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Attitudes, experiences, and usage intentions of artificial intelligence: A population study in Germany

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ABSTRACT

Artificial intelligence (AI) increasingly affects individuals' private and professional lives. Importantly, both the acceptance and adoption of new AI technologies in society is heavily impacted by the attitudes that people hold; yet, there is currently limited information on how people perceive and intend to use AI at the national and demographic levels. Therefore, this study examined a random sample of 1,098 German adults to assess their attitudes, experiences, and usage intentions regarding AI in work, healthcare, and education. The findings indicated that respondents generally held favorable attitudes towards AI, with AI applications in healthcare receiving more positive evaluations than AI in the context of work. Moreover, cognitive evaluations of AI were more positive than emotional or behavioral appraisals. Prior experiences with AI were, however, limited, particularly in healthcare and education. Demographic differences were generally small. Taken together, these findings demonstrate that, in Germany, AI is currently widely accepted in different domains, although most people have little first-hand experience with it. These insights can inform policymakers and stakeholders who care about the proliferation of AI in society.

1. Introduction

Artificial intelligence (AI) is typically used as an umbrella term for software and machines that can execute tasks that were previously expected to require human intelligence. As such, it can be characterized by a certain degree of autonomy, the capacity for learning and adapting, and the ability to handle large amounts of data. There is a broad consensus that AI has begun to change societies

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like no other technology in the past decades (e.g., Stahl et al., 2023; United Nations AI Advisory Board, 2024). These technological advances are multi-faceted and affect many domains of life in the 21st century, including work, healthcare, and education. Moreover, recent innovations such as *Generative AI* (capable of generating seemingly new content in the form of text, images, or audio; Feuerriegel et al., 2024) have made advances in AI salient to individuals and societies. Against this background, the present study examines attitudes toward AI, related user experiences, and usage intentions in the domains of work, healthcare, and education. The aim is to investigate potential differences between these central fields of application—while also disentangling cognitive, affective, and behavioral manifestations of how people consider AI in their daily lives. We further examine the extent to which gender, age, and education predict our focal variables. Extending most prior research, our study is based on a sample that is representative of a country's population (Germany) regarding main sociodemographic factors.

In recent years, rapid technological progress has fueled scientific interest in human attitudes toward AI as well as AI-related behavioral intentions and experiences. Attitudes are generally conceived as evaluations of favor or disfavor towards an attitude object. Following the *Tripartite Model*, these evaluations can be distinguished into cognitive, affective, and behavioral components (e.g., Rosenberg & Hovland, 1960). Moreover, attitudes are a key component of theoretical models that try to explain and predict people's behavior (e.g., the *Theory of Planned Behavior*); in fact, meta-analytic evidence shows a notable association between newly-formed explicit attitudes and behavior (Pearson $r = 0.52$, Glasman & Albarracin, 2006). In this sense, attitudes can also predict the current and future adoption of technologies, emerging as a crucial factor for the successful implementation of AI in different domains.

Importantly, research on technology-related attitudes, experiences, and intentions can also indicate or foreshadow new digital divides in societies (e.g., based on factors such as gender, age, and education)—which may in turn motivate new measures to achieve a more inclusive technological future. However, much of the current evidence on sociodemographic differences concerning general (i.e., domain-independent) attitudes towards AI is based on convenience samples. In terms of self-ascribed gender, many of these studies show that men hold more favorable attitudes than women (e.g., Fietta et al., 2022; Kaya et al., 2024; Schepman & Rodway, 2020), whereas other contributions found no such difference (e.g., Kovačević & Demić, 2024; Stein et al., 2024). Likewise, the overall picture is mixed for age and education with some studies reporting related differences (e.g., Stein et al., 2024) and others not doing so (e.g., Kaya et al., 2024). For example, a review of gender differences in actual usage patterns of *Generative AI* shows that men use the technology substantively more than women (Otis et al., 2025). In addition, in a study based on representative samples from six European countries (Bergdahl et al., 2023), women and participants with a lower educational background indicated more negative attitudes towards AI; yet, the effect sizes were small and revolved around Pearson $r = 0.10$. Regarding age, significantly negative correlations of around the same effect size were observed in some but not all countries, with particularly older people reporting more unfavorable attitudes.

