Technological Change Through the Lens of Competence: Exploring Gender Differences in Attitudes Toward AI and Automation

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Abstract

As artificial intelligence (AI) and work automation become increasingly integrated into modern workplaces, understanding employees' attitudes toward these changes is vital. This study examines how perceived competencies – both linguistic/technical (LC) and non-linguistic (NLC) – relate to Polish workers' attitudes toward AI and automation. Using data from a representative sample of 1,067 employed adults, structural equation modeling (SEM) revealed that LC significantly predicted more positive attitudes, while NLC showed no significant effect. Multi-group analysis indicated gender differences in the strength of these associations. However, measurement invariance was not confirmed, suggesting different interpretations of competence items across gender. These findings underscore the importance of considering both competence profiles and sociocultural contexts when assessing workers' responses to technological change.

Keywords: artificial intelligence, employees, labor, structural equation model

1. Introduction

One of the key indicators of digital transformation is the development of artificial intelligence (AI) and the resulting changes in the world of work. AI disrupts traditional understandings of concepts such as "work," "employee," and "workplace" [41]. On the one hand, this technology enhances the automation of production processes, enables the elimination of many tedious, repetitive, and even hazardous tasks, thereby improving efficiency and reducing production costs [5], [8,9], which contributes to its attractiveness. On the other hand, it poses a threat to human labor, potentially leading to the elimination of numerous jobs, the reduction in demand for certain professions, or a fundamental reshaping of occupational roles [6], [16], [43], [45,46].

It is worth emphasizing that AI may potentially replace humans even in highly advanced tasks; as its capabilities increase, it is likely that many tasks currently performed by humans will be executed more efficiently by AI, which positions it as a serious threat to human employment [20]. Although forecasts regarding the number of jobs at risk of automation vary [1], [24], the literature indicates a growing level of anxiety among employees stemming from employment insecurity and fear of losing their livelihoods [3], [26], [54]. At the same time, AI development may also lead to the creation of new jobs and professions [2], although this does not eliminate the fears and concerns.

Regardless of the direction of labor demand changes, AI development is expected to have a profound impact on the scope of duties, methods of task execution, communication, and social relations in the workplace. According to the Challenge–Hindrance Stress Framework [11], these changes can be perceived either as sources of stress or as motivating challenges, depending on the resources available to the employee – including competencies.

This phenomenon has far-reaching consequences for individuals, organizations, and entire social systems. Understanding how employees respond to the implementation of AI – particularly in relation to their perceived competencies – is essential for managing technological change effectively.

The aim of this article is to present and evaluate employees' attitudes toward work automation and the implementation of AI in the workplace, and to identify the competencies (both linguistic-technical and non-linguistic) that influence these attitudes. Based on existing literature and theoretical models, we formulated three research hypotheses, which are tested and discussed in the following sections.

To verify the hypotheses, a literature review and a quantitative study were conducted on a representative sample of Polish employees. The findings offer important theoretical and practical implications, applicable both to human resource management at the organizational level and to the development of education and labor market policy at the macro-social level.

2. Literature review

Artificial intelligence, described as "the ability of a machine to perform cognitive functions that we associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem solving, decision-making, and even demonstrating creativity" [48], is becoming one of the key instruments in digital work.

It is perceived either as a challenge or a hindrance. According to the assumptions of the Transactional Theory of Stress and Coping (TTSC) [38] and the Challenge–Hindrance Stress Framework [11], the integration of AI into the workplace may be treated as a hindrance stressor. Employees may perceive the implementation of AI as a signal that the organization seeks to replace human labor with advanced technologies, leading to decreased job security and mobility [40]. This perception can generate fear, demotivation, and a desire to reduce responsibilities, resulting in negative emotional and behavioral responses such as decreased self-confidence, lower work engagement, and heightened employment uncertainty. Individuals who feel that such a situation is beyond their control may perceive AI as a source of unemployment and a threat to their career development [7].

In this context, the concept of AI awareness becomes important. It is defined as the awareness that AI technologies, such as robots and algorithmic management systems, may replace one's job in the future and reflects a perceived threat to job continuity [9]. Employees with high AI awareness and concerns about job loss may experience reduced feelings of safety, negatively impacting their engagement, motivation, and willingness to develop competencies [4], [58], which can lead to lower job satisfaction and even occupational burnout. Furthermore, technological anxiety can result in employees feeling uncomfortable or anxious when interacting with technology, thereby reducing their focus and work efficiency [34]. In response, negative behaviors such as procrastination, superficial task completion, or avoidance of technology use may emerge.

Technology-related anxiety may also lead to interpersonal tensions and workplace conflicts. Individuals fearful of technology may react with irritation, resistance, or aversion, which could manifest in strained interactions with colleagues or work tasks [42]. Such an atmosphere of tension weakens team cohesion and collaborative spirit, ultimately diminishing work performance [12].

Conversely, employees who perceive AI as a positive challenge tend to be more motivated to learn and develop new skills. They demonstrate greater engagement, improved performance, and proactive behaviors, particularly in customer service roles [52], [55].

Similar conclusions can be drawn from the Conservation of Resources (COR) Theory [29,30]. Through the challenging path, employees may view AI as an opportunity for professional development, resource enhancement, and relief from physical and mental fatigue through the automation of repetitive tasks. This fosters positive emotions, improves work conditions, and facilitates greater focus on creative aspects of the job. On the hindering path, however, AI may be perceived as a threat to employment, leading to avoidance or even sabotage of AI systems, and reinforcing adverse psychological consequences such as burnout or turnover.

