching platforms have also bolstered autonomy and competence by offering flexibility (Sahin and Sahin, 2022). Moreover, the variety of communication tools and social media platforms has provided opportunities for connection and belonging (Ferrara et al., 2022). These circumstances are not, however, the same across countries as differences exist both in technological adaptation and readiness, and cultural values and expectations. Therefore, it is important to consider cross-national perspectives in basic psychological needs and attitudes toward AI.

Drawing upon prior research, it can be posited that a relationship exists between individuals' basic psychological needs and the factors influencing their attitudes towards technology. Limited evidence, however, exists on the relationship between the basic psychological needs and attitudes toward AI. The current research aims to fill this research gap by examining the connection between basic psychological needs and both positive and negative attitudes towards AI cross-nationally.

1.3. Aims and hypotheses

This article reports findings from two studies that were based on the SDT and basic psychological needs of autonomy, competence, and relatedness (Ryan and Deci, 2017). The first study was a cross-national investigation to fill the existing gaps in cross-national research on attitudes toward AI and basic psychological needs. Our study was focused on ways in which higher basic psychological need fulfillment via new technologies was associated with both positive and negative attitudes towards AI.

We used data from six countries that represent different regions of Europe: North (Finland), Central (France & Germany), West (Ireland), East (Poland), and South (Italy). These countries represent different welfare regimes with identified differences, for example, in income, class, and gender equality (Esping-Andersen, 1999). There are also cultural differences in individualism and cultural values, Finland and Germany representing protestant Europe, France, Poland, and Italy catholic countries and Ireland the English-speaking world (Inglehart and Welzel, 2005; World Values Survey Association, 2023). Furthermore, the chosen countries differ in their levels of technological development (Turja & Oksanen, 2019). Our aim was to analyze potential country differences in technology attitudes. We take heed of the on-going replication crisis (Nosek et al., 2022), which has been associated with a lack of cross-country considerations (Silber et al., 2022), and aim to analyze whether the same main findings emerge in different countries. The second study used longitudinal data from Finland.

Based on our theoretical framework (SDT; Ryan and Deci, 2017) and previous research (eg. De Vreede et al., 2021; Lu et al., 2019; Sahin and Sahin 2022; Ryan, 2023), we hypothesized that technology-related autonomy, competence, and relatedness have a generally positive role in attitudes towards AI indicated by higher AI positivity and lower AI negativity. Our hypotheses were:

H1: Higher autonomy beliefs toward new technologies are associated with a) higher positivity and b) lower negativity toward AI.

H2: Higher competence beliefs toward new technologies are associated with a) higher positivity and b) lower negativity toward AI.

H3: Higher relatedness beliefs toward new technologies are associated with a) higher positivity and b) lower negativity toward AI.

2. Study 1: Cross-national investigation

2.1. Methods

2.1.1. Participants

Study 1 was based on cross-sectional nationally representative samples collected from adult populations aged 18–75 in Finland (*N* = 1,541, 49.45% female, M_{age} = 46.35), France (*N* = 1,561, 52.08% female, M_{age} = 46.88), Germany (*N* = 1,529, 49.90% female, M_{age} = 47.36), Ireland (*N* = 1,112, 51.20% female, M_{age} = 46.77), Italy (*N* = 1,530, 50.90% female, M_{age} = 47.67), and Poland (*N* = 1,533, 51.34% female, M_{age} = 45.69). The samples demonstrate a high degree of comparability with Eurostat's (2022) data in terms of age and gender pertaining to the population of the respective countries within the age group of 18–75 years: Finland (49.67% female, M_{age} = 46.88), France (51.33% female, M_{age} = 46.46), Germany (49.87% female, M_{age} = 46.87), Ireland (50.61% female, M_{age} = 44.52), Italy (50.42% female, M_{age} = 47.89), and Poland (51.03% female, M_{age} = 46.29). Comparisons of countries' samples to their respective populations showed only minor deviation in age and gender; therefore, we did not apply analytical weights.

The data sets were collected in October–November 2022 as part of the Self and Technology Project (PI: Atte Oksanen). Research group designed the survey and the study. Norstat data solutions provider company collected the data. Participants filled out the surveys online. They were invited by Norstat via email and the structured online questionnaires were implemented through Norstat's online survey software. Of all the individuals invited to the survey in each country the response rates were: Finland (40%), France (13.5%), Germany (16.5%), Ireland (18%), Italy (23%), and Poland (27.3%). The mean response times in minutes were the following: Finland (21,30), France (20,90), Germany (21,43), Ireland (21,02), Italy (18,70), and Poland (22,48). We checked the quality of the data according to the pre-registered data quality protocol (Oksanen et al., 2021). Different checks included response speed check, attention checks, and patterned responses checks, such as straight-lining. We also checked internal consistency of scales and sub-scales.

The questionnaire for each country was prepared in the country's most widely used official language. The survey's language was Finnish in Finland, French in France, German in Germany, English in Ireland, Italian in Italy, and Polish in Poland. The survey was originally designed by the research group in English and then translated into other languages by professional-level translators. We checked the accuracy of translations using a back-translation process that involved native speakers. We used validated scales whenever they were available.

The study protocol was reviewed by the academic ethics committee of the Tampere region in Finland (decision 115/2022) in September 2022, who determined that all relevant ethical considerations were fully addressed. Participants were informed about the aims of the study and took part in the study voluntarily. The study complies with the General Data Protection Regulation of the European Union.

