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Predictors of Workplace AI Adoption in a Norwegian Sample

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Abstract

This study examines predictors of workplace adoption of artificial intelligence (AI) in a Norwegian employee sample (N = 196). Hierarchical logistic regression tested whether education, sector, sex, age, leadership, strengths-based leadership (SBL), training, and engagement predicted AI use. Education was the strongest predictor. Employees with a bachelor's degree were 3.64 times, and those with a master's degree more than 11.15 times, more likely to use AI than those with secondary education. Knowledge-intensive sector employees were 2.52 times more likely to adopt AI than those in skills-focused sectors. Men were 2.94 times more likely than women to use AI. Neither age nor leadership role showed significant effects. SBL independently predicted adoption (OR = 1.89). Training and engagement were unrelated to adoption. Overall, findings show that structural, sociodemographic, and organizational factors shape AI adoption, underscoring the need for targeted strategies to ensure equitable, effective uptake across the workforce.

Keywords: artificial intelligence; AI adoption; workplace; education; strengths-based leadership; gender; logistic regression; Norway

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1. Introduction

Following the rapid emergence of increasingly capable generative AI (GenAI), understanding the drivers of workplace adoption has become a critical research priority. Recent studies show that use is uneven across sectors, demographic groups, and organizational factors. At the same time, effective adoption of AI promises substantial gains in efficiency and workforce development, with evidence converging on task-level performance improvements of roughly 5–25% across knowledge-work activities (Choi et al., 2023; Cui et al., 2025; Dell'Acqua et al., 2023; Merali, 2024; Peng et al., 2023).

Education, job sector, age, and gender have consistently emerged as key correlates of AI adoption. Higher levels of education are associated with greater uptake, reflecting both digital literacy and the alignment of AI tools with knowledge-intensive tasks (Brey & van der Marel, 2024a). Sectoral patterns similarly show that adoption is concentrated in information-intensive industries, while use in skill-based sectors remains limited (McElheran et al., 2024). Younger workers also report higher adoption rates than older cohorts in Norway and Denmark (Anne Vibeke Jacobsen & Anton Erenbjerg, 2025; Marina Rybalka, 2024). Gender differences also exist, with men mostly reporting higher confidence and adoption rates than women across surveys (Aldasoro et al., 2024; Dorta-González et al., 2024). However, the extent to which these factors independently predict adoption when considered together in organizational contexts remains less clear.

Organizational and leadership factors may further impact adoption. Research on innovation factors consistently shows that leadership facilitates uptake of new technologies (Damanpour, 1991; Damanpour & Schneider, 2006; Hameed et al., 2012a). Recent evidence extends this to AI, demonstrating that supportive leadership behaviors increase trust and usage of AI tools (Hu et al., 2025a; Zárate-Torres et al., 2025). One leadership approach that may be relevant in this context is strengths-based leadership (SBL), which emphasizes recognizing and developing employees' strengths. Evidence suggests that SBL enhances self-efficacy and confidence (Ding & Quan, 2021a; Van Woerkom et al., 2016; J. Wang et al., 2023a), which may encourage employees to engage with AI systems more constructively and critically (Jeong, 2025; Yamamoto et al., 2025)

Beyond leadership, broader organizational resources may also condition AI adoption. Access to job-embedded training is a key enabler of technology integration and acceptance, and shapes employees' confidence and capacity to apply new tools in their daily work (Boothby et al., 2010; Hu et al., 2025a; Molino et al., 2020). Similarly, work engagement has been linked to employees' willingness to experiment with and sustain the use of innovations (Bakker & Demerouti, 2008; Saks, 2006).

Yet, the influence of leadership, training, and engagement on adoption, independent of demographic and sectoral factors, remains insufficiently understood. To address this gap, we test whether education, job sector, sex, strengths-based leadership (SBL), job-embedded training, and work engagement predict on-the-job GenAI use in a Norwegian employee sample. We estimate hierarchical logistic models that first include sociodemographic and sectoral factors and then add organizational and psychological variables to assess incremental explanatory power. Consistent with prior work, we expect positive associations for higher education (H1) and knowledge-intensive sectors (H2). A male advantage in reported use (H3) and a negative association with age (H4). We further expect positive effects of strengths-based leadership (H5), being a leader (H6), general work training (H7), and employee engagement (H8).

2. Related Works and Study Objectives

2.1. Education

Research consistently shows that education is positively associated with the adoption of AI tools in the workplace. OECD survey data indicate that workers with tertiary education are substantially more likely to use AI than those with lower educational attainment, largely because AI adoption is concentrated in occupations requiring complex, non-routine cognitive tasks (Lane, 2024; Lane et al., 2023). Bick et al., (2024) find that in the U.S., the share of employees using GenAI at work was 39.4% among bachelor's degree holders and 40.9% among those with master's degrees, compared to 19.6% among those without a college degree. Complementary findings by Kacperski et al., (2025), using longitudinal survey data, confirms that higher education significantly predicts ChatGPT use (OR = 1.23).

2.2. Job Sector

AI adoption differs across sectors, reflecting both task differences and workforce skills. Sectors rich in technical talent and digital infrastructure, such as IT services, media, and telecommunications, are consistently early adopters of AI (Lane, 2024). Workforce composition accounts for much of the variation in adoption across sectors. Skills alone might account for roughly half of the difference in adoption rates between sectors, as more educated and digitally proficient workers tend to be the earliest and most proficient adopters (Brey & van der Marel, 2024b). Eurostat survey data shows that by 2024, AI adoption exceeded 25% in information, communication, and professional services, but remained in single digits in construction and hospitality (Eurostat, 2024).

At the occupational level, adoption is highest in knowledge-intensive roles. By late 2024, 28% of U.S. workers reported using generative AI, with nearly half of computer and mathematical scientists (49.6%) and managers (49.0%) reporting use, compared to around 40% in business, finance, and education, and below 25% in routine office support, blue-collar, and personal-service roles (Bick et al., 2024). Higher education mirrors this divide. STEM students and faculty report higher adoption and comfort with GenAI than non-STEM peers (Freeman, 2025; J. Kim et al., 2025; Parviz, 2024).

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Task-level evidence clarifies why these differences emerge. Workers primarily use AI for cognitive activities. For example, a majority of workers use it for writing (57%), information search (49%), and summarization (47%), while few use it for physical tasks (15%) (Bick et al., 2024). This pattern is reinforced by usage data from major AI models. Data from Anthropic's chatbot, Claude, shows nearly half its use concerns software development and writing, while usage of Copilot shows communication and information processing, and the most applicable use cases (Handa et al., 2025; Tomlinson et al., 2025).

2.3. Sex

A synthesis of 18 studies concluded that there is a near-universal gender gap across different regions and sectors, with men reporting higher rates of generative AI use than women (Otis et al., 2024). Norwegian statistics similarly report higher adoption among men (42%) compared to women (30%) (SSB, 2025). This pattern is corroborated by national statistics in Denmark, the United Kingdom (Jacobsen & Erenbjerg, 2025; GOVUK, 2024), and in broader international surveys (Lane et al., 2023). These disparities are not merely a reflection of differing occupational exposure but also persist within the same roles (Otis et al., 2024). Studies find that women tend to report higher levels of AI anxiety and lower perceived AI (Russo et al., 2025), as well as greater wariness about the moral use of AI (Rana et al., 2024). Structurally, women are also often overrepresented in jobs with less AI exposure (Conde-Ruiz et al., 2024). However, some argue that about three-quarters of the difference in adoption can be attributed to differences in AI-related knowledge and training opportunities (Aldasoro et al., 2024). For example, a study among legal-aid attorneys found that gender differences disappeared once all participants were given equal access to technology and adequate training (Chien & Kim, 2024). Additionally, employee adoption rates are dramatically higher when AI use is actively encouraged by leadership (Bick et al., 2024).

