

Generative AI as a Job Resource and Demand: A JD–R Perspective on Work Engagement and Extra-role Behavior

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Abstract. *This study examines the relationship between GenAI job resources, GenAI job demands, work engagement, and extra-role behavior within the Job Demands–Resources framework. Using survey data from 666 employees in Croatian organizations, a moderated mediation model was tested. The results show that GenAI job resources positively predict extra-role behavior. Although GenAI job resources were not directly related to work engagement, the moderated mediation analysis indicates that work engagement functions as a conditional explanatory mechanism. Specifically, the indirect effect becomes stronger when GenAI job demands are higher, highlighting GenAI's dual role as both a job resource and a job demand.*

Keywords. Generative AI, Job Demands–Resources Model, Work Engagement, Extra-role Behavior

1 Introduction

Generative artificial intelligence (GenAI) is rapidly becoming part of everyday organizational life. Tools based on large language models are increasingly used to search for information, generate and summarize text, support decision-making, and solve complex work-related problems (Brynjolfsson & Mitchell, 2017; Mayer et al., 2025). As a result, GenAI is not only changing how employees perform individual tasks, but also how they experience their work, collaborate with others, and contribute to organizational outcomes (Brynjolfsson & Mitchell, 2017; Karunakaran et al., 2025; Przegalińska et al., 2025).

Research on artificial intelligence (AI) suggests that AI is transforming work, occupations, organizations, and labor markets. Brynjolfsson and Mitchell (2017) argue that advances in machine learning create new opportunities for automation and task redesign, while requiring organizations to reconsider how to combine human and machine capabilities. Similarly, recent integrative research shows that AI may reshape work by complementing employee skills, changing skill

requirements, altering access to work opportunities, and creating new forms of workplace inequality (Karunakaran et al., 2025). Evidence from OECD surveys further indicates that both employers and workers are generally positive about the effects of AI on performance and working conditions, although concerns remain regarding job loss, trust, training, and worker consultation (Lane et al., 2023). These findings suggest that the effects of AI at work depend not only on the technology itself, but also on how organizations implement, support, and manage its use.

Although AI has received increasing attention in organizational research, the specific implications of GenAI for employees' motivational and behavioral outcomes remain insufficiently understood. Existing studies indicate that GenAI may support employees by improving access to information, enhancing problem-solving, increasing autonomy, improving work quality, and saving time (Biba & Laumer, 2024; Mas-Machuca et al., 2025). At the same time, GenAI may create new demands by requiring employees to learn new tools, adapt to technological change, and critically evaluate AI-generated outputs (Biba & Laumer, 2024). This dual role suggests that GenAI should not be viewed solely as a productivity-enhancing tool but also as a work-design factor that may simultaneously provide resources and impose demands.

This issue is particularly relevant because employees' responses to AI may shape not only task performance, but also motivational and discretionary behavior at work. Recent research shows that employee–AI collaboration can enhance work engagement by increasing meaningful work and creative self-efficacy, suggesting that AI-enabled work may function as an important motivational resource (L. Sun et al., 2025). However, less is known about whether and how GenAI-related job resources contribute to extra-role behavior, especially through motivational states such as work engagement. To address this gap, the study applies the Job Demands–Resources (JD–R) theory (Bakker et al., 2014; Demerouti et al., 2001) to examine the relationship

between GenAI-related job characteristics, work engagement, and extra-role behavior. Specifically, the study investigates whether GenAI job resources are positively related to extra-role behavior, whether work engagement mediates this relationship, and whether GenAI job demands strengthen the indirect relationship between GenAI job resources and extra-role behavior through work engagement.

The study contributes to the literature in three ways. First, it extends JD–R theory to the emerging context of GenAI use at work by examining GenAI as both a job resource and a job demand. Second, it contributes to research on work engagement by examining engagement as a motivational mechanism through which GenAI job resources may translate into extra-role behavior. Third, it contributes to the growing literature on AI in organizations by shifting attention from broad discussions of productivity and job transformation to employees' perceptions of GenAI and their discretionary behavioral responses at work.

The paper is structured as follows. The next sections present the theoretical framework and develop the hypotheses. The following section describes the research method, sample, and measures. The results section presents the moderated mediation analysis. Finally, the paper discusses theoretical and practical implications, limitations, and directions for future research.

