Generational differences in general attitudes towards AI and the level of trust in artificial faces

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Abstract

With the increase of artificial intelligence in modern society, more people must now cooperate and interact with these systems. Cooperation and interaction with AI are dependent on the level of trust. The level of trust in AI is shaped by experiences over time. Whereas younger generations have grown up in a time where AI technologies were already increasingly prevalent and integrated into their daily lives, older generations had to adjust to the idea of AI. The question arises whether there are generational differences in the level of trust in AI. This study investigates whether the level of trust in AI is different for people from different generations. We compare two age groups on the level of trust in faces labelled as computer-generated and the level of trust in faces labelled as natural. The level of trust in faces labelled as computer-generated, was used to measure trust in AI. Additionally, we measured whether general attitudes towards AI and levels of generalized trust were different for people in the different age groups. This research expands existing knowledge on this topic by including the influence of individuals' self-regulation on the level of trust in AI. As expected, we found that faces labelled as computer-generated were perceived as less trustworthy compared to faces labelled as natural. However, no significant differences were found between the two age groups in the general attitudes towards AI, and general attitudes did not predict trust in AI. Furthermore, no significant differences were found between the two age groups in the level of trust in AI. Finally, individuals' self-regulation did not influence the relationship between age and the level of trust in AI. Our findings suggest that age alone might not be a strong predictor of trust in AI, as, familiarity, and previous experience with AI may be interconnected factors that influence the level of trust in AI. We recommend that other factors should be taken into consideration when investigating the relationship between age and trust in AI in future research. Furthermore, future research is recommended to include more dynamic tasks and control for potential outgroup effects to further explore the relationship between age, self-regulation, and trust in AI.

Keywords: Artificial Intelligence, Trust, Age, Face Perception, GAAIS, Regulatory Focus, RFQ, Social Psychology

Tabel of Content

Introduction

Artificial Intelligence (AI) is a rapidly growing field of computer science that focuses on the development of intelligent machines that can perform tasks that typically require human intelligence, such as recognizing patterns, understanding natural language, and making decisions based on the available data (Russell et al., 2010). AI technologies have advanced significantly in recent years, and they are being used in a wide range of applications across various industries and processes in daily life, including healthcare, education, and recruitment and selection processes (Albert, 2019; Vaishya et al., 2020; Zhai et al., 2021). In 2022, 35 percent of companies reported using AI in their business, which was an increase of 4 percent compared to 2021 (IBM Corporation, 2022). Therefore, more people must now cooperate and interact with these systems. While AI has the potential to positively impact many impacts of society, the new technology brings along some serious risks as well (Zhang & Dafoe, 2019). Some visible risks include privacy violations, discrimination, accidents, and manipulation of political systems for example (Cheatham et al., 2019). Therefore, it is unsurprising that people are still skeptic about certain AI systems. In their study, Zhang and Dafoe (2019) examined the support and concerns towards multiple applications of AI and found that overall, 42 percent of the participants supported AI and 22 percent opposed to it. Whereas more people showed support for AI, 82 percent of all participants expressed their uncertainties. According to Tussyadiah et al. (2021), negative attitudes towards technology are associated with lower levels of trust in these systems. Nevertheless, trust is a crucial factor for interaction and cooperation with AI systems is dependent on the level of trust people have in these systems (Ueno et al., 2022). The growing skepticism can therefore diminish the applicability of AI, as it influences the level of trust in AI (Daveport & Ronanki, 2018).

Trust in AI refers to the confidence and reliance of people in the abilities, reliability, and ethical conduct of artificial intelligent systems (Ryan, 2020). The level of trust in AI is shaped by experiences over time, where past negative experiences with AI are associated with decreased trust in AI (Dikmen & Burns, 2017). While the first developments of AI started as early as the 1960s, it was not until the mid-1990s that the application of AI increased in society and people could start using AI (Lee, 2020). The concept of AI is therefore relatively new to our society. Whereas younger generations have grown up in a time where AI technologies were already increasingly prevalent and integrated into their daily lives, older generations had to adjust to the idea of AI. The question arises whether there are generational differences in the level of trust in AI.

Digital Divide

Previous research has indicated that there is an age gap in the adoption and use of new technologies, indicating that older adults are the least likely of any age cohort to regularly use information and communication technologies (ICTs) (Ball et al., 2017; Charness & Boot, 2022; Lythreatis et al., 2022). This gap is referred to as the so-called ‘digital divide’. The digital divide is defined as a difference in adoption and use of digital technology, caused by personal characteristics, such as age, socio-economic status, and race (Charness & Boot, 2022). In their research, Charness and Boot suggested that general attitudes, including perceived self-efficacy in using technology, interest in using it, and comfort in using it, contribute to the lack of use and adoption by older adults, which consequently contributes to the digital divide. Furthermore, they suggested that there is a large difference between younger and older adults in these general attitudes. Possibly, a similar age difference exists in the general attitudes towards AI. As younger generations are more likely to have had early exposure to AI through various devices, applications, and digital platforms, in their home or at school for example, they might be more comfortable using AI, compared to older generations who were not exposed to AI for the greatest part of their life (Charness & Boot). Previous studies suggested that people higher in age have more negative attitudes towards AI, compared to younger people (Zhang & Dafoe, 2019; Schepman & Rodway, 2022). Based on the previous findings, we proposed that older individuals have more negative attitudes towards AI in general, compared to younger individuals. In this study, we define the younger generation as individuals born since 1984 (e.g., millennials, gen Z), and the older generation as individuals born before 1983 (e.g., gen X, boomers).

Hypothesis 1: The older age group has more negative attitudes towards AI in general compared to the younger age group.

