



Review Article

The Generational Divide in AI Adoption: How Age Shapes the Integration and Use of Intelligent Tools?

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Abstract

With the outbreak of the coronavirus pandemic, which brought work processes worldwide to a standstill for a short time, the working world was forced to take a previously unknown and unintentional full brake. Companies were forced into a situation where employees were quarantined, or complete cities and towns were sealed off for a short time to protect them from the spread of the virus. However, as with disadvantages, advantages can also come from an unintended situation, and so, albeit unintentionally, some major and some minor grievances were uncovered in all companies. The grievances addressed in this statement are primarily the slow introduction of digital options in the context of meetings and division of labor. Until 2020, these important activities in particular were still carried out by means of personal contact and exchange. Since the pandemic, where personal contacts were severely restricted and large meetings were hardly feasible, a change in thinking was established at the management level. The aim was to eliminate these shortcomings using quick solutions, and digital solutions had to be resorted to without further ado. Meetings were held online rather than in person, and work was divided using work-sharing programs. During the course of the presentation, it was noted that meetings can be held much faster and, in some cases, more effectively when they take place via online meetings. In addition, the possibility of working from home was introduced by companies in order to respect quarantine regulations and at the same time have a way to continue working. Arriving in 2025, companies are now faced with the possibility of implementing the knowledge and insights gained during the main period of the pandemic, in such a way that with the options offered for digital work completion, not only are the current regulations served, but also the company itself benefits. Companies mainly benefit when the work performance and productivity as well as the motivation of the employees is right. For this reason, large companies such as Apple or Google are introducing ways to increase productivity in a targeted manner. In order to achieve the best results, they rely on machine learning and artificial intelligence. This paper will address the current mainstream possibilities of digital work solutions and show that artificial intelligence and machine learning have an impact on the division of labor and should be part of the state of the art in most companies in the coming years to be competitive in the future and at the same time attractive for existing and new employees. Furthermore, the study examines the extent to which the age of users influences their use of AI tools. Are we therefore facing a generational divide?

Introduction

Context

The introduction of artificial intelligence has been on a steep rise since 2022 and is advancing at a rapid pace, surpassing itself daily. Over the past three years, we have seen a transformation from a weak and less innovative system to today's intelligent and creative systems. In 2025, we will look back at data from 2024 and examine the results in several contexts. Here, we discuss how the use of artificial intelligence differs and can be explained by age groups. AI is understood as a modern system that is only attractive to young and smart users and is only used by this generation. But are these hypotheses true, or is

AI used and demanded by several generations? Based on the available results, we can already gain some initial insights into this question and many others.

Problem statement

Despite many different new AI functions and providers, companies continue to report on the "big players." These include artificial intelligence from OpenAI (ChatGPT 4o, 4.0, etc.) as well as those from Claude (Bard, Sonnet 3.7) and Google (Google Studio, Gemini, etc.). Nevertheless, there are already many smaller and lesser-known providers for various needs that are also finding favor in companies because they solve a problem or offer a specific integration that can be used in

everyday work. Now, the results and, above all, the available data are limited to the year 2024, as most of the AI models mentioned were not made available to the majority until the beginning of 2025. For this reason, we will refer to “basic” systems such as ChatGPT, Google, and others when considering the results and hypotheses. In order to make a comprehensive statement about the current AI tools, a new survey would have to be launched in 2025 to obtain these results.

Research gap

Previous research has focused primarily on the technical advantages of AI and less on the human component. This study aims to focus on the socio-demographic aspects of AI use rather than the technical components. However, the number of participants in the study and the resulting findings are limited. Further studies are essential to close this gap in order to obtain a comprehensive framework for the successful assessment of socio-demographic data about artificial intelligence.

Research question

How does age influence the adoption and perceived integration of AI tools in organizational contexts?

Objectives

- To assess the relationship between age and the intensity of AI integration in daily work processes.
- To explore generational differences in AI usage and the perceived complexity of AI tools.
- To examine the moderating effect of education level on the relationship between age and AI usage intensity.