2 Theoretical framework

The JD–R theory elucidates the psychological mechanisms by which job design directly influences work engagement and indirectly affects various individual and organizational outcomes, including job performance (Bakker et al., 2014; Demerouti et al., 2001). The model posits that all job characteristics fall into two broad categories: job demands and job resources (Bakker & Demerouti, 2007). It differentiates between two concurrent psychological processes: the health impairment process and the motivational process. The health impairment process occurs when employees expend sustained physical or psychological effort to manage high job demands, such as time pressure or emotionally taxing work (van Wingerden et al., 2018). Extended exposure to these demands may result in exhaustion and adverse outcomes, with strain serving as a key mediator between job demands and outcomes (Bakker & Demerouti, 2017). Conversely, the motivational process highlights the significance of job resources. Resources such as autonomy, social support, and feedback not only facilitate the attainment of work goals but also fulfill fundamental psychological needs for autonomy, competence, and relatedness (Ryan & Deci, 2000; Schaufeli & Bakker, 2004). Empirical evidence indicates that job resources exert a stronger motivational effect when challenges, as a specific type of job demand, are present (Bakker et al., 2012).

Recent research directly applies the JD–R model to GenAI and conceptualizes it as a source of both job demands and job resources. Particularly relevant is the study by Biba and Laumer (2024), which operationalizes generative artificial intelligence within the JD–R framework as both a job demand and a job resource, and develops measurement scales for both constructs. According to their approach, AI-related demands stem from the need to learn new tools, adapt to technological changes, and invest additional cognitive effort to integrate them effectively into everyday work. At the same time, GenAI can serve as a resource by facilitating information processing, accelerating task completion, improving work quality, and supporting problem-solving.

Empirical evidence demonstrates that when GenAI is perceived as a resource, it is positively correlated with employee work engagement, confirming the activation of the motivational process within the JD–R framework (Biba & Laumer, 2024). Conversely, AI-related demands may constitute an additional burden that, without sufficient resources, can trigger the health impairment process (Bakker & Demerouti, 2017). Qualitative research by Mas-Machuca et al. (2025) further indicates that GenAI can enhance employee autonomy, improve access to information, elevate work quality, and save time, thereby supporting its role as a job resource. However, the same technology may also introduce new demands, such as the necessity for ongoing learning or adaptation, reinforcing its dual role within the JD–R framework. Thus, GenAI should be regarded as a contextual factor that modifies the configuration of job demands and resources in job design.

3 Hypotheses development

Building on the dual conceptualization of GenAI as both a job resource and a job demand, GenAI job resources may contribute to extra-role behavior by increasing employees' capacity to perform beyond formal role requirements. Extra-role behavior refers to discretionary behavior that goes beyond formal job requirements and supports organizational functioning (Organ, 2015; Organ et al., 2006). Examples of such behavior include helping a new employee adjust to the job, sharing the workload with a colleague, and training colleagues to use new equipment (Podsakoff et al., 2000). Extra-role behavior may also involve refraining from unnecessarily emphasizing workplace problems, avoiding blame toward colleagues, tolerating organizational difficulties, and preventing tensions and conflicts with coworkers during times of crisis (Polat, 2009).

By helping employees access information, analyze problems, generate ideas, and complete tasks more efficiently, GenAI may increase their capacity to help colleagues, take initiative, and contribute beyond their formal role. This assumption is consistent with

research showing that job resources and favorable job characteristics are related to organizational citizenship behavior and extra-role performance (Fan et al., 2025; Mihalca et al., 2024; Nguyen et al., 2025). It is also supported by studies showing that job crafting and employee-AI collaboration can foster innovative, proactive, and extra-role behaviors by strengthening employees' fit, motivation, and capacity to take initiative (Ok & Lim, 2022; C. Sun et al., 2025). Therefore, employees who perceive GenAI as a job resource may be more likely to engage in discretionary behaviors that support colleagues and the organization.

H1: Generative AI job resources are positively related to extra-role behavior.

Work engagement is a central motivational mechanism in the JD-R framework and is defined as a positive, fulfilling work-related state characterized by vigor, dedication, and absorption (González-Romá et al., 2006; Schaufeli et al., 2002). Similarly, Byrne (2015) describes work engagement as a moment-to-moment motivational state in which employees are psychologically present, focused, and aligned with work and organizational goals. The same author further emphasizes that work engagement involves investing oneself in work and performing with authenticity, passion, persistence, and energy. Prior studies show that job resources foster work engagement by facilitating goal achievement, supporting personal growth, and satisfying basic psychological needs (Bakker & Demerouti, 2007; Schaufeli & Bakker, 2004). More recent research also confirms the importance of job resources for work engagement across sectors and over time (Hakanen et al., 2024; Van den Broeck et al., 2017; Xanthopoulou et al., 2009).

In the GenAI context, resources such as improved information processing, problem-solving support, and creative idea generation may strengthen employees' sense of competence and effectiveness, thereby increasing engagement. Engaged employees are more likely to show extra-role behavior because they have higher levels of energy, involvement, and persistence. Empirical evidence supports this connection: work engagement has been associated with contextual performance and extra-role behavior and has been shown to mediate the relationship between job characteristics and extra-role outcomes (Christian et al., 2011; Demerouti et al., 2015; Ok & Lim, 2022; Sulea et al., 2012).

