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Research Article

Beyond Current AI Use: Perceived AI Automation Potential and Workers' Expectations of Future Job Opportunities

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ABSTRACT

The rapid integration of artificial intelligence (AI) into workplaces has increased uncertainty about its implications for future employment. While existing research has examined workers' current exposure to AI, less attention has been given to how workers perceive the extent to which their current job tasks could potentially be performed by AI. This study examines the relationships between current workplace AI exposure, perceived AI automation potential, and workers' expectations regarding future job opportunities. Drawing on Cognitive Appraisal Theory, the study analyzes data from 3,975 employed respondents in the Pew Research Center's American Trends Panel Wave 157 (2024). Weighted multinomial logistic regression models were used to examine whether perceived AI automation potential provides incremental explanatory value for workers' expectations beyond current workplace AI exposure. The findings indicate that perceived AI automation potential is strongly associated with expectations of fewer future job opportunities, even after controlling for current AI exposure, age, gender, education, income, and industry. Adjusted predictions further show that expectations of fewer opportunities increase from 28.8% among workers perceiving no automation potential to 58.3% among those perceiving that all their work could be performed by AI. The findings highlight the importance of distinguishing between what AI currently does and what workers believe AI could do in the future.

1. Introduction

Artificial intelligence (AI) is becoming increasingly embedded in contemporary workplaces, affecting the tasks employees perform, the skills they require, and how work is organized. The rapid development of generative AI has expanded these possibilities by enabling AI systems to perform or support a growing range of cognitive, communicative, analytical, and information-processing activities. Consequently, AI is increasingly relevant not only to current work practices but also

to workers' expectations about their future employment and careers. Research on AI and careers indicates that technological change can influence career exploration, career management, and career trajectories (Bankins et al., 2024). At the same time, workers may perceive AI in different ways, with workplace AI being associated with both potential opportunities and concerns about employment and job security (Cao et al., 2025; Savolainen et al., 2026).

This distinction is particularly relevant to workers' expectations about future job opportunities. The 2024 Pew Research Center American Trends Panel (ATP) Wave 157 provides a useful empirical setting because it asks workers both about the amount of their work currently done with AI and, among workers reporting relatively limited current AI involvement, the amount of their work they believe could potentially be done with AI. The survey also asks about the expected long-term effect of AI on respondents' own job opportunities. These measures make it possible to examine whether workers' perceptions of AI's potential task reach are associated with future job-opportunity expectations beyond their current experience with AI.

The theoretical relevance of this distinction can be understood through Cognitive Appraisal Theory (CAT) (Lazarus & Folkman, 1984). CAT emphasizes that individuals' responses to circumstances depend partly on how they evaluate their significance and potential consequences. Applied to workplace AI, this perspective suggests that workers may consider not only the extent to which AI is currently present in their work but also what they believe AI could mean for their future circumstances. CAT is used here as a theoretical lens rather than a directly tested psychological mechanism, because the Wave 157 data do not measure appraisal processes such as threat or challenge appraisal, coping, or perceived coping resources.

Although existing research has examined workers' current AI exposure and attitudes toward workplace AI, less attention has been given to whether perceived AI automation potential provides information about future job-opportunity expectations beyond current AI exposure. This constitutes the central empirical gap addressed by the present study. Accordingly, the study examines two related questions:

RQ1: How are current workplace AI exposure and perceived AI automation potential associated with workers' expectations of future job opportunities?

RQ2: Does perceived AI automation potential remain associated with workers' expectations of future job opportunities after accounting for current workplace AI exposure?

The study makes two principal contributions. First, it distinguishes current workplace AI exposure from perceived AI automation potential, thereby introducing a forward-looking dimension to the measurement of workers' experiences with workplace AI. Second, it examines whether perceived AI automation potential is associated with workers' expectations of future job opportunities after accounting for current AI exposure and relevant worker characteristics. The study therefore extends existing survey-based research on workplace AI by considering not only what AI is currently doing in workers' jobs, but also what workers believe AI could potentially do.

2. Literature Review and Theoretical Framework

2.1 AI, Work and Employment Expectations

Artificial intelligence (AI) is reshaping work by altering the tasks performed by employees, the skills required to perform them, and the allocation of responsibilities between humans and technological systems. The development of generative AI has expanded these possibilities by enabling AI systems to perform or support a broad range of cognitive, communicative, analytical, and information-processing activities. However, technological exposure does not necessarily imply complete occupational replacement. Recent research increasingly emphasizes task transformation, augmentation, adaptation, and changes in career trajectories rather than treating AI adoption as synonymous with job elimination (Bankins et al., 2024; Gmyrek et al., 2025a, 2025b; Hyman et al., 2025).