Significance of the study

This study addresses a relevant gap in the literature by investigating how demographic factors, particularly age, influence the adoption and use of artificial intelligence tools in the workplace. While technological readiness is often discussed in aggregate terms, little attention has been paid to generational differences in AI perception and usage. Understanding these dynamics is critical for organizations that aim to implement AI in an inclusive and effective manner. The findings can inform tailored training strategies and digital transformation policies that accommodate age-related needs, enhance user acceptance, and ensure equitable access to innovation.

Hypotheses and methodology

Hypotheses

H1: There is a negative correlation between employee age and the intensity of AI integration in daily operations.

- Independent Variable: Age (I1)
- Dependent Variable: AI Integration Intensity (Q2)

H2: Older employees report lower perceived complexity of AI tools than younger employees.

- Independent Variable: Age (I1)
- Dependent Variable: Perceived Complexity (Q4)

H3: The level of education moderates the relationship between age and the intensity of AI usage.

- Moderator: Education (I3)
- Independent Variable: Age (I1)
- Dependent Variable: AI Integration Intensity (Q2)

Methodology

Research design: This study used an online poll and a quantitative research approach to examine the effects of age and education on the degree of integration and use of AI technologies in the workplace. The hypothesized associations between age, education level, and AI integration were tested using multiple linear regression analysis. Furthermore, interaction words were used to investigate if the impact of age on AI usage differs based on the respondent's educational background.

The normality of residuals (as determined by Q-Q plots), homoscedasticity (as determined by residuals vs. fitted plots), multicollinearity (as determined by VIF statistics), and linearity of correlations were evaluated prior to the interpretation of the regression models. Regression coefficients may be interpreted with confidence since all presumptions were well satisfied.

Data collection: Data was collected through an online survey administered to professionals from various industries who are employees of various industry types. The survey was published in 2024. The survey consisted of structured questions and open-ended responses to capture both quantitative and qualitative data.

Sample characteristics and representativeness: There were 234 individuals in the sample, representing a range of nations, sectors, and occupations. Geographically, most of the participants were from European nations, such as Germany, Austria, and Switzerland, with others from Asia and the United States. In order to ensure coverage across generational cohorts pertinent to examining age-related trends in AI adoption, the age distribution varied from 20 to over 60. The workforce was diversified, with educational backgrounds ranging from high school to postgraduate degrees. More than ten different industries were mentioned by the participants as places of employment, including manufacturing, IT, healthcare, finance, and education (Q5). A thorough understanding of AI integration across hierarchical levels was made possible by the inclusion of management, technical, administrative, and customer-facing job functions (Q6). The sample's diversity in organizational contexts and demography allows for a relevant investigation of the impacts of education and age on AI adoption, even if it is not statistically representative of the worldwide workforce. There is enough diversity in the range of occupations and industries to investigate trends that could be applicable in larger contexts.

Statistical analyses

Descriptive analysis: To describe the demographic and AI usage profiles of respondents.

Correlation analysis: To examine the relationship between age and AI-related variables (I1, I3, Q2, Q4).

Regression analysis: To test whether age predicts AI usage intensity and complexity, including education as a moderator.

ANOVA: To explore differences in AI integration across age groups.

Software and tools: The analysis was conducted using JASP, which offers robust statistical functionalities for mixed-methods research.

Theoretical background and generational context

Important concerns regarding worker adaptation and digital inclusion have been brought up by the introduction of artificial intelligence (AI) into the workplace. The generational divide, which refers to discernible variations in technology usage habits, cognitive processing methods, and digital preparedness between age groups, is one of the most often highlighted obstacles to the adoption of AI [1].

According to Mitzner et al. [2], older workers frequently have lower levels of digital self-efficacy, greater levels of technology anxiety, and less exposure to organized digital learning settings. The way older workers interact with developing technology, such as AI-powered systems, is greatly influenced by these environmental and psychological aspects. According to neuropsychology, age-related reductions in working memory and cognitive flexibility may make it more difficult for people to use sophisticated digital technologies [3].

