Supplementary Material for

Experiences, Attitudes, and Usage Intentions of Artificial Intelligence

A Population Study in Germany

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A. Survey Instruments

Attitudes Towards Artificial Intelligence in Work, Healthcare, and Education Scale (ATTARI-WHE; Gnambs, Stein et al., 2025)

Definition		
We would like to know your opinion on artificial intelligence. Artificial intelligence refers to technical devices that can perform tasks that typically require human intelligence. It enables machines to sense, act, and adapt autonomously. Artificial intelligence can be part of a computer program or an online application, but can also be found in various machines such as robots. It can be used in the workplace, in medicine and nursing as well as in education and training.		
Instruction		
Please indicate your level of agreement for each statement. There are no correct or incorrect answers.		
Domain	**Facet**	**Item**
Work	Cognitive	Artificial intelligence offers good solutions for many job tasks.
	Affective	I have a good feeling when I think about the use of artificial intelligence in daily working life.
	Behavioral	If I have to complete an important task at work, I would rather choose a technology with artificial intelligence than one without.
Healthcare	Cognitive	Artificial intelligence offers good solutions in medicine and nursing.
	Affective	I have a good feeling when I think about how artificial intelligence is being used in healthcare and nursing.
	Behavioral	For the treatment of a serious illness, I would rather choose a technology with artificial intelligence than one without.
Education	Cognitive	Artificial intelligence is helpful for learning and teaching.
	Affective	I have positive feelings when I think about how artificial intelligence is used in education and training.
	Behavioral	If I want to learn something new, I would choose a learning program with artificial intelligence rather than one without.
Response format		
0 = strongly disagree, 1 = disagree, 2 = neither, 3 = agree, 4 = strongly agree -1 = cannot or do not want to answer		

Artificial Intelligence Experience and Attitude Survey (AIEASM, Gnambs, Griese et al., 2025)

Description of AI scenarios

	Workplace	Healthcare	Education
Virtual assistants	Automated helpdesks are computer programs that use artificial intelligence to address common questions from employees. These programs can be used by companies or public institutions as a point of contact and advice. If employees have questions about products or technical problems, they are answered automatically by email or chat without human intervention.	Medical chatbots are computer programs that use artificial intelligence to answer questions about ailments and symptoms of illness. Patients can communicate with the chatbot verbally or via written text entries. When they ask questions about their state of health, they are automatically answered without human intervention.	Virtual assistants are computer programs that use artificial intelligence to answer questions from learners about specific knowledge areas. The dialogue takes place either verbally or via written text. When learners pose questions, they are answered automatically without human intervention.
Recommender systems	Artificial intelligence is used to make suggestions at the workplace as to which tasks need to be completed next and which solutions or work steps are suitable.	Health apps are computer programs that use artificial intelligence to analyze physical activity, sleep patterns, and dietary habits. They provide personalized recommendations for a healthy lifestyle such as fitness or nutrition plans.	Learning software uses artificial intelligence to analyze the learning progress of users. It provides personalized recommendations for learning content that has not yet been fully consolidated or for additional topics.
Robots	Industrial robots with artificial intelligence are machines that can independently manufacture new products on the assembly line with little supervision by human operators.	Care robots with artificial intelligence perform physical tasks in hospitals or nursing homes. They help patients with limited mobility to get out of bed, pick up objects, wash themselves, or get dressed.	Social Robots with artificial intelligence are machines for interacting with people. They can help learners largely independently and individually, for example by participating in interactive learning or helping with language acquisition.
Predictive analytics	Artificial intelligence can analyze job applications to identify suitable candidates. For this, it uses information from application documents or behavior in the interview. This helps organizations to predict the likely professional success of a candidate.	Artificial intelligence can use medical scans (images) or information about a patient’s lifestyle to predict the risk of certain types of cancer or mental illnesses. This can aid in the development of personalized prevention or treatment plans.	Artificial intelligence can analyze information about participants in a training or further education course to predict which individuals are at risk of performing poorly or dropping out of the course. An early warning system like this can help to identify people at risk and provide the necessary support.
Monitoring	Artificial intelligence can automatically monitor the productivity of employees and, for example, analyse computer usage or production and sales figures. This helps companies to optimize work processes and identify employees who need additional support.	Artificial intelligence can monitor various vital signs such as heart rate or blood pressure. Electronic devices that are worn on the body inform in real-time, for example, about the wearer’s health and fitness or potential illnesses.	Computer programs with artificial intelligence can analyze texts from students or participants in training or further education courses to identify plagiarism, that is, text parts written by others.
Content generation	Artificial intelligence can create new and unique content such as texts, illustrations, or photos. It is used, for example, in marketing to develop catchy slogans for ads, design brand logos, or create fictional advertising photos.	Artificial intelligence can analyze medical information about patients to automatically create health reports, doctor’s letters, diagnoses, and treatment plans.	Artificial intelligence can analyze large amounts of text from textbooks or articles and briefly summarize the most important information. This provides learners with a quick and concise overview of complicated topics.

