Artificial Intelligence in the Military: How its Framing as a Decision Support Tool vs. an Autonomous Decision-Maker Affects Trust of Young Adults – A Survey Experiment

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Abstract

As artificial intelligence (AI) is increasingly being integrated into military operations, and raising concerns about safety, effectiveness and ethics, it is essential to understand people's trust in those systems. This study investigates how the framing of such a system as either a decision-support tool (providing recommendations to a human commander) or as an autonomous decision-maker (independently engaging a target) affects trust in young adults. In a survey experiment, participants were randomly allocated to one of those conditions and were presented different scenarios of such an AI application in action. Their trust levels across scenarios were measured using the Trust in Automation Scale. The results revealed that young adults trusted the system significantly more when it acted as a decision-support tool. Moreover, military knowledge was positively correlated with trust, while AI knowledge was not. The findings of this study emphasise the importance of transparency and human oversight for human-AI interactions and particularly for trust in military systems.

Introduction

Militaries increasingly employ AI in decision-making processes, providing recommendations and predictions for strategic approaches such as target recognition (Panella, 2025). Artificial Intelligence (AI) is defined as "the tangible real-world capability of non-human machines or artificial entities to perform, task solve, communicate, interact, and act logically as it occurs with biological humans" (Gil de Zúñiga et al., 2023, p. 320). Upon this, military AI refers to AI used in military applications, for example as drones, robotic vehicles, intelligent surveillance, making recommendations, and cyber defence (Szabadföldi, 2021). With those systems becoming increasingly advanced and autonomous, organisations like NATO have voiced various (ethical) concerns regarding the interoperability with humans (Reynolds & Atalan, 2024; Serhan, 2024). As military personnel must rely on AI for decisions that may have lethal consequences, for example engaging a false target, trust is a key concern (McFarland, 2022).

Conceptualisation of Trust

Trust is a foundational concept in interactions with both humans and technology, although its conceptualisation may differ in these contexts. According to the Cambridge English Dictionary (2025), trust is defined as "[the] belie[f] that someone is good and honest and will not harm you, or that something is safe and reliable." This definition highlights key aspects of trust, such as helpfulness, reliability, and competence, which are central to trust in humans (Mayer et al., 1995). When applied to technology, these aspects take on a slightly different focus, emphasising the system's reliability and competence rather than interpersonal benevolence (McKnight et al., 2011). Choung et al. (2022) further distinguish two facets of trust in AI specifically: Trust in the technology's competence and trust in its ethical alignment with human values.

The current research conceptualises trust in military AI through three key elements: transparency, explainability, and human administration. Previous research has indicated that these aspects are significant contributors to trust in AI decision-making (Kox et al., 2022; Yapar, 2024). The latter, human administration, has been highlighted as particularly relevant in ethically sensitive settings like military operations (Maathuis, 2024; Yapar, 2024). Upon these findings, this study manipulates the level of human administration by presenting two different versions: One with human administration where a human operator makes the final decision on engaging a target or not, and one AI system without human administration where the AI application operates fully autonomously. By this we aim to investigate how different framings of an AI system may influence trust.

Building on the findings from before and also existing literature on trust in technology (e.g., Mcknight et al., 2011), trust in AI can be differentiated into two complementary dimensions. The first is perceived capability, often referred to as objective trust, which relates to the belief that the AI technology is capable, effective, and reliable. The second is subjective trust perception, which reflects the human willingness to rely on the AI technology, influenced by psychological and contextual factors beyond mere technical performance. These dimensions are central to the operationalisation of this study, where trust in AI will be measured using a multi-faceted scale composed of items related to perceived reliability/competence of the system, and items measuring a more subjective perception of trust, such as general trust dispositions in the context of automation.

Previous Research on Trust in AI Applied in Military Decision-Making

The application of AI in military processes has been increasing. Current applications include data processing, target identification, and strategic decision-making (Sentient Digital, Inc., 2024). Some militaries implement AI as tools aiding in decision-making. For example, the U.S. Department of Defense is employing systems such as “Project Maven”, where AI is utilised for processing large amounts of data, aiding human analysts in target identification (Manson, 2024). However, other militaries have introduced more independent systems. For example, the Israel Defense Forces have engaged systems such as "The Gospel" or "Lavender", which use surveillance data to recommend targets (Serhan, 2024). Moreover, Ukraine has been operating AI driven drones planning to shift towards full autonomy (Panella, 2024). While human oversight remains a consistent factor across countries, AI decision-making systems are increasingly acquiring independence, which raises ethical concerns (Reynolds & Atalan, 2024), for example about civilian casualties (Serhan, 2024). Upon this idea, the Netherlands, for instance, emphasises human-centered AI (HCAI) principles, ensuring that AI remains assistive rather than fully autonomous (Xu & Gao, 2024).

Balancing trust and scepticism towards AI systems is essential, particularly in military settings where both under-reliance may impair efficiency, or over-reliance could lead to errors. While AI systems can provide valuable decision-support, military personnel may distrust and ignore AI communication, which reduces their efficiency. On the other hand, research on automation bias has demonstrated that there may also be overreliance on AI, which can result in severe consequences (Alon-Barkat & Busuioc, 2022; Jones-Jang & Park, 2022; Stewart, R., & Hinds, G., 2025). For the military specifically, such critical errors have already been observed (Horowitz & Kahn, 2024), which further emphasises the importance of ensuring an appropriate level of trust.

Additionally, Lushenko (2024) found that trust in AI is enhanced when systems are not fully autonomous but remains highly precise. However, trust repair in the form of apologies (e.g. AI: "I am sorry I made a mistake) appeared to depend on social context, as civilians and military personnel responded differently (Lushenko, 2024). The reason might be that civilians are more responsive to socially framed communication, whereas military personnel may prioritise capability over emotional expression.

While prior research has largely focused on the trust perceptions of military personnel and the general public, limited attention has been given to young adults. Research about attitudes of young adults towards military and technology (Bumbuc, 2023; Barna Group, 2024) shows that younger generations tend to be more open to innovation in military contexts and show more appreciation for transparency, communication, and adaptability than older age groups. Moreover, they judge AI as more accurate compared to older generations (Barna Group, 2024) and generally report higher trust levels than older age groups (Rutgers University, 2025). These generational differences suggest that young adults may form unique expectations toward military AI, making them a highly relevant population for trust research. They form a critical target group, as they represent the next generation of voters, policymakers, and potential military recruits, whose attitudes toward future technologies will influence policies and ethical frameworks.

Hence, this study analyses whether young adults' trust in military AI is related to the framing of its application as a decision-support tool (DST) or autonomous decision-maker (ADM). To do this, a survey experiment will be conducted among young adults, who, after exposure to various framings of AI in military decision-making, will be asked about their trust levels.

Previous research suggests that trust in AI is higher when AI supports human decision-making rather than acting autonomously (Kox et al., 2022; Xu & Gao, 2024). When framed as a decision-support tool, AI aligns with human-centered AI principles, which have been associated with greater user trust (Lushenko, 2024).

Hypothesis

Young adults will show higher trust in AI when it is framed as a decision-support tool compared to an autonomous decision-maker.

