



The Impact of Artificial Intelligence on Employees' Innovative Behavior in the Original Brand Manufacturing Industry

Wahidullah Sangar, Hualiang Ren*, Yihao Su

School of Business, Jiangnan University, Wuxi, China

Email: Wahidullah.Sangar@outlook.com, *renhl@jiangnan.edu.cn, yihao_2004@126.com

How to cite this paper: Sangar, W., Ren, H.L. and Su, Y.H. (2026) The Impact of Artificial Intelligence on Employees' Innovative Behavior in the Original Brand Manufacturing Industry. *Open Access Library Journal*, 13: e15999.
<https://doi.org/10.4236/oalib.1115999>

Received: July 7, 2026

Accepted: September 14, 2026

Published: October 10, 2026

Copyright © 2026 by author(s) and Open Access Library Inc.

This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).

<http://creativecommons.org/licenses/by/4.0/>



Open Access

Abstract

The integration of Artificial Intelligence into Original Brand Manufacturing firms presents both opportunities and challenges for fostering employee innovation. This study investigates how AI adoption influences employees' innovative behavior, with a particular focus on the mediating role of job security and the moderating role of employee well-being. Drawing on the Technology Acceptance Model and Conservation of Resources theory, we developed a conceptual framework that captures the dual-edged nature of AI in innovation-driven workplaces. This study used a two-wave online survey of 251 OBM professionals from innovation-intensive teams. We used Smart PLS 4 to analyze our data. The results showed that AI adoption has a significant negative impact on employee innovative behavior. Furthermore, job security partially mediates this relationship, indicating that perceived job instability serves as a key mechanism through which AI adoption reduces innovative behavior. Additionally, employee well-being does not moderate the relationship between AI adoption and employee innovative behavior, but it moderates the relationship between AI adoption and job security. This study contributes to the theoretical and practical field of AI in the workplace in OBM firms, and helps to understand the impact of AI on employee innovative behavior.

Subject Areas

Human Resource and Organizational Behavior

Keywords

Artificial Intelligence Adoption, Employee Innovative Behavior, Job Security, Employee Well-Being, OBM

1. Introduction

Over the years, technology has not just evolved, it has completely influenced our world and human society. It has driven the economic growth, cultural evolution, and organizational practices [1] [2]. Among these technologies, AI has become one of the most influential developments. It is reshaping industries through automation, predictive analytics, and enhanced decision-making [3] [4]. By 2030, AI is projected to contribute over \$15.7 trillion to the global economy, with manufacturing sectors accounting for a significant share of this growth [5] [6]. Although AI holds significant macroeconomic promise, its effects on individual employees, especially regarding innovation, are still not well understood. While organizations increasingly deploy AI to optimize processes [7], the psychological and organizational consequences for employees, such as shifts in job security and well-being, require scholarly attention [8] [9].

The concept of AI lacks a universal definition, reflecting its multifaceted applications. Scholars broadly categorize AI as “systems that mimic human cognitive functions, such as learning, problem-solving, and adaptation, to perform tasks autonomously” [10]. In OBM firms, AI manifests in smart factories, robotic process automation (RPA), and AI-driven supply chain management, enabling organizations to achieve precision, scalability, and cost-efficiency [11]-[13]. However, the impact of these technologies on individuals is often overlooked in favor of their technical advantages. While prior research has extensively explored AI’s organizational benefits, such as increased productivity and innovation [14] [15], its effects on individual employees, particularly their capacity for creativity and problem-solving, remain underexamined [16] [17]. This oversight is critical, as employees’ innovative behavior is the cornerstone of sustained competitive advantage in knowledge-intensive industries like OBM [18] [19].

Innovative behavior means that an employee can come up with new ideas, promote them, and use them to make things better, like products, processes, or services [20] [21]. In OBM companies, it is very important to create an innovative culture, because being able to quickly adapt to changing market needs and high-quality design are key to success. Encouraging innovation includes motivating teams and also involves setting up systems that support the ongoing innovation of new products and services. By building a workplace culture that values adaptability and new ideas, companies are better positioned to meet customer needs and stay ahead in the market [22] [23]. However, integrating AI into the workplace creates both benefits and challenges. Managing this tension is essential. Innovation drives competitiveness in OBM firms, so understanding how AI affects workers is critical. On one hand, AI supports employees. It reduces cognitive load, automates repetitive tasks, and provides helpful data insights [24] [25]. On the other hand, it increases stress, disrupts workflows, and threatens job security [26]-[28]. These factors lower creativity and reduce employee engagement. For example, [29] found that AI adoption in manufacturing reduced employees’ intrinsic motivation to innovate. This happened because AI lowered their sense of control over

their work. In similar lines, [30] argued that the use of AI in manufacturing firms not only automates tasks, but also restricts employee participation in decision-making processes. This autonomy restriction can create an inflexible work environment, which limits motivation and reduces innovative behavior. These findings show the dual impact of AI: it can both foster and hinder innovation.