According to recent studies in the field of digital health, older individuals' adoption of technology is influenced by their capacity to incorporate it into their daily routines in addition to factors like accessibility and usability [4]. Their study, which is based on the capacity model, emphasizes how crucial autonomy, digital literacy, and contextual assistance are to adoption success. AI preparedness at the organizational level is influenced by behavioral enablers including motivation, perceived utility, and institutional support in addition to technology infrastructure [5]. The Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM) offer a theoretical framework for comprehending how generational disparities in the perceived utility and behavioral intents of AI technologies differ.

This study places the importance of age in AI integration within a multifaceted and multidisciplinary framework by combining viewpoints from digital health, learning psychology, and organizational behavior.

Results

Based on the assumptions, JASP was used to compare and analyze the outcomes using the primary data that was

provided. A data collection of 233 participant results from all around Europe served as the basis for these findings. Broadly speaking, the data is significant enough to give a comprehensive overview of the subject and to allow for more research in the future. However, in order to have the most recent results and evaluations accessible, fresh data will need to be gathered due to the rapid advancements in artificial intelligence and everyday changes.

Descriptive statistics

To establish a foundational understanding of the sample and the core variables, descriptive statistics were computed for age (I1), AI integration intensity (Q2), perceived complexity of AI tools (Q4), and level of education (I3). All variables had complete data for all 233 respondents.

The mean age category of respondents (I1) was 3.74 (SD = 1.48), suggesting that most participants fall within the middle to older age categories, though all age brackets were represented. The average intensity of AI integration (Q2) was 4.09 (SD = 2.59) on a scale from 1 (minimal) to 10 (extensive), indicating moderate levels of integration. Perceived AI complexity (Q4) had a mean of 3.77 (SD = 2.34), suggesting that most respondents view AI tools as moderately complex (Table 1).

The majority had finished university education, as indicated by the histogram, and the mean for educational background (I3) was 2.49 (SD = 0.88). The Pareto plots show that the distributions for Q2 and Q4 are slightly left-skewed, suggesting that the majority of respondents place a lower value on both complexity and AI adoption. Nonetheless, a wide range of answers also points to a variety of experiences with AI in the workplace. These findings offer a solid foundation for examining the proposed connections between age and AI adoption factors, as well as the possible moderating influence of educational achievement.

Pareto plots (Figure 1)

Correlation analysis – age and AI integration intensity

A correlation analysis was performed to evaluate the association between respondents' age (I1) and the perceived level of AI integration in their day-to-day job operations (Q2)

Table 1: Descriptive statistics for key variables (Age [I1], AI integration level [Q2], AI complexity [Q4], Educational attainment [I3])

Descriptive Statistics				
	I1	Q2	Q4	I3
Valid	233	233	233	233
Missing	0	0	0	0
Mean	3.738	4.090	3.773	2.489
Std. Error of Mean	0.097	0.170	0.153	0.058
Std. Deviation	1.478	2.587	2.341	0.881
Minimum	1.000	1.000	1.000	1.000
Maximum	6.000	10.000	9.000	4.000