Methods

Participants

In total, 149 participants started the study. However, to ensure quality and validity, participants who completed less than 90% of the survey were excluded from the analysis, as this invariably indicated that the experimental part was not finished. The age distribution showed an approximately normal curve between ages 18 and 35, with only a small number of outliers older than 40. To maintain a demographically consistent sample and focus the analysis on the target population of young adults, participants over the age of 40 were excluded ($n = 6$), given their small representation and potential differences in familiarity and values regarding AI and military technologies.

Finally, by visual inspection of boxplots, one participant was identified as an outlier on the DST and ADM index scores, suggesting a response pattern that is inconsistent with the rest of the sample. No outliers were detected in the other questionnaires. After this, the final sample consisted of 103 individuals aged between 18 and 35 years ($M = 23.74$, $SD = 3.48$). Of these, 69 (67.0%) identified as female, 33 (32.0%) as male, and 1 (1.0%) as non-binary.

Nationality was diverse with the largest groups being German (39.8%) and Dutch (21.4%). Participants resided primarily in the Netherlands (39.8%) and Germany (30.1%), and the majority were university students in Psychology (68.0%). A full overview of the demographic data can be found in Table 1.

Table 1

Demographic Characteristics of the Final Sample

Variable	Category	n	%
Nationality	Dutch	22	21.4
	German	41	39.8

	Indian	10	9.7
	American	4	3.9
	Other	26	25.2
Residence	Netherlands	41	39.8
	Germany	31	30.1
	India	9	8.7
	United States	3	2.9
	Other	19	18.4
Occupation	University Student (Psychology)	70(30)	68.0(29.1)
	Student (Applied Sciences/HBO)	10	9.7
	Working full-time	10	9.7
	Working part-time	3	2.9
	Self-employed	2	1.9
	Unemployed	4	3.9
	Other	4	3.9

A combination of convenience and snowball sampling was used to recruit participants. Most participants were students from the University of Twente (UT) students, who were recruited through the University of Twente SONA system and encouraged to forward the survey to others.

The research was approved by the University of Twente BMS Ethics Committee. In accordance with its guidelines, all participants were informed about the aim of the study, the confidentiality of their data and the possibility to withdraw from participation at any time and gave online informed consent before participation.

Design

The study followed a 2 (AI role: Decision Support Tool [DST] vs. Autonomous Decision Maker [ADM]; between subjects) × 4 (Scenario 1-4; within-subjects) mixed design. Participants were randomly assigned (by Qualtrics) to one of the two conditions and were each exposed to all four scenarios in which the AI system played either a supportive or autonomous role. The independent variable was the role of the AI system (DST vs. ADM) and the dependent variable was the level of trust, measured by participants' answers to the Trust in Automation Scale (Körber, 2018).

Materials & Procedure

The questionnaire was available in English and German. After giving consent, four questionnaires followed. The first one was a self-constructed pre-experiment questionnaire (see Appendix A), which assessed participants' prior knowledge and attitudes toward AI and military (e.g., "Have you ever used any of the following applications of AI?" or "Have you ever served in the military or undergone military training?"). The items were scored to reflect both the presence and degree of familiarity or experience (see Table 2). Responses were aggregated into three composite knowledge scores: AI Knowledge ($M = 1.62$, $SD = 0.43$, $\alpha = 0.42$), Military Knowledge ($M = 1.80$, $SD = 0.59$, $\alpha = 0.56$), and Military AI Knowledge ($M = 1.27$, $SD = 0.92$, $\alpha = 0.65$), and were calculated by summing the points assigned to each item.

Item Scoring

For checklist-style items (e.g., "Which of the following AI applications have you heard of?"), 1 point was given per selected option. For ordinal items (e.g., "How familiar are you with the roles and responsibilities of the military in your country?") a graduated scoring system (0, 1, or 2 points) was used to capture increasing levels of involvement. In some cases, 0.5-point steps were applied where differences between response levels were meaningful but not large enough to justify a full 1-point increase. For example, in the item "Do you personally know anyone who served in the military?” responses ranged from ‘No’ (0 points), to ‘An acquaintance’ (1 point), to ‘Someone close to me’ (1.5 points), allowing for more nuanced composite scores.

An open-ended question asking participants to define AI, was evaluated on a 5-point scale reflecting clarity, accuracy, and inclusion of keywords (see Appendix D). Responses in both English and German were evaluated using the same list of keywords translated verbatim. All remaining items followed a Likert Scale scoring procedure. The item “Are you familiar with the term ‘Artificial Intelligence (AI)’?” was excluded from further analysis as only one participant answered ‘No’, which we interpreted as an accident as a reasonable definition was provided later on.

Table 2

Overview of Item Scoring for AI and Military Experience Variables

Item ID	Item Text (Abbreviated)	Response Option	Score
A3	Have you studied or worked with AI?	Yes, studied AI	1
		Yes, worked professionally with AI	1
		Both studied and worked with AI	2
		No	0
M2	Heard of AI-based military applications? (Select all that apply)	Autonomous drones or robotic weapons	1
		AI-based surveillance and facial recognition systems	1
		AI-assisted cybersecurity and cyber warfare	1
		AI in logistics and supply chain for the military	1
		None of the above	0

M3	Engaged with military-related content? (Select all that apply)	Studied military history or strategy	1
		Follow military-related news	1
		Played military simulation games	1
		Watched military documentaries or movies	1
		None	0
M4	Served in the military or undergone training?	Currently serving	1.5
		Previously served	1
		Completed training	0.5
		No	0
M5	Personally know anyone who served in the military?	Someone close to me	1.5
		An acquaintance	1
		No	0
AM1	Familiarity with AI in military contexts	Very familiar; studied/worked on it	2
		Read or heard about it	1
		Vague understanding	0.5
		Not familiar	0
AM2	Heard of specific AI military applications? (Select all that apply)	Autonomous drones or robotic weapons	1
		AI-based surveillance and facial recognition systems	1
		AI-assisted cybersecurity and cyber warfare	1
		AI in logistics and supply chain for the military	1
		None of the above	0

Internal Consistency and Construct Validity

To assess the internal consistency and construct validity of the self-constructed knowledge scales, we computed Cronbach's alpha (α) and conducted exploratory factor analyses where applicable.

The AI Knowledge score was comprised of three self-constructed items. A factor analysis using Maximum Likelihood revealed a poor fit for a unidimensional structure, with standardised factor loadings of 0.17 (A2), 1.00 (A3), and 0.05 (A4). The factor explained 34% of the variance, with a mean item complexity of 1 and a low internal consistency ($\alpha = 0.42$).

The Military Knowledge Score contained six items with factor loadings ranging from 0.16 to 0.93. The Kaiser-Meyer-Olkin measure of sampling adequacy was 0.63, suggesting mediocre factorability. Internal consistency was modest ($\alpha = 0.56$). These findings suggest the measure had limited internal consistency and structural validity in this sample. Despite this, the scale was retained for descriptive and correlational analyses, given the nature of knowledge constructs.

Military AI Knowledge Scale consisted of two items addressing knowledge of AI applications in military contexts. Due to the small number of items, no factor analysis was conducted. The inter-item correlation was moderate ($r = 0.71$), and internal consistency was acceptable for such a small scale ($\alpha = 0.65$).