Attitudes and trust in AI

General attitudes contribute to the adoption and use of AI (Charness & Boot, 2022). Similarly, in study by Tussyadiah and colleagues (2021) they investigated the influence of attitudes and trust in technology. In line with earlier findings by Dikmen and Burns (2017), they suggested that negative attitudes towards technology are associated with lower levels of trust in technology. Nevertheless, it should be noted that attitudes towards traditional technologies do not automatically reflect the attitudes towards AI (Schepman & Rodway, 2022). A study that proposes a possible influence of negative attitudes on the level of trust in AI, is the study by Liefooghe et al. (2023). In their study, they investigated whether merely labelling faces as artificial could decrease the level of trust, even when these faces were indistinguishable from faces labelled as natural. While their findings suggest that people judge faces labelled as artificial to be less trustworthy compared to faces labelled as natural, they did not find evidence for an outgroup bias of artificial faces like Balas & Pacella (2017) did in their study. Therefore, they suggested that the label effect could reflect a more general evaluative conditioning effect. Evaluative conditioning (EC) refers to the change or formation of attitudes towards an object solely based on its association with another object that is intrinsically judged positive or negative (Jones et al., 2010). Faces labelled as computer-generated were potentially judged as less trustworthy, due to an intrinsically negative attitude towards AI in general. However, further investigation on the potential effect of negative attitudes on the level of trust in AI is needed. Based on the previous findings, we proposed that there is a negative relationship between negative attitudes towards AI and the level of trust in AI.

Hypothesis 2: There is a negative relationship between negative attitudes towards AI and the level of trust in AI.

Cognitive and Affective trust in AI

Moreover, the development of trust in general is usually determined by three factors of trustworthiness: the perceived ability, benevolence, and perceived integrity of the trustee (Colquitt & Salam, 2015). Similar factors have been found to determine the level of trust in AI. Trust in AI can be developed through both cognitive and affective processes. Cognitive trust in AI can arise when individuals perceive an AI system as transparent, consistent, and reliable for example (Kaplan et al., 2021). Additionally, cognitive trust in AI can stem from the perception of its accuracy and performance (Glikson & Woolley, 2020). On the other hand, affective trust is based on previous positive experiences with AI (Dikmen & Burns, 2017).

Age and trust in AI

While many studies have provided valuable insights on the cognitive and affective routes to trust, less studies have focused on the personal and psychological factors that could influence trust in AI (Gillath et al., 2021). An example of such a factor, is age. Age has been positively associated with generalized trust, implying that older individuals score higher on measures of generalized trust (Li & Fung, 2012). Accordingly, one possible mechanism that could explain this positive association is positive reappraisal. Later adulthood is often accompanied by physical and cognitive declines. The struggle to accomplish all tasks by themselves could increase stress levels in older adults. As a coping strategy, older adults may show an enhanced level of trust, and rely more on others' help (Bookwala, 2011). The increase of AI technologies could potentially reduce the levels of stress in older adults, as it could function as a new potential source of help. Therefore, as older adults show higher levels of generalized trust, one might expect that older adults would have higher levels of trust in AI as well. Nonetheless, in a recent study by Gillath and colleagues (2021), they suggested that older adults and individuals who are less familiar with AI tend to have less trust in AI, even though older adults do recognize the potential of new technologies to facilitate independence (Mitzner et al., 2010),

Regulatory Focus Theory

A possible explanation that could account for this discrepancy, is that older adults may rely on different motivational systems to pursue their goals, compared to younger individuals. According to to the Regulatory Focus Theory (RFT) by Higgins (1997), people are motivated to pursue their goals while focused on either prevention focused self-regulation or on promotion focused self-regulation. People with a promotion focus tend to focus on the accomplishment of positive outcomes, growth, advancement, and progress. On the contrary, people with a prevention focus tend to focus on the avoidance of dangers and threats to prevent negative outcomes. They have a proclivity to be defensive and vigilant, which reflects on a more conservative strategy of risk aversion (Rudman et al., 2012). Prevention focused self-regulation has been associated with decreased levels of trust (Keller et al., 2015). Through the mechanism of risk aversion, people with a prevention focus will most likely project a tendency to prefer natural systems over AI systems, as the outcomes of using AI are still uncertain. According to Lockwood et al. (2005), older adults are more likely to have a stronger prevention focus, compared to younger individuals. Therefore, prevention focused self-regulation could potentially account for the different effect of age on trust in general compared to trust in AI.

As the effect of self-regulation has not been included in studies regarding trust in AI, he relationship between age, prevention focused self-regulation and trust in AI, needs further investigation. Based on the previous findings, we proposed that the older age group has less trust in AI, compared to the younger age group.

Hypothesis 3: Older individuals have less trust in AI compared to younger individuals.

Additionally, we proposed that older individuals have a stronger prevention focus compared to younger individuals, and that a stronger prevention focus decreases the level of trust in general. Finally, we proposed that individuals' prevention focus will influence the relationship between age and the level of trust in AI.

Hypothesis 4: Older individuals have a stronger prevention focus compared to younger individuals.

Hypothesis 5: Prevention focused self-regulation is negatively associated with the level of generalized trust.

Hypothesis 6: Prevention focused self-regulation influences the relationship between age and the level of trust in AI.

This study replicated the first experiment from the study by Liefooghe et al. (2023) to further investigate the relationship between negative attitudes and the level of trust in AI, the influence of age on the level of trust in AI, and the influence of individuals' self-regulation on the relationship between age and trust in AI.

By investigating the interplay between age, prevention focus, and trust in AI, this study aims to provide a deeper understanding of the psychological factors that influence trust dynamics in the context of AI. It also highlights the importance of considering individual differences in self-regulation strategies when examining trust in AI, offering implications for designing AI systems that align with users' cognitive and affective preferences.

Methods

Participants

By means of snowball sampling, 163 participants were initially recruited via the social network of the researcher of this study, and they participated for free. A thorough data cleaning process was conducted to ensure the validity and reliability of the dataset. Participants were excluded from the analysis based on predetermined criteria. Firstly, participants with missing data on the demographic question about age, located at the end of the survey, were excluded. Participants who provided their age, also filled out the other questionnaires, since an answer was required to continue with the survey. As a result, data on the variables of interest were obtained from all participants who provided their age. Secondly, participants who completed the survey in less than 240 seconds were excluded to mitigate the potential impact of inattentiveness or incomplete engagement with the study. Third, participants whose responses on the questions about faces showed no variability ($SD < 0.5$), were excluded. This criterion aimed to ensure an adequate level of variation in the responses and maintain the sensitivity of the analysis. Based on these exclusion criteria 9 participants were excluded. The remaining 154 participants were included in the analyses ($N = 154$, 53 male, 96 female, 2 non-binary/third gender, 1 prefer not to say, 2 other). The sample was split into two groups, 18-39 years ($n = 87$, $M = 24.45$, $SD = 4.30$), and 40-90 years ($n = 67$, $M = 57.46$, $SD = 9.82$).