2.4. Age

Research demonstrates a clear age gradient in AI adoption, a finding supported by both academic studies and large-scale surveys. For instance, in Korean enterprises, age was a significant negative predictor of generative AI use (Kim et al., 2024). Similarly, evidence confirms that older workers adopt workplace technologies more slowly (Dingel et al., 2024; Fazi et al., 2025a). This pattern is quantified in survey data: across 11 European countries, 36% of workers aged 18–34 report using AI at work versus 18% of those aged 55–74 (Da Silva & Weißler, 2025). Norwegian statistics show an even starker trend, with 65–70% of those aged 16–24 using Generative AI compared to just 10% of those 65 and older (SSB, 2024).

The mechanisms behind this age disparity are well-documented. Older users consistently report higher perceived effort and greater technology anxiety, while also demanding clearer enabling conditions, such as training to adopt new systems (A. Wang et al., 2024; Yu & Chen, 2024). In contrast, for younger students, adoption is instead strongly predicted by positive drivers like perceived usefulness, ease of use, and trust (Grassini et al., 2024; Møgelvang & Grassini, 2025)

However, age does not operate in isolation; it often interacts with education. Older individuals with higher education demonstrate greater AI use than their less-educated peers, suggesting that education mitigates some of the barriers associated with age (Draxler et al., 2023). Though comparably, younger individuals with higher education exhibit the strongest adoption rates (Kacperski et al., 2025b). Some studies show that while older people are as motivated to learn AI as younger peers, they face specific challenges in understanding how to start and prefer specific training or tailored support (KangJie et al., 2025; Ko et al., 2025).

2.5. Leadership

In exploring the role of leadership, this study focuses on Strengths-Based Leadership (SBL). Emerging from the principles of positive psychology, SBL is a leadership style centered on identifying, developing, and applying the capabilities or strengths of employees to perform their best (Miglianico et al., 2020; Peterson & Seligman, 2004). Rather than focusing on correcting deficits, SBL focuses on individual capabilities and aligning work tasks accordingly (Straume & Vittersø, 2012). This focus on individual strengths is especially relevant for AI adoption in organizations. Research shows that SBL fosters self-efficacy (Ding & Quan, 2021b; J. Wang et al., 2023b). Higher self-efficacy has been shown to empower employees to approach technologies with confidence rather than anxiety and allows for an environment of experimentation (Li & Kim, 2024). Moreover, enhanced self-confidence and awareness might enable employees to judge when to trust AI outputs and when to apply their own critical expertise, leading to more effective and responsible use of AI tools (Lee et al., 2025). Research on technology adoption has consistently identified management support as a precondition for technology implementations and successful digital transformations (Anderson & Dexter, 2005; Flanagan & Jacobsen, 2003). In healthcare, transformational leadership significantly predicts nurses' intentions to use AI, demonstrating that inspirational motivation enhances readiness for AI integration (Khirfan et al., 2024a). A large study across 250 companies found that leaders focusing on vision and intellectual stimulation were associated with intention to adopt AI among employees (Patnaik & Bakkar, 2024a). Relatedly, a growing body of research highlights leadership as a decisive factor in organizational AI adoption. Bick et al. (2024) show that AI adoption rates reach 82.9% when leaders actively encourage AI use compared to just 7.1% when they discourage it. However, this figure likely underestimates usage, as it fails to capture hidden unsanctioned use of AI by employees (Chin et al., 2025).

2.6. Training

Training has been argued as a primary lever for AI adoption because it builds AI literacy and self-efficacy. This aligns with the Unified Theory of Acceptance and Use of Technology (UTAUT), where training is a facilitating condition that reduces effort expectancy and raises intention to use technology (Ke et al., 2025; Venkatesh et al., 2003a). Markus et al. (2024) found that short AI-understanding modules intention to use by .43 SD. Cao et al. (2025) found that micro-learning interventions significantly raised AI-use self-efficacy, and AI-literacy training in healthcare boosted diagnostic accuracy from 43% to 71% when combined with LLMs (Qazi et al., 2025). Furthermore, training can further promote adoption through knowledge sharing and peer learning (Hu et al., 2025b). Some findings have indicated that gender gaps in adoption disappeared once employees received training and equal access to AI tools and training (Chien & Kim, 2024). Moreover, age differences in adoption have been lessened through targeted training and leadership support (Fazi et al., 2025b; Hofmann & Schalk, 2025).

2.7. Work Engagement

Work engagement has been theorized as both a driver and an outcome of technology adoption, including AI. In accordance with UTAUT, engagement significantly improves behavioral intention to use digital systems (Venkatesh et al., 2003a). Faida et al., (2023) found that the addition of work engagement to their UTAUT model raised the explained variance from 39% to 74%, suggesting that employees with higher engagement are more willing to experiment with new technologies and integrate them into daily work.

AI-specific studies confirm the positive effect of engagement. Among healthcare professionals, engagement directly increased AI adoption intention ($B = 0.41$) (Qian et al., 2023). Conversely, AI use itself can raise engagement. AI users report significantly higher work engagement ($d = 0.89$) (Rick et al., 2024). Longitudinal evidence shows that usage enhances engagement through psychological availability and reduced alienation, but only when AI complements rather than substitutes core tasks (Liu & Li, 2025). Some studies have found a dual effect of AI. Usage can heighten engagement through psychological availability and self-efficacy, but reliance on AI can also undermine absorption and meaning (Chuang et al., 2025; Liu & Li, 2025).

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3. Method

3.1. Participants and Procedure

The sample consisted of 196 employees in Norway, aged 18 years or older. Data were collected with an anonymous online survey in Nettskjema between November 22, 2024, and January 31, 2025. Complete anonymity was ensured by disabling the collection of IP addresses or other identifiers, and no survey items requested personal data. Informed consent was obtained before participation. The survey was distributed via social media, email to organizations, and personal networks. No personal data was collected, and thus approval from the Norwegian Agency for Shared Services in Education and Research (Sikt) was not required.

3.2. Instruments

Validated scales were used to assess SBL and work engagement. Work training (M = 4.47, SD = 1.11) was measured with the question: "In my organization, I received sufficient training to perform my work tasks in a proper manner." All scales were forward- and back-translated (Brislin, 1970). SBL (M = 5.09, SD = 1.20) was measured with the 8-item scale by Wang et al. (2023), adapted from Keenan & Mostert (2013). The scale is answered on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). The scale has a high internal consistency (α = 0.97; wang et al, 2023). After back-translation, the scale had an α of 0.94 in the current study.

Work engagement (M = 5.28, SD = 1.41) was measured with the UWES-3 (Schaufeli, 2003; Schaufeli et al., 2019). The three items capture vigour, dedication, and absorption, rated from 0 (never in the past year) to 6 (daily). In other studies, internal consistency ranges from acceptable to excellent: α = .77 in a nationally representative Korean worker sample (An et al., 2020), α = .94 in a Peruvian worker sample (Merino-Soto et al., 2022), and α = .95 in a Dutch workforce sample (Schaufeli et al., 2019). Reliability of the Norwegian version in the current study was good (α = .85).

3.3. Data Analysis

All analyses were conducted using IBM SPSS Statistics (version 30). Statistical significance was evaluated at $p < .05$ (two-tailed).

We first report the overall percentage of AI users and examined adoption rates across sociodemographic and occupational variables (education, age group, sector, sex, leadership role). For categorical comparisons, Pearson's χ^2 tests were applied, with Fisher's exact test used in 2×2 tables and Monte Carlo correction in tables with sparse cells. For continuous variables (work training, SBL, and engagement), independent samples t-tests were performed to compare users and non-users of AI. Levene's test determined whether equal variances could be assumed. Effect sizes were reported as Cohen's d with 95% CIs.

We modeled the likelihood of AI adoption using a stepwise model-building approach. AI use (0 = non-user, 1 = user) was the dependent variable. Model 1 included the sociodemographic variables of education, age group, sex, leadership role, and work sector. Education and sector were treated as categorical (see Table 1 for an overview). Model 2 added the organizational context variables of work training, SBL, and work engagement.