These changes have implications for how workers perceive their employment futures. AI can provide opportunities through productivity improvements, task assistance, and the development of new forms of work, while simultaneously generating concerns about changing job requirements, occupational relevance, and employment security. A systematic review by Savolainen et al. (2026) identified both positive experiences of workplace AI, including efficiency and productivity benefits, and concerns relating to role changes and job security. Similarly, Cao et al. (2025) found that different forms of AI functionality can be associated with both opportunity- and threat-related appraisals and subsequent employee outcomes. These findings indicate that workers' expectations about AI are not necessarily determined solely by the extent of current technological implementation.

Research on careers further demonstrates the relevance of workers' perceptions of technological change to employment trajectories. Bankins et al. (2024), in a systematic review of research on AI and careers, identified implications for career exploration, career management, and career trajectories and highlighted the need for further research into the longer-term consequences of AI for workers. Consequently, understanding workers' expectations about future employment requires attention to both their current experience of AI and their perceptions of its potential implications.

2.2 Current AI Exposure and Perceived AI Automation Potential

Current workplace AI exposure and perceived AI automation potential represent two related but distinct dimensions of workers' relationship with AI. Current AI exposure concerns the extent to which AI is already involved in performing a worker's tasks. Such exposure can be assessed through occupation- or task-based measures of technological potential or through workers' self-reported experiences. The latter provides information about how much AI is currently involved in an individual's work but does not necessarily indicate what the worker believes AI could do in the future.

Perceived AI automation potential captures this forward-looking dimension. It refers to the extent to which workers believe that their work could potentially be performed by AI, rather than the extent to which AI currently performs that work. The distinction is important because technological capability and workplace implementation may not develop at the same

pace. Workers may therefore perceive substantial potential for AI involvement even when their current exposure remains limited. Conversely, current AI use may be experienced as supportive or complementary rather than as an indication of future job displacement.

This distinction is particularly relevant to the present study because Wave 157 measures both current AI involvement and perceived potential among workers reporting relatively limited current AI involvement. The measures therefore provide an opportunity to examine whether perceptions of AI's potential task reach are associated with workers' expectations about future job opportunities beyond their current AI experience. Importantly, perceived AI automation potential is a subjective assessment rather than an objective measure of technical substitutability. Similarly, expectations of fewer job opportunities should not be interpreted as evidence of actual future job loss.

Existing research provides a basis for expecting a relationship between perceived AI potential and employment expectations. Workers who perceive that AI could perform a substantial proportion of their work may anticipate greater changes to their future employment circumstances, even where current implementation is limited. At the same time, perceptions of AI potential may also be associated with expectations of new or improved opportunities. The relevant empirical question is therefore whether perceived AI automation potential remains associated with future job-opportunity expectations when current AI exposure is considered simultaneously.

Accordingly, the study proposes:

H1: Higher perceived AI automation potential is associated with a greater likelihood that workers expect AI to reduce their future job opportunities.

The distinction between current exposure and perceived potential also motivates the second research question. If perceived potential captures information that is not reflected in current AI exposure, its association with future job-opportunity expectations should remain after current exposure and relevant worker characteristics are taken into account. This is an associational proposition, not a claim that perceived potential causes employment expectations.

H2: Perceived AI automation potential remains significantly associated with workers' expectations of future job opportunities after accounting for current workplace AI exposure and worker characteristics.

2.3 Cognitive Appraisal Theory

Cognitive Appraisal Theory (CAT), originating in the work of Lazarus and Folkman (1984), provides a theoretical perspective for understanding why individuals may respond differently to the same environmental circumstances. The theory emphasizes that individuals evaluate the significance of circumstances in relation to their goals, circumstances, and perceived consequences. Thus, responses to technological change may depend not only on the characteristics of the

technology but also on how individuals interpret its implications.

This perspective is relevant to workplace AI because the same technological development may be perceived as beneficial, challenging, or threatening. AI can support productivity and reduce routine activities while simultaneously raising concerns about changing work requirements and future employment. Recent workplace-AI research provides empirical support for the relevance of such differentiated interpretations. For example, Cao et al. (2025) found that different AI functions were associated with opportunity- and threat-related appraisals, demonstrating that workers' interpretations can vary according to how AI is experienced.