At the start of the survey participants were informed about the purpose of this study and about their rights during the study. All participants had to be of the age of 18 years or older, participation was voluntary, and participants could terminate the survey at any time without an explanation. This study was approved by The Faculty Ethics Review Committee (FETC) of Utrecht University, under number 23-1426. Data has been controlled by Utrecht University according to the General Data Protection Regulation (GDPR).

Design

To investigate the relationship between age and the level of trust in AI, this study used an experimental mixed methods design, with *label of faces* (2 levels: *natural* and *computer-generated*) as a within-subjects factor, and age group as between-subject factor (2 levels: *younger* and *older*). The independent variables were *label of faces* and *age group*. The dependent variables were the *perceived trustworthiness of faces*, *negative attitudes towards AI in general, positive attitudes towards AI in general, generalized trust, promotion focus, and* *prevention focus*. In addition to the main independent variables, *prevention focus* was included as a covariate in the analyses. The inclusion of *prevention focus* as a covariate aimed to account for its potential influence on the relationship between age and trust in AI, controlling for its effects in the statistical models.

Procedure

Using the online software program Qualtrics, a survey was created. The survey was presented in Dutch to participants who were using a web browser with Dutch as their default language. Participants who were using a browser with a language other than Dutch would be presented with the English version of the survey.

The survey started with a cover story in which participants were informed about the main purpose of the study, and the advanced capabilities of current computer technologies in creating faces that are nearly indistinguishable from real faces. Following the cover story, informed consent was asked (see Appendix A for more information on the cover story and the informed consent letter).

The first part of the survey replicated experiment 1 from the study by Liefooghe et al. (2023), in which participants were asked to rate 24 faces, either labelled as 'natural' or as 'computer-generated', on their trustworthiness. Afterwards, a manipulation check was done where participants were asked how believable they found it that the computer-generated faces were indeed generated by a computer on a 7-point Likert scale (1 = Not at all, 7 = Extremely). Then, participants were provided with three questionnaires. First the Regulatory Focus Questionnaire (RFQ), then the General Trust Scale (GTS), and finally the General Attitudes toward Artificial Intelligence Scale (GAAIS) (see Appendix C). All questionnaires, originally in English, were translated to Dutch and then back to English by a bilingual person, to ensure that the questionnaires remained their quality and validity when presented in Dutch. At the start of each questionnaire instructions were provided.

After completing the questionnaires, participants were asked for their age, gender, and the country they currently live in. Finally, participants were thanked and received a debriefing (see Appendix B for more information on the debriefing).

Materials

Trust in faces task

To measure the level of trust in AI, experiment 1 from the study by Liefooghe et al. (2023) was replicated. Using a 7-point Likert scale (1 = 'Absolutely not', 7 = 'Extremely'), participants were asked to rate 24 faces on their trustworthiness. These 24 faces were images of natural faces that were selected from the Chicago Face Database (Ma et al., 2015), and consisted of black and white males and females between the ages of 18 and 40 years. Based on the trustworthiness and attractiveness ratings as provided in this database, four categories of six faces were created, with the most extreme scores on both dimensions. Each category was randomly divided into two sets of three faces that were either labelled as 'computer-generated' or as 'natural'. The experiment resulted into two subscales, that both showed good internal reliability (natural: α = .81, computer-generated: α = .80). All faces were cropped in an oval shape, excluding hair and clothing, to ensure that the faces were rated properly.

In contrast to the original study, the labels underneath the faces were provided in different colors (natural = orange letters, computer-generated = blue letters) to create a better distinction between the two types of faces and make the labels more notable. It was decided to use the colors orange and blue, since these colors are distinguishable for people who are colorblind (Wong, 2011). An example illustrating the task is presented in Figure 1.

Figure 1.

Illustration of the Rating Task and Stimuli of Experiments

Regulatory Focus Questionnaire

To measure participants' predominant type of regulatory focus, the Regulatory Focus Questionnaire (RFQ) (Higgins et al., 2001) was used. This questionnaire is designed to assess individuals' orientations toward their goals. The questionnaire includes 11 items that are scored on a 5-point Likert scale, with the response options varying for each question (see Appendix B). The RFQ includes two subscales, prevention focus and a promotion focus. The Promotion focus subscale assesses an individual's motivation to achieve their aspirations, hopes, and ideals, while the Prevention focus subscale assesses an individual's motivation to avoid negative outcomes and to fulfill their duties and responsibilities. The RFQ includes six questions that quantify Promotion focus (e.g., "How often have you accomplished things that got you 'psyched' to work even harder?") and five questions that quantify Prevention focus (e.g., "How often did you obey rules and regulations that were established by your parents?), resulting in a separate score for both subscales. The Prevention focus subscale showed good internal reliability with a Cronbach's α of .80). The Promotion subscale, however, showed a weak internal reliability of α = .52. Therefore, the Promotion focus subscale was not included in the analyses.

Generalized Trust Scale

General trust was measured using the Generalized Trust Scale (GTS) (Yamagishi & Yamagishi, 1994). This is a questionnaire that uses general statements to measure participants' beliefs about honesty and trustworthiness of others, in general. The GTS includes six items, such as *"Most people are basically honest"*, that are scored on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The GTS showed an acceptable internal consistency with a Cronbach's α of .77.