Items for each AI scenario	
How often have you heard of this type of artificial intelligence?	0 = never, 1 = rarely, 2 = sometimes, 3 = often, 4 = very often, -1 = cannot / do not want to answer
Do you find this type of artificial intelligence generally positive or negative?	0 = negative, … 5 = neutral, … 10 = positive, -1 = cannot / do not want to answer
How much personal experience have you had with this type of artificial intelligence in the last 12 months?	0 = none, 1 = little, 2 = some, 3 = much, 4 = very much, -1 = cannot / do not want to answer
How much personal experience would you like to have with this type of artificial intelligence in the future?	0 = none, 1 = little, 2 = some, 3 = much, 4 = very much, -1 = cannot / do not want to answer

B. Weighting Approach

To enable weighted data analyses that facilitate population-level extrapolations for Germany, we developed survey weights. This process involved correcting survey data from a random sample to account for non-participation. Specifically, we adjusted the distributions of age, gender, employment status (employed vs. not employed), and educational attainment (high: Abitur or higher qualifications; low/medium: all other qualifications) to align with population-level distributions.

The population benchmarks were derived from the 2022 German Microzensus, as it was the most recent data available at the time of weighting. The related distributions were extracted from the *Socioeconomic Panel* (Version 39, waves 1984–2022), which also utilizes the Microzensus to ensure its survey data is representative of the population. The weighted extrapolation corresponds to N = 67,889,101 adults (see Table S1).

Table S1

Population Distributions for Adjustment Survey Weights

Age / Sex		
	Men	Women
18-29 years	5,471,788	5,088,771
30-39 years	5,606,528	5,303,195
40-49 years	4,991,002	4,987,021
50-64 years	9,438,692	9,542,390
Employed / Education		
	High education	low / medium education
Employed	20,841,332	20,679,697
Non-employed	7,595,064	18,773,008

Source: Microzensus 2022 and SOEP (Version 39).

The adjustment of survey weights was performed using the raking method, also referred to as iterative proportional fitting (Valliant & Dever, 2018). This method iteratively adjusts the weights for each variable independently while keeping the other variables fixed. The process continues until the marginal distributions for all variables converge to match the population benchmarks. We implemented the adjustment using R (version 4.3.2) and RStudio (version 2023.12.0), employing the “postStratify” function from the *survey* package (Version 4.4-2) by Lumley (2011). To avoid excessively large or unrealistic weights, trimming was applied at the 95th percentile of the weight distribution (Potter, 1990). Following the trimming process, the adjusted weights were standardized to have a mean of 1, ensuring their suitability for subsequent statistical analyses. The distribution of the trimmed and standardized weights is given in Table S2.

Table S2

Population Distributions for Adjustment Survey Weights

	0%	25%	50%	75%	100%
Trimmed	11,673.41	20,277.16	41,160.05	63,427.75	655,266.53
Standardized	0.17	0.29	0.59	0.91	9.42

C. Descriptive Statistics for Study Variables

Table S3 summarizes the means, standard deviations, and correlations of the administered ATTARI-WHE and AIEAS scales. These results are based on the full sample (*N* = 1098), except those referring to the AIEAS work scales (*N* = 831) which were only administered to employed respondents.