H2: Work engagement mediates the relationship between generative AI job resources and extra-role behavior.

Although GenAI can provide job resources, its use may also create job demands. Employees may need to learn new tools, evaluate AI-generated content, and continuously adapt to technological changes, which can increase cognitive effort and skill requirements (Biba & Laumer, 2024). It is important to distinguish between GenAI-related demands as potential challenge and hindrance demands. Demands may support work engagement when they are perceived as meaningful

and manageable, but may undermine work engagement when they are excessive, unclear, or poorly supported (Crawford et al., 2010). In line with the JD-R framework, job resources may become especially motivational under demanding conditions (Bakker & Demerouti, 2007, 2017). Therefore, this study argues that GenAI resources are more likely to activate work engagement when GenAI demands create a meaningful need for these resources and help employees cope with AI-enabled work requirements. According to JD-R theory, job demands may contribute to strain when employees lack sufficient resources, but they may also strengthen the motivational role of job resources under demanding conditions (Bakker & Demerouti, 2017; Demerouti et al., 2001).

Bakker et al. (2007) showed that job resources boost work engagement, particularly when job demands are high. In the GenAI context, AI-related resources may be especially valuable when employees face higher demands for learning, adaptation, and skill acquisition. Consequently, GenAI job demands are expected to strengthen the indirect relationship between GenAI job resources and extra-role behavior through work engagement.

H3: Generative AI job demands moderate the indirect relationship between GenAI job resources and extra-role behavior through work engagement, such that the indirect effect is stronger when GenAI job demands are higher.

The conceptual research model (Fig. 1) illustrates the proposed relationships among GenAI job resources, GenAI job demands, work engagement, and extra-role behavior. GenAI job resources are expected to have a direct positive effect on extra-role behavior, while work engagement mediates this relationship. GenAI job demands are proposed to moderate the relationship between GenAI job resources and work engagement, thereby strengthening the indirect effect of GenAI job resources on extra-role behavior through work engagement.

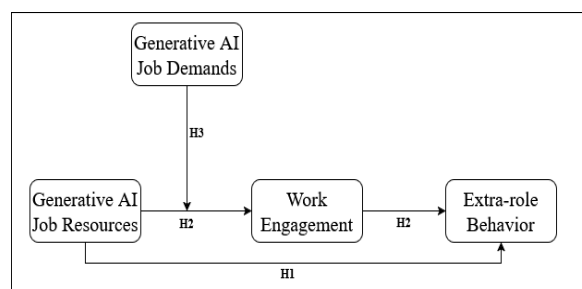


Figure 1. Conceptual research model and hypotheses

4 Method

4.1 Sample

A quantitative online survey questionnaire was used in the study, and primary data were collected from October to December 2025. The data were gathered from 37 Croatian organizations employing at least 20 staff members. The participating organizations came from a broad range of organizational and industry contexts. Based on the organizational information provided by respondents, the sample included employees from private companies, public institutions, and publicly owned organizations. The represented sectors included telecommunications and information technology, retail, manufacturing, food and beverage production, transport and logistics, infrastructure, energy and utilities, financial and insurance services, tourism and hospitality, education, and healthcare. Although the study did not examine industry-level differences, this diversity indicates that the findings are based on respondents from varied organizational settings rather than from a single sector.

Prior to data collection, the study protocol and survey questionnaire were approved by the institutional Ethics Committee. Participation in the study was voluntary and anonymous, and respondents were informed about the purpose of the research before completing the questionnaire.

The sample consisted of 666 respondents. Most participants were 35 years or younger (37.1%) or between 36 and 45 years of age (33.3%), and 56.6% were female. Regarding education, the majority had completed secondary education (36.6%) or held a university degree (29.4%).

In terms of organizational tenure, 40.7% had worked in their organization for 10 years or more, while 27.3% had less than three years of tenure. Most respondents were executive/operational employees (44.3%) or professional administrative staff (32.6%), with fewer participants in lower and middle management (20.9%) and top management (2.3%).

4.2 Measures

The study examined job characteristics related to the use of GenAI applications at work. Job characteristics were measured using the scale developed by Biba and Laumer (2024), who conceptualize GenAI as both a job demand and a job resource within the Job Demands–Resources (JD–R) framework. Their instrument builds on the Work Design Questionnaire (WDQ), originally developed by Morgeson and Humphrey (2006) and adapts it to the GenAI context to capture AI-related cognitive enhancements and skill requirements. Specifically, the scale includes items reflecting AI-related demand (acquiring skills) and AI-related resources (information processing and problem-solving). Although the scales adopted from Biba and Laumer (2024) are relatively recent, they demonstrated satisfactory psychometric properties in the present study. Nevertheless, additional validation across different contexts and samples is warranted to further establish their generalizability.