To create a more parsimonious model, Model 3 was run, containing only the significant predictors from the previous analyses: education, sector, sex, and strength-based leadership. This approach isolates the most influential variables, allowing us to evaluate their value without the statistical noise from the non-contributing predictors. This final model also allowed us to evaluate the incremental value of organizational and psychological variables beyond demographics. Because the "primary school" category had very few cases (n = 2) and produced quasi-separation in Models 1–2, we collapsed it into the upper secondary category, respecifying education as a three-level factor: upper secondary, 3-year higher education, 5-year higher education or more. Similarly, the original sector variable collapsed from ten sectors to a binary indicator to reduce sparse given our sample size. Two categories were created: knowledge-intensive work, composed of Public administration, IT

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& media, Finance & insurance, Education, while Skills-focused work comprised Health & care, Professional services, Retail & service, Construction. Industry (n = 2) and the heterogeneous "Other" category were excluded in the final model. Predictors were entered simultaneously (enter method). Odds ratios (ORs), 95% confidence intervals, and p-values were reported for each predictor in Table x.

4. Results

4.1. Descriptive Statistics

The analytic sample consisted of 196 respondents (1 did not report sex). Overall, 143 participants reported using AI at work, and 53 did not. Most respondents were women (115 vs. 80 men), and 19 held a leadership role. Age groups were distributed as 77 aged 18–34 years, 59 aged 35–49, and 60 people aged 50 and older. Regarding education, two had completed only primary school, 21 had completed upper secondary school, 51 had a bachelor's degree, and 122 had a master's degree. Participants represented a wide range of sectors, with the largest groups from public administration (n = 40), IT and media (n = 36), health and care (n = 30), and education (n = 24). See Table 1.

Table 1. Distribution of Demographic Variables.

Variable	Category	n
AI adoption	No	53
	Yes	143
Sex	Male	80
	Female	115
	Missing	1
Leadership	No	177
	Yes	19
Age	18–34	77
	35–49	59
	50+	60
Education	Primary school	2
	Upper secondary school	21
	Bachelor's degree	51
	Master's degree	122
Sector	Health and care	30
	Public administration	40
	IT and media	36
	Finance and insurance	18
	Education	24
	Other	24
	Professional services	7
	Trade and services	4
	Construction	11
	Industry	2

Note. One case is missing for sex. For regression Model 3, education was recoded by combining Primary school with Upper secondary school. Sector was recoded to a binary indicator: knowledge-intensive (public administration, IT & media, finance & insurance, education) vs. skills-focused (health & care, professional services, trade & services, construction); the Other and Industry categories were excluded in the final model.

4.2. Chi-Square Tests

Chi-square tests were performed to explore demographic differences in AI adoption (Table 2). Adoption was significantly associated with sex, $\chi^2(1, N = 195) = 4.35$, $p = .037$, $\varphi = .15$, with men reporting higher adoption (81%) than women (68%). No significant differences were observed across age groups, $\chi^2(2, N = 196) = 1.81$, $p = .405$, $V = .10$. Education was strongly associated with adoption,

$\chi^2(3, N = 196) = 29.42$, $p < .001$, $V = .39$, with bachelor's/master's degree holders most likely to use AI. Leaders reported higher adoption (90%) compared to non-leaders (71%), but this difference was not significant, $\chi^2(1, N = 196) = 2.91$, $p = .088$, $\varphi = .12$. Adoption also varied by sector, $\chi^2(9, N = 196) = 39.26$, $p < .001$, $V = .45$, with IT, finance, and education showing the highest rates. For education and sector, Monte Carlo simulations with 10,000 samples and a 95% confidence interval confirmed the robustness of the results. See Table 2

Table 2. Chi-Square Tests of AI Adoption by Demographic Variables.

Predictor	χ^2(df)	p	Effect Size
Sex	4.35(1)	.037 a	φ = .15
Age	1.81(2)	.405	V = .10
Education	29.42(3)	<.001 b	V = .39
Leader role	2.91(1)	.088 c	φ = .12
Sector	39.26(9)	<.001 b	V = .45

Notes. Pearson χ^2 reported; effect size is φ for 2×2, Cramér's V otherwise. a Fisher's exact (two-sided) also inspected for robustness: p = .048. b Due to sparse cells, Monte Carlo exact p-values were computed with 10,000 samples and 95% confidence level; conclusions unchanged (p < .001). c For leader (2×2) with borderline expected counts, Fisher's exact (two-sided) = .107.

4.3. Independent Sample t-Tests

Independent samples t-tests compared AI users and non-users on work training, SBL, and work engagement (see Table 3). No differences were observed for Work training, $t(194) = 0.02$, $p = .986$, $d = 0.00$, or work engagement, $t(194) = 0.04$, $p = .968$, $d = 0.01$. However, AI users reported significantly higher SBL ($M = 5.25$, $SD = 0.91$) than non-users ($M = 4.65$, $SD = 1.32$), Welch's $t(77.34) = –2.87$, $p = .005$, $d = 0.52$, indicating a medium effect. Equal variances were assumed for Work Training and engagement. Welch's correction was used for SBL due to unequal variances.

Table 3. Independent Samples t-Tests Comparing AI Users and Non-Users on Work Training, SBL, and Work Engagement.

Variable	Group	n	M	SD	t(df)	p	Cohen's d
Work Training	Non-users	53	4.47	1.12	0.02(194)	.986	0.00
	AI users	143	4.47	1.11			
SBL	Non-users	53	4.65	1.32	–2.87(77.34)	.005	0.52
	AI users	143	5.25	0.91			
Work engagement	Non-users	53	5.29	1.54	0.04(194)	.968	0.01
	AI users	143	5.28	1.36			

Note. Means (M) and standard deviations (SD) are reported per group. Equal variances were assumed for training and work engagement, while Welch's correction was applied for SBL due to unequal variances. Cohen's d uses pooled standard deviation.

4.4. Logistic Regression Analyses

To examine predictors of AI use, we conducted three hierarchical logistic regression models. Model 1 included sociodemographic variables (age, gender, leadership position, education, and sector. The model was significant, $\chi^2(16) = 71.75$, $p < .001$, with Nagelkerke $R^2 = .448$, and correctly classified 81.5% of cases. Hosmer–Lemeshow indicated good fit, $\chi^2(8) = 7.25$, $p = .51$. Education, sector, and gender emerged as significant predictors (see Table 4 for results). Higher levels of education increased the odds of AI use, and working IT and media was associated with greater likelihood of AI use. Men were more likely to report AI use compared to women (OR = 0.36). Education effects were unstable due to a tiny "primary school" group (n = 2).

Table 4. Logistic Regression Predicting AI Use – Model 1 (Sociodemographics).

Predictor	B	SE	OR	95% CI	p
Leader	1.36	.98	3.89	[0.56, 26.44]	.172
Age 35–49	0.71	.55	2.04	[0.69, 5.99]	.196
Age 50+	−0.27	.50	0.77	[0.29, 2.04]	.592
Sex (Female)	−1.03	.45	0.36	[0.15, 0.86]	.021
Education (overall)	—	—	—	—	<.001
Public Admin	0.22	.62	1.25	[0.37, 4.18]	.718
IT & Media	2.60	.78	12.93	[2.87, 59.15]	<.001
Finance	—	—	—	—	.998
Education (sector)	0.84	.74	2.32	[0.55, 9.80]	.253
Other	1.46	.75	4.31	[1.00, 18.58]	.050
Prof. Services	0.16	1.05	1.18	[0.15, 9.23]	.878
Retail/Service	1.85	1.50	6.36	[0.33, 121.14]	.219
Construction	0.94	.97	2.56	[0.38, 17.14]	.333
Industry	−0.90	2.00	0.41	[0.01, 20.48]	.653

Note. Categorical coding: Leader (1 = leader, 0 = non-leader); Sex (1 = female, 0 = male). Finance dummy estimates showed quasi-separation (perfect prediction) due to very small cells. Leader reference = non-leader; Age reference = 18–34; Sex reference = male.