According to Person-Environment Fit Theory [18], employees may experience a misalignment between their current skillset and the technologically evolving work environment, combined with an awareness of being replaceable by machines. As AI advances, it is increasingly capable of performing complex tasks and adapting to dynamic environments through learning from both users and contextual cues. This can lead to the development of AI-related technological anxiety, manifesting as avoidance of new technologies and, in some cases, resignation from work [36]. Previous research has identified various internal and external factors contributing to technological anxiety, such as lack of personal skills or communication competencies, personality traits, perceived complexity or irrelevance of the technology, ethical concerns, cultural influences, habitual changes, technological trends, regulatory challenges, inadequate training, age, and work experience [51]. Possessing adequate competencies – particularly digital and social skills – acts as a protective buffer against the risk of being replaced by AI.

Attitudes toward automation and AI may differ between women and men. Studies indicate that women more frequently express concerns about the impact of technology on job security and the labor market [53], [59]. This may be due to women's higher representation in administrative, educational, or service-oriented professions, which are particularly vulnerable to automation [10]. Moreover, women tend to perceive AI technologies as posing a greater threat to societal stability and express stronger support for regulatory oversight [44]. On the other hand, men are more likely to express enthusiasm about technological progress and report higher readiness to use AI-based tools [31]. These differences may stem not only from structural factors but also from divergent educational experiences, cultural expectations, and trust in technology. Therefore, accounting for gender as a moderating variable appears especially important in studies on attitudes toward automation and AI.

Based on the theoretical framework and prior empirical findings, three hypotheses were formulated. First, it was hypothesized that higher self-perceived linguistic and technical competencies (LC) would be associated with more favorable attitudes toward automation and artificial intelligence (H1). This expectation reflects the notion that individuals who feel confident in their language or digital skills may be more open to technological change and less fearful of automation. Second, non-linguistic competencies (NLC), such as adaptability, creativity, or collaboration, were expected to positively relate to attitudes toward AI (H2), assuming that such broader competencies may foster a sense of preparedness for a transforming labor market. Third, it was hypothesized that the strength or direction of these associations may differ by gender (H3), given documented differences in technological self-efficacy, career expectations, and the gendered framing of soft versus hard skills in the labor market.

3. Methods

The study examining employees' attitudes toward work automation and artificial intelligence was conducted on a representative sample of 1,067 employed adults in Poland. Data were collected using the Computer-Assisted Web Interviewing (CAWI) method. The sample was drawn using stratified random sampling to reflect the working-age population of Poland in terms of gender, age, education level, and region. The survey covered employees across both public and private sectors and was not limited to any specific industry. The panel provider ensured quotas aligned with national labor market statistics.

The analysis followed a structured, multi-phase approach using R software [47] and the psych [49], MVN [37], lavaan [50], semTools [33], and semPlot [19] packages. Given that the data included ordinal variables (Likert-scale responses) and exhibited non-normal distributions, all analyses involving latent variables were conducted using the robust Diagonally Weighted Least Squares estimator (WLSMV). This estimator is considered appropriate for ordinal data and provides more accurate standard errors and fit indices under such conditions [39].

The procedure began with an exploratory factor analysis (EFA) to uncover the latent structure of the self-assessed competencies. The factorability of the correlation matrix was first examined using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity. Factors were extracted using the principal axis method and oblique promax rotation to account for potential correlations among constructs. The number of factors to retain was determined based on eigenvalues greater than 1, parallel analysis, and the interpretability of the solution.

Next, a confirmatory factor analysis (CFA) was used to validate the structure identified in the EFA. Model fit was assessed using multiple indices: the comparative fit index (CFI) and Tucker-Lewis index (TLI) values ≥ 0.90 were considered acceptable, with values ≥ 0.95 indicating good fit; root mean square error of approximation (RMSEA) values < 0.08 indicated reasonable fit, and < 0.05 good fit; and standardized root mean square residual (SRMR) values < 0.08 were regarded as acceptable [32].

Reliability of the latent constructs was assessed using several indices: Cronbach's alpha (α), McDonald's omega (ω), and composite reliability (CR). Values of $\alpha \geq 0.70$ were considered acceptable, although values ≥ 0.60 were tolerated in exploratory contexts [27]. Convergent validity was evaluated using the average variance extracted (AVE), with values ≥ 0.50 considered adequate. Discriminant validity was tested by comparing the AVE values to the squared correlations between constructs [23].

Following CFA, a structural equation model (SEM) was estimated to examine the relationship between latent competencies (language/technical and non-linguistic) and respondents' attitudes toward automation and artificial intelligence (ordinal outcome variable). SEM allowed simultaneous modeling of the measurement and structural components of the hypothesized framework.

To investigate group differences, a multi-group SEM approach was used, with separate models estimated for women and men. To validate whether comparisons of latent constructs across groups were meaningful, a measurement invariance analysis was conducted sequentially at three levels: configural (equal factor structure), metric (equal factor loadings), and scalar (equal loadings and item intercepts). Model comparisons were based on scaled chi-square difference tests [13]. Lack of invariance at a given level indicated that certain measurement properties differed across gender groups, affecting the interpretation of latent mean comparisons.