In the present study, CAT is therefore used as a theoretical lens for interpreting workers' perceptions of AI, rather than as a directly tested psychological mechanism. The Wave 157 data do not measure primary or secondary appraisal, threat or challenge appraisal, coping, or perceived coping resources. Consequently, the study cannot establish whether appraisal processes mediate the relationship between perceived AI potential and employment expectations. Instead, CAT provides a theoretical basis for considering why workers' perceptions of AI's potential capabilities may be relevant to how they anticipate future employment consequences.

2.4 Conceptual Framework and Hypotheses

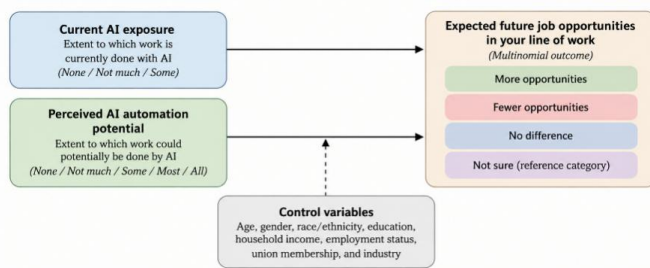
The preceding literature supports a distinction between two principal explanatory dimensions. Current AI exposure represents the extent to which AI is currently involved in a worker's job, whereas perceived AI automation potential represents the worker's assessment of how much of that work could potentially be performed by AI. The present study focuses on whether the latter remains associated with expectations about future job opportunities after accounting for the former.

As a supplementary analytical perspective, the study also derives a perceived AI automation gap, calculated as perceived AI automation potential minus current AI exposure. The gap represents the perceived difference between what AI currently does and what workers believe it could potentially do. It is not treated as a separate psychological construct or objective measure of automation risk. Because perceived potential is algebraically equal to current exposure plus the gap, a model containing current exposure and the gap contains the same underlying information as the corresponding model containing current exposure and perceived potential. The gap is therefore examined only as a complementary reparameterization of the principal relationship rather than as a separate hypothesis.

The conceptual framework consequently places current AI exposure and perceived AI automation potential as the principal explanatory variables and workers' expectations of future job opportunities as the outcome. Age, gender, education, income, and industry are included as covariates. CAT provides the theoretical lens for interpreting how workers may understand the implications of current and potential AI

involvement; it is not represented as a tested mediation pathway. Figure 1 summarizes this framework.

Figure 1. Analytical Model of Workers' Expectations about Future Job Opportunities



Note: Arrows indicate hypothesized associations. All models include control variables. The outcome variable has four categories, with "Not sure" as the reference category in the multinomial logistic regression models.

3. Methodology

3.1 Research Design and Data Source

This study employed a quantitative, cross-sectional research design using secondary data from Wave 157 of the Pew Research Center's American Trends Panel (ATP). Wave 157 was conducted from October 7 to 13, 2024, with 5,395 completed responses from 6,490 sampled panelists. The American Trends Panel is a probability-based panel designed to provide nationally representative estimates of U.S. adults.

The analysis examined three aspects of workplace AI: current AI exposure, perceived AI automation potential, and expectations concerning the long-term effect of AI on respondents' own job opportunities. The Wave 157 production survey weight (WEIGHT_W157) was applied in all analyses. According to the Pew Research Center methodology, the production weights incorporate recruitment, panel attrition, nonresponse, and calibration to population benchmarks, followed by trimming at the 1st and 99th percentiles.

Because the public-use dataset does not provide all design information required to reproduce Pew Research Center's internal variance estimation procedures, robust sandwich variance estimates were used for statistical inference. The resulting standard errors should therefore not be interpreted as exact replications of Pew Research Center's published standard errors.

The study complied with the applicable Pew Research Center data-use requirements.

3.2 Population and Sample Selection

The Wave 157 dataset contained 5,395 respondents. The analysis first identified the employed-worker universe used for the Wave 157 workplace analysis. Respondents reporting one job (JOBNUM_W157 = 1) or multiple jobs with one primary job (JOBNUM_W157 = 2) were retained, resulting in 5,273 employed respondents.