Experimental Part

After the pre-experiment questionnaires, each participant was exposed to four self-constructed scenarios (Appendix B), which illustrated various AI decision-making systems functioning in real-world military contexts. The scenarios covered four different applications, namely (1) autonomous weapons, (2) target identification, (3) automated drones, and (4) predictive analysis. Each participant was presented with all four scenarios in the same order, but in one of two versions: One group of participants read scenarios in which the military system merely provided information and recommendations to a human decision-maker (DST), but in the scenarios of the other group, the system autonomously identified and also engaged a target (ADM). The aim of this part was to assess participants' perceptions of AI trust depending on the level of autonomy of the system.

To do this, a subset of the Trust in Automation Scale (Körber, 2018) was used. The four items from the ‘Understanding/Predictability’ subscale were deemed unapplicable and thus not used for this study. The selection included a list of 15 statements, for example “The system works reliably “. For each statement the participants answered on a 7-point Likert scale ranging from 1 *(Strongly Disagree)* to 7 *(Strongly Agree).*

Next, we conducted a manipulation check for which all participants answered a Realism Questionnaire (Gelder et al., 2018), which uses a 5-point Likert scale ranging from 1 *(Strongly Disagree)* to 5 *(Strongly agree)* to assess the realism and comprehensibility of the scenarios. An example item is, “The scenarios seemed real to me.”. Afterwards, the participants completed a demographics questionnaire, in which they reported their age, gender, academic background, nationality, and country of residence.

In the final part of the survey, the subjects confirmed their participation in a final debriefing (see Appendix C), which thanked the participant and explained the purpose of the research, and how their data would be processed. The full survey was constructed and answered in Qualtrics and took approximately 10-15 minutes to complete.

Data Analysis

All data analysis was conducted in the statistical software R Studio using the packages tidyverse, tidyr, janitor, readr, readxl, psych, ggplot2, dplyr, emmeans, afex, and stringr. The R-code can be found in Appendix E.

To assess the internal consistency of the self-constructed scales, Cronbach's alpha was calculated. Furthermore, descriptive statistics were computed for all variables, including trust scores, demographic information, and perceived realism and comprehensibility of the scenarios.

To test the hypothesis, a mixed ANOVA was performed. Parametric assumptions were tested prior to this. The between-subjects factor was the role of the AI (autonomous vs. support tool), and the within-subjects factor was the four specific scenarios. The dependent variable was the rating of trust in the AI system after each scenario. This analysis allowed for testing the effect of AI role on trust, while accounting for potential variation across different scenarios and exploring for interaction effects.

Further exploratory analyses examined whether trust scores varied by prior AI/military knowledge or demographic variables. One-way ANOVAs were used for this.

Results

Preliminary Analyses

Descriptive statistics and intercorrelations of the knowledge indices are presented in Table 3. The indices show variability with means ranging from 1.37 to 1.80 and standard deviations between 0.43 and 0.92. While most indices correlate quite strongly ($r \geq .85$), indicating high internal consistency, the relationship between AI Knowledge and Military Knowledge is rather low ($r = .41$).

Table 3

Descriptive Statistics and Correlations of the Knowledge Scales

Index	M	SD	1	2	3	4
1. AI Knowledge	1.62	0.43	1.00	0.41	0.85	0.96
2. Military Knowledge	1.80	0.59	0.41	1.00	0.86	0.88
3. Military-AI Knowledge	1.27	0.92	0.85	0.86	1.00	0.97
4. Combined Knowledge	1.56	0.50	0.96	0.88	0.97	1.00

Table 4 displays the mean trust scores across scenarios for each condition. Trust levels were consistently higher in the DST condition than in the ADM condition across all four scenarios.

Table 4

Descriptive Statistics Trust Scores

Scenario	ADM (n = 50)	DST (n = 53)
Scenario 1	3.40 (*SD* = 1.63)	3.66 (*SD* = 1.64)
Scenario 2	3.45 (*SD* = 1.67)	4.03 (*SD* = 1.69)
Scenario 3	3.33 (*SD* = 1.71)	3.87 (*SD* = 1.66)
Scenario 4	3.12 (*SD* = 1.65)	3.99 (*SD* = 1.69)

Preliminary analyses examined correlations between prior knowledge and trust scores (see Table 5). Military knowledge was significantly positively correlated with trust, whereas AI knowledge and military-AI knowledge were not. Detailed correlation coefficients and significance levels are presented in Table 5.

Table 5

Correlations of Knowledge Indices and Trust Scores

	1	**2**	**3**	**4**
1. Trust Scores	1.00	0.17	0.32*	0.02
2. AI Knowledge	0.17	1.00	0.22*	0.31*
3. Military Knowledge	0.32*	0.22*	1.00	0.53*
4. Milit-AI Knowledge	0.02	0.31*	0.53*	1.00

*Note. * indicates $p < 0.05$.

Realism and Comprehensibility

The average realism score was 3.76 (*SD* = 0.61). To ensure that differences in trust were due to the manipulated AI role (ADM vs. DST) and not due to scenario differences, an independent-samples *t*-test was conducted on realism and comprehensibility across conditions. This indicated no significant difference in realism scores between the ADM ($M = 3.70$) and DST ($M = 3.76$) conditions, $t(92.16) = –0.57$, $p = .57$, 95% CI [–0.28, 0.16], suggesting the manipulation was successful.

Hypothesis Testing

Sphericity Assumption

Mauchly's test of sphericity indicated that the assumption of sphericity was violated for both the main effect of scenario and the AI role × scenario interaction, $W = 0.759$, $p < .05$. To correct for this, Greenhouse-Geisser and Huynh-Feldt corrections were applied, and both suggested significant results for the main effect (GG $p = .008$, HF $p = .008$) and the interaction effect (GG $p = .003$, HF $p = .002$), confirming the significance of these effects after adjusting for the violation. The adjusted degrees of freedom and corresponding *p*-values were used in all reported analyses, and the sphericity violation did not alter the interpretation of the effects.

Main Effects and Interaction

To test the hypothesis that trust would be higher in the DST condition than in the ADM condition (H1), a 2 (AI role: ADM vs. DST; between-subjects) × 4 (Scenario; within-subjects) mixed ANOVA was conducted to examine the effects of AI role and scenario on trust in AI.

The analysis demonstrated a significant main effect of AI role on trust, $F(1, 102) = 8.88$, $p = .0036$, $\eta^2 = 0.067$, with trust being higher in the DST condition compared to the ADM condition across scenarios (see Table 4). There was also a significant main effect of scenario, $F(3, 306) = 4.30$, $p = .0054$, $\eta^2 = 0.007$, indicating that trust scores varied across the four scenarios. Post hoc Tukey tests revealed that scenario 2 had a significantly higher trust score than scenario 1 ($\Delta M = 0.21$, $p = .003$) and scenario 4 ($\Delta M = 0.18$, $p = .017$). No other significant differences were found.

Furthermore, a significant interaction between AI role and scenario was observed, $F(3, 306) = 7.14$, $p < .001$, $\eta^2 = 0.012$, suggesting that the effect of scenario on trust depends on the AI role. This difference was smallest in scenario 1 ($\Delta M = -0.26$, $p = .002$) and increased progressively across scenarios, reaching the largest difference in scenario 4 ($\Delta M = -0.86$, $p < .001$).