4. Results

4.1. Sample characteristics

The study sample consisted of 1,067 working adults in Poland (Table 1). Gender was relatively balanced, with 53.9% identifying as male and 46.1% as female. Participants spanned a wide range of ages, with the largest groups being those aged 35–44 (29.2%) and 45–54 (25.9%). Younger individuals (18-24) constituted 5.7% of the sample, while those aged 25-34 made up 21.7%, and individuals aged 55 and above represented 17.4%. In terms of educational attainment, the majority of participants had completed tertiary education (53.9%), followed by secondary education (38.1%). Smaller proportions held basic vocational (7.0%) or lower secondary education or less (1.0%). Regarding place of residence, a significant majority lived in urban areas (81.2%), while 18.8% resided in rural locations.

Table 1. Sample characteristics (N=1067).

Variable	Category	%
Gender	Male	53.9
	Female	46.1
Age	18-24	5.7
	25-34	21.7
	35-44	29.2
	45-54	25.9

	55 and above	17.4
Education level	Not higher than lower secondary	1.0
	Basic vocational	7.0
	Secondary	38.1
	Tertiary	53.9
Place of residence	Urban	81.2
	Rural	18.8

4.2. Exploratory Factor Analysis

To identify latent structures underlying self-assessed competencies, an EFA was performed on eight items (P9.01–P9.08) measured on a 7-point Likert scale. Prior to the analysis, data adequacy was verified. The Kaiser-Meyer-Olkin measure indicated meritorious sampling adequacy (KMO = 0.83), and Bartlett's test of sphericity was significant, $\chi^2(28) = 2504.71$, $p < 0.001$, confirming the appropriateness of factor analysis.

An EFA using principal axis factoring with promax rotation was conducted (Table 2). The eigenvalue criterion (>1) supported a two-factor solution, which accounted for 48.9% of the total variance. The first factor, labeled Non-language Competencies (NLC), comprised six items related to self-organization, critical thinking, stress resistance, adaptability, leadership, and computer use. The second factor, labeled Language/Coding Competencies (LC), included foreign language skills and programming/informatics skills. While the LC factor is composed of only two items, they were selected based on their conceptual relevance to AI readiness and their distinct loadings confirmed by factor analysis. Factor correlation was moderate (r = 0.61), indicating that both constructs are related but distinct.

Table 2. Pattern matrix for promax-rotated two-factor solution (N = 1067).

Item Code	Competency Description	Factor 1 (NLC)	Factor 2 (LC)	Uniqueness
P9.01	Foreign language communication	-	0.545	0.698
P9.02	Computer use and internet skills	0.481	0.251	0.558
P9.03	IT and programming skills	-	0.932	0.312
P9.04	Self-organization (task planning, timeliness)	0.835	-	0.460
P9.05	Critical thinking and decision-making	0.818	-	0.443
P9.06	Leadership and people management	0.426	0.230	0.646
P9.07	Adaptability and continuous learning	0.712	-	0.482
P9.08	Stress resistance	0.499	-	0.716

Internal consistency was high for Factor 1 (Cronbach's $\alpha = 0.81$) and acceptable for Factor 2 ($\alpha = 0.61$), considering it consists of only two items. The exploratory factor analysis revealed a clear and interpretable two-factor solution underlying self-assessed competencies. The first factor represents soft, managerial, and adaptive competencies, essential for modern, flexible work environments. The second factor reflects technical and language-specific skills, often tied to formal education and specialized training. Both dimensions are moderately related yet empirically distinct. The internal consistency of the first factor is robust, whereas the second – though conceptually coherent – requires further validation.

4.3. Confirmatory Factor Analysis

Multivariate normality was assessed using Mardia's test. The results indicated significant multivariate non-normality due to both skewness and kurtosis (skewness = 851.56, kurtosis = 22.48, $p < 0.001$). Univariate tests (Anderson–Darling) similarly showed that none of the analyzed competence variables followed a normal distribution ($p < 0.001$). Consequently, estimation procedures in the CFA and SEM relied on the WLSMV estimator, which is robust to non-normality and appropriate for ordinal data.

Based on prior EFA results, a two-factor model was specified, distinguishing between Language/Coding Competencies and Non-language Competencies. The CFA model demonstrated satisfactory fit. Although the chi-square test was significant, other fit indices indicated an acceptable to good model fit: CFI = 0.974, TLI = 0.962, and SRMR = 0.068 (below the recommended threshold of 0.08). However, the RMSEA value of 0.104 exceeded the acceptable cutoff (>0.08), indicating some degree of model misspecification in terms of parsimony. Overall, the results support a moderately acceptable model fit, consistent with the earlier EFA findings.

The latent constructs were moderately correlated (r = 0.595), which supports the theoretical distinction between the two domains while acknowledging empirical overlap. All factor loadings were statistically significant ($p < 0.001$). The Non-language Competencies scale demonstrated high internal consistency across all reliability metrics. In contrast, the Language/Coding factor showed marginal reliability, likely due to the limited number of indicators (two items). The AVE for both constructs was approximately 0.47 – close to but slightly below the commonly recommended threshold of 0.50 (see Table 3). Nevertheless, discriminant validity was supported: the squared correlation between the two latent factors ($0.595^2 = 0.354$) was lower than the AVE for each construct, thus fulfilling the Fornell–Larcker criterion.

Table 3. Construct reliability and validity indicators.

Construct	Cronbach's α	McDonald's ω	CR	AVE
LC	0.61	0.61	0.61	0.4690
NLC	0.81	0.82	0.83	0.4686

Confirmatory factor analysis confirmed the two-factor structure identified via EFA, distinguishing between technical/language skills and soft, managerial competencies. Although the model fit was only moderately acceptable (due to elevated RMSEA), factor loadings were strong, and most reliability and validity indicators were satisfactory. These results support the construct validity of the proposed competence model, providing a robust basis for further multi-group and structural modeling.