Model 2 added the organizational context variables as a blockto the analyses. Adding Work training, SBL, and engagement improved model fit, $\chi^2(3) = 10.67$, $p = .014$. The overall model was significant, $\chi^2(19) = 82.42$, $p < .001$, Nagelkerke $R^2 = .50$, with 81.0% classification accuracy. Hosmer–Lemeshow indicated good fit, $\chi^2(8) = 4.71$, $p = .79$. SBL was a strong predictor of AI use (OR = 2.03), indicating that individuals who perceive their leaders as better (i.e., higher SBL) use AI more. Gender and education remained significant, whereas sector effects were attenuated once ability was included.

Table 5. Logistic Regression Predicting AI Use – Model 2 (Added Occupational Variables).

Predictor	B	SE	OR	95% CI	p
Leader	1.08	1.06	2.95	[0.37, 23.47]	.307
Age 35–49	0.50	0.58	1.65	[0.53, 5.13]	.391
Age 50+	−0.54	0.54	0.58	[0.20, 1.68]	.317
Sex (Female)	−1.08	0.45	0.34	[0.14, 0.83]	.017
Education (overall)	—	—	—	—	<.001
Public administration	−0.08	0.66	0.92	[0.25, 3.38]	.899
IT & media	2.35	0.81	10.53	[2.14, 51.82]	.004
Finance & insurance	—	—	—	—	.998
Education (sector)	0.94	0.81	2.55	[0.52, 12.43]	.248
Other	1.26	0.76	3.54	[0.79, 15.79]	.098
Professional services	−0.25	1.08	0.78	[0.09, 6.48]	.815
Retail/Service	1.71	1.40	5.55	[0.36, 85.51]	.219
Construction	0.81	1.02	2.24	[0.31, 16.41]	.426
Industry	−0.75	2.14	0.47	[0.01, 31.47]	.727
Work training	−0.34	0.23	0.72	[0.46, 1.12]	.146
SBL	0.71	0.24	2.03	[1.28, 3.23]	.003
Engagement	−0.05	0.17	0.95	[0.68, 1.33]	.774

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Note. Categorical coding: Leader (1 = leader, 0 = non-leader); Sex (1 = female, 0 = male); Age reference = 18–34; Sector reference = Health & care. Finance & insurance shows quasi-separation. OR = odds ratio; CI = confidence interval.

To create a more parsimonious model, Model 3 was run, containing only the significant predictors from the previous analyses: education, sector, sex, and strength-based leadership. This approach isolates the most influential variables, allowing us to evaluate their value without the statistical noise from the non-contributing predictors. This final model also allowed us to evaluate the incremental value of organizational and psychological variables beyond demographics. Because the "primary school" category had very few cases (n = 2) and produced quasi-separation in Models 1–2, we collapsed it into the upper secondary category, respecifying education as a three-level factor: upper secondary, 3-year higher education, 5-year higher education or more. Similarly, the original sector variable collapsed from ten sectors to a binary indicator to reduce sparse given our sample size. Two categories were created: knowledge-intensive work, composed of Public administration, IT & media, Finance & insurance, Education, while Skills-focused work comprised Health & care, Professional services, Retail & service, Construction. Industry (n = 2) and the heterogeneous "Other" category were excluded in the final model. Predictors were entered simultaneously (enter method). Odds ratios (ORs), 95% confidence intervals, and p-values were reported for each predictor in Table x Descriptive Statistics The analytic sample consisted of 196 respondents (1 did not report sex). Overall, 143 participants reported using AI at work, and 53 did not. Most respondents were women (115 vs. 80 men), and 19 held a leadership role. Age groups were distributed as 77 aged 18–34 years, 59 aged 35–49, and 60 people aged 50 and older. Regarding education, two had completed only primary school, 21 had completed upper secondary school, 51 had a bachelor's degree, and 122 had a master's degree. Participants represented a wide range of sectors, with the largest groups from public administration (n = 40), IT and media (n = 36), health and care (n = 30), and education (n = 24). See Table 1.

SBL, sex, education, and sector type all significantly predictedAI adoption. Each one-point increase in SBL was associated with almost double the odds of AI use (OR = 1.89). Employees in knowledge-intensive sectors were about 2.5 times more likely to use AI compared to those in skills-focused sectors (OR = 2.52). Women had substantially lower odds than men, at roughly one-third the likelihood of adoption (OR = 0.34). Education showed the strongest gradient: compared to respondents with only secondary education or less, those with a bachelor's degree were nearly four times more likely to adopt AI (OR = 3.64), and those with a master's degree or higher were more than eleven times more likely (OR = 11.15). A follow-up comparison between bachelor's and master's degree holders confirmed that adoption was significantly higher among the latter ($\chi^2(1) = 7.10$, p = .008, OR = 3.06, 95% CI [1.34, 7.01]).

Table 6. Logistic Regression Predicting AI Use – Model 3 (Recoded Education, Knowledge Sector).

Predictor	B	SE	OR	95% CI	p
Strengths-based leadership	0.64	0.17	1.89	[1.35, 2.64]	<.001
Knowledge sector	0.92	0.42	2.52	[1.12, 5.68]	.026
Sex (Female)	−1.09	0.44	0.34	[0.14, 0.80]	.013
Education (overall)					<.001
3 years	1.29	0.60	3.64	[1.12, 11.91]	.032
5 years +	2.41	0.58	11.15	[3.59, 34.92]	<.001

Note. Reference categories were ≤ upper secondary education, skills-focused sectors (health & care, professional services, retail/trade & services; industry and "other" were excluded), and male (for sex). Education and sector were entered as categorical variables with dummy coding. OR = odds ratio; CI = confidence interval.

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To evaluate predictive performance, a ROC curvewas computed for the final model. The model discriminated between AI users and non-users at an acceptable-to-good level, AUC = .778, 95% CI [.696, .860], $p < .001$. This indicates that, given a randomly selected pair of an AI user and a non-user, the model correctly assigns a higher predicted probability of adoption to the user in about 78% of cases.

5. Discussion

This study examined factors associated with workplace AI adoption in a Norwegian sample of employees. AI adoption (H1) increased sharply with higher levels of education, with employees holding a bachelor's degree being 3.6 times more likely to adopt AI than those with secondary education or less, and those with a master's degree or higher being over 11 times more likely. Employees in knowledge-intensive sectors were also more likely to adopt AI than those in skills-focused sectors, confirming H2.AI adoption was common, with 72.9% of employees reporting AI use at work. 81% of men reported AI adoption compared to 68% of women. However, analyses showed that men were nearly three times more likely than women to use AI (OR = 2.94) after accounting for education and sector, confirming H3. Regarding H4, age groups did not predict AI use when controlling for the other variables. AI adoption was linked to leadership, confirming H5: Employees who reported stronger SBL from their leaders were significantly more likely to use AI, even when controlling for sociodemographic and sector. However, having a leadership role was not associated with AI adoption (H6). General work training (H7) and engagement (H8) did not differ between AI users and non-users.

The first notable finding was that education emerged as the strongest predictor of AI adoption, with a clear gradient even when sex, sector, and leadership were controlled. Compared to respondents with secondary education or less, those with a bachelor's degree were significantly more likely to adopt AI (OR = 3.64) when controlling for sex, sector and SBL. Moreover, those with a master's degree or higher were more than eleven times more likely (OR = 11.15) to adopt AI. These findings suggest an educational gradient, where higher levels of formal education substantially increase the likelihood of integrating AI tools into work practices. This trend is consistent with previous research, although the overall magnitude of the educational gradient observed here appears stronger (Bick et al., 2024; Kacperski et al., 2025b; Lane, 2024; Lane et al., 2023). Higher education has generally been associated with stronger digital literacy, problem-solving capacity, and adaptability to new technologies (Polyportis, 2024; Ahmad et al., 2024). Logically, the same competencies provide the cognitive, technical, and attitudinal resources needed to integrate AI tools into everyday work practices. Notably, the educational gradient remained significant even when controlling for sector, indicating that higher education predicts adoption beyond the fact that AI is more common in knowledge-intensive roles.