Discussion

This study aimed to examine to what extent the framing of AI systems in military decision-making as either Decision Support Tools (DST) or Autonomous Decision-Makers (ADM), influences trust among young adults. The study hypothesised that trust would be higher when AI is framed as a decision support tool than when it is an autonomous decision-maker. This hypothesis was supported by the data. Moreover, trust was consistently higher in the DST condition across all four military scenarios. These findings align with previous literature suggesting that human-centered AI systems, which retain human oversight and emphasise transparency and explainability, tend to advance greater trust (Kox et al., 2022; Xu & Gao, 2024; Maathuis, 2024).

This study focused on young adults ages 18 to 35 but older age groups may have different outcomes due to generational differences and varying attitudes regarding technology and military. For example, older adults may show decreased trust in autonomous systems due to lower exposure to AI and other technologies, while younger adults may be more accepting due to enhanced familiarity with technology (Rahman et al., 2024).

The results also reflect broader societal concerns regarding accountability and control in lethal decision-making processes, where the absence of a human final decision-maker is often perceived as ethically problematic (McFarland, 2022; Lushenko, 2024). For example, some authors have been referring to autonomous weapon systems as “killer robots”, criticising that war crimes may be committed without consequences for a liable individual (Crootof, 2014), and “dehumanise” warfare due to the lack of emotions like regret, discomfort and hesitation (Lin et al., 2008). Tangredi and Galdorisi (2021) further highlight how the integration of AI and machine learning in military contexts is changing warfare but also raising essential ethical questions about lethal AI decision-making, stressing the importance of human oversight, ensuring accountability and compliance with international law.

Interestingly, the difference in trust between DST and ADM conditions grew across scenarios, reaching its peak in the fourth scenario, which dealt with predictive analysis and preventative attacks. This suggests that participants may perceive predictive autonomy as especially sensitive or risky. Predictive autonomy involves making decisions based on forecasts of potential future events, which often implies increased feelings of uncertainty (Stødle et al., 2024) and therefore lower perceived trust (Lewis, 2008). These findings highlight not only the importance of how AI is used, but also how its role and limitations are communicated to stakeholders such as military personnel and the public (Horowitz, 2018; Tangredi & Galdorisi, 2021).

In addition to this effect, exploratory analyses exposed that military knowledge was significantly correlated with higher trust in AI, while AI knowledge and military AI knowledge were not. This might suggest that individuals with a better understanding of military operations are more open to technological integration, possibly viewing AI as a useful tool rather than a threat (Schmid et al., 2022). In contrast, the results revealed that AI knowledge and military AI knowledge are not correlated with higher trust in AI. These findings may support findings from Zhang and Dafoe (2019) indicating that individuals with increased AI knowledge show higher awareness of the technology's uncertainties and other limitations. However, it is important to note that the findings from the present study should be interpreted with caution as some of the knowledge scales showed low internal consistency.

Implications

These findings offer valuable insight for military organisations and policymakers who want to implement AI systems ethically and effectively. Transparency and perceived human control are shown to be essential for improving public and personnel trust. Framing AI as a decision-support tool may improve acceptance, particularly among younger demographics (Rahman et al., 2024) who are both more likely to start participating in the military and/or politics in the near future (Sahay, 2018). This demographic's attitudes towards AI will shape the future integration of such technologies in defence sectors worldwide.

Furthermore, a clear communication about the role and limitations of the AI system is crucial for fostering trust. Explicitly stating that a human commander will make the final decision can reduce concerns about autonomy, ethics, and accountability of military personnel and the public (Hadlington et al., 2024). In a military setting, assuring an appropriate level of trust in the system, is necessary for effective and efficient integration of AI technologies into military processes (Mayer, 2023). Highlighting the support function and lack of autonomy of AI systems can help align efficiency with ethical standards, and expectations of stakeholders (Schmid et al., 2022).

Limitations

There are also some limitations to be considered. First, as mentioned, the internal consistency of the self-constructed knowledge scales was limited, impairing the confidence of correlations between prior knowledge and trust. Second, the sample was relatively diverse in nationality but largely composed of psychology students from Western countries (primarily Germany and the Netherlands) who have limited military experience. This affects the generalisability to other populations, such as ones with different cultural backgrounds and people with a military background. Third, the scenarios, while realistic and well-rated in terms of comprehensibility, were hypothetical and simplified to optimise generalisability. Thus, they may not fully capture the complexities of real-world AI deployment. Lastly, social desirability bias (Bernardi et al., 2011) may have influenced some responses, particularly on sensitive topics like military action and ethics, since European students often hold anti-war attitudes (McAlister et al., 2001).

Future Research

Upon the current study, future research could extend this work by replicating the experiment across different countries with other cultural backgrounds or societies, as they represent differing attitudes regarding the control of AI (Ge et al., 2024). Moreover, other cultures may be characterised by higher perceived external threat as this may shape their perception of the necessity for effective AI systems in military contexts (Dinev et al., 2008).

Another interesting focus could be to compare the current findings with other target groups like participants from military academies.

Next, future studies could replicate this study in more valid settings, such as employing virtual reality simulations (Harris et al., 2020) to help participants more vividly imagine or see the scenarios and therefore achieve more accurate perceptions. Alternatively, as some of the knowledge scales contained a low number of items, one could try to improve the internal consistency of these scales, for example by adding more items (Robinson, 2017).

Moreover, one could examine whether other framing dimensions (e.g., emotional tone, source credibility, or inclusion of uncertainty) further influence trust. For example, Kox et al. (2022) found that trust for partnering with machines can be elevated by communicating uncertainty, such as reporting the chance of an error. Although previous studies have employed some of these dimensions (Tomsett et al., 2020; Kox et al., 2022), future research could investigate the effects of adding those to the scenarios that were used in the present study.

Conclusion

To conclude, this study contributes to literature on human-AI interaction by showing that the framing of AI roles significantly affects trust among young adults in military contexts. Specifically, AI systems presented as decision-support tools rather than autonomous decision makers leads to elevated trust levels in young adults. These findings highlight the importance of transparency and human oversight when AI systems are employed in high-stakes environments like the military.

Moreover, young adults are a particularly relevant group in this context, as they are both likely to influence future defence policy and to represent the next generation of military personnel (Schmid et al., 2022). Understanding their concerns and building trust through transparency and clear communication are essential for ethically grounded AI implementation in military settings.

Finally, these findings provide a ground for future research to explore whether there are differences across cultures, age groups, and professional backgrounds. Investigating how people in military academies or conflict-prone regions respond to similar AI framing could provide valuable comparative insights, especially as the role of AI continues to grow (Lushenko, 2024).

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Appendices

Appendix A: Pre-experiment Questionnaire

A In this part we are interested in your knowledge about AI. Please answer the following questions.

A1 Are you familiar with the term "Artificial Intelligence" (AI)?