General Attitudes toward Artificial Intelligence Scale

To capture the general beliefs, opinions, and sentiments participants hold regarding AI technology, the General Attitudes toward Artificial Intelligence Scale (GAAIS) (Schepman & Rodway, 2020) was used. Through two subscales, the GAAIS distinguishes between positive and negative attitudes toward AI. The GAAIS includes twelve questions that quantify the positive attitudes, such as *"Artificial Intelligence is exciting"* (positive), and eight questions that quantify the negative attitudes, such as *"I think artificially intelligent systems make many errors"* (negative), resulting in independent scores for positive and negative attitudes towards AI. Additionally, an attention check was embedded in the questionnaire. The questions are scored on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Both subscales showed good internal consistency (positive: $\alpha = .87$; negative: $\alpha = .83$).

Data-analysis

The statistical analyses were conducted using *IBM SPSS statistics v27*. First, prior to the analyses, the data was prepared and scanned on inclusion criteria, and the standard deviations were calculated for the scores on trustworthiness of faces. Participants who did not meet the inclusion criteria or had missing data were removed from the sample. Additionally, participants who failed the attention check from the GAAIS scale were excluded from analyses regarding the GAAIS. An explorative analysis was conducted for all variables to check for outliers. All analyses were conducted with and without outliers, to check whether they could have influenced the findings.

Secondly, all items on the negative subscale from the GAAIS, and item 1, 2, 4, 6, 8, 9, and 11 on the RFQ needed to be reverse coded. The scale scores were calculated when the Cronbach's alpha (α) was above 0.7. The descriptive statistics and Pearson correlations of the data were analyzed. Then, a one sample T-test was conducted to examine whether the mean score on the manipulation check question (e.g., 'How believable did you find it that the computer-generated faces were indeed generated by a computer?') was significantly different from the middle of the Likert scale for both groups.

Then all dependent variables were checked for normality using the Shapiro-Wilk test. The Shapiro-Wilk tests showed that the distributions were significantly normal for the variables CG_mean ($W(154)= 0.98$, $p = .034$), GAAIS_positive ($W(154) = 0.98$, $p = .01$), GTS_mean ($W(154) = 0.95$, $p < .001$), and RFQ_prevention ($W(154) = 0.98$, $p = .04$). The distributions were significantly non-normal for the variables NAT_mean ($W(154) = .99$, $p = .19$), GAAIS_negative ($W(154) = .99$, $p = .20$). However, when visualizing the scores on these variables using histograms, the data was normally distributed for all variables. The assumption check for normality was therefore met. While a test for sphericity is usually required as an assumption check for a repeated measures ANOVA, in this study it was not necessary as there were only two levels of the within-subject factor (Park et al., 2009). Thus, there was no need for a correction on the degrees of freedom, and data was interpreted under the assumption of sphericity.

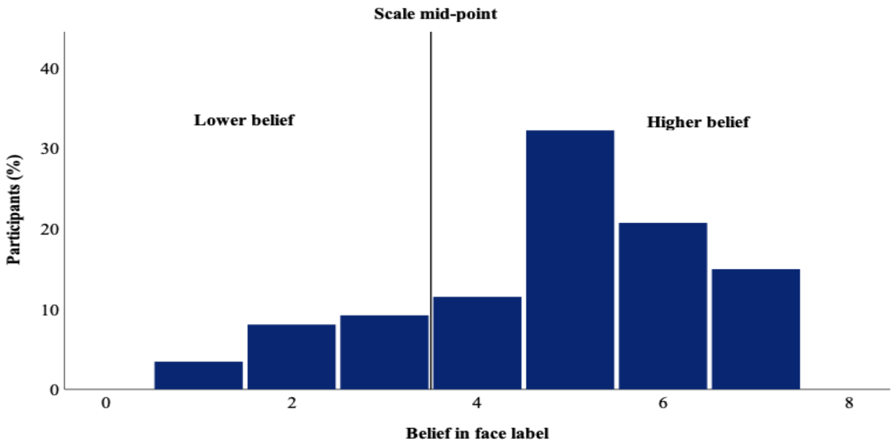
Two one-way ANOVAs were conducted to test whether the two age groups had scored differently on the GAAIS positive- and negative subscale. Then, to test our main hypothesis that older individuals have different levels of trust in AI compared to younger individuals, a repeated measures 2x2 ANOVA was conducted with *label of faces* (2) as within-factor, and *age group* (2) as between-factor. Next, a one-way ANOVA was conducted to test whether older individuals had a stronger prevention focus compared to younger individuals. Finally, to test whether prevention focused self-regulation influenced the effect of age on trust in faces, a repeated measures 2x2 ANCOVA was conducted with *label of faces* (2) as within-factor, *age group* (2) as between-factor, and *prevention focus* as covariate.

Results

Manipulation and Attention check

The overall belief of participants in the younger age group that the computer-generated faces were actually generated by a computer was 4.83 (*SE* = .17). This was significantly higher than the middle of the Likert scale, t (87) = 7.74, $p < .001$. The overall belief of participants in the older age group was 4.63 (*SE* = .20), which was similarly significantly higher than the middle of the Likert scale, t (67) = 5.69, $p < .001$. The percentage of participants distributed across the belief scale is shown in Figure 2.

Figure 1.
Distributions of Believability Ratings



Age and General Attitudes towards AI

Of all participants (N = 154) who completed the survey, 66 participants failed the attention check in the GAAIS. Therefore, only the participants who passed the attention check (N = 88) were included in the analyses regarding the GAAIS. First, two univariate ANOVAs were conducted to test whether there was a difference between the two age groups on the negative and positive attitudes towards AI in general. The mean scores and standard errors are reported in Table 1. The results indicated that the younger age group scored lower on the negative attitudes towards AI scale compared to the older group. However, the difference between the two groups was not statistically significant, F (1,86) = 3.42, p = .07, η^2 = .04. Additionally, no significant difference was found between the scores of the younger and the older group on positive attitudes towards AI in general, F (1,86) = 2.21, p = .14, η^2 = .03. These results indicate that there were no significant differences in the general attitudes towards AI between the two age groups. Therefore, hypothesis 1was not supported.