Table S3

Means, Standard Deviations, and Correlations of AI Scales

		M	*SD*	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.
	Abstract AI Attitudes																			
1.	Work	2.44	0.82	(.77)																
2.	Healthcare	2.55	0.94	.56	(.83)															
3.	Education	2.44	0.86	.68	.52	(.79)														
	Specific AI Attitudes																			
4.	Work	2.81	0.73	.74	.76	.79	(.72)													
5.	Healthcare	1.79	0.75	.25	.23	.27	.82	(.76)												
6.	Education	1.63	0.75	.25	.22	.27	.78	.93	(.76)											
	Specific AI Awareness																			
7.	Work	2.06	0.68	.52	.49	.51	.22	.24	.25	(.62)										
8.	Healthcare	2.48	0.75	.55	.54	.53	.22	.26	.26	.93	(.69)									
9.	Education	2.47	0.73	.55	.53	.54	.21	.24	.25	.89	.92	(.69)								
	Specific AI Experience																			
10.	Work	1.07	0.63	.20	.18	.22	.41	.41	.41	.24	.23	.21	(.58)							
11.	Healthcare	0.62	0.61	.15	.15	.20	.35	.35	.35	.25	.21	.19	.72	(.59)						

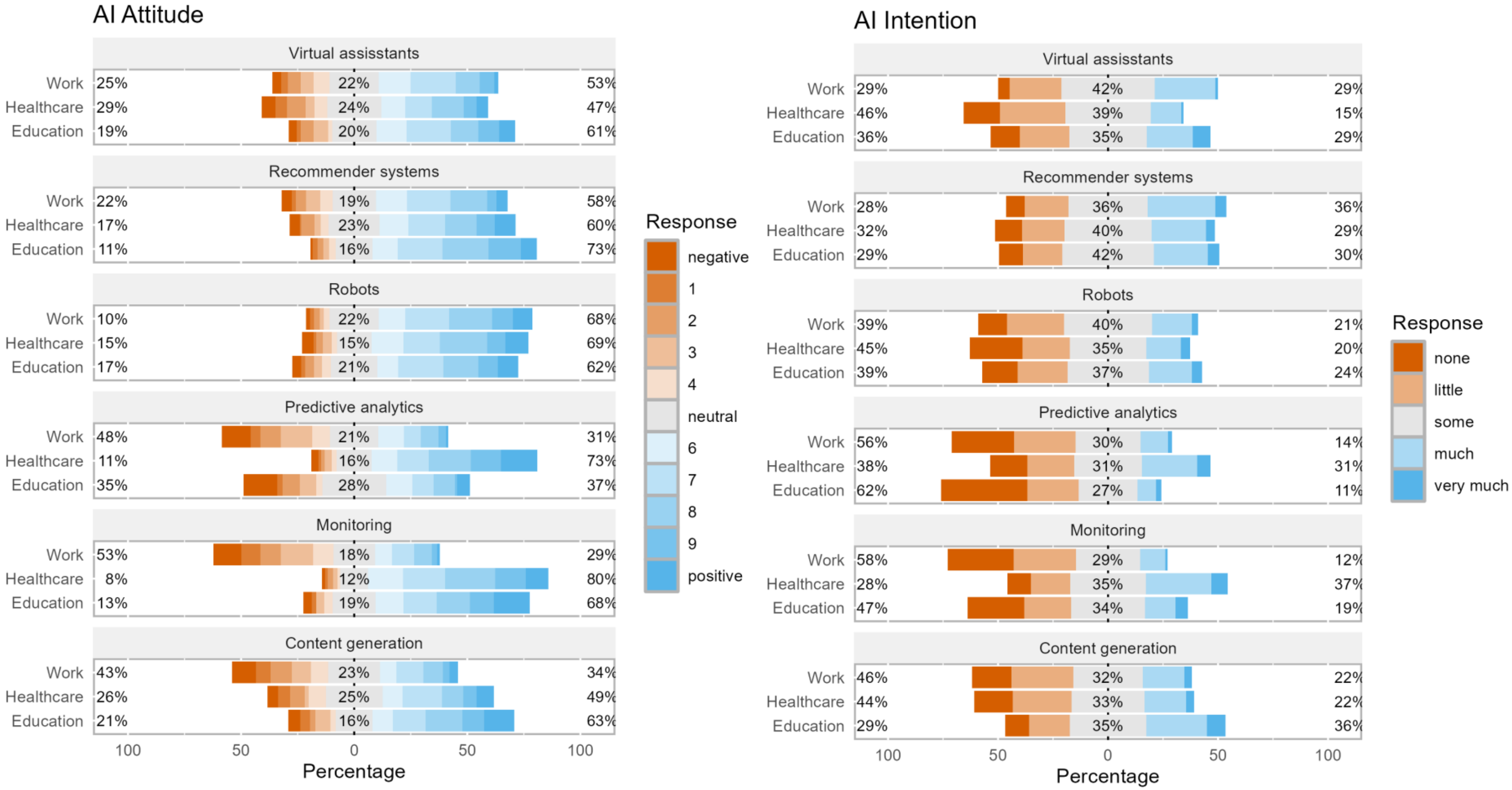
		M	*SD*	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.
12.	Education	0.70	0.69	.17	.16	.24	.39	.39	.40	.26	.23	.22	.80	.72	(.63)					
	Specific AI Use Intentions																			
13.	Work	1.67	0.73	.49	.42	.48	.27	.29	.30	.54	.53	.51	.37	.36	.37	(.68)				
14.	Healthcare	1.7	0.78	.44	.35	.43	.25	.29	.29	.51	.49	.46	.34	.32	.31	.81	(.72)			
15.	Education	1.63	0.8	.45	.35	.45	.25	.32	.33	.51	.48	.48	.33	.30	.33	.81	.78	(.72)		
	Demographic information																			
16.	Gender (0 = men, 1 = women)	0.52	0.50	-.02	.02	.04	-.11	-.02	-.03	-.06	-.01	.02	-.12	-.07	-.04	-.13	-.12	-.09		
17.	Age (in years)	52.64	14.83	.03	.10	.05	-.03	-.05	-.06	-.09	-.05	-.03	-.04	-.10	-.12	-.07	-.14	-.11	.09	
18.	Education (0 = low, 1 = high)	0.41	0.49	.05	.01	.00	.02	.04	.05	.11	.07	.06	-.01	.01	.03	.10	.12	.11	-.01	-.32