2.1.2. Measures

Attitudes toward AI. We used a shortened version of Schepman and Rodway's (2020, 2022) General Attitudes towards Artificial Intelligence Scale (GAAIS). GAAIS is a two-factor scale that is specifically used to indicate people's attitudes towards AI. The scale includes two subscales on positive and negative attitudes: Former express opportunities, benefits, and positive emotions toward AI, and the latter concerns and negative emotions on AI. In our study, four items measured positive attitudes toward AI (e.g., "Much of society will benefit from a future full of Artificial Intelligence"), and four items measured negative attitudes toward AI (e.g., "I think Artificial intelligence is dangerous", see Appendix A). Response options for each item ranged from 1 (*strongly disagree*) to 7 (*strongly agree*). The score of each item was added together, but both AI positivity and AI negativity were returned to the scale of 1 to 7, with higher scores indicating higher AI positivity or AI negativity. It should be noted that previous studies have used a Likert scale from 1 to 5. In our study, we use a Likert scale of 1 to 7. The reliability of both scales ranged from good to excellent in all countries based on McDonald's omega coefficient (Finland: AI positivity ω = 0.89, AI negativity ω = 0.90; France: AI positivity ω = 0.82, AI negativity ω = 0.84; Germany: AI positivity ω = 0.86, AI negativity ω = 0.88; Ireland: AI positivity ω = 0.87, AI negativity ω = 0.86; Italy: AI positivity ω = 0.89, AI negativity ω = 0.86; Poland: AI positivity ω = 0.82, AI negativity ω = 0.86).

Autonomy, competence, and relatedness in use of new technologies. We included the items from Technology Effects on Need Satisfaction in Life (TENS-Life), which was introduced in Peters et al. (2018), and is based on the validated Basic Psychological Need Satisfaction and Frustration Scale (Chen et al., 2015). In our study, all items referred to the use of new technologies. Respondents rated 10 statements on the use of new technologies for each dimension on a scale from 1 (*totally disagree*) to 7 (*totally agree*). Four items referred to autonomy (e.g., "The new technologies end up making me do things I don't want to do"). Based on confirmatory factory analysis (CFA), one item was dropped out (see appendix A for details). Competence (e.g., "Using the new technologies has made me feel insecure about my abilities") and relatedness (e.g., "Using the new technologies has helped me feel a greater sense of belonging to a larger community") were measured with three items each. For each dimension, items were reverse coded when necessary to indicate higher autonomy, competence, and relatedness in use of new technology. Scales varied from 3 to 21. Reliability of the scales ranged from good to excellent (Finland: autonomy ω = 0.82, competence ω = 0.92, relatedness ω = 0.89; France: autonomy ω = 0.84, competence ω = 0.90, relatedness ω = 0.89; Germany: autonomy ω = 0.85, competence ω = 0.90, relatedness ω = 0.89; Ireland: autonomy ω = 0.84, competence ω = 0.92, relatedness ω = 0.90; Italy: autonomy ω = 0.81, competence ω = 0.93, relatedness ω = 0.90; Poland: autonomy ω = 0.81, competence ω = 0.93, relatedness ω = 0.92).

Daily smart technology use. We measured smart technology use with the following question: "How often do you use the following technologies?" The provided items included (a) a mobile robot or another intelligent device (e.g., robot vacuum cleaner, robot lawn mower, assistance robot), (b) a virtual assistant via smart speaker, computer, or smartphone app (e.g., Siri, Alexa), (c) wearable smart technology (e.g., smart watch, smart ring), (d) augmented reality (AR) technology, and (e) virtual reality (VR) technology. Answers were rated on a scale from 0 to 4 (0 = *never*, 1 = *less than weekly*, 2 = *weekly*, 3 = *daily*, 4 = *many times a day*). A dummy variable was created to indicate the respondents who used at least one of the technologies daily (0 = *less than once a day or no use*, 1 = *at least once a day*).

Sociodemographic variables. We included questions on age in years, gender (0 = male, 1 = female), monthly gross income on a scale from 1 (below 1,000€) to 8 (at least 7,000€), educational attainment (0 = no university degree, 1 = university degree), and work life status (0 = not working, 1 = working).

Happiness. Happiness was measured on a scale from 1 (*extremely unhappy*) to 7 (*extremely happy*) with the following question: "All things considered, how happy would you say you are?".

2.1.3. *Statistical techniques*

We ran all analyses with Stata 17. We reported means, standard deviations, frequencies, and McDonald's ω coefficients to ensure the reliability of the measurements in Table 1 and Pearson correlation coefficients in Appendix B. We conducted the main analyses with linear regression, using both AI positivity and AI negativity as dependent variables. We checked all assumptions with standard ordinary least squares regression. We did not detect multicollinearity, but residuals were heteroscedastic based on the Breusch–Pagan test. We identified potential outliers with Cook's distance measure and values greater than $4/N$. We further checked outliers using the dfbeta postestimation command in Stata and excess values of $2/\sqrt{(n)}$. As we still detected outliers, we implemented robust regression for analysis, using the robreg command in Stata, which is the most advanced command for robust regression (Jann, 2022). We used the second-generation MM-estimator, which is considered to provide the most sensitive and reliable solution, because it is highly resistant to outliers and normal errors in the model (Jann, 2012; Verardi and Croux, 2009). This modeling solution provides standard errors that are robust to heteroscedasticity and asymmetric errors (Verardi and Croux, 2009). All the models used the suggested 85% efficiency. We reported regression coefficients (b) and their standard errors (b SE), p values for statistical significance, and the R^2 coefficient of determination. All independent variables were standardized to a default mean of 0 and a standard deviation of 1. We standardized the variables to make the regression coefficients comparable.

2.2. *Results*

Descriptive analysis showed that AI positivity was highest in Finland ($M = 4.80$, $SD = 1.24$), followed by Poland ($M = 4.54$, $SD = 1.32$), Italy ($M = 4.52$, $SD = 1.39$), Germany ($M = 4.48$, $SD = 1.37$), Ireland ($M = 4.35$, $SD = 1.32$), and France ($M = 4.26$, $SD = 1.27$). AI negativity was highest in France ($M = 4.44$, $SD = 1.43$), followed by Germany ($M = 4.14$, $SD = 1.58$), Ireland ($M = 4.08$, $SD = 1.48$),

Table 1
Descriptive Statistics of the Study 1 Variables From Finland (N = 1,541), France (N = 1,561), Germany (N = 1,529), Ireland (N = 1,112), Italy (1,530), and Poland (N = 1,533).