Our second notable finding is that AI adoption differs significantly across job sectors. Descriptive analyses revealed that adoption was highest in IT & Media, Finance & Insurance, and Education, and lowest in Construction and Health Care. This sectoral divide was reinforced in the regression models. The final model showed that employees in knowledge-intensive sectors were 2.52 times more likely to adopt AI compared to those in skills-focused sectors, even when controlling for education, sex, and leadership. These results support the view that sectoral context itself creates distinct influences impacting adoption, and are consistent with the work tasks of different sectors (Eurostat, 2024; Handa et al., 2025). Knowledge-based jobs typically involve information processing, analysis, and communication tasks that are more easily supported by AI systems such as ChatGPT(Bick et al., 2024). In contrast, the skills-focused sectors of Construction, Trade and services, Professional services, and Healthcare often rely on physical work, interpersonal interactions, and context-dependent judgment, which current AI tools support only to a limited extent (Tomlinson et al., 2025).

The sectoral pattern we observe aligns closely with international evidence. OECD data show that adoption is consistently highest in digitally mature industries such as IT services, media, and

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professional services, while adoption in sectors like construction and hospitality remains low (Lane et al., 2023). Similarly, Bick et al. (2024) report that nearly half of computer and mathematical scientists and managers in the U.S. used generative AI by late 2024, compared to less than a quarter of routine office and blue-collar roles. Our results mirror this divide, finding that employees in knowledge-intensive sectors were more than twice as likely to adopt AI as those in skills-focused sectors.

The third notable finding concerns sex differences in AI adoption. Descriptively, men reported higher use than women (81% vs. 68%). This aligns with previous studies and Norwegian statistics (Jacobsen & Erenbjerg, 2025; Otis et al., 2024; SSB, 2025). At face value, this gap suggests a moderate imbalance. However, once education and sector were accounted for in regression models, the gender effect became stronger, with men having nearly three times the odds of adoption compared to women (OR = 2.94). This is somewhat contrary to previous studies finding that women's lower AI use could be explained by sectoral composition (Conde-Ruiz et al., 2024). Similarly, general work training did not attenuate the gender gap in AI adoption. Although previous studies have found that training explains a large part of gender differences (i.e., Aldasoro et al., 2024; Chien & Kim, 2024), it showed no significant effect on adoption likelihood. However, note that this is a measure of general work training, not AI-specific training, and thus this finding should be interpreted with caution. As gender differences remain robust across models, this suggests that factors beyond structural variables, such as culture, norms, perceptions, or anxiety, are explanations for the gender gap in AI adoption.

Contrary to expectations, age groups did not predict AI use when controlling for the other variables. This differs from other studies, which generally find a significant effect of younger age on higher adoption of technology in general and AI (e.g., Da Silva & Weißler, 2025; Dingel et al., 2024; Fazi et al., 2025b; Y. Kim et al., 2024; SSB, 2025). A plausible explanation is that the age categories used in this study may not have captured sufficient variation between participants. However, age might not be as significant a predictor as often reported. Previous research indicates that older individuals with higher education levels exhibit greater AI use than their less educated peers, suggesting that education mitigates some age-related barriers (Draxler et al., 2023). Thus, the inclusion of education as a strong predictor. This, together with the significant effects of sector, SBL, and sex, may have reduced the apparent contribution of age in the present model.

Our findings underscore the importance of leadership on AI adoption. Employees who experienced higher levels of SBL were substantially more likely to adopt AI (Or = 1.89), suggesting that leadership behaviors play a decisive role in shaping employee AI adoption. This supports prior research emphasizing that leadership support and vision are critical enablers of digital transformation (i.e., Hameed et al., 2012b; Kurup & Gupta, 2022; Tarisayi, 2024). Whereas much of the literature highlights top-management vision and governance, our results show that leaders who focus on employees' strengths can directly impact adoption. We propose that SBL-style is especially effective for AI adoption because of its unique focus, which combines the motivational aspects of transformational leadership with a practical emphasis on individual capabilities, both of which have been linked to higher technology adoption (Bunjak et al., 2022). This focus on capabilities enhances employee self-efficacy, encouraging them to view AI not as a replacement but as a tool to augment their unique talents. This aligns with studies demonstrating that inspirational and empowering leadership styles increase technology engagement across sectors (Khirfan et al., 2024b; Patnaik & Bakkar, 2024b) Furthermore, SBL may enhance employees' ability to integrate AI effectively by promoting reflective judgment about when to rely on AI outputs versus their own expertise.

Contrary to expectations, our results showed that general work training and work engagement were not associated with higher AI adoption. The finding for engagement diverges from prior research emphasizing its role as a key enabling condition for new digital technologies (Ke et al., 2025; Venkatesh et al., 2003b). This finding might indicate that while engaged employees may be more motivated in general, this motivation may not translate into adopting AI tools unless it is combined with targeted opportunities, interests, and support. The null finding for training is also noteworthy. This result likely reflects a mismatch between our measure of general job training and the specific support needed for GenAI adoption. The adoption of such tools likely depends not on an employee's

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overall training satisfaction, but on targeted, AI-specific interventions that build necessary AI literacy and self-efficacy. This suggests that while training is likely crucial, its type and specificity are the decisive factors.

The absence of an effect for being a leader is also noteworthy, given strong prior claims about leadership as a contextual driver of adoption (Hameed et al., 2012b; Kurup & Gupta, 2022). Our findings suggest that simply occupying a leadership position does not increase the likelihood of using AI. Instead, it was specific leadership behaviors (SBL) that mattered to AI adoption among employees. This distinction underscores that leadership style is more predictive than leadership status, and the importance of good leadership styles to the adoption of AI.

5.1. Limitations

Several limitations should be acknowledged. The sample was non-probabilistic and drawn from Norway, which restricts transferability to other countries and contexts. All data were self-reported, which introduces potential for common-method variance and perceptual bias (Podsakoff et al., 2003). Measurement and modeling choices also constrain interpretation. Sparse cells in education and sector categories led to quasi-separation in early models, resulting in unstable estimates. To improve estimation, categories were collapsed, and the heterogeneous "Other" and Industry groups were excluded from the final model. While this strengthened parsimony, it narrowed generalizability and reduced sectoral and educational detail. AI Adoption was measured as a binary outcome, not capturing frequency, task scope, or quality of use. The training measure was a single general item assessing the adequacy of overall job training rather than AI-specific enablement. As such, the null association observed here likely underestimates the role of training specifically directed at AI skills. Similarly, age groups might have been too general to capture age-related nuance in adoption.

Future research would benefit from longitudinal or quasi-experimental designs, probability samples, multi-source leadership ratings, and richer measures of training, task demands, and organizational factors. We also suggest that future research assesses AI literacy and differential use of AI to get a more nuanced view of AI adoption and use. Doing so would provide a more fine-grained view of the factors that predict and enable effective AI integration in the workplace.

5.2. Implications

These findings carry several practical implications for organizations seeking to enhance AI adoption among employees. First, the strong effect of education suggests that adoption may exacerbate existing skill divides. Organizations should therefore prioritize tailored enablement strategies for employees with lower formal education. Second, the persistent gender gap highlights the need for interventions targeted towards females. SBL, which emphasizes recognizing and leveraging employee capabilities, was strongly associated with adoption. This suggests that leadership style, not just leadership status, plays a decisive role in shaping whether employees integrate AI into their work. Investing in leadership development may thus be an effective way of improving AI adoption among employees. Finally, the null effect of general work training implies that organizations cannot rely on broad, non-specific training initiatives to drive the adoption of AI.