Questionnaire routing imposed an important restriction on the analytical sample. The current AI exposure question was not administered to respondents who had not heard or read about AI being used in the workplace. The perceived AI automation potential question was subsequently administered only to respondents reporting that some, not much, or none of their

current work was done with AI. Consequently, respondents reporting "Most" or "All" current AI exposure could not be included in the principal comparison because the potential measure was not administered to them.

After applying these routing criteria, 4,276 respondents were eligible for the principal comparison. Complete cases for the outcome, predictors, covariates, and survey weight produced a final analytical sample of 3,975 respondents. A sensitivity analysis excluding respondents who selected "Not sure" for future job opportunities resulted in 3,439 respondents.

Sample-selection stage	Respondents
Wave 157 total respondents	5,395
Employed adults with one job or multiple jobs with one primary job	5,273
Eligible for perceived AI automation potential question	4,276
Complete cases for principal analysis	3,975
Sensitivity analysis excluding "Not sure"	3,439

The principal analytical sample is therefore a routed and complete-case subsample of employed respondents rather than the full Wave 157 worker population. The findings should consequently not be interpreted as estimates for all U.S. workers without qualification.

3.3 Measures and Variable Operationalization

3.3.1 Current Workplace AI Exposure

Current workplace AI exposure was measured using AIWRKDONE1_W157, which asks: "Now thinking of the tasks you do in your job, how much of your work is done with AI?" For the principal analysis, the applicable ordered categories were coded as:

- None = 0
- Not much = 1
- Some = 2

Responses of "Most" and "All" were excluded because these respondents were not subsequently administered the perceived AI automation potential question.

3.3.2 Perceived AI Automation Potential

Perceived AI automation potential was measured using AIWRKDONE2_W157, which asks: "Regardless of how much of your work is currently done with AI, how much of what you do in your job do you think can be done with AI?"

The response categories were coded:

- None = 0
- Not much = 1
- Some = 2
- Most = 3
- All = 4

This variable represents respondents' subjective perceptions of the extent to which their work could potentially be performed by AI. It is therefore not an objective measure of technical automation feasibility or occupational substitutability.

3.3.3 Perceived AI Automation Gap

As a supplementary analytical indicator, the perceived AI automation gap was calculated as:

Perceived AI automation gap = perceived AI automation potential – current AI exposure

Positive values indicate that respondents perceived greater potential for AI involvement than was currently present in their work. Because both underlying measures are ordinal and the gap is algebraically derived from them, it is treated as a supplementary reparameterization rather than an independent theoretical construct.

3.3.4 Future Job-Opportunity Expectations

The dependent variable, AIWRKOPPO_W157, measures respondents' expectations concerning the long-term effect of AI on their own job opportunities. The categories were coded as:

- More opportunities = 0

Table 1. Variable Operationalization

Construct	Wave 157 variable	Operationalization	Role
Current AI exposure	AIWRKDONE1_W157	None = 0; Not much = 1; Some = 2	Predictor
Perceived AI automation potential	AIWRKDONE2_W157	None = 0; Not much = 1; Some = 2; Most = 3; All = 4	Principal predictor
Perceived AI automation gap	Derived	Potential – Current exposure	Supplementary predictor
Future job opportunities	AIWRKOPPO_W157	More = 0; Fewer = 1; No difference = 2; Not sure = 3	Outcome
Age	F_AGE CAT	18–29; 30–49; 50–64; 65+	Control
Gender	F_GENDER	Man; Woman; Other	Control
Education	F_EDUCCAT2	Six-category education measure	Control
Income	F_INC_TIER2	Lower; Middle; Upper	Control
Industry	INDUSTRYCOMBO_W157	11-category industry measure	Control
Survey weight	WEIGHT_W157	Wave 157 production weight	Weight

Note. The principal analytical sample includes respondents for whom the relevant survey questions were administered and the outcome, predictors, covariates, and survey weight were valid.

3.4 Analytical Strategy

Because the dependent variable consists of four nominal categories—more opportunities, fewer opportunities, no difference, and not sure—multinomial logistic regression was used (Long, 1997). “Not sure” was specified as the reference outcome category in the primary analysis. All models included age, gender, education, income, and industry as control variables.

A hierarchical sequence of four models was estimated to distinguish current AI exposure from perceived AI automation potential.

Model 1 included current AI exposure and the control variables. This model established the association between

- Fewer opportunities = 1
- No difference = 2
- Not sure = 3

The primary multinomial models used “Not sure” as the reference category. A sensitivity analysis excluded “Not sure” responses and used “No difference” as the reference category.