Work engagement was measured using the Utrecht Work Engagement Scale (UWES) developed by Schaufeli et al. (2002). The scale captures the three core dimensions of engagement: vigor, dedication, and absorption. Extra-role behavior was measured using the Organizational Citizenship Behavior Scale (3 items) developed by Motowidlo (2000). All items were measured using a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree).

All measurement items were administered in Croatian. The original English items were translated into Croatian by the research team and reviewed to ensure conceptual equivalence, clarity, and suitability for the Croatian organizational context. Where necessary, minor wording adjustments were made to preserve the original meaning while making them understandable to Croatian respondents. The GenAI job resources and GenAI job demands scales were adapted to refer specifically to the use of GenAI applications in the workplace.

Table 1 presents the descriptive statistics for all items (N = 666). AI-related resource items show moderate mean values (M = 2.944–3.153), while AI-related demand items are slightly lower (M = 2.808–2.977), indicating moderate perceptions of GenAI as both a resource and a demand. Work engagement items show moderate to relatively high mean values (M = 3.069–4.033), indicating generally positive engagement among respondents. Extra-role behavior items show relatively high mean values (M = 4.030–4.198), indicating that respondents generally report frequently engaging in discretionary behaviors such as taking initiative and investing additional effort beyond formal job requirements.

Table 1. Descriptive statistics of items

Items	M	SD
<i>Utilizing GenAI apps enhances my ability to interact with vast amounts of information.</i>	3.096	1.136
<i>Utilizing GenAI apps enhances my ability to reflect more deeply and think critically.</i>	2.944	1.123
<i>Utilizing GenAI apps enhances my ability to consider multiple perspectives and ideas.</i>	3.153	1.141
<i>Utilizing GenAI apps enhances my ability to analyze and evaluate information.</i>	3.086	1.120
<i>Utilizing GenAI apps enhances my ability to find solutions for problems without clear or definitive answers.</i>	3.066	1.114
<i>Using GenAI apps enhances my creativity and ability to explore innovative ideas.</i>	3.050	1.137

<i>Using GenAI apps enhances my ability to address problems I have not encountered before.</i>	3.062	1.138
<i>Utilizing GenAI apps enhances my ability to develop novel approaches to problems.</i>	3.132	1.125
<i>Utilizing GenAI apps requires a variety of skills.</i>	2.977	1.114
<i>Using GenAI apps requires me to draw on a variety of skills.</i>	2.919	1.098
<i>Utilizing GenAI apps requires me to use several high-level skills.</i>	2.808	1.083
<i>Using GenAI apps requires several skills.</i>	2.856	1.097
<i>When I get up in the morning, I feel like going to work.</i>	3.326	1.098
<i>My job inspires me.</i>	3.396	1.059
<i>At my job, I feel strong and vigorous.</i>	3.368	1.056
<i>At my work, I feel bursting with energy.</i>	3.069	1.061
<i>I am enthusiastic about my job.</i>	3.414	1.039
<i>I am proud of the work that I do.</i>	3.842	1.032
<i>I feel happy when I am working intensely.</i>	3.707	1.066
<i>I get carried away when I am working.</i>	3.751	1.010
<i>I am immersed in my work.</i>	4.033	.974
<i>I do tasks beyond those required without being asked.</i>	4.030	1.006
<i>I put in additional effort at work to complete tasks successfully when necessary.</i>	4.198	0.863
<i>I put forth additional effort in my job to make the business a success.</i>	4.107	0.948

4.3 Data analysis

Common method bias was addressed using both procedural and statistical remedies. Procedurally, participation was voluntary and anonymous, respondents were informed about the purpose of the study, and no personal identifiers were collected. The questionnaire also included clear instructions, and respondents were assured that there were no right or wrong answers. Statistically, Harman's single-factor test was conducted by entering all measurement items into an unrotated exploratory factor analysis and extracting a single factor.

Before testing the hypothesized relationships, the measurement model was assessed. A confirmatory factor analysis (CFA) was conducted in JASP to examine the distinctiveness of the four constructs: GenAI job demands, GenAI job resources, work engagement, and extra-role behavior. In addition, reliability, convergent validity, and discriminant validity were assessed using SmartPLS. Internal

consistency reliability was evaluated using Cronbach's alpha and composite reliability (CR), convergent validity was assessed using the average variance extracted (AVE), and discriminant validity was examined using the heterotrait-monotrait ratio of correlations (HTMT).