4.4. Structural equation modeling

To explore how different types of competencies shape attitudes toward technological change, a SEM was specified. The outcome variable was attitude toward automation and AI (P6), operationalized as an ordinal measure of respondents' perceptions of technology-driven change in the labor market: 1) A normal consequence of technological progress, not a concern, 2) Positive: machines perform tedious tasks, 3) Concerned: humans may be less needed in future labor markets, 4) Fearful: robots may one day escape control. This scale reflects a continuum from acceptance to apprehension regarding automation and artificial intelligence.

The model included two latent constructs reflecting types of competencies, based on previous factor analyses: Language/Coding Competencies and Non-language Competencies. These two latent constructs were modeled to predict attitudes toward automation and AI (P6). Figure 1 presents a graphical representation of the estimated model. Table 4 shows the estimates along with standard errors, p-values, and 95% confidence intervals (CIs).

All factor loadings for the measurement part of the model were statistically significant ($p < .001$) and above the recommended threshold of 0.5. Standardized loadings ranged from 0.574 (P9.08) to 0.747 (P9.03, P9.05), indicating good item–construct relationships.

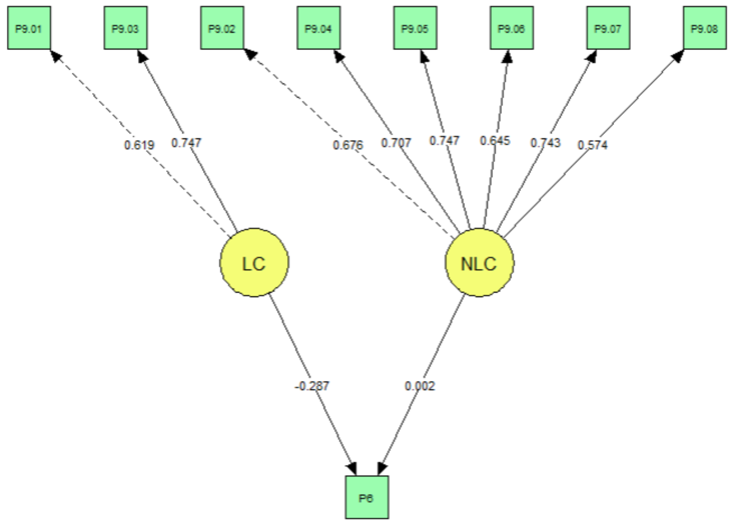

Fig. 1. Path model estimates using WLSMV.

Table 4. Results from SEM.

Path	Std. Estimate	SE	*p*-value	95% CI (lower–upper)
Measurement model				
LC → P9.01 (language)	0.619	0.028	<.001	[0.563, 0.675]
LC → P9.03 (programming)	0.747	0.029	<.001	[0.690, 0.803]
NLC → P9.02 (computer)	0.676	0.019	<.001	[0.640, 0.713]
NLC → P9.04 (organization)	0.707	0.019	<.001	[0.670, 0.744]
NLC → P9.05 (critical think)	0.747	0.019	<.001	[0.710, 0.783]
NLC → P9.06 (leadership)	0.645	0.019	<.001	[0.608, 0.683]
NLC → P9.07 (adaptability)	0.743	0.016	<.001	[0.711, 0.774]
NLC → P9.08 (stress resist.)	0.574	0.020	<.001	[0.535, 0.614]
Structural model				
P6 ← LC	–0.287	0.053	<.001	[–0.391, –0.183]
P6 ← NLC	0.002	0.049	.970	[–0.094, 0.098]

Only LC (language and coding competencies) was significantly associated with P6. Importantly, the relationship was negative: the higher the respondent's self-assessed language and coding skills, the more positive their attitude toward automation and AI (i.e., lower values on P6, which reflect openness and optimism).

NLC, encompassing managerial, adaptive, and organizational competencies, had no significant predictive power for attitudes toward technological change.

The model accounted for 8.2% of variance in attitudes toward automation and AI (R^2 = 0.082), suggesting a small but meaningful effect.

4.5. Multi-Group SEM: Gender Differences in the Effects of Competencies on Attitudes Toward Automation and AI

To examine whether the relationship between competencies and attitudes toward automation/AI differs by gender, a multi-group SEM was estimated (Figure 2).

Among women, higher LC competencies significantly predicted more positive attitudes toward automation and AI. NLC had no significant effect. It can therefore be concluded that women with stronger language/IT competencies are less fearful and more optimistic about automation.

Among men, LC had a weaker but still significant negative effect on fear of automation. NLC showed a negative trend, suggesting that more general non-language competencies may reduce fear of automation, but not at conventional significance (p = 0.062). For men, both types of competencies may contribute to confidence toward AI, though effects are smaller and less differentiated than among women.