6. Conclusions

In conclusion, this study shows that AI adoption in the Norwegian sample is strongly shaped by education, sector, gender, and leadership. Higher educational attainment and working in knowledge-intensive sectors markedly increased the likelihood of adoption. At the same time, men were significantly more likely than women to use AI, even after controlling for structural factors. SBL nearly doubled the odds of adoption, underscoring the importance of leadership style. In contrast, general work training, engagement, and holding a leadership role were not predictive. These findings highlight that adoption is not only a matter of skills or infrastructure but also of leadership, with practical implications for organizations. Targeted AI-specific training, sector-specific focus, leadership development, and gender-inclusive strategies are important to ensure that the benefits of AI are broadly and fairly distributed across the workforce.

References

1. Aldasoro, I., Armantier, O., Doerr, S., Gambacorta, L., & Oliviero, T. (2024). The gen AI gender gap. Economics Letters, 241, 111814. https://doi.org/10.1016/j.econlet.2024.111814
2. An, J., Kim, J., Yoon, S., Woo, K.-H., Cho, S., Kim, K., & Jo, H. (2020). Association of work–life balance with occupational injury and work-related musculoskeletal pain among Korean workers. Annals of Occupational and Environmental Medicine, 32, e20. https://doi.org/10.35371/aoem.2020.32.e20
3. Anderson, R. E., & Dexter, S. (2005). School Technology Leadership: An Empirical Investigation of Prevalence and Effect. Educational Administration Quarterly, 41(1), 49–82. https://doi.org/10.1177/0013161X04269517
4. Anne Vibeke Jacobsen & Anton Erenbjerg. (2025, August 25). 3 ud af 4 unge bruger generativ AI. https://www.dst.dk/da/Statistik/nyheder-analyser-publ/nyt/NytHtml?cid=51815
5. Bakker, A. B., & Demerouti, E. (2008). Towards a model of work engagement. Career Development International, 13(3), 209–223. https://doi.org/10.1108/13620430810870476
6. Bick, A., Blandin, A., & Deming, D. J. (2024). The rapid adoption of generative AI. National Bureau of Economic Research.
7. Boothby, D., Dufour, A., & Tang, J. (2010). Technology adoption, training and productivity performance. Research Policy, 39(5), 650–661.
8. Brey, B., & van der Marel, E. (2024a). The role of human-capital in artificial intelligence adoption. Economics Letters, 244(C). https://ideas.repec.org//a/eee/ecolet/v244y2024ics0165176524004336.html
9. Brey, B., & van der Marel, E. (2024b). The role of human-capital in artificial intelligence adoption. Economics Letters, 244(C). https://ideas.repec.org//a/eee/ecolet/v244y2024ics0165176524004336.html
10. Brislin, R. W. (1970). Back-Translation for Cross-Cultural Research. Journal of Cross-Cultural Psychology, 1(3), 185–216. https://doi.org/10.1177/135910457000100301
11. Bunjak, A., Bruch, H., & Černe, M. (2022). Context is key: The joint roles of transformational and shared leadership and management innovation in predicting employee IT innovation adoption. International Journal of Information Management, 66, 102516. https://doi.org/10.1016/j.ijinfomgt.2022.102516
12. Chien, C. V., & Kim, M. (2024). Generative AI and Legal Aid: Results from a Field Study and 100 Use Cases to Bridge the Access to Justice Gap (SSRN Scholarly Paper No. 4733061). Social Science Research Network. https://papers.ssrn.com/abstract=4733061
13. Chin, T., Li, Q., Mirone, F., & Papa, A. (2025). Conflicting impacts of shadow AI usage on knowledge leakage in metaverse-based business models: A Yin-Yang paradox framing. Technology in Society, 81, 102793.
14. Choi, J. H., Monahan, A., & Schwarcz, D. B. (2023). Lawyering in the Age of Artificial Intelligence. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4626276
15. Chuang, Y.-T., Chiang, H.-L., & Lin, A.-P. (2025). Insights from the Job Demands–Resources Model: AI's dual impact on employees' work and life well-being. International Journal of Information Management, 83, 102887. https://doi.org/10.1016/j.ijinfomgt.2025.102887
16. Conde-Ruiz, J. I., Ganuza Fernandez, J. J., García, M., & Victoria Lanzón, C. (2024). AI and Digital Technology: Gender Gaps in Higher Education. CESifo Economic Studies, 70(3), 244–270. https://doi.org/10.1093/cesifo/ifae020
17. Cui, K. Z., Demirer, M., Jaffe, S., Musolff, L., Peng, S., & Salz, T. (2025). The Effects of Generative AI on High-Skilled Work: Evidence from Three Field Experiments with Software Developers.
18. Da Silva, A. D., & Weißler, M. (2025). AI adoption and employment prospects. https://www.ecb.europa.eu/press/blog/date/2025/html/ecb.blog20250321~6af1337b6b.en.html
19. Damanpour, F. (1991). Organizational Innovation: A Meta-Analysis of Effects of Determinants and Moderators. The Academy of Management Journal, 34(3), 555–590. https://doi.org/10.2307/256406

20. Damanpour, F., & Schneider, M. (2006). Phases of the Adoption of Innovation in Organizations: Effects of Environment, Organization and Top Managers. British Journal of Management, 17(3), 215–236. https://doi.org/10.1111/j.1467-8551.2006.00498.x
21. Dell'Acqua, F., McFowland, E., Mollick, E. R., Lifshitz-Assaf, H., Kellogg, K., Rajendran, S., Krayer, L., Candelon, F., & Lakhani, K. R. (2023). Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4573321
22. Department for Science, Innovation and technology, Science, Innovation, & & Technology. (2024, December 16). Public attitudes to data and AI: Tracker survey (Wave 4) report. GOV.UK. https://www.gov.uk/government/publications/public-attitudes-to-data-and-ai-tracker-survey-wave-4/public-attitudes-to-data-and-ai-tracker-survey-wave-4-report
23. Ding, H., & Quan, G. (2021a). How and when does follower's strengths-based leadership relate to follower innovative behavior: The roles of self-efficacy and emotional exhaustion. The Journal of Creative Behavior, 55(3), 591–603.
24. Ding, H., & Quan, G. (2021b). How and when does follower's strengths-based leadership relate to follower innovative behavior: The roles of self-efficacy and emotional exhaustion. The Journal of Creative Behavior, 55(3), 591–603.
25. Dingel, J., Kleine, A.-K., Cecil, J., Sigl, A. L., Lermer, E., & Gaube, S. (2024). Predictors of Health Care Practitioners' Intention to Use AI-Enabled Clinical Decision Support Systems: Meta-Analysis Based on the Unified Theory of Acceptance and Use of Technology. Journal of Medical Internet Research, 26(1), e57224. https://doi.org/10.2196/57224
26. Dorta-González, P., López-Puig, A. J., Dorta-González, M. I., & González-Betancor, S. M. (2024). Generative artificial intelligence usage by researchers at work: Effects of gender, career stage, type of workplace, and perceived barriers (No. arXiv:2409.14570). arXiv. https://doi.org/10.48550/arXiv.2409.14570
27. Draxler, F., Buschek, D., Tavast, M., Hämäläinen, P., Schmidt, A., Kulshrestha, J., & Welsch, R. (2023). Gender, Age, and Technology Education Influence the Adoption and Appropriation of LLMs (No. arXiv:2310.06556). arXiv. https://doi.org/10.48550/arXiv.2310.06556
28. Eurostat. (2024). Use of artificial intelligence in enterprises. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Use_of_artificial_intelligence_in_enterprises
29. Faida, E. W., Wahyuni, T., Sutha, D. W., & Elisanti, A. D. (2023). Role of work engagement in behavioural intention to use electronic medical records: A cross-sectional study. Pharmacy Education, 23(4), 92–98.
30. Fazi, L., Zaniboni, S., & Wang, M. (2025a). Age differences in the adoption of technology at work: A review and recommendations for managerial practice. Journal of Organizational Change Management, 38(8), 138–175.
31. Fazi, L., Zaniboni, S., & Wang, M. (2025b). Age differences in the adoption of technology at work: A review and recommendations for managerial practice. Journal of Organizational Change Management, 38(8), 138–175.
32. Flanagan, L., & Jacobsen, M. (2003). Technology leadership for the twenty-first century principal. Journal of Educational Administration, 41(2), 124–142. https://doi.org/10.1108/09578230310464648
33. Freeman, J. (2025). Student generative AI survey 2025. Higher Education Policy Institute: London, UK.
34. Grassini, S., Aasen, M. L., & Møgelvang, A. (2024). Understanding University Students' Acceptance of ChatGPT: Insights from the UTAUT2 Model. Applied Artificial Intelligence, 38(1), 2371168. https://doi.org/10.1080/08839514.2024.2371168
35. Hameed, M. A., Counsell, S., & Swift, S. (2012a). A meta-analysis of relationships between organizational characteristics and IT innovation adoption in organizations. Information & Management, 49(5), 218–232. https://doi.org/10.1016/j.im.2012.05.002
36. Hameed, M. A., Counsell, S., & Swift, S. (2012b). A meta-analysis of relationships between organizational characteristics and IT innovation adoption in organizations. Information & Management, 49(5), 218–232. https://doi.org/10.1016/j.im.2012.05.002
37. Handa, K., Tamkin, A., McCain, M., Huang, S., Durmus, E., Heck, S., Mueller, J., Hong, J., Ritchie, S., Belonax, T., Troy, K. K., Amodei, D., Kaplan, J., Clark, J., & Ganguli, D. (2025). Which Economic Tasks are