Beyond sociodemographic differences, theory suggests that the acceptance of AI crucially depends on the domains and focal tasks it is applied to (e.g., De Freitas et al., 2023; Gray et al., 2007). Related research (e.g., Gray & Wegner, 2012; Shank et al., 2021; Waytz & Norton, 2014) contrasted the perceived abilities of humans and AI, suggesting that humans usually perceive AI to be capable of tasks that require agency (the ability to plan and act) but limited in tasks that require experience (the ability to feel, sense, and have a personality). Accordingly, the acceptance of AI might turn out higher for applications that involve rational thinking or problem-solving instead of emotionality or interpersonal communication. Matching this assumption, initial research has shown that people experience particular concerns and fears towards emotionally capable AI, for instance in the healthcare sector (Ho et al., 2023) or as part of virtual work meetings (Behn et al., 2024). On the other hand, the prospect (or immediate reality) of workforce shortages in specific domains—such as the much-publicized need for additional healthcare professionals around the world (e.g., Michaeli et al., 2024) or ongoing teacher shortages (e.g., Gorard et al., 2024)—also raise individuals' awareness of the benefits brought by new AI-powered systems. Of course, this may only hold true as long as people do not worry about their own jobs; after all, research has underscored the fear of being replaced by AI at the workplace as one of the main barriers to public acceptance (e.g., Moran & Shaikh, 2022; Stein et al., 2019). This clearly highlights the need to disentangle different attitude facets: Although individuals might comprehend on a cognitive level the need for new technologies that address societal problems, they might still experience negative emotions (affective level) or decide to engage with the technology apprehensively in their own life (behavioral level).

Lastly, going beyond the comparison of different domains in which AI is used, further insight might also rest in an even more nuanced examination of specific applications—as attitudes, experiences, and intentions might vary substantially between different technologies that are employed within the same domain (e.g., Schepman & Rodway, 2020). For example, individuals might feel more open towards the notion of AI-supported diagnosis systems with high recognition rates in the healthcare sector, yet hold less favorable attitudes towards fully autonomous nursing robots. Likewise, systems perceived as supporting human work at the workplace will likely receive more positive evaluations than those seemingly replacing a complete human task set (e.g., lecturing texts or driving a car). Therefore, the specificity of an implemented AI technology should also not be overlooked when investigating individual responses to AI in different domains.

2. Study overview

Addressing the described research gaps, we surveyed a sample representative of the German population to investigate attitudes, experiences, and usage intentions toward AI. After briefly defining AI, we examined domain-level attitudes focusing on the use of AI in work, healthcare, and education (RQ1), also looking at potential differences between cognitive, affective, and behavioral attitude facets (RQ2). Next, we proceeded to examine evaluations, experiences, and intentions regarding specific AI applications in the three described domains (RQ3). Finally, statistical associations between participants' AI acceptance and several sociodemographic factors were investigated (RQ4).

3. Materials and method

3.1. Sample and procedure

Participants were randomly selected from an online probability panel designed to represent the German population. Panel members were recruited by phone to ensure the representativeness of adults aged 18 and older. Then, 4,000 panel members (70 % employed and 30 % out of the labor force) were invited to complete an unproctored web-based survey. In the end, 1,107 individuals (45 % women) participated. However, nine respondents were excluded because they did not provide any valid response to one or more of the administered instruments. This resulted in an analysis sample of 831 employed participants and 267 individuals out of the labor force. The age of the respondents fell between 20 and 76 years with a mean of 52.34 years ($SD = 11.99$). About 63 % of them had educational qualifications granting access to higher education in Germany.

3.2. Instruments

3.2.1. Domain-level attitudes towards AI

After a brief introduction to the concept of AI, participants were administered the domain-specific *Attitudes Towards Artificial Intelligence Scale* (ATTARI-WHE; Gnambs et al., 2025b). This instrument consists of nine items, each to be rated on five-point response scales ranging from 0 = "strongly disagree" to 4 = "strongly agree". The ATTARI-WHE assesses attitudes towards AI as an abstract concept in the domains of work, healthcare, and education. In line with the tripartite structure of attitudes (Rosenberg & Hovland, 1960), it encompasses cognitive, affective, and behavioral facets. Each of the three domains and facets is represented by three items, allowing for the calculation of domain and facet scores by averaging the items in each subscale. In the present sample, the omega reliabilities (Flora, 2020) for the work, healthcare, and education scores were 0.77, 0.83, and 0.79, respectively. Reliability estimates for the cognitive, affective, and behavioral scores were 0.73, 0.76, and 0.75. In applied research, score reliabilities of about 0.70 are often considered satisfactory (Taber, 2018). The instrument is provided in the supplementary material.