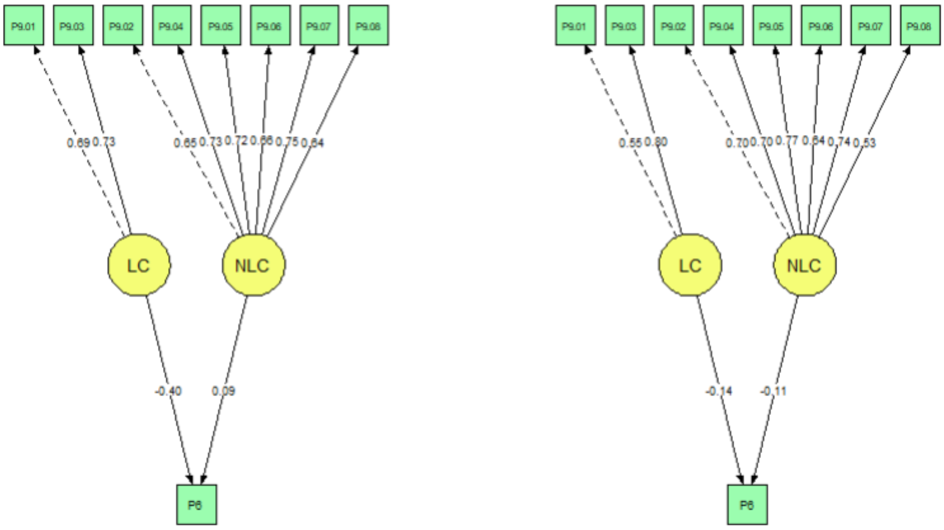

Fig. 2. Path model estimates by gender: (a) Females, (b) Males

Women show stronger differentiation: only technical competencies (LC) significantly reduce fear of AI. Men appear more generally resilient; both LC and NLC show weaker, non-significant or marginal effects. The explanatory power of competencies for predicting attitudes toward automation is higher for women. These results suggest gendered differences in how competencies relate to perceptions of technological change. Women's attitudes toward automation appear more sensitive to their perceived technical skillsets, whereas men's attitudes are less dependent on self-assessed competence levels.

The structural model accounted for 12.2% of the variance in attitudes toward automation and AI among women, compared to only 5.0% among men. This suggests that the model explains over twice as much variance in women's attitudes as it does in men's, indicating potentially stronger or more consistent relationships between the latent constructs and attitudinal outcomes within the female subsample.

To ensure that the observed gender differences in the structural paths were not artifacts of measurement non-equivalence, a multi-group measurement invariance analysis was conducted. This procedure followed a hierarchical approach, beginning with a configural model (with no cross-group constraints), then testing for metric invariance (equal factor loadings across groups), and finally scalar invariance (equal loadings and item intercepts). The results are shown in Table 5.

Table 5. Measurement invariance testing across gender

Model	χ^2	df	$\Delta\chi^2$	Δdf	p-value	Interpretation
Configural Model	279.08	50	—	—	—	Baseline model (unconstrained)
Metric Model	305.59	56	20.17	6	0.0026 **	Metric invariance not supported
Scalar Model	456.89	96	199.43	40	< .001 ***	Scalar invariance not supported

The configural model demonstrated acceptable fit, indicating that the basic factor structure of the model – with two latent constructs: linguistic/technical competencies and non-linguistic competencies – was similar across genders. However, the model fit significantly worsened when metric constraints were applied ($\Delta\chi^2 = 20.17$, $\Delta df = 6$, $p = 0.0026$), and this deterioration was even more pronounced under scalar invariance constraints ($\Delta\chi^2 = 199.43$, $\Delta df = 40$, $p < 0.001$).

These results suggest that the measurement model is not invariant across gender groups – that is, men and women do not interpret or respond to the items measuring LC and NLC in the same way. Without at least metric invariance, it is not statistically appropriate to compare latent factor means or structural paths across genders. Therefore, the interpretation of group differences should focus on within-group associations (e.g., how LC and NLC predict attitudes toward automation within each gender), rather than comparing the groups directly.

5. Conclusions

5.1. Key Findings

The results confirm the proposed hypotheses and are, in many cases, consistent with previous research. AI is transforming the functioning of organizations, reshaping business models, and consequently changing work organization. Alongside its many benefits, this shift also brings concerns related to the potential risk of job displacement due to the replacement of human labor by AI. Such concerns may lead to decreased engagement or even burnout.

Understanding employees' reactions is essential for developing effective strategies to mitigate negative outcomes and foster the creation of a positive and adaptable workforce in the face of AI-driven transformations [21], [25], [45].

The aim of the present study was to analyze the relationship between employees' perceived competencies and their attitudes toward work automation and artificial intelligence, with particular emphasis on gender differences. The structural equation modeling results provided partial support for the proposed hypotheses.

Hypothesis H1, which posited that a higher level of perceived linguistic and technical competencies (LC) would be associated with more positive attitudes toward AI and automation, was confirmed. Both in the overall sample and in the multi-group analysis (separately for women and men), LC competencies were a significant predictor of attitudes toward AI: the higher respondents rated their linguistic and programming skills, the more optimistic they were about technological change.

Hypothesis H2, which proposed a positive relationship between non-linguistic competencies (NLC) – such as stress resilience, work organization, or adaptability – and positive attitudes toward AI, was not supported. In both the general analysis and the separate models for women and men, no statistically significant associations were found between NLC and perceptions of the impact of automation and AI on the labor market.

Hypothesis H3, which concerned the moderating effect of gender on the strength or direction of these relationships, received partial descriptive support but could not be conclusively confirmed due to a lack of measurement invariance. The analyses showed that women and men may interpret the items measuring competencies differently, making direct group comparisons invalid. Nevertheless, SEM models estimated separately for women and men revealed that LC competencies had a stronger and more consistent influence on attitudes toward AI among women than men. For men, there was also a trend suggesting a potential effect of NLC, although it did not reach statistical significance at the conventional 0.05 level.