The hypotheses were tested using the PROCESS macro for SPSS (Hayes, 2018), Model 7. A moderated mediation model was estimated, with GenAI job resources as the independent variable, work engagement as the mediator, extra-role behavior as the dependent variable, and GenAI job demands as the moderator of the relationship between GenAI job resources and work engagement. The analysis was conducted using 5,000 bootstrap samples and 95% confidence intervals. The index of moderated mediation was used to determine whether the indirect effect of GenAI job resources on extra-role behavior through work engagement varied significantly across levels of GenAI job demands.

5 Results

The four-factor CFA model demonstrated an acceptable fit to the data, $\chi^2(246) = 1104.700$, $p < .001$, $\chi^2/df = 4.49$, CFI = .946, TLI = .939, RMSEA = .073, and SRMR = .043. Although the chi-square test was significant, this result was expected given the large sample size. Overall, the CFA results support the adequacy of the four-factor measurement model.

Reliability and convergent validity results are presented in Table 2. Internal consistency reliability was supported, as Cronbach's alpha values ranged from .886 to .963, while CR values ranged from .929 to .972, exceeding the recommended threshold of .70. Convergent validity was also supported, as all AVE values ranged from .648 to .897 and were above the recommended threshold of .50. All HTMT values were below the conservative threshold of .85, with the highest value observed between GenAI job resources and GenAI job demands (HTMT = .681). These results indicate satisfactory reliability, convergent validity, and discriminant validity of the measurement model.

Table 2. Reliability, convergent validity, and discriminant validity

Construct	Cronbach's α	CR	AVE
GenAI job resources	.962	.969	.817
GenAI job demands	.967	.972	.897
Work engagement	.932	.943	.648
Extra-role behavior	.882	.929	.815

Note. CR = composite reliability; AVE = average variance extracted.

Harman's single-factor test was conducted to assess potential common method bias. All measurement items were entered into an unrotated exploratory factor analysis, and a single factor was extracted. The results showed that the single factor explained 41.55% of the total variance, which is below the commonly used threshold of 50%. This suggests that common method bias is unlikely to be a major concern in this study.

Table 3 presents the results of the moderated mediation analysis. GenAI job resources had a positive and significant direct effect on extra-role behavior ($B = .061$, $SE = .029$, $p = .032$), supporting H1. This suggests that employees who perceive GenAI as a useful job resource are more likely to engage in behaviors that go beyond their formal job requirements. The regression model predicting work engagement was statistically significant, $F(3, 662) = 19.72$, $p < .001$, explaining 8.2% of the variance in work engagement ($R^2 = .082$).

The direct relationship between GenAI job resources and work engagement was not significant ($B = .041$, $SE = .073$, $p = .574$). However, work engagement was strongly and positively related to extra-role behavior ($B = .504$, $SE = .035$, $p < .001$). In addition, GenAI job demands were negatively associated with work engagement ($B = -.165$, $SE = .084$, $p = .049$). In contrast, the interaction between GenAI job resources and GenAI job demands was significant ($B = .061$, $SE = .023$, $p = .008$). The interaction term explained an additional 1.0% of the variance in work engagement beyond the main effects ($\Delta R^2 = .010$, $F = 6.99$, $p = .008$), indicating a modest but statistically significant moderation effect. This indicates that GenAI job demands moderate the relationship between GenAI job resources and work engagement, such that GenAI job resources become more positively associated with work engagement as GenAI job demands increase. The regression model predicting extra-role behavior was also statistically significant, $F(2, 663) = 126.06$, $p < .001$, explaining 27.6% of the variance in extra-role behavior ($R^2 = .276$).

Table 3. Results of moderated mediation analysis

	Work engagement	Extra-role behavior
GenAI-JR	.041 (.073)	.061* (.029)
GenAI-JD	-.165* (.084)	—
GenAI-JR × GenAI-JD	.061** (.023)	—
Work engagement	—	.504*** (.035)

Note. Unstandardized coefficients are reported, with standard errors shown in parentheses. $p < .05$, ** $p < .01$, *** $p < .001$.

Table 4 shows that the index of moderated mediation was statistically significant (Index = .031,

Boot SE = .014, 95% CI [.004, .057]), as the confidence interval did not include zero. The results do not support H2 in its simple mediation form. GenAI job resources were not significantly related to work engagement, indicating that work engagement does not function as a general mediator between GenAI job resources and extra-role behavior. However, the significant interaction between GenAI job resources and GenAI job demands shows that the relationship between GenAI job resources and work engagement depends on the level of GenAI job demands. Furthermore, the significant index of moderated mediation indicates that the indirect effect of GenAI job resources on extra-role behavior through work engagement is conditional on GenAI job demands. Therefore, work engagement should be interpreted as a conditional explanatory mechanism rather than as a universal mediator. Accordingly, H2 is not supported in its simple form, while H3 is supported.