Continuous variables	Range	Finland		France		Germany		Ireland		Italy		Poland	
		M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
AI positivity	1–7	4.80	1.24	4.26	1.27	4.48	1.37	4.35	1.32	4.52	1.39	4.54	1.32
AI negativity	1–7	3.51	1.43	4.44	1.43	4.14	1.58	4.08	1.48	4.04	1.48	3.94	1.52
Autonomy	3–21	16.37	3.96	14.97	4.59	15.73	4.67	15.41	4.55	14.85	4.35	15.65	4.38
Competence	3–21	17.33	4.04	15.65	4.74	16.93	4.51	16.98	4.39	15.78	4.77	16.27	4.59
Relatedness	3–21	8.84	4.53	9.30	4.84	8.52	4.81	9.37	4.90	11.37	4.88	9.26	4.95
Age	18–75	46.35	16.34	46.88	15.84	47.36	15.16	46.77	14.50	47.67	15.34	45.69	15.41
Income	1–8	3.11	1.62	2.84	1.47	3.29	1.79	3.60	1.91	2.28	1.26	3.47	1.71
Happiness	1–7	4.84	1.22	4.68	1.29	4.64	1.41	4.83	1.36	4.58	1.37	4.69	1.37
Categorical variables	Range	n	%	n	%	n	%	n	%	n	%	n	%
Daily smart tech use	0/1	506	32.84	449	28.76	607	39.70	549	49.4	678	44.3	704	45.92
Female	0/1	762	49.45	813	52.08	763	49.90	569	51.2	779	50.9	787	51.34
University degree	0/1	413	26.80	572	36.64	450	29.43	564	50.7	592	38.7	835	54.47
Works	0/1	836	54.25	876	56.12	930	60.82	719	64.7	871	56.9	524	34.18

Italy ($M = 4.04$, $SD = 1.48$), Poland ($M = 3.94$, $SD = 1.52$), and Finland ($M = 3.51$, $SD = 1.43$).

AI positivity was higher in Finland than in Poland ($p < 0.001$), Italy, ($p < 0.001$), Germany ($p < 0.001$), Ireland ($p < 0.001$), and France ($p < 0.001$). AI positivity was higher in Poland than in Ireland ($p < 0.001$) and France ($p < 0.001$), and higher in Italy than in Ireland ($p = 0.002$) and France ($p < 0.001$). AI positivity was higher in Germany than in Ireland ($p < 0.001$) and France ($p < 0.001$). Finally, AI positivity was higher in Ireland than in France ($p < 0.001$).

AI negativity was significantly higher in France than in Germany ($p < 0.001$), Ireland ($p < 0.001$), Italy ($p < 0.001$), Poland ($p < 0.001$) and Finland ($p < 0.001$). AI negativity was higher in Germany than in Poland ($p < 0.001$) and Finland ($p < 0.001$). AI negativity was higher in Ireland than in Poland ($p = 0.018$) and Finland ($p < 0.001$). Finally, AI negativity was higher in Italy than in Finland ($p < 0.001$), and higher in Poland than in Finland ($p < 0.001$).

Table 2 shows that higher relatedness and competence were associated with higher AI positivity in all six countries ($p < 0.001$), but higher autonomy was only associated with higher AI positivity in Finland ($p < 0.001$). In all six countries, lower autonomy, competence, and relatedness were associated with higher AI negativity ($p < 0.001$; see Table 3). In other words, the results suggest a positive role of higher relatedness and higher competence in AI attitudes.

Table 2 also shows that daily smart technology use was associated with higher AI positivity in all six countries ($p < 0.001$). Females reported lower AI positivity in all six countries ($p < 0.001$). Older age was negatively associated with AI positivity in Germany ($p = 0.002$). Higher education was positively associated with AI positivity in all six countries ($p < 0.001$). Having a job was negatively associated with AI positivity in France ($p = 0.037$), Germany ($p < 0.001$), Italy ($p = 0.034$), and Poland ($p < 0.021$). Higher income was related to higher AI positivity in Germany ($p = 0.002$), Italy ($p = 0.021$), and Poland ($p = 0.018$). Higher happiness was associated with higher AI positivity in Finland ($p = 0.014$), France ($p = 0.028$), and Germany ($p = 0.040$).

Table 3 shows that those using smart technologies daily reported lower AI negativity in France, Germany, Ireland, and Poland. Females reported higher AI negativity in all six countries ($p < 0.001$). Older age was associated with higher AI negativity in Germany ($p = 0.015$), Italy ($p < 0.001$), and Poland ($p < 0.010$). Those having a university degree reported lower AI negativity in Finland ($p = 0.004$). Higher income was associated with lower AI negativity in Germany ($p = 0.038$), Italy ($p < 0.009$), and Poland ($p < 0.008$). Happiness was positively associated with AI negativity only in France ($p = 0.023$).

Table 2
Robust Regression Models on AI Positivity in Six Countries.