In summary, the study demonstrated that perceived technical competencies are an important resource that protects employees – especially women – from anxiety related to automation and AI. At the same time, the findings emphasize the importance of accounting for sociocultural and gender-related factors in research on self-perceived competencies and adaptation to technological change.

5.2. Theoretical and Practical Implications

The conducted study has significant theoretical implications, extending the understanding of job insecurity caused by AI and its consequences for organizations. It contributes to the integration of AI-driven workplace transformation within the framework of the Conservation of Resources (COR) theory proposed by Hobfoll [29]. Specifically, it identifies AI-induced job insecurity as a threat to employees' valued resources while emphasizing the importance of self-assessment of knowledge and competencies as a distinctive asset in facing the challenges posed by AI implementation.

The practical dimension of the study offers insights at both the micro and macro levels – particularly for organizational stakeholders such as managers and human resources (HR) professionals, as well as for policymakers in the fields of education and labor market governance. All actors, regardless of position, should be aware of the changes brought by AI and their inevitability. This constitutes a shared challenge for employees, employers, public institutions, and local governments alike.

Mitigating employees' negative perceptions of AI requires proactive management, especially with a focus on communication strategies that transparently convey how AI will be integrated and reassure workers that it is intended to augment – not replace – human competencies. To alleviate employee concerns, leaders should consider holding regular town hall meetings, workshops, and one-on-one discussions. Training programs should focus on developing competencies that reduce the risk of being replaced by AI, while also promoting employee well-being and psychological empowerment [35], equipping them to deal competently with this dilemma. Implementing practices such as job crafting [56] and providing adequate job resources [15] may also help organizations maximize the benefits of AI.

Furthermore, it is advisable to consider adopting the "human-AI collaboration" model proposed by Daugherty and Wilson [17]. By framing AI implementation as an opportunity for employee skill development and role enrichment – rather than as a threat organizations may alleviate the negative effects of AI-induced job insecurity, which can otherwise hinder knowledge sharing and overall productivity.

Although the model explains a modest portion of the variance in attitudes, the results highlight key leverage points for practical interventions. For instance, organizations could prioritize targeted training in digital and language-related skills, particularly among female employees, to enhance adaptability and confidence in AI-rich environments.

5.3. Limitations

This study has several limitations that open avenues for future research.

Although the two-factor model of self-assessed competencies generally exhibited an acceptable fit, the relatively high RMSEA value observed in the confirmatory factor analysis points to potential issues with model specification. Future research could address this by refining or expanding the competency measures to achieve a better structural fit.

Another limitation lies in the measurement invariance findings. Since the data showed that men and women may interpret competency items differently, cross-group comparisons must be approached with caution. Future research should investigate the potential sources of this non-invariance – such as differences in educational background, digital exposure, or socialization processes – which may influence how men and women self-assess their competencies.

Moreover, while the sample was representative of Polish employees, it remains unclear whether the findings would generalize to different national, cultural, or industrial contexts. Replicating the study across varied environments would help assess the robustness of the results. Besides, the study included only participants who identified as male or female, which limits the generalizability of gender-related findings to non-binary individuals.

Additionally, this study did not control for organizational and sector-specific factors that might influence attitudes toward AI. Considering variables such as industry type, organizational size, and occupational role could offer more nuanced insights into how employees experience technological change.

Lastly, the cross-sectional design of the research limits the ability to draw causal conclusions. Longitudinal studies could help clarify how shifts in competencies over time influence attitudes toward automation and AI as workplace technologies continue to evolve.

Despite these limitations, the study offers valuable insights into the role of perceived competencies in shaping employee responses to AI-driven workplace transformations and highlights critical gender-related nuances worthy of further exploration.

5.4. Future Research

In the existing research and literature, the prevailing perspective emphasizes the negative impact of AI on employee behaviors and emotions, including reduced career satisfaction [9], diminished well-being [28], and heightened job insecurity [57]. These studies often overlook the dynamic nature of employees' knowledge and competencies, as well as their capacity for development, which may lead to an overly simplistic understanding of human–AI interactions.

To provide a more balanced view, it is important to consider empirical evidence suggesting that AI-induced stress can be perceived by employees as a potential opportunity for growth. When effectively managed, such stress may be interpreted as supportive and beneficial [14], [22]. In this context, employees may actively seek to acquire knowledge about AI. Future studies could incorporate contextual work-related variables such as sector, organizational culture, or job role to better understand how they interact with attitudes toward AI and automation.

Unfortunately, few studies have investigated the conditions under which AI-related stress motivates employees to engage in learning. Expanding research in this area is crucial, especially considering that the advancement of AI will increasingly require workers to gain knowledge and develop the skills necessary to navigate a rapidly evolving AI-integrated workplace. This involves overcoming challenges and fostering personal development.