- ○ Yes (1)
- ○ No (2)

A2 Have you ever used any of the following applications of AI? (Select all that apply)

- ▢ Virtual assistants (e.g., Siri, Alexa, Google Assistant) (1)
- ▢ Chatbots (e.g., ChatGPT, Google Bard) (2)
- ▢ Facial recognition (e.g., phone unlocking) (3)
- ▢ AI in social media (e.g., recommendation algorithms, deepfake detection) (4)
- ▢ AI in finance (e.g., fraud detection, stock market prediction) (5)
- ▢ AI in military technology (e.g., autonomous drones, AI surveillance, cybersecurity) (6)
- ▢ None of the above (7)

A3 Have you ever studied or worked with AI in an academic or professional setting (e.g., AI-related courses, programming AI models, research on AI, working in AI-related fields)?

- ○ Yes, I have studied AI in a course or training. (1)
- ○ Yes, I have worked with AI professionally. (2)
- ○ Yes, I have both studied and worked with AI. (3)
- ○ No, I have never formally studied or worked with AI. (4)

A4 In your own words, how would you define AI (Artificial Intelligence)?

____

____

____

____

____

End of Block: AI Knowledge

Start of Block: Military Knowledge

M In this part we will ask about your military knowledge and affinity. Please answer the following questions.

M1 How familiar are you with the roles and responsibilities of the military in your country?

- ○ Not familiar at all (1)
- ○ Slightly familiar (2)
- ○ Moderately familiar (3)
- ○ Very familiar (4)
- ○ Extremely familiar (5)

M2 Which of the following military functions are you familiar with? (Select all that apply)

- ☐ National defense against external threats (1)
- ☐ Peacekeeping missions and international security operations (2)
- ☐ Disaster relief and humanitarian aid (3)
- ☐ Cybersecurity and defense against digital threats (4)
- ☐ Intelligence gathering and counterterrorism (5)
- ☐ None of the above (6)

M3 Have you ever engaged with military-related content? (Select all that apply)

- ☐ I have studied military history or strategy in an academic setting. (1)
- ☐ I regularly follow military-related news and developments. (2)
- ☐ I have played military simulation games (e.g., strategy games, combat simulators). (3)
- ☐ I have watched military documentaries or movies about warfare and defense. (4)
- ☐ I have not engaged with military topics. (5)

M4 Have you ever served in the military or undergone military training?

- Yes, I am currently serving in the military. (1)
- Yes, I have previously served in the military. (2)
- Yes, I have completed some form of military training. (3)
- No, I have never served or trained in the military. (4)

M5 Do you personally know anyone (beside yourself) who has served in the military?

- Yes, someone close to me (like a family member or close friend). (1)
- Yes, an acquaintance. (2)
- No, I do not. (3)

M6 How do you feel about the role of the military in modern society? Please try to avoid answering 'neutral'

- Very negatively (1)
- Negatively (2)
- Neutrally/unsure (3)
- Positively (4)
- Very positively (5)

End of Block: Military Knowledge

Start of Block: AI in Military Knowledge

AM Worldwide, many military organisations use AI. In this part we are interested to what extent you are aware of them. Please answer the following questions.

AM1 Have you ever heard about AI being used in military contexts (e.g. autonomous weapons, surveillance drones, etc.)?

- ○ Yes, I am very familiar and have studied or worked on this topic. (1)
- ○ Yes, I have read or heard about it in news, books, or media. (2)
- ○ Yes, but I only have a vague understanding. (3)
- ○ No, I am not familiar with AI in military applications. (4)

AM2 Which AI-based military applications have you heard of? (Select all that apply)

- ▢ Autonomous drones or robotic weapons (1)
- ▢ AI-based surveillance and facial recognition systems (2)
- ▢ AI-assisted cybersecurity and cyber warfare (3)
- ▢ AI in logistics and supply chain for the military (4)
- ▢ None of the above (5)

Appendix B: Scenarios DST and ADM

ADM1 Scenario 1:

In the middle of an ongoing conflict, military forces deploy an advanced AI-powered weapon system to the battlefield. This system constantly scans the area, identifying threats based on patterns of movement and behaviour. The goal is to quickly neutralise enemy combatants while reducing unintended harm. However, the AI must make decisions in high-pressure situations where hesitation could mean danger. The AI not only predicts threats but also takes direct action based on its findings: Without waiting for human approval, it may arrange troops or launch defensive attacks to prevent danger.

ADM2 Scenario 2:

A military intelligence team, that is trained to plan and conduct tactical operations, aims to identify enemy positions using satellite images and drone footage. To help them analyse large amounts of data, they rely on an AI system that scans for possible threats such as hidden weapons, unusual movements, or suspicious activity. The AI automatically classifies certain locations as enemy positions based on its analysis. Without additional human review, it marks these targets for military action, which may lead to immediate strikes.

ADM3 Scenario 3:

During a high-risk military operation, a fleet of AI-controlled drones is deployed for surveillance and support. These drones navigate complex terrain, track enemy movements, and provide crucial battlefield intelligence. In addition to gathering information, they can also take direct action when necessary. The drones assess the situation in real time and autonomously decide whether to attack. They engage targets based on their analysis, without waiting for human confirmation.

ADM4 Scenario 4:

Military leaders rely on intelligence to anticipate enemy actions and make strategic decisions. An AI system is introduced to analyse various sources such as news reports, social media activity, and movement patterns, to predict potential threats before they happen. The AI not only predicts threats but also takes direct action based on its findings. Without waiting for human approval, it may deploy troops or even launch preventative attacks to prevent what it sees as an imminent danger.

DST1 Scenario 1:

In the middle of an ongoing conflict, military forces deploy an advanced AI-powered weapon system to the battlefield. This system constantly scans the area, identifying threats based on patterns of movement and behaviour. The goal is to quickly neutralise enemy combatants while reducing unintended harm. However, the AI must make decisions in high-pressure situations where hesitation could mean danger. The AI analyses the battlefield and identifies potential threats, highlighting them on a screen for a well-trained human operator to review. This operator carefully considers the recommendations before deciding whether to engage a target.

DST2 Scenario 2:

A military intelligence team (they plan and conduct tactical operations) is tasked with identifying enemy positions using satellite images and drone footage. To help them analyse large amounts of data, they rely on an AI system that scans for possible threats such as hidden weapons, unusual movements, or suspicious activity. The AI highlights areas of concern, flagging possible locations of enemy weapons and people. A team of skilled human analysts then reviews the AI's findings, cross-checking with other intelligence sources before making a final decision on whether the targets should be acted upon.

DST3 Scenario 3:

During a high-risk military operation, a fleet of AI-controlled drones is deployed for surveillance and support. These drones navigate complex terrain, track enemy movements, and provide crucial battlefield intelligence. In addition to gathering information, they can also take direct action when necessary. The drones send detailed reports to skilled human commanders. Based on these insights, the commanders decide how to proceed, whether to engage hostile forces, or adjust mission plans.

DST4 Scenario 4:

Military leaders rely on intelligence to anticipate enemy actions and make strategic decisions. An AI system is introduced to analyse various sources such as news reports, social media activity, and movement patterns, to predict potential threats before they happen. Human decision-makers review these predictions and decide on the best course of action, such as increasing surveillance or preparing defensive measures.