Table 1

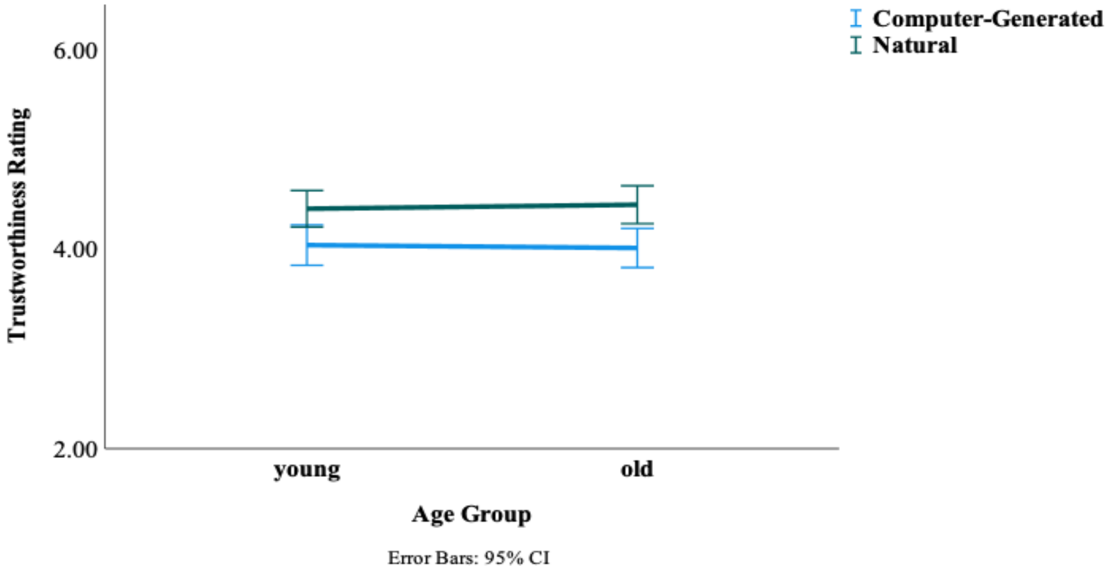
Mean scores and SE's for both age groups on all dependent variables

	Younger (18-39 years)			Older (40-90 years)		
Variable	N	M	SE	N	M	SE
Trust 'Natural' faces	87	4.40	.09	67	4.44	.10
Trust 'Computer-generated' faces	87	4.04	.10	67	4.01	.11
Average Trust in Faces	87	4.22	.08	67	4.23	.09
Negative Attitudes towards AI	66	2.71	.08	22	2.99	.13
Positive Attitudes towards AI	66	3.39	.07	22	3.60	.12
General Trust	87	3.52	.06	67	3.77	.07
Prevention Focused self-regulation	87	3.24	.09	67	3.56	.09

Age and Trust in AI

Secondly, a repeated measures 2X2 ANOVA was conducted to test whether there was a difference between the two age groups on the level of trust in AI. The mean scores and standard errors are reported in Table 1. A significant main effect of label was found on the level of trust in the faces, replicating the results from the study by Liefooghe et al. (2023). This means that the faces labelled as computer-generated (M = 4.03; SE = .07) were rated to be less trustworthy compared to faces labelled as natural (M = 4.42; SE = .07), $F(1,152) = 39.07$, $p < .001$, $\eta^2 = .20$. Nevertheless, the results showed no significant main effect of age on the level of trust. Thus, there was no significant difference between the older group (M = 4.23; SE = .09) and the younger group (M = 4.22; SE = .08) on ratings of trustworthiness, F (1,152) = .002, p = .96. Finally, there was no significant interaction effect between age group and label of faces, F (1,152) = .29, p = .59, η^2 = .002. This means that the effect of label on the level of trust in faces was similar for the older group and the younger group. Therefore, hypothesis 3 was not supported. Figure 3 shows the mean trustworthiness scores, and standard errors for both age groups.

Figure 3.
Main Effect of Label on Trustworthiness ratings



Age and prevention focus

Third, a univariate ANOVA was conducted to test whether the older group had a stronger prevention focus compared to the younger group. The analysis revealed that the older group (*M* = 3.56; *SE* = .098) scored significantly higher on the prevention focus scale compared to the younger group (*M* = 3.24; *SE* = .09), *F* (1,152) = 6.10, *p* = .02, η^2 = .04. Hypothesis 4 was therefore supported.

Age, Trust in AI, and prevention focus

Then, a repeated measures 2X2 ANCOVA was conducted to test whether prevention focused self-regulation influenced the effect of age group and label on the level of trust in faces. The results showed that prevention focused self-regulation did not influence the relationship between age and the level of trust in faces, *F* (1,151) = .64, *p* = .42. Furthermore, there was no significant main effect of age group on the level of trust in faces, *F* (1,151) = .01, *p* = .91. This means that the non-significant effect of age group on the level of trust in faces was not influenced by participants' prevention focused self-regulation, and consequently hypothesis 6 was not supported.

Correlation analysis

Next, a correlation analysis was conducted for all variables to examine the relationships between the variables. Results of the correlation analysis are reported in table 1. The correlation analysis revealed that there was no significant correlation between negative attitudes towards AI and the level of trust in computer-generated faces. Hypothesis 2 was therefore not supported. Moreover, there was a significant, weak, positive correlation between prevention focused self-regulation and trust in general, r (154) = .17, p < .05. Hypothesis 5 was not supported, as we expected to find a negative correlation between prevention focus and generalized trust. Then, a significant, moderate positive correlation was found between the trustworthiness ratings of the natural and the computer-generated faces, r (154) = .58, p < .001, and between the negative and positive general attitudes towards AI, r (88) = .43, p < .001.

Additionally, the results indicated a significant, weak, positive correlation between age and the level of generalized trust, r (154) = .23, p < .001. We conducted a univariate ANOVA to further investigate the differences between the two age groups. There was a significant difference between the older group (M = 3.77; SE = .07) and the younger group (M = 3.52; SE = .06) on scores of generalized trust, F (1,152) = 7.71, p = .006, η^2 = .05. These findings indicated that older participants scored higher on measures of generalized trust compared to younger participants.