3.3.5 Control Variables

The models controlled for age, gender, educational attainment, household income tier, and industry. These variables were based on the standardized Wave 157 classifications:

- Age: 18–29, 30–49, 50–64, 65+
- Gender: man, woman, other
- Education: six-category educational attainment measure
- Income: lower, middle, upper income tiers
- Industry: 11-category industry classification

Values coded as 99 in the public-use data were treated as missing.

workers' current experience of AI and their future job-opportunity expectations.

Model 2 included perceived AI automation potential and the same control variables. This model provided the initial assessment of H1 concerning the association between perceived AI automation potential and expectations of fewer future job opportunities.

Model 3 simultaneously included current AI exposure, perceived AI automation potential, and all control variables. This was the principal model and assessed whether perceived AI automation potential remained associated with future job-opportunity expectations after accounting for current AI exposure and worker characteristics. This model provides the primary assessment of H2.

Model 4 replaced perceived AI automation potential with the derived perceived AI automation gap while retaining current AI exposure and the control variables. Because perceived AI automation potential equals current AI exposure plus the gap, Model 4 is an algebraic reparameterization of Model 3 using the same underlying information. It was therefore treated as a supplementary analysis, not as an independent hypothesis test.

All models incorporated the Wave 157 production survey weight (WEIGHT_W157) and used robust sandwich variance estimation. Results are reported as odds ratios (ORs) with 95% confidence intervals and p -values. For the ordered predictor variables, an OR greater than 1 indicates higher relative odds of the specified outcome category relative to “Not sure” for a one-category increase in the predictor, holding other variables constant.

For example, an OR of 1.536 for perceived AI automation potential in the “Fewer vs. Not sure” comparison indicates that a one-category increase in perceived potential is associated with approximately 53.6% higher relative odds of expecting fewer rather than being unsure about future job opportunities, conditional on current AI exposure and the control variables.

Joint Wald tests were used to assess the overall association of the focal predictors across the three non-reference outcome categories. Because the study is based on cross-sectional data, all regression results are interpreted as associations rather than causal effects.

4. Results

4.1 Sample and Descriptive Results

The Wave 157 dataset contained 5,395 respondents, of whom 5,273 were included in the employed-worker universe. Because of the questionnaire routing described in Section 3, 4,276 respondents were eligible for both the current AI exposure and perceived AI automation potential questions. After excluding cases with missing outcome, predictor, covariate, or survey-weight information, the principal analytical sample comprised 3,975 respondents.

Table 2 presents the weighted distributions of the principal analytical variables. Regarding current AI exposure, 50.4% reported that none of their work was currently done with AI, 31.2% reported that not much was done with AI, and 18.4% reported that some was done with AI. Perceived AI automation potential was higher: 19.7% believed none of their work could potentially be performed by AI, while 32.8% selected “Not much,” 40.4% “Some,” 6.1% “Most,” and 1.1% “All.” For future job opportunities, 7.4% expected more opportunities, 38.9% expected fewer opportunities, 40.2% expected no difference, and 13.5% were unsure. The perceived AI automation gap was zero for 41.1% of respondents, while 36.3% had a gap of one category and 14.9% a gap of two categories.

Table 2. Weighted Descriptive Statistics for Principal Analytical Variables

Variable		Category	Weighted %
Current AI exposure		None	50.4
		Not much	31.2
		Some	18.4
Perceived AI automation potential		None	19.7
		Not much	32.8
		Some	40.4
		Most	6.1
		All	1.1
Future job opportunities		More	7.4
		Fewer	38.9
		No difference	40.2
		Not sure	13.5
Perceived AI automation gap		-2	0.4
		-1	4.8
		0	41.1
		1	36.3
		2	14.9
		3	2.3
		4	0.2

Note. Percentages are weighted using the Wave 157 production survey weight. Percentages may not sum exactly to 100 because of rounding.

4.2 Multinomial Regression Results

Table 3 reports the weighted multinomial logistic regression results. Models 1 and 2 examine current AI exposure and perceived AI automation potential separately, while Model 3 is the principal model incorporating both predictors.