3.2.2. Attitudes, experiences, and intentions regarding specific AI applications

Respondents completed the *AI Experience and Attitude Survey* (AIEAS; Gnambs et al., 2025a), which measures awareness, attitudes, experiences, and intentions related to specific AI applications in the domains of work, healthcare, and education. Each domain featured six AI applications which covered major areas of AI use that are accessible to the general public. Three of these applications referred to specific technological systems including virtual assistants (e.g., automated helpdesks), recommender systems (e.g., health apps), and robots (e.g., industrial manufacturing robots), while three described specific tasks supported by AI such as predictive analytics (e.g., for employee selection), monitoring (e.g., with smart devices), and content generation (e.g., learning content). The respective AI scenarios are provided in the supplementary material. For each AI application, four items assessed (a) prior awareness of the AI application, (b) positive versus negative attitudes toward it, (c) personal experience with the application in the last 12 months, and (d) intentions for future use. Awareness, experience, and intention were measured with five-point response scales (coded 0 to 4), while attitudes were initially rated on eleven-point scales, which were recoded to a range of 0 to 4 for consistency. To reduce participant burden, a planned missingness design was employed (see Zhang & Sackett, 2023) whereby each respondent was randomly administered four or six AI applications. Additionally, applications within the work domain were only administered to participants currently employed, whereas all respondents received items regarding applications from the healthcare and education domains. Following the test authors' recommendations (Gnambs et al., 2025a), responses to the awareness, attitude, experience, and intention subscales within each domain were scaled using item response theory to estimate 100 plausible values per respondent (Mislevy, 1991). Plausible values allow analyzing effects corrected for measurement error. The marginal reliabilities (Adams, 2005) for the different subscales fell between 0.58 and 0.76 ($Mdn = 0.69$).

3.2.3. Demographic measures

Respondents' gender was recorded using three categories (0 = male, 1 = female, 2 = diverse). However, due to the small number of respondents identifying themselves as diverse ($n = 3$), this category was excluded from further analysis. Age was reported in years, while education level was classified into two categories that distinguished between respondents with school-leaving qualifications granting access to higher education (e.g., university) and those without such qualifications. A more detailed categorization was not considered feasible due to small category sizes.

3.3. Statistical analyses

Comparisons between the three application domains were conducted using analyses of variance (ANOVA), while sociodemographic effects on AI attitudes and experiences were analyzed with linear regression models. The primary effect size for these analyses was the standardized mean difference d (Cohen, 1988) that was calculated for multi-group comparisons following Correll et al. (2020). Published effect sizes in different areas of social psychology including attitude research tend to hover around $d = 0.36$, on average, rarely falling below $d = 0.15$ or exceeding 0.65 (Lovakov and Agadullina, 2021). Therefore, the present study considered values of $d =$ 0.15 and 0.35 as small and moderate effects, respectively. For all inference tests, a significance threshold of 0.05 was adopted. Further methodological details including information on the sampling weights to account for unequal participation probabilities, handling of missing values, and the statistical software used are given in the supplementary material. The raw data will be released as part of the data distribution for the *German Socioeconomic Panel Study* (GSOEP Version 41).[6] The statistical code including the results of the analysis is available at https://osf.io/eha58.

3.4. Ethics statement

This study fully adhered to the ethical standards established in the Declaration of Helsinki and the principles outlined in the European Code of Conduct for Research Integrity. It also complied with the German *Federal Data Protection Act* to ensure the privacy and security of all collected and analyzed data. Informed consent was obtained from all participants, and their rights, autonomy, and confidentiality were respected throughout the research.

4. Results

Detailed statistical results, including means, standard deviations, and correlations for all variables, are provided in the supplementary material. In the following, the main findings of these analyses are summarized.

4.1. Attitudes towards AI

The respondents provided rather positive evaluations of AI as an abstract concept. The mean attitude rating across all domains was $M = 2.48$ ($SD = 0.74$) on a scale from 0 to 4, indicating that, on average, participants viewed AI more favorably than unfavorably. However, notable differences were observed between domains (see Fig. 1). Attitudes towards AI were more favorable in the healthcare domain ($M = 2.55$, $SD = 0.94$) than in the work ($M = 2.44$, $SD = 0.82$) or education domains ($M = 2.45$, $SD = 0.86$). A one-way ANOVA revealed statistically significant differences in attitudes across the three domains, $F(2, 2313.85) = 10.26$, $p < 0.001$, Cohen's $d = 0.20$. Furthermore, attitudes were more favorable when respondents were asked about their thoughts on AI—that is, the cognitive facet of attitudes ($M = 2.81$, $SD = 0.73$)—than when they evaluated emotional ($M = 2.33$, $SD = 0.85$) or behavioral aspects ($M = 2.29$, $SD = 0.88$). Again, a one-way ANOVA substantiated significant differences in attitudes between the three psychological facets, $F(2, 975.03) = 321.08$, $p < 0.001$, Cohen's $d = 1.15$.