	Finland			France			Germany		
	B	SE	p	B	SE	p	B	SE	p
Autonomy	0.18	0.04	<0.001	−0.06	0.05	0.182	0.01	0.05	0.870
Competence	0.21	0.04	<0.001	0.32	0.05	<0.001	0.36	0.05	<0.001
Relatedness	0.51	0.03	<0.001	0.62	0.04	<0.001	0.56	0.05	<0.001
Daily smart tech use	0.08	0.03	0.005	0.13	0.03	<0.001	0.13	0.04	<0.001
Female	−0.12	0.03	<0.001	−0.06	0.03	0.043	−0.15	0.03	<0.001
Age	−0.04	0.03	0.266	0.01	0.03	0.839	−0.10	0.03	0.002
University degree	0.14	0.03	<0.001	0.09	0.03	0.005	0.13	0.03	<0.001
Works	−0.03	0.04	0.445	−0.07	0.03	0.037	−0.13	0.04	<0.001
Income	0.07	0.04	0.091	0.05	0.03	0.130	0.12	0.04	0.002
Happiness	0.08	0.03	0.014	0.07	0.03	0.028	0.07	0.04	0.040
Constant	4.85	0.03	<0.001	4.28	0.03	<0.001	4.55	0.03	<0.001
Model n	1,541			1,561			1,529		
Model R^2	0.19			0.22			0.19		
	Ireland			Italy			Poland		
	B	SE	p	B	SE	p	B	SE	p
Autonomy	0.05	0.06	0.432	0.03	0.05	0.529	0.09	0.05	0.092
Competence	0.25	0.06	<0.001	0.22	0.05	<0.001	0.28	0.05	<0.001
Relatedness	0.64	0.05	<0.001	0.82	0.04	<0.001	0.52	0.04	<0.001
Daily smart tech use	0.14	0.04	<0.001	0.14	0.03	<0.001	0.17	0.03	<0.001
Female	−0.13	0.04	0.001	−0.10	0.03	0.001	−0.09	0.03	0.008
Age	0.03	0.05	0.579	−0.03	0.03	0.300	−0.04	0.04	0.231
University degree	0.10	0.04	0.015	0.06	0.03	0.045	0.10	0.03	0.004
Works	−0.03	0.05	0.504	−0.07	0.03	0.034	−0.08	0.04	0.021
Income	0.07	0.05	0.155	0.08	0.03	0.021	0.09	0.04	0.018
Happiness	−0.01	0.04	0.792	0.05	0.04	0.174	0.05	0.04	0.158
Constant	4.43	0.04	<0.001	4.56	0.03	<0.001	4.60	0.03	<0.001
Model n	1,112			1,530			1,533		
Model R^2	0.19			0.28			0.18		

Note. All independent variables are standardized for the models. MM-estimator used in robust regression with 85% efficiency.

Table 3
Robust Regression Models on AI Negativity in Six Countries.

	Finland			France			Germany		
	B	SE	*p*	B	SE	*p*	B	SE	*p*
Autonomy	−0.34	0.06	<0.001	−0.19	0.05	<0.001	−0.33	0.06	<0.001
Competence	−0.45	0.06	<0.001	−0.56	0.05	<0.001	−0.54	0.05	<0.001
Relatedness	−0.45	0.04	<0.001	−0.56	0.05	<0.001	−0.58	0.05	<0.001
Daily smart tech use	−0.06	0.03	0.083	−0.10	0.04	0.011	−0.20	0.04	<0.001
Female	0.13	0.04	<0.001	0.12	0.03	<0.001	0.26	0.04	<0.001
Age	−0.07	0.04	0.055	0.07	0.04	0.084	0.11	0.05	0.015
University degree	−0.10	0.04	0.004	−0.03	0.04	0.375	−0.06	0.04	0.158
Works	−0.02	0.04	0.645	−0.04	0.04	0.336	0.05	0.05	0.281
Income	−0.04	0.04	0.391	−0.01	0.04	0.801	−0.11	0.05	0.038
Happiness	−0.07	0.04	0.084	0.09	0.04	0.023	0.02	0.04	0.613
Constant	3.41	0.04	<0.001	4.42	0.04	<0.001	4.09	0.04	<0.001
Model n	1,541			1,561			1,529		
Model R^2	0.20			0.22			0.21		
	Ireland			Italy			Poland		
	B	SE	*p*	B	SE	*p*	B	SE	*p*
Autonomy	−0.35	0.08	<0.001	−0.45	0.07	<0.001	−0.39	0.06	<0.001
Competence	−0.34	0.07	<0.001	−0.50	0.06	<0.001	−0.46	0.06	<0.001
Relatedness	−0.50	0.06	<0.001	−0.50	0.05	<0.001	−0.52	0.05	<0.001
Daily smart tech use	−0.15	0.05	0.002	−0.02	0.04	0.586	−0.15	0.04	<0.001
Female	0.12	0.05	0.011	0.11	0.04	0.003	0.11	0.04	0.003
Age	0.10	0.05	0.061	0.13	0.04	0.001	0.11	0.04	0.010
University degree	−0.07	0.05	0.150	−0.06	0.04	0.088	0.01	0.04	0.762
Works	−0.01	0.06	0.791	−0.01	0.04	0.725	0.08	0.04	0.089
Income	−0.05	0.06	0.421	−0.11	0.04	0.009	−0.12	0.04	0.008
Happiness	−0.02	0.05	0.651	0.09	0.05	0.055	0.02	0.04	0.562
Constant	4.05	0.05	<0.001	3.97	0.04	<0.001	3.86	0.04	<0.001
Model n	1,112			1,530			1,533		
Model R^2	0.17			0.24			0.20		

3. Study 2: Longitudinal investigation

3.1. Methods

3.1.1. Participants

We collected two-wave AI in Society Survey from Finnish respondents from May to June 2021 (T1: $N = 1{,}226$) and from May to June 2022 (T2: $N = 828$). The questionnaires addressed respondents' perceptions of AI, experiences of technology use, and psychological factors. The initial sample (T1) was demographically balanced to represent the Finnish adult population aged 18–80 years; the mean age of the respondents was 50.30 years ($SD = 16.67$, 51.15% female).

The AI in Society Survey was part of the Urban Utopias and Dystopias: Artificial Intelligence in Art and Society (UrbanAI) project (PI: Atte Oksanen). The research group designed the study and the survey. The sample was collected from an online research panel operated by Norstat Finland. Of all the people invited to the survey, the response rate for the first time point (T1) was 30.81%. The follow-up survey (T2) maintained 67.55% of those who responded to the first survey. The mean response time for T1 was 16 min and 6 s, and for T2, 17 min and 6 s. Responders were informed about the aims of the research and were provided contact information for the project and a link to the privacy notice. Before running the analyses, we quality-checked the dataset according to a pre-registered data quality protocol (Oksanen et al., 2021).

The respondents were made aware of their right to quit the survey at any time without providing explanations. Only the answers of those who responded to the entire longitudinal survey were included in the final dataset. Prior to data collection, the Academic Ethics Committee of the Tampere region in Finland stated that all ethical considerations were fully addressed (decision 29/2021).