In Model 1, current AI exposure was associated with higher odds of expecting more opportunities rather than being unsure (OR = 1.616, 95% CI [1.266, 2.062], $p < .001$) but was not associated with expecting fewer opportunities ($p = .823$). The overall association of current exposure with the multinomial outcome was statistically significant, $\chi^2(3) = 43.95$, $p < .001$.

In Model 2, perceived AI automation potential was associated with higher odds of expecting both more opportunities (OR = 1.805, 95% CI [1.412, 2.307], $p < .001$) and fewer opportunities (OR = 1.425, 95% CI [1.218, 1.668], $p < .001$), relative to being unsure. The overall association was also statistically significant, $\chi^2(3) = 69.95$, $p < .001$.

Table 3. Weighted Multinomial Logistic Regression Results

Predictor	More vs. Not sure OR (95% CI)	p	Fewer vs. Not sure OR (95% CI)	p	No difference vs. Not sure OR (95% CI)	p
Model 1: Current exposure only						
Current AI exposure	1.616 (1.266–2.062)	<.001	0.981 (0.826–1.164)	.823	0.812 (0.689–0.957)	.013
Model 2:						

Perceived potential only						
Perceived AI automation potential	1.805 (1.412–2.307)	<.001	1.425 (1.218–1.668)	<.001	0.945 (0.810–1.103)	.471
Model 3: Current + perceived potential						
Principal model						
Current AI exposure	1.305 (1.013–1.682)	.039	0.808 (0.671–0.972)	.024	0.801 (0.669–0.959)	.016
Perceived AI automation potential	1.677 (1.284–2.191)	<.001	1.536 (1.295–1.823)	<.001	1.026 (0.866–1.217)	.765

Note. All models control for age, gender, education, income, and industry. OR = odds ratio; CI = confidence interval. Reference outcome = “Not sure.” Estimates use the Wave 157 production weight with robust sandwich variance estimation. $N = 3,975$.

4.3 Principal Model: Current Exposure and Perceived AI Automation Potential

Model 3 simultaneously included current AI exposure and perceived AI automation potential. Perceived AI automation potential remained significantly associated with both expectations of more opportunities (OR = 1.677, 95% CI [1.284, 2.191], $p < .001$) and fewer opportunities (OR = 1.536, 95% CI [1.295, 1.823], $p < .001$) relative to being unsure. These associations remained after adjustment for current AI exposure and worker characteristics. The joint Wald test was significant, $\chi^2(6) = 94.53$, $p < .001$.

Current AI exposure also remained statistically significant across the three outcome comparisons, although its pattern differed from that of perceived potential. In particular, current exposure was associated with more opportunities (OR = 1.305, 95% CI [1.013, 1.682], $p = .039$) and fewer opportunities (OR = 0.808, 95% CI [0.671, 0.972], $p = .024$) relative to being unsure.

Overall, the principal model indicates that perceived AI automation potential remains associated with future job-opportunity expectations after accounting for current AI exposure. This provides support for H2 as formulated in the study as an associational proposition.

4.4 Adjusted Predicted Probabilities

To aid interpretation of the principal model, adjusted predicted probabilities were calculated by varying perceived AI automation potential across its five levels while retaining the observed distribution of current AI exposure and the control variables. The results are presented in Table 4.

Table 4. Adjusted Predicted Probabilities by Perceived AI Automation Potential

Perceived AI automation potential	More opportunities	Fewer opportunities	No difference	Not sure
None	4.4%	28.8%	49.3%	17.5%
Not much	6.2%	36.5%	42.8%	14.6%
Some	8.3%	44.4%	35.7%	11.7%
Most	10.7%	51.8%	28.5%	9.0%
All	13.2%	58.3%	21.9%	6.6%

The predicted probability of expecting fewer future job opportunities increased from 28.8% among respondents perceiving no AI automation potential to 58.3% among those perceiving that all of their work could potentially be performed by AI, a 29.5-percentage-point increase. The probability of expecting more opportunities also increased, from 4.4% to 13.2%, while the probabilities of expecting no difference and being unsure declined.

Thus, higher perceived AI automation potential was associated with a shift toward more definite expectations, particularly expectations of fewer future job opportunities.

4.5 Supplementary Analysis: Perceived AI Automation Gap

Model 4 re-expressed the principal model using current AI exposure and the derived perceived AI automation gap. As expected from the algebraic relationship between perceived potential, current exposure, and the gap, the resulting estimates were equivalent to Model 3. The gap was significantly associated with expectations of both more opportunities (OR = 1.677, 95% CI [1.284, 2.191], $p < .001$) and fewer opportunities (OR = 1.536, 95% CI [1.295, 1.823], $p < .001$), relative to being unsure.