Furthermore, attitude ratings were found to depend on the specificity of AI as the attitude object, with more specific AI use cases yielding higher ratings than abstract AI (measured by the ATTARI-WHE). This was corroborated by a 3 (domain: work, healthcare, or education) × 2 (specificity: abstract or specific) ANOVA which yielded a significant main effect of specificity, $F(1, 231.32) = 5.54$, $p = 0.019$, Cohen's $d = 0.11$, and a significant interaction with domain, $F(2, 1466.64) = 65.57$, $p < 0.001$, Cohen's $d = 0.36$. In the work domain, attitudes for specific AI applications (see the right-top plot in Fig. 2), were substantially more negative ($M = 2.07$, $SD = 0.65$) than the respective ratings for abstract AI ($M = 2.38$, $SD = 0.77$), $t(2244.36) = 7.18$, $p < 0.001$, Cohen's $d = 0.63$. In contrast, no significant differences were observed between attitudes towards abstract and specific AI in the healthcare ($M = 2.50$, $SD = 0.71$) and education ($M = 2.47$, $SD = 0.70$) domains, $t(783.09) = 1.17$, $p = 0.241$, Cohen's $d = 0.07$ and $t(748.26) = -0.52$, $p = 0.606$, Cohen's $d = -0.04$. These results indicate that AI attitudes depend on the specific application domain, the attitude component, and to some extent also the specificity of the presented AI applications.

4.2. Experiences with AI

Despite the generally positive attitudes towards AI, most respondents indicated that they had limited or no prior experience with the presented AI applications (see the left-bottom plot in Fig. 2). Although respondents reported greater experience with virtual assistants and AI for content generation than with other AI applications, the respective rates were rather low, reaching a maximum of 17 % to 21 % at the most (see the right plot in Fig. 3). The mean score for employed respondents indicated greater experience with AI in the work domain ($M = 1.08$, $SD = 0.60$) than in the healthcare ($M = 0.69$, SD = 0.66) or education domains ($M = 0.77$, $SD = 0.72$). A one-way ANOVA revealed statistically significant differences in experiences with AI across the three domains, $F(2, 225.80) = 82.61$, $p < 0.001$, Cohen's $d = 0.88$.

Despite the lack of experience with AI, a considerable proportion of respondents indicated to have at least heard of the respective applications (see the left-top plot in Fig. 2). Up to 58 % of the respondents were aware of some of the presented AI applications, primarily regarding virtual assistants and AI for content generation (see the left plot in Fig. 3). Again, AI applications in work ($M = 1.90$, $SD = 0.72$) were more widely known than respective applications in healthcare ($M = 1.82$, $SD = 0.72$) and education ($M = 1.67$, $SD = 0.74$). Statistically significant differences in AI awareness between the three domains were also supported by a one-way ANOVA, $F(2, 242.65) = 28.98$, $p < 0.001$, Cohen's $d = 0.51$. These results indicate that, although some AI applications are known to the general public, they are still rarely used.

4.3. Intentions to use AI

The ratings for future usage intentions of specific AI applications indicated that most respondents currently exhibited some

[6] https://www.diw.de/en/diw_01.c.601584.en/data_access.html.