3.1.2. Measures

Attitudes toward AI. We used the full 20-item version of the GAAIS by Schepman and Rodway (2020, 2022). The scale consists of 12 positive (opportunities, benefits, and positive emotions) and eight negative (concerns and negative emotions) items. Twelve statements measured positive attitudes toward AI (e.g., "Artificial Intelligence can provide new economic opportunities for this country"), and eight statements measured negative attitudes toward AI (e.g., "I think Artificial Intelligence is dangerous"). Items were summed for both AI positivity and AI negativity and returned to the scale of 1 to 7 to maintain comparability to Study 1. It should be noted that previous studies have used a Likert scale from 1 to 5. In our study we use a Likert scale of 1 to 7. The reliability of both scales ranged from good to excellent for both time points (T1 & T2) on McDonald's ω coefficient (T1: AI positivity ω = 0.92, AI negativity ω =

0.88; T2: AI positivity ω = 0.93, AI negativity ω = 0.88).

Autonomy, competence, and relatedness in the use of new technologies. Our measures were formed with items modified and combined from previous research (Lee et al., 2015; Sørebø et al., 2009, see Appendix A for details). Respondents rated nine statements on the use of new technologies on a scale from 1 (*totally disagree*) to 7 (*totally agree*). There were three items on autonomy (e.g., "I feel I have the ability to influence how I use new technologies"), three on competence (e.g., "Other people tell me I am good at using new technologies") and three on relatedness (e.g., "New technologies give me more opportunities to interact with others"). We created a three-item sum variable for each dimension (autonomy, competence, and relatedness), with values between 3 and 21. Reliability of the scales was from good to excellent (T1: autonomy ω = 0.81, competence ω = 0.83, relatedness ω = 0.87; T2: autonomy ω = 0.81, competence ω = 0.83, relatedness ω = 0.88).

Daily smart technology use. We measured smart technology use with the question: "How often do you use the following technologies?" The provided response items included (a) a smart home system (e.g., smart lighting), (b) an immobile smart home appliance or other appliance (e.g., smart TV), (c) a mobile robot or another intelligent device (e.g., robot vacuum cleaner, robot lawn mower, assistance robot), (d) a virtual assistant via smart speaker, computer, or a smartphone app (e.g., Siri, Alexa), and (e) wearable smart technology (e.g., smart watch, smart ring). Answers were given on a scale from 0 to 4 (0 = *never*, 1 = *less than weekly*, 2 = *weekly*, 3 = *daily*, and 4 = *many times per day*). A dummy variable was created to indicate those respondents who used at least one of the technologies daily (0 = *less than once a day or no use* and 1 = *at least once a day*).

Personality. Personality traits of openness to new experiences, extraversion, and neuroticism were measured. These traits were selected as suitable controls on both empirical and theoretical basis. Low extraversion, low openness and high neuroticism are expected to have some influence on technology attitudes. Agreeableness and conscientiousness were not measured in the survey. We measured openness, extraversion, and neuroticism using items from the Big Five Inventory (BFI-S; Hahn et al., 2012). Respondents rated 3 statements for each personality trait on a scale from 1 (*does not describe me at all*) to 7 (*describes me completely*). We created a three-item sum variable for each trait, with values between 3 and 21. Reliability of the scales was from good to excellent (openness ω = 0.75, extraversion ω = 0.88, neuroticism ω = 0.79).

Sociodemographic variables. We included questions on age, gender (0 = male and 1 = female), monthly gross income on a scale from 1 (below 1,000€) to 8 (at least 7,000€), educational attainment (0 = no university degree, 1 = university degree), and work status (0 = not working and 1 = working).

3.1.3. Statistical techniques

In addition to descriptive statistics (Table 4) and Pearson correlation coefficients (Appendix C), we reported results based on longitudinal analysis. We performed hybrid multilevel regression models with the xthybrid command in Stata 17, which is a shell for mixed effects in generalized linear models (Schunck, 2013; Schunck and Perales, 2017). Hybrid models are recommended as a solution for the shortcomings of both fixed-effect and random-effect models, and they incorporate both within-person effects and between-person effects into the same models. Within-person effects indicate changes in the dependent variables predicted by the changes over time in the independent variables. Between-person effects demonstrate group differences between individuals. Hybrid models are also more flexible with the assumptions related to random-effect and fixed-effect models, such as the assumptions of distributions of unobserved effects in random-effect models and the assumptions of homogeneity in fixed-effect models (Schunck and Perales, 2017).

Table 5 shows regression coefficients (*b*) and their standard errors (*SE b*), *Z* scores for effect size, and *p* values for statistical significance. We standardized all independent variables (autonomy, competence, relatedness, daily technology use, gender, age, higher education, income, having a job, and personality traits: openness, extroversion, and neuroticism) for the analysis to increase the comparability of the coefficients. We report within and between person effects for autonomy, competence, relatedness, daily smart

Table 4
Descriptive Statistics of the Study 2 Variables (Finland, Longitudinal Sample, N = 827).

Continuous variables	T1			T2		
	Range	M	SD	M	SD	Within-person differences, SD
AI positivity	1–7	4.20	1.15	4.15	1.15	0.43
AI negativity	1–7	3.80	1.23	3.74	1.19	0.50
Autonomy	3–21	12.75	3.95	13.06	3.91	1.93
Competence	3–21	11.82	4.25	11.85	4.24	1.37
Relatedness	3–21	9.97	4.08	10.17	4.06	1.89
Age	18–80	50.30	16.67	–	–	–
Income	1–8	3.11	1.52	3.24	1.56	0.43
Openness	3–21	14.06	3.75	–	–	–
Extraversion	3–21	13.59	4.58	–	–	–
Neuroticism	3–21	11.76	4.15	–	–	–
Categorical variables	n	%		n	%	
Daily smart tech use	198	23.94		240	29.02	
Works	399	48.25		410	49.58	
Female	423	51.15		–	–	
College/university degree	328	39.66		–	–	

Table 5
Hybrid Model Showing Within-person and Between-person Effects on Positivity and Negativity Towards AI.