References

1. Acemoglu, D., Restrepo, P.:Robots and jobs: evidence from US labor markets. Journal of Political Economy. 128 (6), 2188-2244 (2020)
2. Agrawal, A., Gans, J.S., Goldfarb, A.: Artificial intelligence: the ambiguous labor market impact of automating prediction. J. Econ. Perspect. 33, 31-50 (2019)
3. Aleksander, I.: Partners of Humans: A Realistic Assessment of the Role of Robots in the Foreseeable Future. Journal of Information Technology. 32 (1), 1-9 (2017)
4. Alisic, A., Wiese, B.S.: Keeping an insecure career under control: the longitudinal interplay of career insecurity, self-management, and self-efficacy. Journal of Vocational Behavior, 120, p. 103431 (2020)
5. Bankins, S., Ocampo, A.C., Marrone, M., Restubog, S.L.D., Woo, S.E.: A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. Journal of organizational behavior. 45 (2), 159-182 (2024)
6. Baptista, J., Stein, M.K., Klein, S., Watson-Manheim, M.B. Lee, J.: Digital work and organisational transformation: Emergent Digital/Human work configurations in modern organisations. The Journal of Strategic Information Systems. 29 (2), 101618 (2020)
7. Başer, M.Y., Büyükbeşe, T., Ivanov, S.: The effect of STARA awareness on hotel employees' turnover intention and work engagement: the mediating role of perceived organisational support. Journal of Hospitality and Tourism Insights. 8 (2), 532-552 (2025)
8. Bowen, J., Morosan, C.: Beware hospitality industry: the robots are coming. Worldwide Hospitality and Tourism Themes. 10 (6), 726-733 (2018)
9. Brougham, D., Haar, J.: Smart technology, artificial intelligence, robotics, and algorithms (STARA): employees' perceptions of our future workplace. Journal of Management and Organization. 24 (2), 239-257 (2018)
10. Brussevich, M., Dabla-Norris, M.E., Kamunge, C., Karnane, P., Khalid, S., Kochhar, M.K.: Gender, technology, and the future of work. International Monetary Fund, Washington D.C. (2018)
11. Cavanaugh, M.A., Boswell, W.R., Roehling, M.V., Boudreau, J.W.: An empirical examination of self-reported work stress among US managers. Journal of applied psychology. 85 (1), 65 (2000)
12. Chen, A., Xiang, M., Wang, M., Lu, Y.: Harmony in intelligent hybrid teams: the influence of the intellectual ability of artificial intelligence on human members' reactions. Information Technology & People. 36 (7), 2826-2846 (2023)
13. Chen, F.F.: Sensitivity of goodness of fit indexes to lack of measurement invariance. Structural equation modeling: a multidisciplinary journal. 14 (3), 464-504 (2007)
14. Cheng, B., Lin, H., Kong, Y.: Challenge or hindrance? How and when organizational artificial intelligence adoption influences employee job crafting. Journal of Business Research. 164, 113987 (2023)
15. Cheng, J.C., Yi, O.: Hotel employee job crafting, burnout, and satisfaction: The moderating role of perceived organizational support. International Journal of Hospitality Management. 72, 78-85 (2018)
16. Christou, P., Simillidou, A., Stylianou, M.C.: Tourists' perceptions regarding the use of anthropomorphic robots in tourism and hospitality. International Journal of Contemporary

Hospitality Management. 32 (11) (2020)
17. Daugherty, P.R., Wilson, H.J.: Humanþ Machine: reimagining Work in the Age of AI. Harvard Business Review Press. Boston, MA (2018)
18. Edwards, J.R., Caplan, R.D., Harrison, R.V.: Person-environment fit theory: Conceptual foundations, empirical evidence, and directions for future research. Theories of organizational stress. 28, 28-67 (1998)
19. Epskamp, S. (2022), semPlot: Path diagrams and visual analysis of various SEM packages' output (R package version 1.1.6). https://CRAN.R-project.org/package=semPlot. Accessed December 23, 2024
20. Fast, E., Horvitz, E.: Long-Term Trends in the Public Perception of Artificial Intelligence. In: Proceedings of the AAAI Conference on Artificial Intelligence, 31 (1), 963 (2017)
21. Felicetti, A.M., Corvello, V., Ammirato, S.: Digital innovation in entrepreneurial firms: a systematic literature review. Review of Managerial Science. 18 (2), 315-362 (2024)
22. Feng, L.: Investigating the effects of artificial intelligence-assisted language learning strategies on cognitive load and learning outcomes: A comparative study. Journal of Educational Computing Research. 62 (8), 1961-1994 (2025)
23. Fornell, C., Larcker, D.F.: Evaluating structural equation models with unobservable variables and measurement error. Journal of marketing research. 18 (1), 39-50 (1981)
24. Frey, C.B. Osborne, M.A.: The future of employment: how susceptible are jobs to computerization?. Technological Forecasting and Social Change. 114, 254-280 (2017)
25. Ghislieri, C., Molino, M., Cortese, C.G.: Work and organizational psychology looks at the fourth industrial revolution: how to support workers and organizations?. Frontiers in psychology. 9, 2365 (2018)
26. Haenlein, M., Kaplan, A.: A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence. California Management Review. 61 (4), 5-14 (2019)
27. Hair Jr, J.F., Black, W.C., Babin, B.J., Anderson, R.E.: Multivariate data analysis. In: Multivariate data analysis, pp. 785-785. Cengage Learning, EMEA Cheriton House, Andover (2008)
28. Henkel, A.P., Čaić, M., Blaurock, M., Okan, M.: Robotic transformative service research: deploying social robots for consumer well-being during COVID-19 and beyond. Journal of Service Management. 31 (6), 1131-1148 (2020)
29. Hobfoll, S.E.: Conservation of resources: a new attempt at conceptualizing stress. American psychologist. 44 (3), 513 (1989)
30. Hobfoll, S.E., Freedy, J., Lane, C., Geller, P.: Conservation of social resources: Social support resource theory. Journal of Social and Personal Relationships. 7 (4), 465-478 (1990)
31. Hosanagar, K., Jair, V.: We need transparency in algorithms, but too much can backfire. Harvard Business Review. 25, 2018 (2018)
32. Hu, L.T., Bentler, P.M.: Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural equation modeling: a multidisciplinary journal. 6 (1), 1-55 (1999)
33. Jorgensen, T.D., Pornprasertmanit, S., Schoemann, A.M., Rosseel, Y. (2025), semTools: Useful tools for structural equation modeling (Version 0.5-7). https://cran.r-project.org/package=semTools. Accessed March 18, 2025
34. Khasawneh, O.Y.: Technophobia without boarders: The influence of technophobia and emotional intelligence on technology acceptance and the moderating influence of organizational climate. Computers in Human Behavior. 88, 210-218 (2018)
35. Kong, H., Sun, N. and Yan, Q.: New generation, psychological empowerment: can empowerment lead to high career competencies and career satisfaction?., International Journal of Contemporary Hospitality Management. 28 (11), 2553-2569 (2016)
36. Kong, H., Yuan, Y., Baruch, Y., Bu, N., Jiang, X. Wang, K.: Influences of artificial intelligence (AI) awareness on career competency and job burnout, International Journal of Contemporary Hospitality Management. 33 (2), 717-734 (2021)
37. Korkmaz, S., Goksuluk, D., Zararsiz, G.: MVN: An R package for assessing multivariate normality. The R Journal. 6 (2), 151-162 (2014)
38. Lazarus, R.S., Folkman, S.: Stress, appraisal, and coping. Springer publishing company,