Table 2

Pearson correlations.

Variable	1	2	3	4	5	6	7
1. Age	–						
2. Trust ‘natural’ faces	.02	–					
3. Trust ‘computer-generated’ faces	-.03	.58**	–				
4. Negative Attitudes Towards AI (N = 88)	.21	-.001	.01	–			
5. Positive Attitudes towards AI (N = 88)	.12	-.06	.11	.43**	–		
6. General Trust	.23**	.02	.04	.20	.07	–	
7. Prevention Focus	.24**	.09	.03	.11	-.06	.17*	–

* Correlation is significant at the 0.05 level (2-tailed).

** Correlation is significant at the 0.01 level (2-tailed).

Discussion

The main purpose of this study was to further investigate the relationship between negative attitudes and the level of trust in AI, and additionally investigate whether age, and individuals' self-regulation influenced the level of trust in AI.

Firstly, we successfully replicated the findings from the study by Liefooghe et al. (2023), demonstrating that faces labelled as computer-generated were perceived as less trustworthy compared to faces labelled as natural. This suggests that the label effect observed in the previous study extends to our sample, indicating a general evaluative conditioning effect towards computer-generated faces.

While previous studies suggested that people higher in age have more negative attitudes towards AI, compared to younger people (Zhang & Dafoe, 2019; Schepman & Rodway, 2022), we found no significant difference between the two age groups in their attitudes towards AI in general. Furthermore, based on the study by Tussyadiah and colleagues (2021), we expected that negative attitudes towards AI would decrease the level of trust in AI. In addition, we hypothesized that the older group would have less trust in AI compared to the younger group, based on the findings in the study by Gillath and colleagues (2021), in which they suggested that older adults and individuals who are less familiar with AI tend to have less trust in AI. However, we found no effects of either general attitudes or age on the level of trust in AI. Furthermore, our findings suggest that older individuals showed a stronger prevention focus compared to younger individuals, which was in line with the findings by Lockwood et al. (2005). While we proposed that prevention focus would be negatively associated with generalized trust (Keller et al., 2015), as opposed to our expectations, the analysis indicated a positive association between prevention focus and generalized trust. However, this was a weak association, and the effect can be neglected. Additionally, prevention focus did not influence the level of trust in AI, nor did it influence the effect of age on trust in AI.

A possible explanation for the non-significant relationship between general attitudes and trust in AI, could be related to the fact that our hypothesis was based on a study that measured slightly different constructs. Specifically, the current study used the General Attitudes towards Artificial Intelligence Scale (GAAIS) to assess individuals' general attitudes towards AI. In contrast, Tussyadiah and colleagues applied the Computer Attitudes Scale (CAS) (Nickell & Pinto, 1986) to measure positive and negative attitudes towards computers.

Moreover, while the present study aimed to measure trust in AI, and more specifically trust in faces labelled as artificial, in their study Tussyadiah et al. (2021) focused on trust in technology in the context of self-driving vehicles. Besides trust, the level of perceived risk is a major determinant in the adoption of new technologies (Kenesei et al., 2022). The potential physical risk of trusting self-driving cars, is much larger than the potential risk of trusting computer-generated faces. As potential risks of using AI systems increases, attitudes become increasingly important in relation to the level of trust and acceptance in AI. Therefore, there might be a difference in the relationship between general attitudes and the level of trust in AI, in the context of self-driving autonomous vehicles, compared to the context of faces generated by a computer.

Furthermore, our findings suggest that age did not influence the general attitudes and the level of trust in AI. A possible explanation could reflect on the idea that age alone does not serve as a strong enough predictor of individuals' attitudes and trust towards AI. For example, trust in AI is shaped by previous experiences over time (Dikmen & Burns, 2017). Moreover, trust in AI can be influenced by a range of individual differences, including education, socioeconomic background, personal experiences, and cultural beliefs (Kaplan et al., 2021). Our expectation that age would influence the level of trust in AI, was based on the study by Gillath et al. (2021), in which an effect of age on the level of trust in AI was found. They suggested that older people, and people who are less familiar with AI, have less trust in AI. However, age, familiarity, and previous experience with AI may be interconnected factors that influence the level of trust in AI systems. For instance, Dikmen and Burns (2017) suggested that past negative experiences with AI are associated with decreased trust in AI. These factors are likely to have a more substantial impact on trust in AI than age alone. As we did not include other factors that could potentially be interconnected with age, it is possible that we did not measure a direct effect of age on the general attitudes and the level of trust in AI.

Another possible explanation for the absence of a significant effect of age on the level of trust in AI is that the faces used in the experiment potentially formed an outgroup for the older participants. According to Nakano and Yamamoto (2022), people tend to trust faces that are similar to their own. Facial similarity is affected by multiple factors, like the shape, size, and the arrangement of facial parts. In this study, we selected faces with the highest and lowest ratings for attractiveness and trustworthiness, as provided in the Chicago Face Database (Ma et al., 2015), to ensure that these facial characteristics would not influence the ratings of trustworthiness. Facial similarity can, however, also be affected by age or ethnicity for example. While the set of faces in the present study encompassed several ethnicities, the set was limited to faces to males and females between the ages of 18 and 40 years. It is possible that these faces formed an outgroup for the older group that included participants between the age of 40 and 90 years, due to the lack of similarity. The level of trust towards outgroup members is often lower than the level of trust towards ingroup members (Tamborini et al., 2018). Assuming that the faces were considered as an outgroup by the older age group, initial levels of trust could have potentially been higher and concealed by an outgroup effect.

However, in a recent study by Pehlivanoglu and colleagues (2022), they found that older individuals rated middle-aged faces and older faces as least trustworthy, in comparison to younger faces. Consequently, this would mean that the initial scores of the older group could have been lower, if the experiment included middle-aged or older faces. However, a bias in facial trustworthiness perception of own-age compared to other-age faces, might only be present in dynamic task contexts compared to appearance-based evaluation (Pehlivanoglu et al., 2022). This suggestion is supported by earlier research, in which they observed a greater truth bias for own-age faces in a video-based lie/truth detection task (Slessor et al., 2013). Therefore, it could be possible that by using a more dynamic task to measure trust in AI, age differences would appear.