Within-person effects	AI positivity				AI negativity			
	B	SE (B)	Z	*p*	B	SE (B)	Z	*p*
Autonomy	0.14	0.03	3.96	<0.001	−0.13	0.04	−3.31	0.001
Competence	0.05	0.06	0.82	0.411	0.07	0.06	1.26	0.209
Relatedness	0.22	0.03	6.50	<0.001	−0.13	0.04	−2.90	0.004
Daily smart tech use	−0.03	0.03	−0.94	0.349	0.03	0.04	0.68	0.498
Works	0.02	0.04	0.59	0.557	0.05	0.05	0.91	0.362
Income	−0.05	0.05	−1.04	0.297	−0.19	0.07	−2.70	0.007
Between-person effects								
Autonomy	0.21	0.05	4.27	<0.001	−0.29	0.06	−5.09	<0.001
Competence	0.12	0.05	2.25	0.025	−0.16	0.06	−2.64	0.008
Relatedness	0.47	0.05	9.51	<0.001	−0.20	0.05	−3.66	<0.001
Daily smart tech use	0.07	0.03	2.07	0.038	−0.10	0.04	−2.56	0.011
Works	−0.02	0.04	−0.54	0.591	0.10	0.05	2.20	0.028
Income	0.04	0.04	0.96	0.339	−0.08	0.05	−1.56	0.118
Controls								
Female	−0.16	0.06	−2.66	0.008	−0.14	0.04	−3.81	<0.001
Age	0.02	0.04	0.46	0.648	−0.04	0.04	−0.92	0.360
College/univ. degree	0.15	0.03	4.77	<0.001	−0.07	0.04	−1.89	0.059
Bf: openness	0.07	0.03	2.10	0.036	0.06	0.04	1.62	0.106
Bf: extraversion	−0.10	0.03	−2.78	0.005	0.03	0.04	0.79	0.432
Bf: neuroticism	0.00	0.03	−0.05	0.964	0.15	0.04	3.62	<0.001

Note. All independent measures are standardized in models. All models include a total of 1,654 observations from 827 participants.

tech use, working status and income. The rest of the variables were measured in one timepoint only and were treated as control variables.

3.2. Results

Descriptive results showed that AI positivity and AI negativity did not vary much over time and their change was not statistically significant based on multilevel fixed effects regression. Table 4 shows that the mean of AI positivity was 4.20 ($SD = 1.15$) at T1 and 4.15 ($SD = 1.15$) at T2. Similarly, the mean of AI negativity was fairly consistent over time (T1: $M = 3.80$, $SD = 1.23$; T2: $M = 3.74$, $SD = 1.19$). For the dimensions on the use of new technologies, autonomy had the highest mean at T1 ($M = 12.75$) and at T2 ($M = 13.06$), followed by competence (T1: $M = 11.82$; T2: $M = 11.85$) and relatedness (T1: $M = 9.97$; T2: $M = 10.17$). Approximately 24% were daily AI tech users at T1, with that percentage increasing to 29% at T2. Nearly half were working at the times of measurement (T1: $M = 48.25$; T2: $M = 49.58$).

Table 5 reports the results of our hybrid multilevel regression models. We found that autonomy ($p < 0.001$) and relatedness ($p < 0.001$) had statistically significant within-person effects on AI positivity. This indicates that an increase in autonomy or in relatedness leads to an increase in AI positivity. Several between-person effects were significant. Those who reported higher autonomy ($p < 0.001$), competence ($p = 0.025$), relatedness ($p < 0.001$), and daily use of smart technologies ($p = 0.038$) reported higher AI positivity. Out of the control variables, female gender ($p = 0.008$) and extraversion ($p = 0.005$) were negatively associated with AI positivity. In addition, having a degree from college or university ($p < 0.001$) and openness ($p = 0.036$) were positively associated with AI positivity.

Hybrid modelling of AI negativity also resulted in statistically significant findings. We found that higher autonomy ($p = 0.001$) and relatedness ($p = 0.004$) had inverse within-person effects on AI negativity. Thus, an increase in autonomy led to a decrease in AI negativity. Similarly, those who experienced an increase in relatedness decreased their AI negativity. An increase in income was related to a decrease in AI negativity over time ($p = 0.007$). Between-person effects showed that those who reported higher autonomy ($p < 0.001$), competence ($p = 0.008$), relatedness ($p < 0.001$), daily use of smart technologies ($p = 0.011$), and current employment ($p = 0.028$) reported lower AI negativity. Out of the control variables, female gender ($p < 0.001$) was negatively associated with AI negativity, and neuroticism ($p < 0.001$) was positively associated with AI negativity.

4. Discussion

4.1. General overview of the results

This article is based on two studies that analyzed how perceived autonomy, competence, and relatedness regarding new technologies are associated with positive and negative AI attitudes. Our hypotheses were based on previous research on self-determination theory and on the basic psychological needs and attitudes toward technologies (e.g., De Vreede et al., 2021; Lu et al., 2019; Sahin and Sahin 2022; Ryan, 2023). We expected that higher autonomy, competence, and relatedness would be associated with higher AI positivity and lower AI negativity. The results of both studies confirmed these hypotheses. In the cross-national study, we found that competence and relatedness were positively associated with AI positivity in all countries, and autonomy was associated with AI positivity in Finland. Autonomy, competence, and relatedness were negatively associated with AI negativity in all countries. The longitudinal study with Finnish data showed that increasing the satisfaction of the needs for autonomy and relatedness was associated with an increase in AI positivity and a decrease in AI negativity. This means that people who experience more fulfillment of these needs will also experience more positivity and less negativity toward AI. We also found statistically significant between-person effects in autonomy, competence, and relatedness, which were all connected to less negative attitudes toward AI, whereas individuals with higher perceived autonomy and competence expressed both less negativity and more positivity toward AI.

4.2. Theoretical and practical implications

The potential of SDT to explain AI attitudes has been previously discussed, but there is a lack of empirical research on the matter (Cascio and Montealegre, 2016; Park and Woo, 2022). Our study is the first to examine associations between meeting basic psychological needs and attitudes toward AI. SDT posits that environments that support autonomy, competence, and relatedness are more likely to foster intrinsic motivation and well-being (Deci and Ryan, 2000; Ryan and Deci, 2017; Ryan, 2023). Based on previous literature, if psychological needs for autonomy, competence, and relatedness are met, people will have more positive attitudes toward the elements in their environment that meet those needs (Ferrara et al., 2022; Sahin and Sahin, 2022). Our results provide support for this notion, suggesting it also applies to introducing AI to one's environment. This could be used to plan the introduction of future AI technologies in a way that avoids or alleviates the negative reactions that followed the sudden public launch of ChatGPT, for instance (e.g., Sanders and Schneier, 2023).