Source: Rieder E., Data from Survey 2024 – JASP Results, 2025

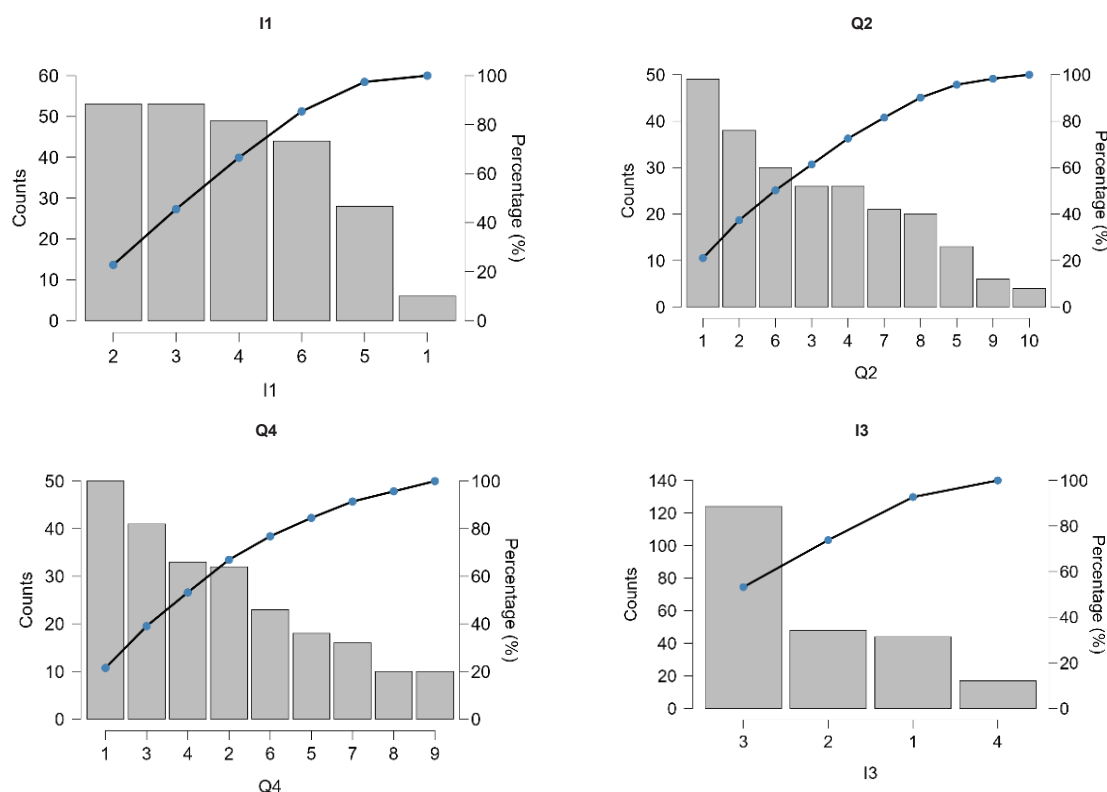


Figure 1: Histogram and cumulative distribution of age (I1), AI integration level (Q2), perceived AI complexity (Q4), and education level (I3). Source: Rieder E., Data from Survey 2024 – JASP Results, 2025.

in order to test Hypothesis 1. The findings show that age and the degree of AI integration are significantly correlated negatively, with a Spearman's rho of -0.239 ($p < .001$) and a Pearson's rho of -0.228 ($p < .001$) (Table 2).

These results lend credence to H1, which states that older workers often report fewer instances of AI integration in their day-to-day tasks. The correlation's negative direction suggests that AI adoption is generational, with younger people more likely to encounter or participate in increasing degrees of AI integration. This finding is consistent with earlier studies showing age-related variances in digital adoption, which frequently arise from variations in organizational support systems, cognitive flexibility, or technology familiarity [5]. It reaffirms the necessity of focused assistance and training programs that take into account aging as a possible obstacle to digital transformation.

Correlation plot (Figure 2)

This pattern is supported by the accompanying scatterplot, which indicates that AI integration scores somewhat decline with age.

Correlation analysis – age and perceived AI complexity

A correlation study between respondents' age (I1) and their assessment of the complexity of AI tools (Q4) was carried out in order to assess Hypothesis 2. With a Spearman's rho of -0.085 ($p = 0.196$) and a Pearson's r of -0.086 ($p = 0.192$), the findings indicated a negative but non-significant connection (Figure 3).

Table 2: Pearson's r and Spearman's ρ correlations between age (I1) and AI integration level (Q2).