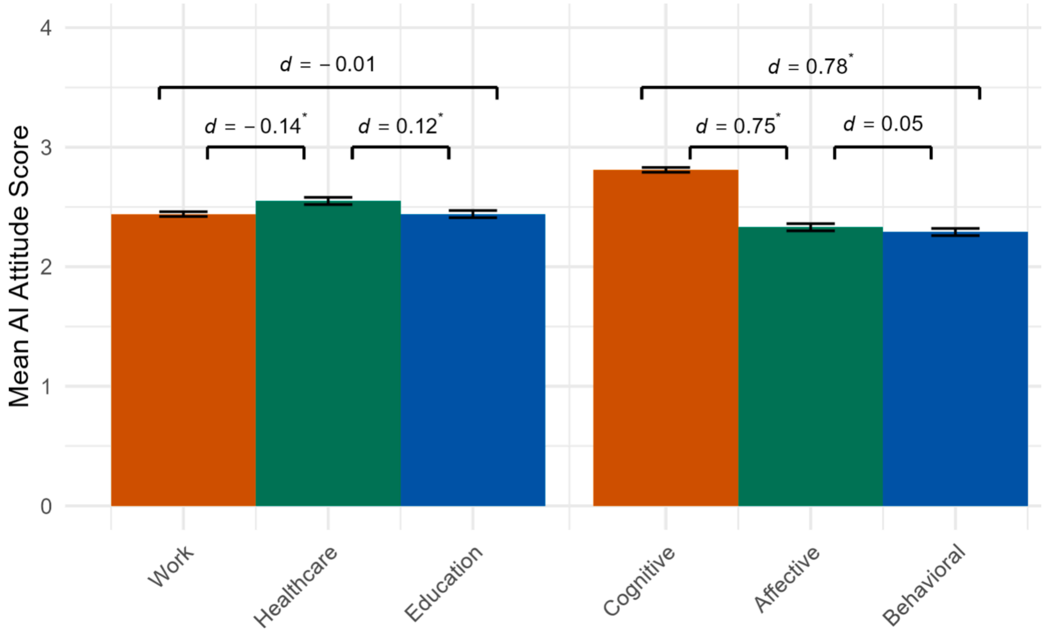

Fig. 1. General AI Attitudes for Domains and Facets. *Note*. Mean scores with standard errors. d = Standardized mean difference; * $p < 0.05$.

reluctance to use AI (see the right-bottom plot in Fig. 2). Although a one-way ANOVA suggested significant differences in AI usage intentions of employed respondents between domains, $F(2, 264.24) = 5.77$, $p = 0.004$, Cohen's $d = 0.23$, they were rather low across all three domains, work ($M = 1.66$, $SD = 0.69$), healthcare ($M = 1.77$, $SD = 0.81$), and education ($M = 1.69$, $SD = 0.83$).

4.4. Demographic differences in AI attitudes, experiences, and usage intentions

The association between respondent characteristics and AI evaluations was examined by regression of the scale scores on gender (coded 0 for men and 1 for women), age (in years, divided by 10), education (coded 0 for lower education and 1 for higher education), and employment status (coded 0 for non-employment and 1 for employment). The results of the respective analyses as summarized in Table 1 show few notable differences between respondent groups. AI attitudes in the work domain were significantly ($p < 0.05$) more positive among higher-educated respondents as compared to individuals with lower education, with effect sizes of Cohen's $d = 0.15$ and Cohen's $d = 0.20$ for abstract and specific AI attitudes, respectively. At the same time, these groups showed no significant differences with regard to AI experience or usage intentions. Men reported a significantly higher willingness to use AI in the future than women. The size of the respective effects was rather consistent for the work, healthcare, and education domains, yielding a median Cohen's d of 0.21. However, these differences were not reflected in specific AI attitudes, which were comparable between genders. Notable age differences were not found for any of the administered scales, although younger respondents expressed more experience and higher usage intentions of AI in healthcare and education. Taken together, these results suggest a rather small impact of demographic differences on AI attitudes and experiences.

5. Discussion

The introduction of AI into many fields is proceeding at an unprecedented pace, influencing how people conduct their work, support their health, or experience learning and training. Despite these technological changes, little is known about public perceptions of the on-going AI transformation in different domains. Likewise, evidence is lacking on how attitudes towards AI and related usage patterns are distributed in the general public—and whether they differ across diverse demographic groups. The present study addressed these gaps by examining AI attitudes and experiences within a random sample of German adults. The findings revealed a notable divide between individuals' attitudes towards AI and their actual or intended use in different contexts. While the German public generally held rather favorable views of AI, especially for the healthcare domain, most respondents reported limited firsthand experience with AI. Furthermore, there was notable reluctance to adopt AI in the future, even in domains where attitudes were predominantly positive.

Arguably, this mismatch between attitudes and (intended) behavior may stem from limited awareness or exposure to specific AI applications. At the current time, many individuals might simply be unaware which AI solutions are available in areas such as healthcare and education, where AI technologies are still relatively novel. Consequently, participants may also have limited understanding of concrete use cases that could be relevant to them. In some situations, individuals also lack the necessary autonomy to freely choose AI technologies, even if they prefer them. In occupational contexts, for example, workers often have to adhere to internal