Overall, we found that competence and relatedness were associated with AI positivity in all six countries, suggesting that people who relate to other technology users and feel competent in using new technologies perceive AI more positively consistently across these countries (Finland, France, Germany, Ireland, Italy, and Poland). The results imply that experiencing competence and relatedness in relation to new technologies, is associated with less negative attitudes toward them, specifically toward AI. Some country-specific differences were also observed: most importantly, that autonomy was associated with AI positivity only in Finland. There are likely contextual factors at play contributing to Finnish participants' higher prioritization of autonomy in technology use and AI positivity. A recent report by the European Commission provided some insight into this, ranking Finland among the leading countries in digitalization and digital performance in Europe (European Commission, 2022). Increased exposure factors, namely personal autonomy and experience in interacting with new technology and AI, likely explain this positive relationship, especially in Finland.

Our results fill an important research gap by utilizing a framework of basic psychological needs in the context of new technologies and attitudes toward AI. Whereas competence and relatedness were associated with positive attitudes toward AI across countries, the role of autonomy was less consistent, only being positively associated with positive attitudes toward AI in Finland. It is possible that the sense of autonomy relates to a positive outlook on AI and reduced fears around it, as exposure to this new technology increases. Future longitudinal and experimental studies should investigate and test this hypothesis.

At the individual- and group-level examinations, we discovered within-person effects, namely an increase in either autonomy or relatedness, led to an increase in AI positivity. Between-person effects showed that those who reported higher autonomy, competence, and relatedness reported higher AI positivity and lower AI negativity. An increase in autonomy and relatedness led to an increase AI positivity and a decrease AI negativity. This aligns with the expectations drawn from our theoretical background because SDT states that if an individual's social environment supports their need for autonomy, competence, and relatedness then they are more likely to develop positive attitudes toward that environment (Deci and Ryan, 2000; Ryan and Deci, 2017; Ryan, 2023). Therefore, a lack of self-determination might make individuals more susceptible to having negative attitudes toward AI, and an increase of self-determination might make individuals more accepting toward AI.

Previous studies have also stated that people's general attitudes toward AI are linked to their acceptance and the use of AI in their daily lives (Choung et al., 2023; Gillespie et al., 2021; Kelly et al., 2023; Lancelot Miltgen et al., 2013; Schepman and Rodway, 2020; Schepman and Rodway, 2022). Hence, a better understanding of attitudes toward AI can lead to more efficient implementation and usability of these technologies (Kelly et al., 2023; Schepman and Rodway, 2020; Schepman and Rodway, 2022). Through our study, we addressed existing research gaps in cross-national and longitudinal research in this area and found self-determination to be connected to attitudes toward AI. Hence, it is imperative to acknowledge basic psychological needs as crucial factors when examining individuals' dispositions toward AI.

4.3. Limitations

A notable strength of this study is the large cross-national data that are especially valuable when there is a lack of cross-national research on attitudes toward technology. Furthermore, cross-national data following the same design in each country provide the ability to tackle some challenges posed by a replication crisis, mainly concerning whether the examined phenomena can be observed in different contexts, and general notions of small datasets collected from a singular country or only from a very specific population (e.g., college samples). Also, we were able to provide much needed longitudinal evidence of attitudes on AI. Our study has, however, some limitations, such as the use of self-reported information. As this article reported findings from two different studies there are some differences in the measures. The full 20-item GAAIS scale was used only in Study 2. In Study 1, we used the shortened 8-item version. Study 1 used TENS-Life (Peters et al., 2018) to measure autonomy, competence, and relatedness beliefs toward new technologies. We dropped one item to improve the reliability of the scale. In Study 2, we used a scale derived from other studies of autonomy, competence, and relatedness beliefs toward new technologies (Lee et al., 2015; Sørebø et al., 2009). These two scales (see Appendix A) are, however, adequately matching and measure essentially the same theoretical constructs. Our longitudinal study is based only on data from Finland. Therefore, it is not feasible to make any definitive statements regarding the changes in attitudes toward AI and the dimensions of self-determination in other countries. Investigating the evolution of AI attitudes is crucial when considering potential country-specific variations in relation to self-determination.

4.4. Conclusions

With the spread and wide use of AI, investigating people's attitudes toward AI has become highly relevant. Our study provided consistent cross-national findings on the role of basic psychological needs (autonomy, competence, and relatedness) in attitudes toward AI in Finland, France, Germany, Ireland, Italy, and Poland. We also found longitudinal evidence that autonomy and relatedness increased AI positivity and decreased AI negativity in Finland. Based on the results of this study, self-determination is an important factor in both negative and positive attitudes on AI. Fulfillment of the basic psychological needs of autonomy, competence, and relatedness can affect the acceptance of AI, which has implications for the adoption and rapid development of new AI applications. Our study tested AI acceptance in different settings and represents a robust cross-national and longitudinal investigation of the relationship between the basic social psychological needs and attitudes toward AI. The results have both theoretical and practical implications providing a solid foundation for future research on this topic.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Atte Oksanen reports financial support was provided by Kone Foundation.

Data availability

Data will be made available on request.

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Appendix A

Shortened version of the General Attitudes towards Artificial Intelligence Scale (GAAIS; Schepman and Rodway, 2020; Schepman and Rodway, 2022).

1. Artificial Intelligence can provide new economic opportunities for this country.
2. There are many beneficial applications of Artificial Intelligence.
3. Much of society will benefit from a future full of Artificial Intelligence.
4. Artificial intelligence can have positive impacts on people's wellbeing.
5. I find Artificial Intelligence sinister.
6. I shiver with discomfort when I think about future uses of Artificial Intelligence.
7. Artificial Intelligence might take control of people.
8. I think Artificial intelligence is dangerous.