Appendix C: Final debriefing

Thank you very much for your participation. Your perceptions are valuable. The aim of this study is to investigate to what extent young adults trust the use of AI in the military. You were allocated to one of two conditions, in which the AI system is either working fully autonomous or as a decision-support tool for military personnel, in order to investigate how the framing of AI affects trust in young adults. The collected data will be analysed to identify trends and will contribute to my research project. All responses will remain anonymous and will only be used for academic purposes. If you have any questions or would like to receive a summary of the findings, please contact this E-mail address: c.a.biester@student.utwente.nl.

Please confirm that you have understood the survey’s purpose and consent to your responses being used for research (when clicking 'no', your data will be deleted).

- I confirm (1)
- No (2)

Appendix D: AI Definition (Item A4) Scoring

Scoring Procedure for AI Definition Participants were asked to define Artificial Intelligence (AI) in an open-ended format. Each definition was evaluated on a 5-point scale reflecting clarity, accuracy, and inclusion of key AI concepts. The rubric was as follows:

Score	Meaning
4	Excellent: clear and includes more than 2 key aspects such as learning, problem-solving, use of data, or mimicking human intelligence.
3	Good: mentions 1–2 relevant aspects but is somewhat incomplete or vague.
2	Average: general idea present but lacking most key concepts.
1	Poor: vague or mostly incorrect, but some minor understanding present.
0	Incorrect or empty response (e.g., "I don't know").

Cambridge definition:

the use or study of computer systems or machines that have some of the qualities that the human brain has, such as the ability to interpret and produce language in a way that seems human, recognize or create images, solve problems, and learn from data supplied to them.

Keywords for AI Definitions

- Learning / Self-learning
- Data / Database
- Problem-solving
- Decision-making
- Information processing
- Human behavior imitation / Mimicking human intelligence

- Algorithms
- Pattern recognition
- Predictions / Forecasting
- Continuous improvement / Development
- Automation
- Reasoning
- Understanding language (Natural Language Processing)
- Image or speech recognition
- Assistance / Support in tasks
- Generating new content

Cambridge definition: the use or study of computer systems or machines that have some of the qualities that the human brain has, such as the ability to interpret and produce language in a way that seems human, recognize or create images, solve problems, and learn from data supplied to them:

Keywords for AI Definitions

- Learning / Self-learning
- Data / Database
- Problem-solving
- Decision-making
- Information processing
- Human behavior imitation / Mimicking human intelligence
- Algorithms
- Pattern recognition
- Predictions / Forecasting
- Continuous improvement / Development
- Automation
- Reasoning
- Understanding language (Natural Language Processing)
- Image or speech recognition