Correlation Table			
Variable		I1	Q2
1. I1	Pearson's r	—	
	p - value	—	
	Spearman's rho	—	
	p - value	—	
2. Q2	Pearson's r	-0.228	—
	p - value	< .001	—
	Spearman's rho	-0.239	—
	p - value	< .001	—

Source: Rieder E., Data from Survey 2024 – JASP Results, 2025

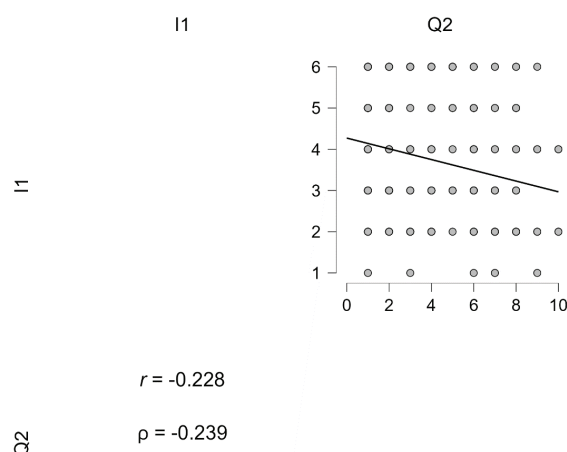


Figure 2: Scatterplot with regression line showing the negative correlation between age (I1) and AI integration level (Q2). Source: Rieder E., Data from Survey 2024 – JASP Results, 2025

These numbers point to a mild inverse association, suggesting that older people may view AI technologies as somewhat simpler. This trend is not strong, though, and might just be the result of chance because it lacks statistical significance.

Correlation plot (Figure 4)

Consequently, the evidence does not support Hypothesis 2. Assumptions from technology acceptance literature [5] that older users find new technologies more challenging to use are in contrast to this study. The older workers in the sample may already work in tech-oriented settings or have acclimated via previous exposure and training, which might be one reason for this discrepancy. The accompanying scatterplot, which displays no discernible linear relationship between perceived complexity and age, supports the weak and flat trend.

Regression analysis with interaction: Age \times education as predictors of AI integration

A multiple linear regression analysis with interaction terms was used to test Hypothesis 3, which proposed that educational attainment (I3) moderates the link between age (I1) and the perceived intensity of AI integration (Q2). Q2 was the dependent variable, while the independent factors were age, educational attainment, and their interaction (I1 \times I3) (Tables 3,4).

A little but statistically significant amount of the variation in AI utilization was described by the regression model ($R^2 = .135$, $p = .009$). The practical importance is still low, even if the statistical significance points to a non-random relationship between the predictors and the result. While demographic factors do affect AI usage, their predictive value is limited when considered alone, as seen by the tiny impact sizes of individual predictors (e.g., age, education) (standardized $\beta < .3$).

Furthermore, the interaction factors between education and age did not provide statistically significant coefficients, indicating that formal education levels in this sample do not significantly alter the impact of age on the use of AI tools.

Correlation Table			
Variable		I1	Q4
1. I1	Pearson's r	—	
	p - value	—	
	Spearman's rho	—	
	p - value	—	
2. Q4	Pearson's r	-0.086	—
	p - value	0.192	—
	Spearman's rho	-0.085	—
	p - value	0.196	—

Figure 3: Pearson's correlation between age (I1) and perceived AI complexity (Q4). Source: Rieder E., Data from Survey 2024 – JASP Results, 2025.

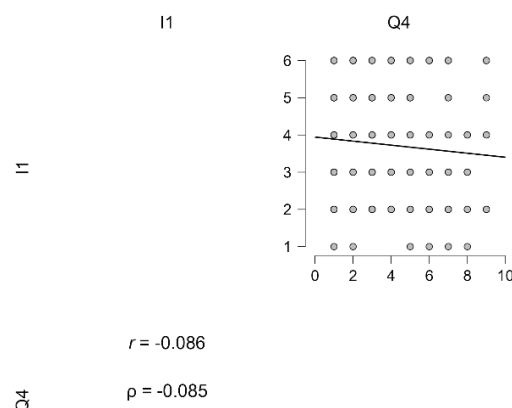


Figure 4: Scatterplot showing the correlation between participants' age (I1) and the perceived complexity of AI tools used in the organization (Q4). Pearson's $r = -0.086$, Spearman's $\rho = -0.085$ ($n = 233$; $p = 0.192$, n.s.)