Performed with AI? Evidence from Millions of Claude Conversations (No. arXiv:2503.04761). arXiv. https://doi.org/10.48550/arXiv.2503.04761

38. Hofmann, E. J., & Schalk, R. (2025). Perceived Usefulness and Actual Usage of Generative Artificial Intelligence in the Workplace: The Moderating Role of Age.
39. Hu, X., Gao, H., Agafari, T., Zhang, M. Q., & Cong, R. (2025a). How and when artificial intelligence adoption promotes employee knowledge sharing? The role of paradoxical leadership and technophilia. Frontiers in Psychology, 16. https://doi.org/10.3389/fpsyg.2025.1573587
40. Hu, X., Gao, H., Agafari, T., Zhang, M. Q., & Cong, R. (2025b). How and when artificial intelligence adoption promotes employee knowledge sharing? The role of paradoxical leadership and technophilia. Frontiers in Psychology, 16. https://doi.org/10.3389/fpsyg.2025.1573587
41. Jeong, J. (2025). The innovative side of AI adoption in South Korea: How job crafting and technology self-efficacy influence employee innovative work behaviour. Asia Pacific Business Review, 1–34.
42. Kacperski, C., Ulloa, R., Bonnay, D., Kulshrestha, J., Selb, P., & Spitz, A. (2025a). Characteristics of ChatGPT users from Germany: Implications for the digital divide from web tracking data. PloS One, 20(1), e0309047.
43. Kacperski, C., Ulloa, R., Bonnay, D., Kulshrestha, J., Selb, P., & Spitz, A. (2025b). Characteristics of ChatGPT users from Germany: Implications for the digital divide from web tracking data. PLOS ONE, 20(1), e0309047. https://doi.org/10.1371/journal.pone.0309047
44. KangJie, E. T., Song, T., Zhu, Z., Li, J., & Lee, Y.-C. (2025). AI Literacy Education for Older Adults: Motivations, Challenges and Preferences (No. arXiv:2504.14649). arXiv. https://doi.org/10.48550/arXiv.2504.14649
45. Ke, Q., Gong, Y., & Ke, C. (2025). Bridging AI literacy and UTAUT constructs: Structural equation modeling of AI adoption among Chinese university students. Humanities and Social Sciences Communications, 12(1), 1452. https://doi.org/10.1057/s41599-025-05775-y
46. Keenan, E. M., & Mostert, K. (2013). Perceived organisational support for strengths use: The factorial validity and reliability of a new scale in the banking industry. SA Journal of Industrial Psychology, 39(1), 12.
47. Khirfan, R., Kotb, H., Atiyeh, H., Khalifah, A., AlHasan, N., & Abdelalla, S. (2024a). Exploring the Influence of Transformational Leadership on Nurses' Intentions towards Artificial intelligence Utilization in Non-AI Implemented Hospitals. Research Journal of Pharmacy and Technology, 17(11), 5469–5479. https://doi.org/10.52711/0974-360X.2024.00837
48. Khirfan, R., Kotb, H., Atiyeh, H., Khalifah, A., AlHasan, N., & Abdelalla, S. (2024b). Exploring the Influence of Transformational Leadership on Nurses' Intentions towards Artificial intelligence Utilization in Non-AI Implemented Hospitals. Research Journal of Pharmacy and Technology, 17(11), 5469–5479. https://doi.org/10.52711/0974-360X.2024.00837
49. Kim, J., Klopfer, M., Grohs, J. R., Eldardiry, H., Weichert, J., Cox, L. A., & Pike, D. (2025). Examining Faculty and Student Perceptions of Generative AI in University Courses. Innovative Higher Education, 50(4), 1281–1313. https://doi.org/10.1007/s10755-024-09774-w
50. Kim, Y., Blazquez, V., & Oh, T. (2024). Determinants of Generative AI System Adoption and Usage Behavior in Korean Companies: Applying the UTAUT Model. Behavioral Sciences, 14(11), 1035. https://doi.org/10.3390/bs14111035
51. Ko, E. G., Nanayakkara, S., & Jr, E. W. H. (2025). 'We need to avail ourselves of GenAI to enhance knowledge distribution': Empowering Older Adults through GenAI Literacy. Proceedings of the Extended Abstracts of the CHI Conference on Human Factors in Computing Systems, 1–7. https://doi.org/10.1145/3706599.3720032
52. Kurup, S., & Gupta, V. (2022). Factors Influencing the AI Adoption in Organizations. Metamorphosis, 21(2), 129–139. https://doi.org/10.1177/09726225221124035
53. Lane, M. (2024). Who will be the workers most affected by AI?: A closer look at the impact of AI on women, low-skilled workers and other groups. OECD Publishing.
54. Lane, M., Williams, M., & Broecke, S. (2023). The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers. OECD Publishing.