New York (1984)

39. Li, C.H.: Confirmatory factor analysis with ordinal data: Comparing robust maximum likelihood and diagonally weighted least squares. Behavior research methods. 48, 936-949 (2016)
40. Mabungela, M.: Artificial Intelligence (AI) and Automation in the World of Work: A Threat to Employees?. Research in Social Sciences and Technology. 8 (4), 135-146 (2023)
41. Malik, A., Budhwar, P., Patel, C., Srikanth, N.R.: May the bots be with you! Delivering HR cost-effectiveness and individualized employee experiences in an MNE. International Journal of Human Resource Management. 33 (6), 1148-1178 (2022)
42. McClure, P.K.: You're fired, says the robot: the rise of automation in the workplace, technophobes, and fears of unemployment. Social Science Computer Review. 36 (2), 139-156 (2018)
43. Moro, S., Esmerado, J., Ramos, P., Alturas, B.: Evaluating a guest satisfaction model through data mining. International Journal of Contemporary Hospitality Management. 32 (4), 1523-1538 (2019)
44. Naidoo, M.: Artificial intelligence and global governance: How AI ethics and standards should be addressed at the global level. The iJournal: Student Journal of the Faculty of Information. 7 (1), 1-12 (2021)
45. Pereira V., Hadjielias E., Christofi M., Vrontis D.: A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective. Human Resource Management Review. 33 (1) (2023)
46. Prettner, K., H. Strulik.: Innovation, Automation, and Inequality: Policy Challenges in the Race Against the Machine. Journal of Monetary Economics. 116 (C), 249-265 (2020)
47. R Core Team (2025). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.r-project.org/. Accessed January 02, 2025
48. Rai, A., Constantinides, P., Sarker, S.: Next-Generation Digital Platforms: Toward Human-AI Hybrids. MIS Quarterly. 43 (1), iii–x (2019)
49. Revelle, W.: psych: Procedures for Psychological, Psychometric, and Personality Research. Northwestern University, Evanston, Illinois. R package version 2.5.3, (2025) https://CRAN.R-project.org/package=psych. Accessed March 31, 2025
50. Rosseel, Y.: lavaan: An R package for structural equation modeling. Journal of Statistical Software. 48 (2), 1-36 (2012)
51. Salamzadeh, Y., Mirakhori, A.R., Mobaraki, L., Targhi, Z.H.: Technophobia in universities: To be or not to be, this is the problem. Global J Technol. 3, 186-190 (2013)
52. Skinner, N., Brewer, N.: The dynamics of threat and challenge appraisals prior to stressful achievement events. Journal of personality and social psychology. 83 (3), 678 (2002)
53. Smith, A.: Public attitudes toward computer algorithms. Pew Research Center, http://www.pewinternet.org/2018/11/16/public-attitudes-toward-computer-algorithms/, Accessed January 06, 2025
54. Wang, W., Siau, K.: Artificial Intelligence, Machine Learning, Automation, Robotics, Future of Work and Future of Humanity: A Review and Research Agenda. Journal of Database Management. 30 (1), 61-79 (2019)
55. Webster, J.R., Beehr, T.A., Love, K.: Extending the challenge-hindrance model of occupational stress: The role of appraisal. Journal of Vocational Behavior. 79 (2), 505-516 (2011)
56. Wrzesniewski, A., Dutton, J.E.: Crafting a job: revisioning employees as active crafters of their work. Academy of Management Review. 26 (2), 179-201 (2001)
57. Yam, K.C., Tang, P.M., Jackson, J.C., Su, R., Gray, K.: The rise of robots increases job insecurity and maladaptive workplace behaviors: Multimethod evidence. Journal of Applied Psychology. 108 (5), 850 (2023)
58. Yousef, D.A.: Organizational commitment, job satisfaction and attitudes toward organizational change: a study in the local government. International Journal of Public Administration. 40 (1), 77-88 (2017)
59. Zhang, B., Dafoe, A.: Artificial intelligence: American attitudes and trends (2019). https://ssrn.com/abstract=3312874, Accessed January 28, 2025