Table 4. Index of moderated mediation

	Index	Boot SE	Boot LLCI	Boot ULCI
GenAI-JD	.031	.014	.004	.057

6 Discussion, contribution and limitations

The findings support the dual role of GenAI within the JD–R framework. GenAI job resources were positively associated with extra-role behavior, suggesting that when employees perceive GenAI as useful for information processing, problem-solving, and idea generation, they are more likely to engage in discretionary behaviors beyond formal job requirements. This finding is consistent with JD–R research showing that job resources and favorable job characteristics can support positive performance-related outcomes (Demerouti et al., 2015; Mihalca et al., 2024; Schaufeli & Bakker, 2004), as well as with studies linking job resources and new ways of working to organizational citizenship and extra-role behavior (Fan et al., 2025; Nguyen et al., 2025). The results also align with emerging AI-related research suggesting that employee–AI collaboration may foster proactive behavior by reducing workload and strengthening employees' capacity to take initiative (C. Sun et al., 2025).

One of the most interesting findings of this study is that GenAI job resources were not directly related to work engagement. This suggests that the mere availability or perceived usefulness of GenAI tools may not be sufficient to motivate employees. GenAI resources may not automatically increase vigor, dedication, and absorption unless the work context creates a meaningful need for these resources. When employees face higher GenAI-related demands, such

as the need to learn new skills, evaluate AI-generated outputs, or adapt to AI-enabled work processes, GenAI resources may become more salient and motivationally relevant. This finding refines the JD–R perspective by showing that the motivational role of GenAI resources depends on the demand context in which they are embedded.

The study contributes to the literature in three ways. First, it extends the JD–R model to the emerging context of GenAI use at work by examining GenAI simultaneously as a job resource and a job demand, following the approach proposed by Biba and Laumer (2024). Second, it contributes to research on work engagement by showing that engagement functions as a conditional explanatory mechanism rather than a universal mediator. Although GenAI job resources were not directly related to work engagement, the indirect effect on extra-role behavior became stronger when GenAI job demands were higher. This supports the JD–R assumption that job resources may become more salient and motivational under demanding work conditions (Bakker et al., 2007, 2014). Third, the study contributes to research on AI in organizations by shifting attention from broad discussions of productivity and automation to employees' perceptions of GenAI and their discretionary behavioral responses at work.

From a managerial perspective, the findings suggest that organizations should avoid treating GenAI implementation as a purely technical process. Introducing GenAI tools is unlikely to enhance work engagement on its own. Managers should ensure that employees understand how GenAI can support their work, provide sufficient training, and create opportunities for employees to use GenAI in tasks where it has clear practical value. At the same time, organizations should be careful not to interpret higher GenAI-related demands as automatically beneficial. Demands may become motivational only when they are manageable and accompanied by adequate resources, support, and skill development. Without such support, GenAI demands may function as hindrance demands, reducing work engagement.

Several limitations should be noted. First, the study used cross-sectional survey data, which limits causal interpretation of the relationships among GenAI job resources, work engagement, and extra-role behavior. Future studies should use longitudinal or experimental designs to examine how employees' perceptions of GenAI change over time. Second, the data were collected from Croatian organizations, which may limit the generalizability of the findings to other cultural or organizational contexts. Third, all variables were measured using self-reported data collected from the same respondents, which may increase the risk of common method bias. Although procedural remedies and Harman's single-factor test were used to assess and reduce this concern, common method bias cannot be fully excluded. Future research should use multi-source designs, particularly by collecting supervisor or

peer ratings of extra-role behavior, as such ratings would provide a more objective assessment of discretionary employee behavior. Nevertheless, the high reliability values for GenAI job resources and GenAI job demands suggest that future studies could further examine whether shorter versions of these scales may reduce potential item redundancy while preserving content validity.