Source: Rieder E., Data from Survey 2024 – JASP Results, 2025

Table 3: Regression model overview for the dependent variable Q2 (degree of AI integration) with age (I1), education level (I3), and their interaction (I1 \times I3) as predictors.

Model Summary - Q2								
Model	R	R ²	Adjusted R ²	RMSE	R ² Change	df1	df2	p
M ₀	0.000	0.000	0.000	2.587	0.000	0	232	
M ₀	0.368	0.135	0.071	2.494	0.135	16	216	0.009

Note: M₀ includes I1, I3, I1_I3_Interaction

Source: Rieder E., Data from Survey 2024 – JASP Results, 2025

Table 4: ANOVA results for the regression model M₁ predicting perceived AI integration intensity (Q2). The model, which includes age (I1), education (I3), and their interaction terms, is statistically significant ($F(16, 216) = 2.109$, $p = .009$)

ANOVA						
Model		Sum of Squares	df	Mean Square	F	p
M ₁	Regression	209.882	16	13.118	2.109	0.009
	Residual	1343.226	216	6.219		
	Total	1553.107	232			

Note: M₁ includes I1, I3, I1_I3_Interaction

Note: The intercept model is omitted, as no meaningful information can be shown.

Source: Rieder E., Data from Survey 2024 – JASP Results, 2025

Model summary and fit

The extended model (M₁), which included the interaction terms, was statistically significant:

- $F(16, 216) = 2.109$,
- $p = .009$,
- $R^2 = 0.135$, indicating that approximately 13.5% of the variance in perceived AI integration intensity was explained by the model.

Main effects and interaction terms

- Age (I1) and education (I3), when included in the full model, did not show statistically significant main effects:

- o I1: $\beta = 0.055$, $p = 0.902$
- o I3: $\beta = 0.424$, $p = 0.398$
- The interaction terms ($I1 \times I3$), included as a set of dummy-coded effects, were also not statistically significant:
- o All p-values $> .1$ (e.g., I1_I3_Interaction (2): $\beta = -0.197$, $p = 0.844$; I1_I3_Interaction (20): $\beta = -0.703$, $p = 0.486$)

This suggests that education level does not significantly moderate the relationship between age and AI integration in the surveyed sample (Table 5).

Conclusion of hypothesis 3:

H3: Educational attainment moderates the association between perceived AI integration intensity and age. The outcome is not supported.

Age and education do not appear to have a substantial interaction effect on how AI integration is regarded, according to the study. The interaction terms did not significantly add to the explanation of variation, even though the overall model achieved significance.

Discussion

Interpretation of key findings

The subject of this study was the relationship between

demographic variables – primarily age and level of education – and the intensity with which companies integrate AI. In addition, the question of whether education plays a moderating role in the relationship between age and intensity of AI use was investigated. The descriptive statistics and visualizations demonstrated a wide dispersion across all age and education groups. Although the regression analysis showed that the overall model was statistically significant, age and education level alone did not have a significant influence on the degree of AI integration. Furthermore, the interaction effect (age x education) was not statistically significant, indicating that educational background does not have a significant influence on the relationship between age and perceived AI usage intensity in the workplace.

Age and AI integration

The correlation analysis showed a significant negative correlation between age and the perceived intensity of AI integration ($r = -0.228$, $p < 0.001$). This suggests that younger respondents tend to report a higher degree of AI use in their everyday work. This result confirms earlier research findings that suggest that the digital and technological affinity of different generations can influence the acceptance and use of new technologies [1,5]. However, when educational and interaction terms were introduced into the regression model, this effect was weakened, suggesting the presence of additional moderating or mediating factors.

Table 5: Regression coefficients for predicting perceived AI integration intensity (Q2) based on age (I1), education (I3), and their interaction ($I1 \times I3$).