- Assistance / Support in tasks
- Generating new content

Appendix E: R code

```
#packages
install.packages("tidyverse")
install.packages("janitor")
install.packages("readxl")
install.packages("psych")
library(tidyverse)
library(janitor)
library(readr)
library(readxl)
library(psych)

#load dataset
X06mei_final_clean_values <- read_csv("data/06mei_final_clean_values.csv")
View(X06mei_final_clean_values)

### DATA PREPARATION
## already done in excel:
# - exclude IDs who have finished less than 90% of the survey
# - exclude survey preview
# - delete columns from the dataset that arent needed for analyses

##rename dataset
data <- X06mei_final_clean_values
view(data)

## drop IDS who are too old:
#histogram age
```

```
data$age <- as.numeric(as.character(data$age))
ggplot(data, aes(x = age)) +
  geom_histogram(binwidth = 1)

# Count how many participants are under 40
sum(data$age < 40)

# Count how many participants are 40 or older
sum(data$age >= 40)
# Total number
total <- 104 + 6
# Percentage over 40
percentage_over_40 <- (6 / 110) * 100    # = 5.45
# filter people over 40
young_adults <- data %>%
  filter(age <= 40)
view(young_adults)
nrow(data) # >> 104 are left <<



### RECODING
## SCORING OF AI, MILITARY AND MILITARY-AI KNOWLEDGE

# m2, m3 am2 recoded/scored in excel
# a3 scores - "4" -> 0, "3" -> 2, "2" -> 1, "1" -> 1
data <- data %>%
  mutate(a3_score = recode(A3, `1` = 1L, `2` = 1L, `3` = 2L, `4` = 0L ))
# m4 scores - "4" -> 0, "3" -> 0.5, "2" -> 1, "1" -> 1.5
data <- data %>%
  mutate(m4_score = recode(M4, `1` = 1.5, `2` = 1, `3` = 0.5, `4` = 0 ))
view(data$m4_score)
# m5 scores - "3" -> 0, "2" -> 1, "1" -> 1.5
data <- data %>%
  mutate(m5_score = recode(M5, `1` = 1.5, `2` = 1, `3` = 0 ))
```

```
# am1 scores - "4" -> 0, "3" -> 0.5, "2" -> 1, "1" -> 2
data <- data %>%
  mutate(am1_score = recode(AM1, `1` = 2, `2` = 1, `3` = 0.5, `4` = 0 ))



# create indices for the knowledge scores


colnames(data2)
data2 <- data %>%
  rowwise() %>%
  mutate(
    # AI Knowledge Index: Sum or mean of AI knowledge-related variables
    ai_know_index = mean(c_across(c("a2_score", "a3_score", "A4_def_score")), na.rm = TRUE),


# Military Knowledge Index: Sum or mean of Military knowledge-related variables
    milit_know_index = mean(c_across(c("M1", "m2_score", "m3_scores", "m4_score", "m5_score",
"M6")), na.rm = TRUE),
# Military AI Knowledge Index: Sum or mean of Military and AI knowledge-related variables
    aimilit_index = mean(c_across(c("am1_score", "am2_score")), na.rm = TRUE),
 # Combined Index: Average of the three indexes
    combi_index = mean(c(ai_know_index, milit_know_index, aimilit_index), na.rm = TRUE)
  ) %>%
  ungroup()
head(data2[, c("ai_know_index", "milit_know_index", "aimilit_index", "combi_index")])
summary(data2[, c("ai_know_index", "milit_know_index", "aimilit_index", "combi_index")])


## REVERSE CODING OF EXPERIMENTAL PART


#item 3
data2 <- data2 %>%
  mutate(ADM1_3_R = recode(ADM1_3, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))
data2 <- data2 %>%
  mutate(DST1_3_R = recode(DST1_3, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))
data2 <- data2 %>%
  mutate(ADM2_3_R = recode(ADM2_3, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))
```

```
data2 <- data2 %>%
  mutate(DST2_3_R = recode(DST2_3, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))
data2 <- data2 %>%
  mutate(ADM3_3_R = recode(ADM3_3, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))
data2 <- data2 %>%
  mutate(DST3_3_R = recode(DST3_3, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))

data2 <- data2 %>%
  mutate(ADM4_3_R = recode(ADM4_3, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))
data2 <- data2 %>%
  mutate(DST4_3_R = recode(DST4_3, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))

#item 5
data2 <- data2 %>%
  mutate(ADM1_5_R = recode(ADM1_5, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))
data2 <- data2 %>%
  mutate(DST1_5_R = recode(DST1_5, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))
data2 <- data2 %>%
  mutate(ADM2_5_R = recode(ADM2_5, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))
data2 <- data2 %>%
  mutate(DST2_5_R = recode(DST2_5, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))
data2 <- data2 %>%
  mutate(ADM3_5_R = recode(ADM3_5, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))
data2 <- data2 %>%
  mutate(DST3_5_R = recode(DST3_5, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))
data2 <- data2 %>%
  mutate(ADM4_5_R = recode(ADM4_5, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))
data2 <- data2 %>%
  mutate(DST4_5_R = recode(DST4_5, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))


#item 11
data2 <- data2 %>%
  mutate(ADM1_11_R = recode(ADM1_11, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L
))
```

```
data2 <- data2 %>%
  mutate(DST1_11_R = recode(DST1_11, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))
data2 <- data2 %>%
  mutate(ADM2_11_R = recode(ADM2_11, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L
))
data2 <- data2 %>%
  mutate(DST2_11_R = recode(DST2_11, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))

data2 <- data2 %>%
  mutate(ADM3_11_R = recode(ADM3_11, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L
))
data <- data %>%
  mutate(DST3_11_R = recode(DST3_11, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))
data2 <- data2 %>%
  mutate(ADM4_11_R = recode(ADM4_11, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L
))
data2 <- data2 %>%
  mutate(DST4_11_R = recode(DST4_11, `1` = 7L, `2` = 6L, `3` = 5L, `5` = 3L, `6` = 2L, `7` = 1L ))

# remove old variables
data2 <- data2 %>%
  select(
    -ADM1_3, -DST1_3, -ADM2_3, -DST2_3, -ADM3_3, -DST3_3, -ADM4_3, -DST4_3,
    -ADM1_5, -DST1_5, -ADM2_5, -DST2_5, -ADM3_5, -DST3_5, -ADM4_5, -DST4_5,
    -ADM1_11, -DST1_11, -ADM2_11, -DST2_11, -ADM3_11, -DST3_11, -ADM4_11, -DST4_11
  )

### identify outliers in experimental part

library(ggplot2)
library(dplyr)
# index scores
data2 <- data2 %>%
  rowwise() %>%
  mutate(
    adm_index = sum(c_across(starts_with("ADM")), na.rm = TRUE),
```

```
    dst_index = sum(c_across(starts_with("DST")), na.rm = TRUE),
    index_score = coalesce(adm_index, dst_index)
  ) %>%
  ungroup()
data2$adm_index
data2$dst_index
# Filter non-zero scores
filtered_data <- data2 %>%
  filter(adm_index != 0 | dst_index != 0) %>%
  mutate(
    score_type = case_when(
      adm_index != 0 ~ "ADM",
      dst_index != 0 ~ "DST"
    ),
    score_value = if_else(adm_index != 0, adm_index, dst_index)
  )

# Boxplot
ggplot(filtered_data, aes(x = score_type, y = score_value, fill = score_type)) +
  geom_boxplot(outlier.color = "red", outlier.shape = 8) +
  labs(title = "Boxplot of ADM and DST Scores (Excluding Zeros)",
       x = "Score Type", y = "Index Score") +
  theme_minimal()
# filter the outlier (australian, 26, female)
data2 <- data2 %>% slice(-53)


## OUTLIERS IN KNOWLEDGE QUETSIONNAIRES?

library(ggplot2)
library(tidyr)
library(dplyr)
# Pivot the data to long format for easy plotting
long_indices <- data2 %>%
```

```
  select(ai_know_index, milit_know_index, aimilit_index, combi_index) %>%
  pivot_longer(cols = everything(), names_to = "Index", values_to = "Score")
# Create boxplots
ggplot(long_indices, aes(x = Index, y = Score)) +
  geom_boxplot(outlier.colour = "red", outlier.shape = 8) +
  theme_minimal() +
  labs(title = "Boxplots of Knowledge Indices with Outliers Highlighted",
       x = "Index", y = "Score")

### RELIABILITY AND VALIDITY TEST FOR KNOWLEDGE SCALES
## 1. AI Knowledge Index
# AI Knowledge Items
ai_items <- data %>% select(a2_score, a3_score, A4_def_score)
# Factor Analysis
ai_fa <- fa(ai_items, nfactors = 1, fm = "ml")
print(ai_fa)
fa.diagram(ai_fa)
# Consider dropping a2_score
  # Select remaining items
ai_items_reduced <- data %>% select(a3_score, A4_def_score)
  # Factor Analysis
ai_fa_reduced <- fa(ai_items_reduced, nfactors = 1, fm = "ml")
print(ai_fa_reduced)
fa.diagram(ai_fa_reduced)
  # not possible, conduct PCA instead
ai_items_scaled <- scale(ai_items)
pca_result <- principal(ai_items_scaled, nfactors = 1, rotate = "none")
print(pca_result)

#If the first component explains a decent amount of variance (≥ 50%), you're good to go:
ai_knowledge_score <- pca_result$scores[,1]
# correlation of a2 with a3 and a4
cor(ai_items_scaled$a2_score, ai_items_scaled$a3_score)
cor(ai_items_scaled$a2_score, ai_items_scaled$A4_def_score)