References

- Bakker, A. B., & Demerouti, E. (2007). The Job Demands-Resources model: State of the art. *Journal of Managerial Psychology*, 22(3), 309–328.
- Bakker, A. B., & Demerouti, E. (2017). Job demands–resources theory: Taking stock and looking forward. *Journal of Occupational Health Psychology*, 22(3), 273–285. <https://doi.org/10.1037/ocp0000056>
- Bakker, A. B., Demerouti, E., & Sanz-Vergel, A. I. (2014). Burnout and Work Engagement: The JD–R Approach. *Annual Review of Organizational Psychology and Organizational Behavior*, 1(1), 389–411. <https://doi.org/10.1146/annurev-orgpsych-031413-091235>
- Bakker, A. B., Hakanen, J. J., Demerouti, E., & Xanthopoulou, D. (2007). Job resources boost work engagement, particularly when job demands are high. *Journal of Educational Psychology*, 99(2), 274–284. <https://doi.org/10.1037/0022-0663.99.2.274>
- Bakker, A. B., Tims, M., & Derks, D. (2012). Proactive personality and job performance: The role of job crafting and work engagement. *Human Relations*, 65(10), 1359–1378. <https://doi.org/10.1177/0018726712453471>
- Biba, S., & Laumer, S. (2024). Generative AI as Job Demand and Resource: First Results of an Empirical Study. *Proceedings of the Twenty-Ninth DIGIT Workshop*.
- Brynjolfsson, E., & Mitchell, T. (2017). What can machine learning do? Workforce implications. *Science*, 358(6370), 1530–1534. <https://doi.org/10.1126/science.aap8062>
- Byrne, Z. S. (2015). *Understanding employee engagement: Theory, research, and practice*. Routledge.
- Christian, M. S., Garza, A. S., & Slaughter, J. E. (2011). Work Engagement: A Quantitative Review and Test of Its Relations with Task and Contextual Performance. *Personnel Psychology*, 64(1), 89–136. <https://doi.org/10.1111/j.1744-6570.2010.01203.x>

- Crawford, E. R., LePine, J. A., & Rich, B. L. (2010). Linking job demands and resources to employee engagement and burnout: A theoretical extension and meta-analytic test. *Journal of Applied Psychology*, 95(5), 834–848. <https://doi.org/10.1037/a0019364>
- Demerouti, E., Bakker, A. B., & Gevers, J. M. P. (2015). Job crafting and extra-role behavior: The role of work engagement and flourishing. *Journal of Vocational Behavior*, 91, 87–96. <https://doi.org/10.1016/j.jvb.2015.09.001>
- Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The Job Demands-Resources Model of Burnout. *Journal of Applied Psychology*, 86(3), 499–512. <https://doi.org/10.1037/0021-9010.86.3.499>
- Fan, L., Yang, J., Hou, Q., Feng, S., Chen, A., & Han, L. (2025). Impact of job resources on organizational citizenship behavior among primary care staff in Guangzhou, China: A cross-sectional study. *Frontiers in Public Health*, 13, 1580148. <https://doi.org/10.3389/fpubh.2025.1580148>
- González-Romá, V., Schaufeli, W. B., Bakker, A. B., & Lloret, S. (2006). Burnout and work engagement: Independent factors or opposite poles? *Journal of Vocational Behavior*, 68(1), 165–174. <https://doi.org/10.1016/j.jvb.2005.01.003>
- Hakanen, J. J., Bakker, A. B., & Turunen, J. (2024). The relative importance of various job resources for work engagement: A concurrent and follow-up dominance analysis. *BRQ Business Research Quarterly*, 27(3), 227–243. <https://doi.org/10.1177/23409444211012419>
- Hayes, A. F. (2018). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach* (Second edition). The Guilford Press.
- Karunakaran, A., Lebovitz, S., Narayanan, D., & Rahman, H. A. (2025). Artificial Intelligence at Work: An Integrative Perspective on the Impact of AI on Workplace Inequality. *Academy of Management Annals*, 19(2), 693–735. <https://doi.org/10.5465/annals.2023.0230>
- 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 Social, Employment and Migration Working Papers No. 288; OECD Social, Employment and Migration Working Papers, Vol. 288). <https://doi.org/10.1787/ea0a0fe1-en>
- Mas-Machuca, M., Akhmedova, A., & Marimon, F. (2025). Generative AI and Workplace Productivity: A Qualitative Study in Spain. *Proceedings of Central European Conference on Information and Intelligent Systems*, 625–631.
- Mayer, H., Yee, L., Chui, M., & Roberts, R. (2025). *Superagency in the workplace: Empowering people to unlock AI's full potential*. McKinsey & Company. <https://www.mckinsey.com/capabilities/tech-and-ai/our-insights/superagency-in-the-workplace-empowering-people-to-unlock-ais-full-potential-at-work>
- Mihalca, L., Ratiu, L., Helm, C., Brendea, G., & Metz, D. (2024). The relationship of job characteristics with in-role and extra-role performance: The mediating effect of job crafting. *Baltic Journal of Management*, 19(2), 163–182. <https://doi.org/10.1108/BJM-05-2023-0191>
- Morgeson, F. P., & Humphrey, S. E. (2006). The Work Design Questionnaire (WDQ): Developing and validating a comprehensive measure for assessing job design and the nature of work. *Journal of Applied Psychology*, 91(6), 1321–1339. <https://doi.org/10.1037/0021-9010.91.6.1321>
- Motowidlo, S. J. (2000). Some Basic Issues Related to Contextual Performance and Organizational Citizenship Behavior in Human Resource Management. *Human Resource Management Review*, 10(1), 115–126. [https://doi.org/10.1016/S1053-4822\(99\)00042-X](https://doi.org/10.1016/S1053-4822(99)00042-X)
- Nguyen, P. N.-D., Giang, T. T., Duong, H. C., & Nguyen, H. H. (2025). Empowering Workplaces: How New Ways of Working Foster Organizational Citizenship Behaviors? *Sage Open*, 15(4), 21582440251393887. <https://doi.org/10.1177/21582440251393887>
- Ok, C. M., & Lim, S. (Edward). (2022). Job crafting to innovative and extra-role behaviors: A serial mediation through fit perceptions and work engagement. *International Journal of Hospitality Management*, 106, 103288. <https://doi.org/10.1016/j.ijhm.2022.103288>
- Organ, D. W. (2015). Organizational Citizenship Behavior. In *International Encyclopedia of the Social & Behavioral Sciences: Second Edition*. <https://doi.org/10.1016/B978-0-08-097086-8.22031-X>
- Organ, D. W., Podsakoff, P. M., & MacKenzie, S. B. (2006). *Organizational Citizenship Behavior: Its Nature, Antecedents, and Consequences*. SAGE Publications.
- Podsakoff, P. M., MacKenzie, S. B., Paine, J. B., & Bachrach, D. G. (2000). Organizational Citizenship Behaviors: A Critical Review of the Theoretical and Empirical Literature and Suggestions for Future Research. *Journal of Management*, 26(3).
- Polat, S. (2009). Organizational citizenship behavior (OCB) display levels of the teachers at secondary schools according to the perceptions of the school administrators. *Procedia - Social and Behavioral*