Coefficients							95% CI	
Model		Unstandardized	Standard Error	Standardized ^a	t	p	Lower	Upper
M ₀	(Intercept)	4.090	0.170		24.130	< .001	3.756	4.424
M ₁	(Intercept)	3.408	2.559		1.332	0.184	-1.636	8.453
	I1	0.096	0.782	0.055	0.123	0.902	-1.445	1.637
	I3	1.245	1.470	0.424	0.847	0.398	-1.653	4.143
	I1_I3_Interaction (2)	-0.331	1.677		-0.197	0.844	-3.635	2.974
	I1_I3_Interaction (3)	-2.054	2.166		-0.948	0.344	-6.322	2.215
	I1_I3_Interaction (4)	-1.293	2.634		-0.491	0.624	-6.485	3.899
	I1_I3_Interaction (5)	-4.135	3.661		-1.129	0.260	-11.352	3.082
	I1_I3_Interaction (6)	-1.839	3.824		-0.481	0.631	-9.377	5.698
	I1_I3_Interaction (8)	-2.899	4.045		-0.717	0.474	-10.872	5.073
	I1_I3_Interaction (9)	-3.183	4.661		-0.683	0.495	-12.371	6.005
	I1_I3_Interaction (10)	-3.380	4.893		-0.691	0.490	-13.024	6.263
	I1_I3_Interaction (12)	-3.742	5.474		-0.684	0.495	-14.532	7.047
	I1_I3_Interaction (15)	-3.273	6.174		-0.530	0.597	-15.443	8.897
	I1_I3_Interaction (16)	-0.275	7.044		-0.039	0.969	-14.159	13.609
	I1_I3_Interaction (18)	-4.722	6.927		-0.682	0.496	-18.375	8.932
	I1_I3_Interaction (20)	-5.621	7.682		-0.732	0.465	-20.762	9.520
	I1_I3_Interaction (24)	-4.592	8.390		-0.547	0.585	-21.130	11.945

^a Standardized coefficients can only be computed for continuous predictors.

Source: Rieder E., Data from Survey 2024 – JASP Results, 2025

Educational attainment and AI complexity

Contrary to expectations, the level of education showed no significant correlation with the perceived complexity of AI tools (Q4). Although it seems obvious that people with higher education are better able to handle complex technologies, our data did not confirm this hypothesis. This result is consistent with some critiques that argue that the influence of formal education on practical technology adaptation is overestimated [6]. Experience with AI tools seems to play a more decisive role in perceived usability than formal education.

Age, education, and interaction effects

The regression analysis, which took into account interaction terms between age and education, showed an overall statistically significant model ($R^2 = 0.135$; $p = 0.009$), although no single interaction term was statistically significant. This suggests that the current data provide no evidence of an influence of education on the relationship between age and AI integration. Theoretically, this may seem intuitive, but the empirical evidence suggests that age and education largely function as independent rather than interacting factors.

The role of age in AI usage

This study investigated the significance of age for the perception of the intensity of AI integration in the workplace. The correlation analysis showed a significant negative relationship between age and the reported degree of AI integration. This suggests that younger employees are more likely to encounter or use AI systems in their daily tasks. This supports previous findings on generational differences in the adoption of digital technologies and is consistent with the concept of digital natives. After integrating educational attainment and interaction effects into the regression model, age lost its significance as a predictor. Furthermore, the hypothetical moderating effect of educational attainment on the relationship between age and AI integration was not confirmed, as none of the interaction terms were statistically significant. These results suggest that although age appears to have an influence initially, this influence is not robust when other factors are taken into account. Overall, the results suggest that age-related differences in AI acceptance may be overestimated when considered in isolation. Companies could benefit more from promoting equitable AI use across demographic groups by paying attention to technological experience, organizational support, and task relevance rather than focusing solely on chronological age.