Note. *N* = 1,098 except for specific AI outcomes in the work domain (*N* = 831). Based on 100 multiply imputed data sets and plausible values with sampling weights. Omega reliabilities are given in the diagonals.

D. Handling of Missing Values

Up to 5% of the ATTARI-WHE scores exhibited missing values and up to 7% of the respondents did not provide any response to the AIEAS. Therefore, all analyses were based on multiply imputed data where missing values were imputed 100 times using classification and regression trees (Burgette & Reiter, 2010). Because the work domain for the AIEAS was only administered to employed individuals, respective scores were systematically missing for non-employed respondents. In this case, no imputations were performed because the missingness was informative. Item responses for the AIEAS that were missing by design were not imputed. The results of the statistical analyses that were conducted independently for each imputed data set were combined following Rubin's (1987) rules. *F* statistics from ANOVAs were pooled with the D_2 statistic suggested by Enders (2010).

E. Specific AI Attitude and Use Intention 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.

F. Software

The analyses were conducted in *R* (R Core Team, 2024). Item response analyses were performed with *TAM* (Robitzsch et al., 2024) and *sirt* (Robitzsch, 2024). Multiple imputation analyses used *mice* (Version 3.16.0; Van Buuren & Groothuis-Oudshoorn, 2011) and *miceadds* (Robitzsch & Grund, 2024). Descriptive analyses relied on *Hmisc* (Harrell, 2024) and *MBESS* (Kelley, 2023), while the ANOVAs were estimated with *lme4* (Version 1.1-35.5; Bates et al., 2015) and *lmerTest* (Version 3.1-3; Kuznetsova et al., 2017). Plots were generated with *ggplot2* (Version 3.5.1; Wickham, 2016). General data handling was supported by *tidyr* (Wickham et al., 2024) and *dplyr* (Wickham et al., 2023).

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