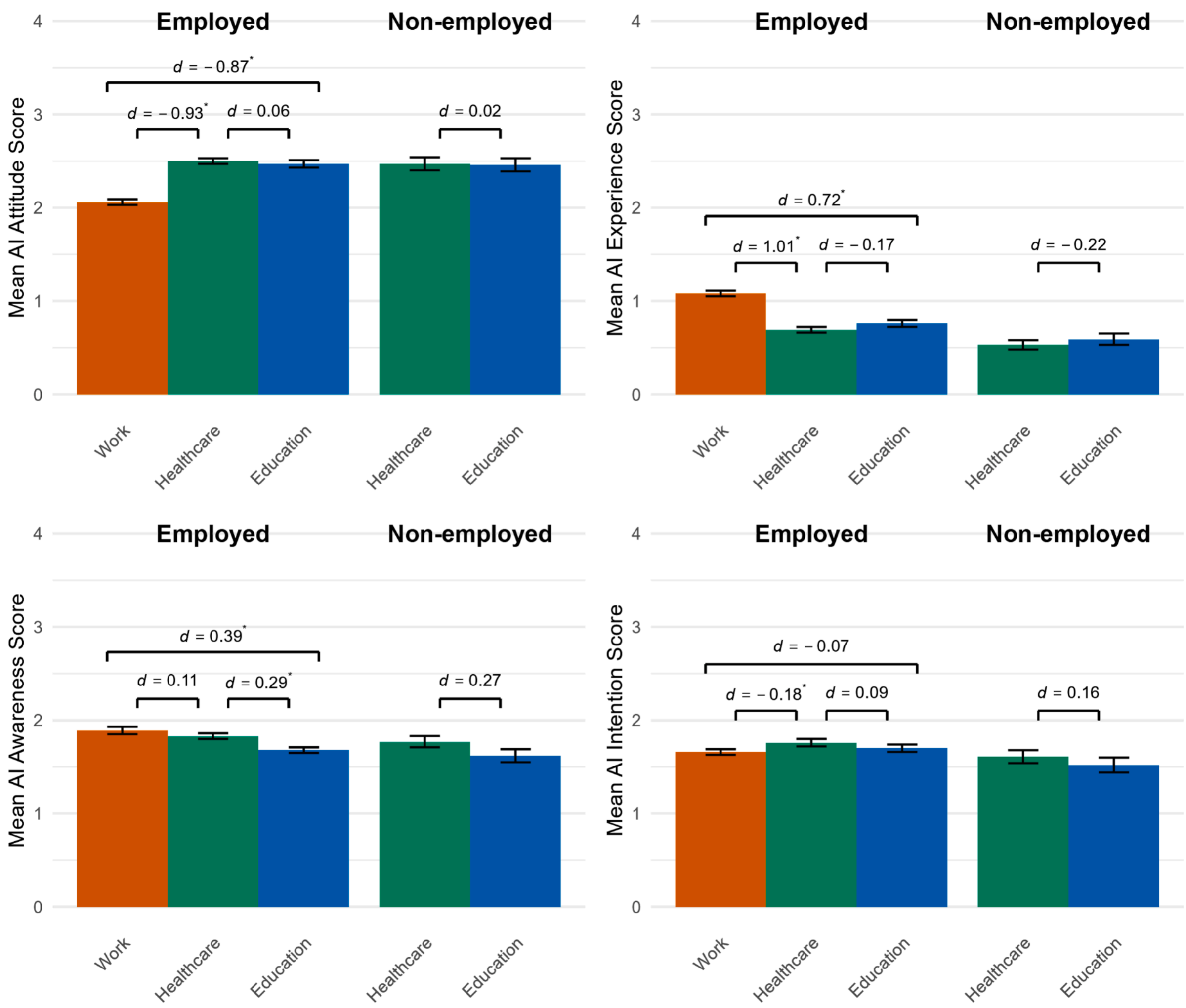

Fig. 2. Specific AI Experiences, Attitudes, and Use Intentions by Employment Status. *Note*. Mean scores with standard errors. d = Standardized mean difference;
* $p < 0.05$.

company policies, thereby preventing them from adopting AI. Along the same lines, a lack of prior experience with AI could also mean that related concerns and fears have not yet been prompted, manifesting in a more positive attitude. Alternatively, the identified mismatch between personal views and actual use of AI could also reflect attitudinal ambivalence (see Van Harreveld et al., 2009), that is, a conflict between more positive cognitive evaluations and more cautious emotional or behavioral appraisals. Whereas respondents might rationally recognize the benefits of AI, they may at the same time feel somewhat wary in the face of the new technology. This aligns with prior research documenting pronounced fears and anxiety surrounding AI in some societies (Liang & Lee, 2017). Because attitude ambivalence might lead to hesitations and difficulty committing to certain behaviors (Schneider & Schwarz, 2017), this may represent a barrier to widespread AI adoption, even where general attitudes appear favorable.

Similar to prior research (e.g., Bergdahl et al., 2023; Kaya et al., 2024; Stein et al., 2024), demographic factors did not offer a substantial contribution to explaining AI attitudes and use. Although men showed a greater willingness to use AI across all observed domains and higher-educated individuals expressed more favorable attitudes towards AI in the workplace, the respective effects were quite small. Overall, AI attitudes and experiences were more similar than different across genders, age, and educational levels. This suggests a general acceptance of AI in Germany, despite limited direct interaction with AI technologies. Accordingly, our results are not indicative of new digital divides affecting the engagement with (or openness towards) AI as the most important technological transformation of our time. Still, we suggest that follow-up surveys remain observant of this risk, so as to prevent systemic disadvantages to those less inclined to accept or use AI.