Furthermore, the fact that the measure of trust in AI was merely based on appearance-based evaluations, could possibly account for the absence of an influence by prevention focused self-regulation on the relationship between age and AI. As the evaluation of faces in the current experiment did not have any consequences, and participants could not gain or lose anything by completing the experiment, the type of self-regulation did not account for the level of trust in AI in the current study.

Limitations and Recommendations

Despite the valuable insights as obtained in the current study, there are several limitations that should be considered. First, the current study focused solely on trust in faces as a measure of trust in AI. As the task to measure trust in AI was not based on any type of interaction with an actual AI system, known factors that influence trust in AI, such as transparency, consistency, and reliability (Kaplan et al., 2021), did not influence trust during the experiment. However, it is possible that these factors did shape the attitudes towards AI, prior to the experiment, and therefore contributed to the ratings of trustworthiness. A more dynamic task could potentially control for such factors, and therefore rule out other explanations that could have led to an effect on trust in AI. Furthermore, a more dynamic task, might elicit the possibility to find age related biased in facial evaluations (Slessor et al., 2013), and increase the chance to find an effect of self-regulation on the level of trust in AI. We recommend that future research compares the results of multiple tasks measuring trust in AI, to gain a better understanding of the influence of age and self-regulation on the level of trust in AI.

A second limitation of the current study is that we did not measure familiarity with AI, nor did we ask participants about their prior experiences with AI. As age, familiarity, and previous experience with AI may be interconnected factors that influence the level of trust in AI (Gillath et al., 2021), we recommend that all these factors should be taken into consideration when investigating the relationship between age and trust in AI in future research. By comparing people with similar levels of familiarity and similar experiences with AI, the possibility to measure the effect of age alone increases.

Third, a potential limitation of the current study is the possibility of an outgroup effect due to the age range of the faces used in the experiment. As mentioned earlier, the set of faces in the present study encompassed males and females between the ages of 18 and 40 years, while the older age group included participants between the ages of 40 and 90 years. Further research is recommended in which, in order to test for a potential outgroup effect, faces representative of the whole sample should be used. In addition, a more dynamic task could increase the chance of finding such an age-related bias in facial evaluations (Slessor et al., 2013).

Conclusion

In conclusion, our findings suggest that age alone might not be a strong enough predictor of trust in AI, as age might be interconnected with other factors that influence the level of trust in AI. This study obtained some valuable insights on various aspects influencing trust in AI. However, future research is necessary to further investigate the relationship between age and trust in AI.

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Appendix A
Cover Story and Informed Consent

Welcome!
Hi!

Thank you for your interest in participating in this study.

This study is conducted by Sophie Heezen (me), a master's student from the Social, Health and Organizational Psychology master program at Utrecht University. Ruud Hortensius is supervising this project. Contact details can be found on the next page.

For my master's thesis I'm investigating the perception of computer-generated faces. These are faces that do not belong to real existing people, but are completely created by a computer. The technology in this field is already highly developed, due to which extremely realistic faces can be created by using software. Research has shown that it is very difficult for people to distinguish computer-generated faces from natural faces.

To explore this, we would like to present you with some computer-generated faces and some natural faces and ask you to rate these on their trustworthiness.

After completing the experiment, we would like to ask you some more questions general questions.

Informed Consent

You are asked to participate in a scientific research. Before you decide to participate in this study, it is important that you understand the purpose of this study. Please read through the information below carefully. If you have any questions please contact us using the contact information below. Participation is completely voluntary.

Data collected in this study is for the purpose of scientific research only. Data will be controlled by Utrecht University according to the General Data Protection Regulation (GDPR). The data provided by you does not contain any personal information that could identify you.

The data from this study may be shared in a public repository for research purposes and be presented in scientific publications. Participation is completely voluntary. The survey takes about 15 minutes. You have the right to terminate the study at any moment.

If you have any questions, don't hesitate to contact us:
- Sophie Heezen (s.l.c.heezen@students.uu.nl) or
- Ruud Hortensius (r.hortensius@uu.nl.)

By clicking the button below, you acknowledge that:

- Your participation in the study is voluntary.
- You are 18 years of age or older.
- You are aware that you may choose to terminate your participation at any time for any reason.

Appendix B

Debriefing

We thank you for taking part in this study.

In this study you were asked to rate the trustworthiness of two types of faces: computer-generated and natural faces. We told you that the computer-generated faces were completely created by a computer (with artificial intelligence). However, these faces were not actually created by a computer, but were in fact all natural (real) faces. We told you that these faces were computer-generated to show that only mentioning that something is created by a computer (while in fact it is not), leads to less trust.

But more specifically, we were investigating whether this effect was influenced by your age and motivational style.

Expectations (continue to next page to finish the survey)

Previous research has shown that people judge faces merely labeled as being artificial to be less trustworthy, compared to faces labeled as natural. In this study we are investigating whether this effect is different for different age groups.

According to the Regulatory Focus Theory (RFT), what matters when we want to predict someone's behavior is to understand the motivational state the person is in. Regulatory focus refers to an individual's tendency to focus on either prevention (avoiding negative outcomes) or promotion (pursuing positive outcomes).

Research suggests that older individuals tend to have a more prevention-focused regulatory focus, which may make them more cautious and less willing to trust new technologies like AI. They may be more concerned about the potential negative consequences of AI, such as job loss or privacy breaches, and less likely to embrace the potential benefits.

Therefore, we expect that older people will have less trust in the computer-generated faces, compared to younger people because of the motivational state they are in. To determine what motivational state you were in during the experiment, you were asked to answer some questions about how frequently specific events occur or have occurred in your life.

Afterwards, you had to answer some questions about trust in general. And finally, you were asked some questions about your attitudes toward AI in general.