55. Lee, H.-P., Sarkar, A., Tankelevitch, L., Drosos, I., Rintel, S., Banks, R., & Wilson, N. (2025). The impact of generative AI on critical thinking: Self-reported reductions in cognitive effort and confidence effects from a survey of knowledge workers. 1–22.
56. Li, L., & Kim, M. (2024). It is like a friend to me: Critical usage of automated feedback systems by self-regulating English learners in higher education. Australasian Journal of Educational Technology, 40(1), 1–18.
57. Liu, X., & Li, Y. (2025). Examining the Double-Edged Sword Effect of AI Usage on Work Engagement: The Moderating Role of Core Task Characteristics Substitution. Behavioral Sciences, 15(2), 206. https://doi.org/10.3390/bs15020206
58. Marina Rybalka. (2024, August 24). 7 av 10 unge bruker KI. SSB. https://www.ssb.no/teknologi-og-innovasjon/informasjons-og-kommunikasjonsteknologi-ikt/statistikk/bruk-av-ikt-i-husholdningene/artikler/7-av-10-unge-bruker-ki
59. McElheran, K., Li, J. F., Brynjolfsson, E., Kroff, Z., Dinlersoz, E., Foster, L., & Zolas, N. (2024). AI adoption in America: Who, what, and where. Journal of Economics & Management Strategy, 33(2), 375–415. https://doi.org/10.1111/jems.12576
60. Merali, A. (2024). Scaling Laws for Economic Productivity: Experimental Evidence in LLM-Assisted Translation (No. arXiv:2409.02391). arXiv. https://doi.org/10.48550/arXiv.2409.02391
61. Merino-Soto, C., Lozano-Huamán, M., Lima-Mendoza, S., Calderón de la Cruz, G., Juárez-García, A., & Toledano-Toledano, F. (2022). Ultrashort Version of the Utrecht Work Engagement Scale (UWES-3): A Psychometric Assessment. International Journal of Environmental Research and Public Health, 19(2), 890. https://doi.org/10.3390/ijerph19020890
62. Miglianico, M., Dubreuil, P., Miquelon, P., Bakker, A. B., & Martin-Krumm, C. (2020). Strength use in the workplace: A literature review. Journal of Happiness Studies, 21(2), 737–764.
63. Møgelvang, A., & Grassini, S. (2025). Validating the AI attitude scale (AIAS-4) and exploring attitudinal differences in a large sample of Norwegian university students. Discover Education, 4(1), 212. https://doi.org/10.1007/s44217-025-00657-6
64. Molino, M., Cortese, C. G., & Ghislieri, C. (2020). The Promotion of Technology Acceptance and Work Engagement in Industry 4.0: From Personal Resources to Information and Training. International Journal of Environmental Research and Public Health, 17(7), 2438. https://doi.org/10.3390/ijerph17072438
65. Otis, N. G., Delecourt, S., Cranney, K., & Koning, R. (2024). Global Evidence on Gender Gaps and Generative AI. Open Science Framework. https://doi.org/10.31219/osf.io/h6a7c
66. Parviz, M. (2024). AI in education: Comparative perspectives from STEM and Non-STEM instructors. Computers and Education Open, 6, 100190.
67. Patnaik, P., & Bakkar, M. (2024a). Exploring determinants influencing artificial intelligence adoption, reference to diffusion of innovation theory. Technology in Society, 79(C). https://ideas.repec.org//a/eee/teinso/v79y2024ics0160791x24002987.html
68. Patnaik, P., & Bakkar, M. (2024b). Exploring determinants influencing artificial intelligence adoption, reference to diffusion of innovation theory. Technology in Society, 79, 102750. https://doi.org/10.1016/j.techsoc.2024.102750
69. Peng, S., Kalliamvakou, E., Cihon, P., & Demirer, M. (2023). The Impact of AI on Developer Productivity: Evidence from GitHub Copilot (No. arXiv:2302.06590). arXiv. https://doi.org/10.48550/arXiv.2302.06590
70. Peterson, C., & Seligman, M. E. (2004). Character strengths and virtues: A handbook and classification (Vol. 1). Oxford university press.
71. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. The Journal of Applied Psychology, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879
72. Qazi, I. A., Ali, A., Khawaja, A. U., Akhtar, M. J., Sheikh, A. Z., & Alizai, M. H. (2025). AI-literacy training enhances physician-LLM diagnostic collaboration in a resource-limited setting: A randomized controlled trial (p. 2025.06.06.25329104). medRxiv. https://doi.org/10.1101/2025.06.06.25329104

73. Rana, Md. M., Siddiqee, M. S., Sakib, Md. N., & Ahamed, Md. R. (2024). Assessing AI adoption in developing country academia: A trust and privacy-augmented UTAUT framework. Heliyon, 10(18), e37569. https://doi.org/10.1016/j.heliyon.2024.e37569
74. Rick, V. B., Stebner, M., Dräger, L., Franken, A., Mertens, A., & Nitsch, V. (2024). Effects of AI-based technologies on employees' work engagement: Implications for the human-centered design of digital work. Zeitschrift Für Arbeitswissenschaft, 78(3), 323–334. https://doi.org/10.1007/s41449-024-00438-1
75. Russo, C., Romano, L., Clemente, D., Iacovone, L., Gladwin, T. E., & Panno, A. (2025). Gender differences in artificial intelligence: The role of artificial intelligence anxiety. Frontiers in Psychology, 16. https://doi.org/10.3389/fpsyg.2025.1559457
76. Saks, A. M. (2006). Antecedents and consequences of employee engagement. Journal of Managerial Psychology, 21(7), 600–619. https://doi.org/10.1108/02683940610690169
77. Schaufeli, W. (2003). UWES–Utrecht work engagement scale: Test manual. (No Title).
78. Schaufeli, W. B., Shimazu, A., Hakanen, J., Salanova, M., & De Witte, H. (2019a). An Ultra-Short Measure for Work Engagement. European Journal of Psychological Assessment, 35(4), 577–591. https://doi.org/10.1027/1015-5759/a000430
79. Schaufeli, W. B., Shimazu, A., Hakanen, J., Salanova, M., & De Witte, H. (2019b). An Ultra-Short Measure for Work Engagement. European Journal of Psychological Assessment, 35(4), 577–591. https://doi.org/10.1027/1015-5759/a000430
80. SSB (2024). Use of artificial intelligence (AI) in the last three months, by sex and age (per cent) 2024. Statbank Norway. (n.d.). SSB. Retrieved 12 September 2025, from https://www.ssb.no/en/system/
81. SSB. (2025, September 11). Use of artificial intelligence (AI) in the last three months, by sex and age (per cent) 2024. Statbank Norway. SSB. https://www.ssb.no/en/system/
82. Straume, L. V., & Vittersø, J. (2012). Happiness, inspiration and the fully functioning person: Separating hedonic and eudaimonic well-being in the workplace. The Journal of Positive Psychology, 7(5), 387–398. https://doi.org/10.1080/17439760.2012.711348
83. Tarisayi, K. S. (2024). Strategic leadership for responsible artificial intelligence adoption in higher education. 11, 4–14.
84. Tomlinson, K., Jaffe, S., Wang, W., Counts, S., & Suri, S. (2025). Working with AI: Measuring the Applicability of Generative AI to Occupations (No. arXiv:2507.07935). arXiv. https://doi.org/10.48550/arXiv.2507.07935
85. Van Woerkom, M., Oerlemans, W., & Bakker, A. B. (2016). Strengths use and work engagement: A weekly diary study. European Journal of Work and Organizational Psychology, 25(3), 384–397.
86. Venkatesh, Morris, Davis, & Davis. (2003a). User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly, 27(3), 425. https://doi.org/10.2307/30036540
87. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003b). User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly, 27(3), 425–478. JSTOR. https://doi.org/10.2307/30036540
88. Wang, A., Zhou, Y., Ma, H., Tang, X., Li, S., Pei, R., & Piao, M. (2024). Preparing for aging: Understanding middle-aged user acceptance of AI chatbots through the technology acceptance model. Digital Health, 10, 20552076241284903.
89. Wang, J., van Woerkom, M., Breevaart, K., Bakker, A. B., & Xu, S. (2023a). Strengths-based leadership and employee work engagement: A multi-source study. Journal of Vocational Behavior, 142, 103859.
90. Wang, J., van Woerkom, M., Breevaart, K., Bakker, A. B., & Xu, S. (2023b). Strengths-based leadership and employee work engagement: A multi-source study. Journal of Vocational Behavior, 142, 103859.
91. Wang, J., van Woerkom, M., Breevaart, K., Bakker, A. B., & Xu, S. (2023c). Strengths-based leadership and employee work engagement: A multi-source study. Journal of Vocational Behavior, 142, 103859. https://doi.org/10.1016/j.jvb.2023.103859
92. Yamamoto, M., Xu, S., Kee, K. F., & Li, W. (2025). Testing a dynamic model of trust in AI: How trust develops and affects critical thinking in the American workforce. Journal of Trust Research, 15(1), 12–31.

Yu, S., & Chen, T. (2024). Understanding older adults' acceptance of Chatbots in healthcare delivery: An extended UTAUT model. Frontiers in Public Health, 12. https://doi.org/10.3389/fpubh.2024.1435329

93. Zárate-Torres, R., Rey-Sarmiento, C. F., Acosta-Prado, J. C., Gómez-Cruz, N. A., Rodríguez Castro, D. Y., & Camargo, J. (2025). Influence of Leadership on Human–Artificial Intelligence Collaboration. Behavioral Sciences, 15(7), 873. https://doi.org/10.3390/bs15070873