Because the gap contains the same underlying information as perceived AI automation potential when current exposure is included, this analysis is interpreted as a complementary reparameterization rather than an independent test.

4.6 Sensitivity Analyses

Two sensitivity analyses examined whether the principal association depended on the treatment of “Not sure” responses. First, excluding these respondents and using “No difference” as the reference category produced a similar association between perceived AI automation potential and expectations of fewer opportunities (OR = 1.471, 95% CI [1.290, 1.676], $p < .001$). Second, when the outcome was collapsed into fewer opportunities versus not fewer opportunities, perceived AI automation potential remained significantly associated with expectations of fewer opportunities (OR = 1.417, 95% CI [1.259, 1.595], $p < .001$).

Taken together, the sensitivity analyses indicate that the principal association between perceived AI automation potential and expectations of fewer future job opportunities was consistent across alternative treatments of outcome uncertainty.

5. Discussion

5.1 Principal Findings and Theoretical Interpretation

This study examined whether workers' expectations about future job opportunities were associated with current workplace AI exposure and perceived AI automation potential. The results

indicate that these measures capture related but distinct dimensions of workers' experience of AI. Most importantly, perceived AI automation potential remained significantly associated with expectations of fewer future job opportunities after accounting for current AI exposure and worker characteristics. This association was also evident in the sensitivity analyses using alternative outcome specifications.

The findings are consistent with an appraisal-based interpretation of workplace AI. Cognitive Appraisal Theory proposes that individuals' responses to circumstances depend partly on how they evaluate their significance and potential consequences (Lazarus & Folkman, 1984). Recent research similarly indicates that workplace AI can be associated with both opportunity- and threat-related interpretations (Bankins et al., 2024; Cao et al., 2025; Savolainen et al., 2026). The present findings suggest that workers' perceptions of what AI could potentially do may be relevant to their expectations about future employment, beyond their reported current experience with AI. However, because the Wave 157 data do not directly measure appraisal processes, the study does not establish CAT as a causal mechanism.

5.2 Perceived AI Automation Potential and Future Job Opportunities

The adjusted predicted probabilities provide a substantive interpretation of this relationship. As perceived AI automation potential increased from "None" to "All," the predicted probability of expecting fewer future job opportunities increased from 28.8% to 58.3%. The probability of expecting more opportunities also increased from 4.4% to 13.2%, while expectations of no difference and uncertainty declined.

This pattern suggests that greater perceived AI automation potential is associated with a shift toward more definite expectations, particularly expectations of fewer future job opportunities. Importantly, perceived potential should not be interpreted as an objective measure of automation risk, nor do these expectations indicate actual future job displacement. Rather, the findings indicate that workers' perceptions of AI's potential task reach are associated with how they anticipate the future employment implications of AI.

5.3 Implications for Research and Practice

The findings suggest that research on workplace AI should distinguish between current AI exposure and perceived AI automation potential, rather than treating AI exposure as a single dimension. Future studies could examine whether these perceptions predict subsequent changes in work tasks, employment, occupational mobility, or retraining.

For organizations and workforce-development initiatives, the findings indicate the relevance of addressing not only current AI implementation but also workers' perceptions of how AI may affect future tasks and career pathways. These implications should be interpreted cautiously, as the present cross-sectional analysis does not establish that particular organizational or training interventions would change workers' expectations or employment outcomes.

5.4 Limitations and Future Research

Several limitations should be considered. First, the cross-sectional design prevents conclusions about temporal or causal relationships. Second, perceived AI automation potential is based on a single self-reported item and represents workers' perceptions rather than objective technical feasibility. Third, the perceived AI automation gap is derived from ordinal measures and should therefore be interpreted as a difference between ordered response categories rather than as a metric measure of unrealized automation.

Fourth, questionnaire routing restricted the principal analysis to workers who were eligible for the perceived AI automation potential question, limiting generalization to the full employed population. In addition, the public-use data does not provide all design information required to reproduce Pew Research Center's internal variance estimation procedures; robust sandwich variance estimates were therefore used. Finally, the analysis does not include potentially relevant factors such as occupation, organizational AI strategy, prior AI experience, or perceived job replaceability. Longitudinal research combining workers' perceptions with occupation- and task-level measures could provide stronger evidence about whether perceived AI automation potential is associated with subsequent employment and career outcomes.