Implications for theory and practice

From a theoretical perspective, the results offer only limited support for models that postulate strong demographic determinants of the intensity of AI integration, such as interactions between age and education. Although the Technology Acceptance Model (TAM) highlights perceived user-friendliness and usefulness as key factors for acceptance [7], this study suggests that these perceptions may be less influenced by immutable demographic factors than previously thought. In practice, companies seeking more intensive AI integration should go beyond demographic segmentation when

planning training and change management measures. Instead, usage-based profiling or experiential learning could be more effective approaches to improving AI readiness across age and educational boundaries.

Practical insights for inclusive AI adoption

The study's quantitative findings provide a number of insights into the dynamics of workplace AI integration across generations. In particular, the data showed notable variations in the intensity of AI use by age group, with younger workers reporting higher levels of engagement with AI tools more often than older cohorts, who exhibited more cautious usage patterns.

The regression study also showed that the frequency of AI usage is negatively correlated with age ($\beta = -0.368$, $p = 0.009$), indicating that older workers are less likely to use AI systems extensively. Higher education may also somewhat mitigate the drop in AI adoption among older respondents, according to interaction effects between age and education. This is a significant result for workforce planning.

Responses to the survey also showed that perceived competency and the availability of training were important factors. Older workers identified two main obstacles in their open-ended responses: a lack of specialized training and a fear of being replaced by technology. Younger individuals, on the other hand, highlighted how easily AI was incorporated into their everyday tasks.

These results lead to a number of practical suggestions for businesses looking to promote the use of AI in a more inclusive manner:

- Make an investment in specialized AI training for senior staff members, which should include interactive workshops and peer-led tutorials catered to their individual learning styles.
- Taking use of intergenerational learning by promoting reverse mentorship initiatives, in which younger employees who are proficient in digital technology assist more senior colleagues with AI-related work.
- Explain the useful advantages of AI to people of all ages, particularly with regard to decision help and task reduction.
- Create training curricula that take educational background into consideration, as certain generational gaps seem to be mediated by higher education.
- Put in place ongoing feedback systems to sustain engagement with developing AI technologies and modify support tactics over time.

Organizations may make sure that attempts to implement digital transformation do not unintentionally widen generational gaps but rather promote a culture of mutual learning and advancement by tackling both structural and perceptual hurdles to AI deployment.

Limitations and future research

This study has several limitations. First, it relies on self-reported survey data, which may be influenced by response bias and subjective interpretations of AI-related terms. A second drawback of the cross-sectional design is that it does not allow causal conclusions to be drawn about the relationships between the variables. Third, the interaction analysis focused only on linear effects, which may have overlooked non-linear or context-specific moderations. Future studies could use longitudinal designs to track the development of AI adoption in relation to workforce aging and retraining measures. In addition, qualitative analyses would be able to identify more differentiated patterns of how education influences attitudes toward the use of AI in different occupational fields. Expanding the model to include factors such as corporate culture, depth of training, or digital maturity could contribute to a more comprehensive understanding of the dynamics of adoption.

Based on these limitations, several promising avenues for future research are proposed:

- **Longitudinal studies:** Future research should employ longitudinal tracking to record behavioral shifts and adaption curves in order to comprehend how AI adoption varies over time across age groups and educational levels.
- **Nonlinear and threshold effects:** Current models might be improved by looking at possible nonlinear links (such as if AI usage declines sharply beyond a particular age) or discovering threshold effects (such as the minimal training required for adoption).
- **Cross-cultural comparisons:** By extending research to other nations or cultural contexts, it may become clearer how social views or national educational systems affect the disparities in AI adoption between generations.
- **Mixed methods approach:** Future research would have greater explanatory power and be able to catch subtleties not captured by numerical data alone if surveys were

combined with qualitative interviews or observational case studies.

- **Organizational and behavioral factors:** To reduce generational differences in AI preparation, future research should look at the impact of training formats, leadership commitment, and business culture.
- **Cognitive and psychological frameworks:** Behavioral science ideas (such as the Technology Acceptance Model and cognitive aging) may be incorporated to assist explain why older workers might be reluctant to use sophisticated AI technologies.

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