- Sciences*, 1(1), 1591–1596. <https://doi.org/10.1016/j.sbspro.2009.01.280>
- Przegalinska, A., Triantoro, T., Kovbasiuk, A., Ciechanowski, L., Freeman, R. B., & Sowa, K. (2025). Collaborative AI in the workplace: Enhancing organizational performance through resource-based and task-technology fit perspectives. *International Journal of Information Management*, 81, 102853. <https://doi.org/10.1016/j.ijinfomgt.2024.102853>
- Ryan, R. M., & Deci, E. L. (2000). Self-Determination Theory and the Facilitation of Intrinsic Motivation, Social Development, and Well-Being. *American Psychologist*, 55(1), 68–78.
- Schaufeli, W. B., & Bakker, A. B. (2004). Job demands, job resources, and their relationship with burnout and engagement: A multi-sample study. *Journal of Organizational Behavior*, 25(3), 293–315. <https://doi.org/10.1002/job.248>
- Schaufeli, W., Salanova, M., González-Romá, V., & Bakker, A. (2002). The Measurement of Engagement and Burnout: A Two Sample Confirmatory Factor Analytic Approach. *Journal of Happiness Studies*, 3(1), 71–92. <https://doi.org/10.1023/A:1015630930326>
- Sulea, C., Virga, D., Maricutoiu, L. P., Schaufeli, W., Zaborila Dumitru, C., & Sava, F. A. (2012). Work engagement as mediator between job characteristics and positive and negative extra-role behaviors. *Career Development International*, 17(3), 188–207. <https://doi.org/10.1108/13620431211241054>
- Sun, C., Zhao, X., Guo, B., & Chen, N. (2025). Will Employee–AI Collaboration Enhance Employees’ Proactive Behavior? A Study Based on the Conservation of Resources Theory. *Behavioral Sciences*, 15(5), 648. <https://doi.org/10.3390/bs15050648>
- Sun, L., Hu, R., & Su, H. (2025). Unlocking human potential in the AI Age: How employee-AI collaboration transforms work engagement through dual psychological pathways. *Frontiers in Psychology*, 16, 1705671. <https://doi.org/10.3389/fpsyg.2025.1705671>
- Van den Broeck, A., Elst, T. V., Baillien, E., Sercu, M., Schouteden, M., De Witte, H., & Godderis, L. (2017). Job Demands, Job Resources, Burnout, Work Engagement, and Their Relationships: An Analysis Across Sectors. *Journal of Occupational & Environmental Medicine*, 59(4), 369–376. <https://doi.org/10.1097/JOM.0000000000000964>
- van Wingerden, J., Derks, D., & Bakker, A. B. (2018). Facilitating interns’ performance: The role of job resources, basic need satisfaction and work engagement. *Career Development International*, 23(4), 382–396. <https://doi.org/10.1108/CDI-12-2017-0237>
- Xanthopoulou, D., Bakker, A. B., Demerouti, E., & Schaufeli, W. B. (2009). Reciprocal relationships between job resources, personal resources, and work engagement. *Journal of Vocational Behavior*, 74(3), 235–244. <https://doi.org/10.1016/j.jvb.2008.11.003>

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