6. Conclusion

This study examined the relationships between current workplace AI exposure, perceived AI automation potential, and workers' expectations of future job opportunities. The findings show that perceived AI automation potential remained significantly associated with expectations of fewer future job opportunities after accounting for current AI exposure and worker characteristics. This association was also consistent across the sensitivity analyses. Current AI exposure showed a different pattern, particularly in relation to expectations of more opportunities.

The study contributes to workplace AI research by distinguishing between what AI currently does in workers' jobs and what workers believe AI could potentially do. This forward-looking dimension provides an additional perspective for understanding workers' expectations about the future employment implications of AI. The findings are consistent with an appraisal-based interpretation of workplace AI, although the mechanisms proposed by Cognitive Appraisal Theory were not directly measured or tested.

Future research should use longitudinal and occupation-level data to examine whether perceptions of AI automation potential are associated with subsequent changes in employment, occupational mobility, work tasks, and retraining. Combining workers' perceptions with objective measures of AI exposure and occupational task characteristics could further clarify how perceived AI capability relates to future employment outcomes.

Data-use, attribution and disclaimer statement

The empirical analysis uses data from the Pew Research Center's American Trends Panel under the data-use terms

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References

- Bankins, S., Jooss, S., Restubog, S. L. D., Marrone, M., Ocampo, A. C., & Shoss, M. K. (2024). Navigating career stages in the age of artificial intelligence: A systematic interdisciplinary review and agenda for future research. *Journal of Vocational Behavior*, 153, 104011. <https://doi.org/10.1016/j.jvb.2024.104011>
- Cao, J., Yao, J., & Zhang, F. (2025). Not all forms of artificial intelligence are perceived equal: AI functions and work outcomes. *Journal of Open Innovation: Technology, Market, and Complexity*, 11(2), 100521. <https://doi.org/10.1016/j.joitmc.2025.100521>
- Gmyrek, P., Berg, J., Kamiński, K., Konopczyński, F., Ładna, A., Nafradi, B., Rosłaniec, K., & Troszyński, M. (2025a). *Generative AI and jobs: A refined global index of occupational exposure* (ILO Working Paper 140). International Labour Organization. <https://doi.org/10.54394/HETP0387>
- Gmyrek, P., Berg, J., Kamiński, K., Konopczyński, F., Ładna, A., Nafradi, B., Rosłaniec, K., & Troszyński, M. (2025b). *Generative AI and jobs: A 2025 update*. International Labour Organization. <https://doi.org/10.54394/QFBQ1907>
- Hyman, B. G., Lahey, B., Ni, K. X., & Pilossoph, L. (2025). *How retrainable are AI-exposed workers?* (NBER Working Paper No. 34174). National Bureau of Economic Research. <https://doi.org/10.3386/w34174>
- Lazarus, R. S., & Folkman, S. (1984). *Stress, appraisal, and coping*. Springer Publishing Company
- Lin, L., & Parker, K. (2025, February 25). *AI and workers: Methodology*. Pew Research Center.
- Lin, L., & Parker, K. (2025, February 25). *U.S. workers are more worried than hopeful about future AI use in the workplace*. Pew Research Center.
- Lin, L., & Parker, K. (2025, February 25). *Workers' exposure to AI*. Pew Research Center.
- Lin, L., & Parker, K. (2025, February 25). *Workers' views of AI use in the workplace*. Pew Research Center.
- Long, J. S. (1997). *Regression models for categorical and limited dependent variables*. Sage.
- Pew Research Center. (n.d.). *2024 Pew Research Center's American Trends Panel Wave 157 October 2024: Final topline*. https://www.pewresearch.org/wp-content/uploads/sites/20/2024/11/SR_24.11.19_dei-workplace_topleft.pdf
- Pew Research Center. (n.d.). *The American Trends Panel*. <https://www.pewresearch.org/the-american-trends-panel/>
- Savolainen, I., Ylinen, L., Grönroos, R., & Oksanen, A. (2026). AI transformation in working life: A systematic review of usage and attitudes towards AI among workers. *Digital Business*, 6(1), 100162. <https://doi.org/10.1016/j.digbus.2025.100162>
- White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, 48(4), 817–838. <https://doi.org/10.2307/1912934>