Taken together, the findings reveal an ambivalent pattern of AI attitudes and experiences, which aligns with related research documenting public perceptions of AI in other countries (e.g., Beets et al., 2023; Gnambs & Appel, 2019; Scantamburlo et al., 2025). For example, a study across eight European countries found that respondents generally held positive attitudes toward AI in various contexts (Scantamburlo et al., 2025). Consistent with our own findings, attitudes toward AI were notably more negative in human

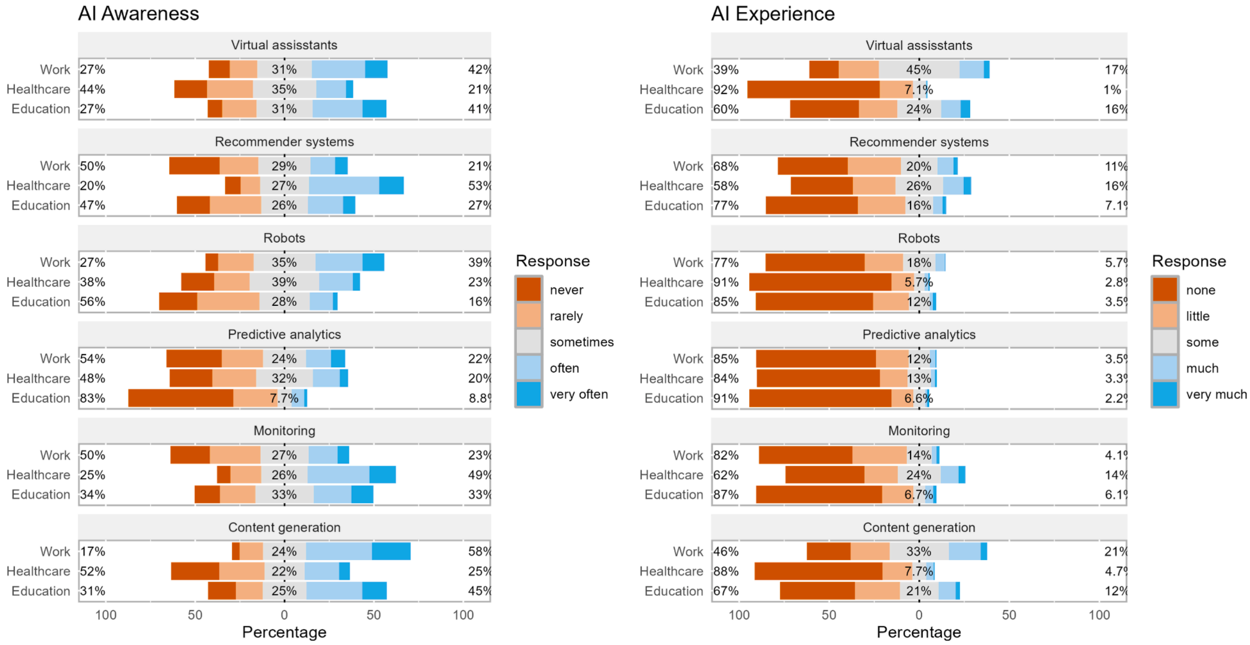

Fig. 3. Specific AI Awareness and Experience by AI Application. *Note*. Percentages indicate shares of negative (left), neutral (middle), and positive (right) responses. Results for the work domain are based on employed respondents only.

Table 1
Results of linear regressions of AI scales on demographic variables.

Scale	Gender			Age			Education		
	B	*SE*	*d*	*B*	*SE*	*d*	*B*	*SE*	*d*
Abstract AI attitudes									
Work	−0.05	0.05	−0.06	0.03	0.02	0.04	0.12*	0.05	0.15
Healthcare	0.01	0.06	0.01	0.07*	0.02	0.09	0.09	0.06	0.11
Education	0.06	0.05	0.07	0.03	0.02	0.04	0.03	0.06	0.03
Specific AI Attitudes									
Work	−0.09	0.06	−0.14	−0.03	0.03	−0.05	0.13*	0.07	0.20
Healthcare	0.00	0.07	−0.01	−0.02	0.02	−0.01	0.08	0.06	0.11
Education	0.03	0.07	0.04	−0.01	0.02	−0.01	0.09	0.06	0.13
Specific AI Awareness									
Work	−0.12	0.07	−0.17	−0.02	0.03	−0.03	−0.02	0.08	−0.03
Healthcare	−0.01	0.07	−0.02	−0.02	0.02	−0.03	0.04	0.07	0.06
Education	−0.04	0.08	−0.05	−0.02	0.03	−0.03	0.04	0.07	0.06
Specific AI Experience									
Work	−0.11*	0.06	−0.20	−0.03	0.03	−0.06	−0.05	0.06	−0.08
Healthcare	−0.05	0.05	−0.09	−0.04*	0.02	−0.07	−0.03	0.05	−0.05
Education	−0.06	0.06	−0.08	−0.06*	0.02	−0.09	0.00	0.06	0.00
Specific AI Use Intentions									
Work	−0.16*	0.06	−0.24	−0.04	0.03	−0.06	0.09	0.07	0.13
Healthcare	−0.16*	0.07	−0.21	−0.05*	0.02	−0.07	0.13	0.07^{+}	0.17
Education	−0.13^{+}	0.07	−0.17	−0.06*	0.03	−0.07	0.15	0.07*	0.19