A shortened version was used due to the limitation of space within the Self and Technology Survey Study. We used the AI in Society survey collected in May 2021 for the item selection that was conducted with confirmatory factor analysis (CFA) and using reliability statistics.

Technology effects on need satisfaction in life (TENS-Life; Peters et al., 2018).

Autonomy:

1. I spend more time on the new technologies than I feel I should.
2. The new technologies end up making me do things I don't want to do.
3. The new technologies intrude in my life.

Competence:

4. Using the new technologies has made me feel insecure about my abilities.

5. Using the new technologies has made me feel less capable in my life.
6. Using the new technologies has lowered my confidence.

Relatedness:

7. Using the new technologies has helped me feel a greater sense of belonging to a larger community.
8. Using the new technologies has helped me feel close and connected with other people who are important to me.
9. Because of these new technologies, I feel closer to some others.

TENS-life includes four items for autonomy, but we dropped one item ("Now that I use the new technologies, I feel pressured to use those more often than I'd like") during the analysis on the basis of confirmatory factory analysis (CFA) and reliability statistics. CFA was conducted using structural equation modelling and we used cutoff criteria of >0.95 for CFI and TLI, <0.06 for RMSEA, and <0.08 for SRMR as suggested by Hu and Bentler (1999).

Basic psychological needs in the use of new technologies questionnaire was modified and combined from items used in prior research (Lee et al., 2015; Sørebø et al., 2009).

Autonomy.

I feel I have the ability to influence how I use new technologies.
I feel that I can use new technologies pretty much the way I want.
I don't have many opportunities to decide for myself how to use new technologies.

Competence.

Other people tell me I am good at using new technologies.
I don't feel very competent when using new technologies.
I am better than others at using new technologies.

Relatedness.

New technologies give me more opportunities to interact with others.
I feel close to others when using new technologies.
I have more opportunities to experience closeness with others when using new technologies.

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Appendix B

Zero-order Pearson correlation coefficients of the study 1 variables

	Finland		France		Germany		Ireland		Italy		Poland	
	AI pos	AI neg	AI pos	AI neg	AI pos	AI neg	AI pos	AI neg	AI pos	AI neg	AI pos	AI neg
AI negativity	−0.50***	–	−0.36***	–	−0.42***	1	−0.43***	1	−0.34***	–	−0.37***	–

(continued on next page)

(*continued*)

	Finland		France		Germany		Ireland		Italy		Poland	
	AI pos	AI neg	AI pos	AI neg	AI pos	AI neg	AI pos	AI neg	AI pos	AI neg	AI pos	AI neg
Autonomy	0.06*	−0.28***	−0.15***	−0.19***	−0.12***	−0.15***	−0.04	−0.21***	−0.09***	−0.31***	−0.01	−0.23***
Competence	0.13***	−0.34***	0.06*	−0.34***	0.03	−0.27***	0.04	−0.26***	0.06*	−0.39***	0.11***	−0.29***
Relatedness	0.36***	−0.17***	0.48***	−0.23***	0.38***	−0.14***	0.38***	−0.18***	0.52***	−0.17***	0.35***	−0.15***
Daily smart tech use	0.14***	−0.08**	0.27***	−0.19***	0.24***	−0.21***	0.25***	−0.18***	0.27***	−0.10***	0.25***	−0.20***
Female	−0.11***	0.09***	−0.11***	0.11***	−0.14***	0.16***	−0.13***	0.08**	−0.11***	0.08**	−0.10***	0.10***
Age	−0.06	−0.05	−0.09***	0.12***	−0.14***	0.07**	−0.05	0.03	−0.11***	0.04	−0.04	0.03
Univ. degree	0.15***	−0.10***	0.13***	−0.07**	0.17***	−0.11***	0.15***	−0.09**	0.08**	−0.05*	0.09***	−0.01
Works	0.02	−0.04	0.04	−0.08**	0.04	−0.05	0.07*	−0.07*	0.03	−0.04	0.01	−0.02
Income	0.10***	−0.11***	0.09***	−0.02	0.16***	−0.13***	0.11***	−0.08**	0.14***	−0.09***	0.11***	−0.10***
Happiness	0.09***	−0.11***	0.08**	−0.01	0.13***	−0.09**	0.01	−0.07*	0.16***	−0.06*	0.09***	−0.05*

Note. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Appendix C

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. AI positivity	–												
2. AI negativity	−0.52***	–											
3. Autonomy	0.45***	−0.38***	–										
4. Competence	0.44***	−0.30***	0.49***	–									
5. Relatedness	0.53***	−0.30***	0.45***	0.43***	–								
6. Daily smart tech use	0.19***	−0.17***	0.15***	0.27***	0.18***	–							
7. Works	0.03	0.05	−0.01	0.11**	0.03	0.09*	–						
8. Income	0.12***	−0.12***	0.07*	0.15***	0.01	0.08*	0.38***	–					
9. Female	−0.17***	0.02	−0.12***	−0.23***	−0.02	0.02	−0.07*	−0.24***	–				
10. Age	−0.10**	−0.01	−0.14***	−0.29***	−0.18***	−0.12***	−0.37***	0.15***	0.02	–			
11. College/univ. degr.	0.27***	−0.18***	0.11**	0.17***	0.14***	0.05	0.10**	0.33***	−0.05	−0.01	–		
12. Bf: openness	−0.03	−0.07	0.09*	0.03	0.03	0.04	−0.04	0.15***	0.12**	0.16***	0	–	
13. Bf: extroversion	0.19***	−0.08*	0.21***	0.21***	0.15***	0.05	−0.05	0.03	0.01	−0.00	0.08*	0.28***	–
14. Bf: neuroticism	−0.13***	0.22***	−0.20***	−0.19***	−0.04	−0.01	0.05	−0.25***	0.25***	−0.30***	−0.11**	−0.32***	−0.12***

Zero-order Pearson correlation coefficients of the Study 2 variables at T1.

Note. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

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