```

```
cor(ai_items_scaled)
#### Cronbach's Alpha
alpha(ai_items)



## 2. Military Knowledge Index
# Military Knowledge Items
milit_items <- data %>% select(M1, m2_score, m3_scores, m4_score, m5_score, M6)
# Kaiser-Meyer-Olkin measure of sampling adequacy (optional but recommended)
KMO(milit_items)
# Factor Analysis
milit_fa <- fa(milit_items, nfactors = 1, fm = "ml")
print(milit_fa)
fa.diagram(milit_fa)
# Cronbach's Alpha
alpha(milit_items)

## 3. Military AI Knowledge Index
# Military AI Knowledge Items
militai_items <- data %>% select(am1_score, am2_score)
# Factor Analysis
militai_fa <- fa(militai_items, nfactors = 1, fm = "ml")
print(militai_fa)
fa.diagram(militai_fa)
# Just two items, so better cor instead of fa
cor(data$am1_score, data$am2_score, use = "complete.obs")
# Cronbach's Alpha
alpha(militai_items)

## validity and reliability were a fail, descriptives:
summary(data2$ai_know_index)
sd(data2$ai_know_index)
```

```
summary(data2$milit_know_index)
sd(data2$milit_know_index)
summary(data2$aimilit_index)
sd(data2$aimilit_index)
summary(data2$combi_index)
sd(data2$combi_index)


## demographic descriptives

# Load libraries
library(dplyr)

# Gender breakdown
table(data2$gender)
prop.table(table(data2$gender))

# Age summary
summary(data2$age)
sd(data2$age, na.rm = TRUE)

# Nationality breakdown
table(data2$nationality)
prop.table(table(data2$nationality))
table(data2$other_nat)

# Residence breakdown
table(data2$residence)
prop.table(table(data2$residence))
table(data2$other_res)

# Occupation breakdown
table(data2$occupation)
prop.table(table(data2$occupation))
```

```
table(data2$other_occ)
table(data2$occ_field)

## descriptives for realism
colnames(data2)



#### EXPERIMENTAL PART ####
data2$adm_index
data2$dst_index

## DESCRIPTIVES n, m, sd
library(dplyr)
library(tidyr)
library(stringr)

#how many participants per condition
sum(!is.na(data2$ADM1_1)) #50
sum(!is.na(data2$DST1_1)) #53

# Create long format but keep only filled values
data_selected <- data2 %>%
  rename(duration = `Duration (in seconds)`) %>%
  mutate(participant_id = row_number()) %>%
  select(starts_with("ADM"), starts_with("DST"), participant_id)

data_long <- data_selected %>%
  pivot_longer(
    cols = -participant_id,
    names_to = "condition_scenario",
    values_to = "score"
  ) %>%
  filter(!is.na(score))  # keep only actual responses
```

```
# Extract condition and scenario
data_long <- data_long %>%
  mutate(
    condition = ifelse(str_detect(condition_scenario, "^ADM"), "ADM", "DST"),
    scenario = str_extract(condition_scenario, "[1-4]")
  )

)

#remove participants in both between-subject conditions
library(dplyr)
data_clean <- data_long %>%
  group_by(participant_id) %>%
  filter(condition == first(condition)) %>%
  ungroup()
data_clean <- droplevels(data_clean)

#test
data_clean %>%
  group_by(participant_id) %>%
  summarise(n_conditions = n_distinct(condition)) %>%
  filter(n_conditions > 1)
contrasts(data_clean$condition) <- contr.sum(2)
contrasts(data_clean$scenario) <- contr.sum(4)

# run anova
library(afex)
data_clean$participant_id <- as.factor(data_clean$participant_id)
anova_result <- aov(score ~ scenario, data = data_clean)
summary(anova_result)

# Check how many rows per participant now
count_per_participant <- data_clean %>%
  group_by(participant_id) %>%
```

```
  summarise(n = n())
print(count_per_participant)

# Summary stats
result <- data_clean %>%
  group_by(condition, scenario) %>%
  summarise(
    mean_score = mean(score, na.rm = TRUE),
    sd_score = sd(score, na.rm = TRUE),
    .groups = "drop"
  )
print(result)

### post hoc analyses
## experimental part

# ANOVA
anova_result <- aov(score ~ scenario, data = data_clean)
summary(anova_result)
# Post hoc Tukey HSD
tukey_res <- TukeyHSD(anova_result)
print(tukey_res)
# Or with emmeans
library(emmeans)
em <- emmeans(anova_result, ~ scenario)
pairs(em, adjust = "tukey")

## interaction effect post hoc
library(emmeans)
# Fit te model with interaction
anova_interaction <- aov(score ~ condition * scenario, data = data_clean)
# Get estimated means for interaction
em <- emmeans(anova_interaction, ~ scenario * condition)
# Post hoc comparisons: scenarios within each AI role
```

```
posthoc_scenarios_within_AI <- pairs(em, by = "condition", adjust = "tukey")
print(posthoc_scenarios_within_AI)
# Post hoc comparisons: AI roles within each scenario
posthoc_AI_within_scenario <- pairs(em, by = "scenario", adjust = "tukey")
print(posthoc_AI_within_scenario)

## AI Role and Scenario Effects on Trust Scores post hoc

anova_result <- aov(score ~ condition * scenario, data = data_clean)
# Estimated marginal means for interaction
em <- emmeans(anova_result, ~ condition * scenario)
# Post hoc main effects
pairs(emmeans(anova_result, ~ condition), adjust = "tukey")
pairs(emmeans(anova_result, ~ scenario), adjust = "tukey")
# Post hoc interaction
pairs(em, by = "condition", adjust = "tukey")   # scenarios within each AI role
pairs(em, by = "scenario", adjust = "tukey")  # AI roles within each scenario

#### manipulation check
## realism scores
data2 <- data %>%
  rowwise() %>%
  mutate(
    # realism index
    realism_index = mean(c_across(c("F2_1", "F2_2", "F2_3", "F2_4", "F2_5", "F2_6")), na.rm = TRUE),
  ) %>%
  ungroup()
print(data2$realism_index)
mean(data2$realism_index)
sd(data2$realism_index)

## manipulation check --> passed
# Independent t-tests for manipulation checks
data2$participant_id <- data_long %>%
```

```
  distinct(participant_id) %>%
  pull(participant_id)

t.test(score ~ condition, data = data_long)
data_long <- data_long %>%
  left_join(
    data2 %>% select(participant_id, realism_index),
    by = "participant_id"
  )
# Manipulation check with realism index
realism_check <- data_long %>%
  distinct(participant_id, condition, realism_index)  # remove duplicates

t.test(realism_index ~ condition, data = realism_check)
)

colnames(data2)
colnames(data_long)

# Alternatively: one-way ANOVA
summary(aov(score ~ condition, data = data_long))
summary(aov(realism_index ~ condition, data = data2))

### MIXED ANOVA HYPOTHESIS TESTING
# Check if participant_id has duplicates across condition x scenario
# Remove rows with missing values in the 'scenario' column
data_long_clean <- data_long %>%
  filter(!is.na(scenario))

# Check if any rows were removed
count_after_cleaning <- data_long_clean %>%
  group_by(participant_id, condition) %>%
  summarise(n = n())
```

```r
print(count_after_cleaning)

# Run the mixed ANOVA after cleaning the data
ez_results <- ezANOVA(
  data = data_long_clean,
  dv = .(score),
  wid = .(participant_id),
  within = .(scenario),
  between = .(condition),
  type = 3,
  detailed = TRUE
)

print(ez_results)

# Ensure variables are factors
data_long$participant_id <- as.factor(data_long$participant_id)
data_long$condition <- as.factor(data_long$condition)
data_long$scenario <- as.factor(data_long$scenario)

# Run the mixed ANOVA
ez_results <- ezANOVA(
  data = data_long,
  dv = .(score),
  wid = .(participant_id),
  within = .(scenario),
  between = .(condition),
  type = 3,
  detailed = TRUE
)
print(ez_results)
# means and std
data_long %>%
  group_by(condition) %>%
```

```
  summarise(
    M = mean(score, na.rm = TRUE),
    SD = sd(score, na.rm = TRUE),
    n = n()
  )

#### EXPLORATORY ANALYSES

# Compute Pearson correlations
colnames(data2)
colnames(data_long)

# Merge knowledge scores into data_long
# Add participant_id to data2 by matching order
data2$participant_id <- data_long %>%
  distinct(participant_id) %>%
  pull(participant_id)
# Merge knowledge scores into data_long
data_merged <- data_long %>%
  left_join(data2 %>% select(participant_id, ai_know_index, milit_know_index, aimilit_index), by = "participant_id")

trust_summary <- data_long %>%
  group_by(participant_id) %>%
  summarise(mean_trust = mean(score, na.rm = TRUE))
# Assuming data2 now has participant_id and knowledge variables
cor_data <- trust_summary %>%
  left_join(data2 %>% select(participant_id, ai_know_index, milit_know_index, aimilit_index), by = "participant_id")

# Correlation: AI knowledge vs. trust
cor.test(cor_data$ai_know_index, cor_data$mean_trust)
# Correlation: Military knowledge vs. trust
cor.test(cor_data$milit_know_index, cor_data$mean_trust)
# Correlation: Military AI Knowledge vs. trust
```

```
cor.test(cor_data$aimilit_index, cor_data$mean_trust)
```