Note. B = Regression coefficient, SE = Standard error of B, d = Regression coefficient standardized with respect to the outcome (comparable to Cohen's d). Gender was coded 0 for men and 1 for women. Age was measured in years divided by 10. Education was coded 0 for lower education and 1 for higher education. The specific AI scales for the work domain were only administered to employed respondents (N = 831), while the remaining scales were administered to the full sample (N = 1098).

* $p < 0.05$.

$^{+}$ $p < 0.10$.

resources and job recruitment but more positive in healthcare. Arguably, these similar observations might be explained by the fact that encounters with AI at the workplace are perceived as less voluntary (and, thus, less controllable) than the technology's implementation in health or education contexts. More so, respondents might already be more familiar with certain concerns when thinking of AI in the work domain (e.g., job replacement, increasing productivity standards), limiting their acceptance in this context. On the other hand, a public opinion survey on automation and robotics among European citizens revealed substantially greater support for robots assisting with workplace tasks than for their use in medical and elderly care settings (Gnambs & Appel, 2019)—suggesting a rather nuanced pattern of attitudes for different applications within the respective domains. However, given the limited awareness of how AI is currently used in practice, the obtained judgements might still be rooted in speculation and irrational fears rather than in direct experience. This also aligns with a recent review of public perceptions of AI in healthcare (Beets et al., 2023), which highlighted that most Americans are rather unaware of specific AI applications in healthcare but generally expect various benefits from advances in AI. Thus, positive cognitive evaluations of AI, combined with limited direct experience, appear to be a common trend in many countries worldwide.

Our findings present several intriguing opportunities for follow-up research. First, this study focused on three domains that have seen a significant increase in AI applications in recent years. However, AI is also influencing other fields, such as finances (e.g., online brokers), software development (e.g., coding tools), and entertainment (e.g., video games). Extending the analysis to other domains could provide a more comprehensive understanding of the impact of AI. Second, it remains unclear whether these findings are unique to Germany or reflect broader trends across societies worldwide. Cross-national comparisons could identify shared and unique patterns of AI attitudes and usage, offering insights into the global diffusion of AI. Third, future research could take a closer look at specific sociodemographic and occupational groups. For example, workers in sectors with a high risk of being replaced by AI may hold more negative attitudes compared to those in less vulnerable positions. Also, respondents working in healthcare and education professions might hold different AI attitudes than the general public. Comparisons between different segments of the population could shed light on how AI adoption varies in subpopulations depending on the context and the immediate life reality. Finally, it was beyond the scope of our research to examine the reasons underlying individual ambivalence or negative attitudes towards AI in depth. We encourage future research to investigate related hypotheses derived from the present research. This could include qualitative approaches and reflections on ethical dimensions in applying AI in the focused fields of work, health, and education (Young et al., 2021).

In conclusion, this study highlighted a notable gap between positive public attitudes toward AI and limited direct experience or willingness to adopt AI technologies, particularly in healthcare and education. This mismatch may be driven by a lack of awareness of available applications or by attitudinal ambivalence—considering that cognitive and emotional evaluations of AI diverged particularly strongly. Demographic differences played a negligible role in our research. The findings underscore the importance of addressing barriers to AI adoption, for example, by improving public knowledge and reducing fears about AI.

CRediT authorship contribution statement

Timo Gnambs: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Jan-Philipp Stein:** Writing – original draft, Conceptualization. **Sabine Zinn:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Formal analysis, Data curation. **Florian Griese:** Writing – review & editing, Investigation, Data curation. **Markus Appel:** Writing – original draft, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tele.2025.102265.

Data availability

Data access will be provided after signing a data usage contract: https://www.diw.de/en/diw_01.c.601584.en/data_access.html.

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