Goal of this study

The main purpose of this study is to determine what factors might influence the level of trust people have in AI. By figuring out which factors might be of influence, the possibility to manipulate these factors increases. The ability to manipulate factors that either decrease or increase the level of trust in AI, is of great relevance when trust is crucial for an AI system to function properly, for example in medical contexts. Also, scientifically this study can be of great relevance to rule out some factors that increase or decrease trust in AI.

Appendix C

Scales

Regulatory Focus Questionnaire (RFQ) (Higgins et al., 2001)

This set of questions asks you **HOW FREQUENTLY** specific events actually occur or have occurred in your life. Please indicate your answer to each question by circling the appropriate number below it.

1. Compared to most people, are you typically unable to get what you want out of life?

   1 2 3 4 5

   never or seldom — sometimes — very often

2. Growing up, would you ever "cross the line" by doing things that your parents would not tolerate?

   1 2 3 4 5

   never or seldom — sometimes — very often

3. How often have you accomplished things that got you "psyched" to work even harder?

   1 2 3 4 5

   never or seldom — a few times — many times

4. Did you get on your parents' nerves often when you were growing up?

   1 2 3 4 5

   never or seldom — sometimes — very often

5. How often did you obey rules and regulations that were established by your parents?

   1 2 3 4 5

   never or seldom — sometimes — always

6. Growing up, did you ever act in ways that your parents thought were objectionable?

   1 2 3 4 5

   never or seldom — sometimes — very often

7. Do you often do well at different things that you try?

   1 2 3 4 5

   never or seldom — sometimes — very often

8. Not being careful enough has gotten me into trouble at times.

   1 2 3 4 5

   never or seldom — sometimes — very often

9. When it comes to achieving things that are important to me, I find that I don't perform as well as I ideally would like to do.

   1 2 3 4 5

   never true — sometimes true — very often true

10. I feel like I have made progress toward being successful in my life.

    1 2 3 4 5

    certainly false — certainly true

11. I have found very few hobbies or activities in my life that capture my interest or motivate me to put effort into them.

    1 2 3 4 5

    certainly false — certainly true

<u>RFQ Scoring Key:</u>

The RFQ yields independent scores for Promotion and Prevention, both ranging from 1-5. There are 3 reverse-scored questions for the promotion subscale and 4 reverse-scored questions for the prevention subscale.

Six questions quantify Promotion and five questions quantify Prevention Therefore, the promotion sums must be divided by 6, and the prevention sums must be divided by 5 in order to place scores for both orientations on the same 1-5 scale:

Promotion = [(6 – Q1) + Q3+ Q7 + (6 – Q9) + Q10 + (6 – Q11)] / 6

Prevention = [(6 – Q2) + (6 – Q4) + Q5 + (6 – Q6) + (6 – Q8)] / 5

Given a large enough sample, expect a correlation between Promotion and Prevention scores of *r* = .11

General Attitudes Towards AI Scale (GAAIS) (Schepman & Rodway, 2020)

Instructions for participants: We are interested in your attitudes towards Artificial Intelligence. By Artificial Intelligence we mean devices that can perform tasks that would usually require human intelligence. Please note that these can be computers, robots or other hardware devices, possibly augmented with sensors or cameras, etc. Please complete the following scale, indicating your response to each item. There are no right or wrong answers. We are interested in your personal views.

Response Options at presentation:

Strongly disagree, Disagree, Neutral, Agree, Strongly agree

List of items:

The item order has been re-randomised and an attention check has been included, so that the scale is ready for use.

Subscale (not for display)	Number (not for display)	Item
Positive	1	For routine transactions, I would rather interact with an artificially intelligent system than with a human.
Positive	2	Artificial Intelligence can provide new economic opportunities for this country.
Negative	3	Organisations use Artificial Intelligence unethically.
Positive	4	Artificially intelligent systems can help people feel happier.
Positive	5	I am impressed by what Artificial Intelligence can do.
Negative	6	I think artificially intelligent systems make many errors.
Positive	7	I am interested in using artificially intelligent systems in my daily life.
Negative	8	I find Artificial Intelligence sinister.
Negative	9	Artificial Intelligence might take control of people.
Negative	10	I think Artificial Intelligence is dangerous.
Positive	11	Artificial Intelligence can have positive impacts on people's wellbeing.
Positive	12	Artificial Intelligence is exciting.
Attention Check	**A**	I would be grateful if you could select agree.
Positive	13	An artificially intelligent agent would be better than an employee in many routine jobs.
Positive	14	There are many beneficial applications of Artificial Intelligence.
Negative	15	I shiver with discomfort when I think about future uses of Artificial Intelligence.
Positive	16	Artificially intelligent systems can perform better than humans.
Positive	17	Much of society will benefit from a future full of Artificial Intelligence
Positive	18	I would like to use Artificial Intelligence in my own job.
Negative	19	People like me will suffer if Artificial Intelligence is used more and more.
Negative	20	Artificial Intelligence is used to spy on people

Scoring: Check compliance with the Attention Check, then discount it from the scoring. Score items marked “Positive” as Strongly disagree = 1, Disgree = 2, Neutral = 3, Agree = 4, and Strongly agree = 5. Score the items marked “Negative” in reverse so that Strongly disagree = 5, Disgree = 4, Neutral = 3, Agree = 2, and Strongly agree = 1. Then take the mean of the positive items to form an overall score for the positive subscale, and the mean of the negative items to form the negative subscale. The higher the score on each subscale, the more positive the attitude. We do not recommend calculating an overall scale mean.

Generalized Trust Scale (GTS) (Yamagishi & Yamagishi, 1994).

Using the following scale, please indicate how much you agree or disagree with the following statements:

1 *Strongly Disagree*	2 *Disagree*	3 *Neutral*	4 *Agree*	5 *Strongly Agree*

1.) Most people are basically honest.
2.) Most people are trustworthy.
3.) Most people are basically good and kind.
4.) Most people are trustful of others.
5.) I am trustful.
6.) Most people will respond in kind when they are trusted by others.

Scoring:

The score for each item is averaged together to form a continuous measure of generalized trust.