While scholarly interest in AI's workplace impact has expanded considerably, significant research gaps remain. To date, the majority of research has concentrated on organizational-level effects, particularly improvements in operational efficiency and financial performance [31] [32]. However, far less attention has been given to how these technological changes influence employees (individuals) directly. Second, researchers widely recognize that job security and well-being are known to influence technology adoption [33]-[36]. However, their interaction with AI-driven innovation in OBM firms has not been thoroughly explored. Third, AI-innovation research has mostly concentrated on service-based industries like healthcare and finance [15] [37]. While manufacturing firms like OBM, which is defined by design-driven, high-value manufacturing, have received less attention. In this study, job security, defined as employees' perceived stability and continuity in employment [34]. According to [38], the psychological and emotional resources that enable employees to effectively adapt to changes in the workplace are referred to as employee well-being. Thus, this study addresses a significant research gap: how AI adoption influences employee innovative behavior at the individual level within OBM firms. To address this, we pose the following research questions:

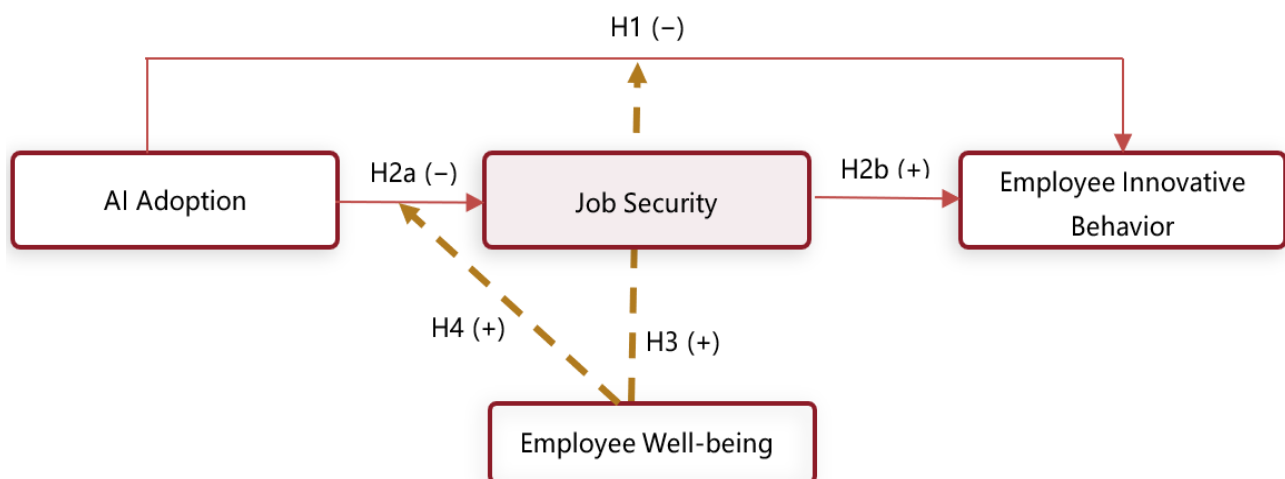
How does AI adoption influence employees' innovative behavior in the OBM?

How do job security and employee well-being influence the relationship between AI adoption and employee innovative behavior, with job security acting as a mediator and employee well-being as a moderator?

This study uses two theoretical frameworks: the Technology Acceptance Model (TAM) and the Conservation of Resources (COR) theory. According to [39], employees are more likely to accept new technology when they believe it is useful and easy to use. TAM explains how employees interpret AI in the workplace. Some see AI as a tool for automating tasks or improving decisions. Others see it as a threat, especially to job security. These views shape their level of engagement in innovative work [40]-[42]. COR theory, developed by [38], focuses on personal resources such as emotional well-being and job stability. When employees feel that AI threatens these resources, they respond defensively. They conserve their psychological energy. As a result, they become less willing to take creative risks or invest in innovation [43]-[46]. By combining TAM and COR theory gives us a deeper understanding of how AI affects innovation. It shows how employees' views of technology and their need to protect personal resources influence their behavior.

By applying TAM and COR to the context of OBM firms, we uncovered new perspectives on how employees psychologically interact with AI at the individual level. As a result, our study contributes to both theory and practice in three im-

portant ways. At first, it expands on the literature on AI-innovation. By moving the focus from the organizational level to the individual-level psychological processes. In particular, we highlight that how job security and employee well-being act as mediators and moderators in shaping how employees respond to AI adoption through innovative behavior. However, previous research has examined how AI affects employee performance [47] and job displacement. Limited attention has been given to how these factors together influence innovative behavior [24] [48]. Second, it extends the TAM and COR frameworks to the OBM context, demonstrating their applicability in understanding AI's dual effects. Third, it offers actionable insights for OBM managers, such as designing AI implementation strategies that balance efficiency gains with employee well-being, thereby fostering a culture of innovation. For example, organizations might invest in upskilling programs to mitigate job insecurity or implement AI tools that augment, rather than replace, human creativity [7] [49] [50]. **Figure 1** presents our research model.



Source(s): Created by authors

Figure 1. Conceptual model.

2. Literature Review and Hypothesis Development

2.1. AI Adoption and Employee Innovative Behavior in Original Brand Manufacturing (OBM)

The OBM industry is experiencing a major transformation due to AI adoption. Unlike OEM or ODM models, OBM firms not only produce goods but also build their own brands, which requires constant innovation and customer engagement [30] [51]-[53]. Many manufacturing firms use AI to enhance product development, streamline production, and optimize supply chains [12] [27] [54] [55]. Therefore, Employees remain central to product and process innovation, which underpin brand value. When AI adoption undermines job security or reduces employees' sense of ownership, their motivation to take creative risks and innovate declines [56]. Studies show that perceiving AI as a threat lowers engagement and stifles innovation. To counter this, recent research emphasizes collaborative intel-

ligence, using AI to support, rather than replace, human creativity [57]-[60]. Understanding how AI acts as both an enabler and a barrier to innovation is vital. Analyzing this dual impact through established theories can provide deeper insight into AI's role in shaping innovative behavior at work.

2.2. AI as a Driver of Innovation in OBM

Beyond automating routine tasks, AI in OBM firms enables intelligent decision-making, predictive analytics, complex problem-solving, and generative design [12] [24] [61] [62]. Through technologies such as machine learning, computer vision, and natural language processing, AI systems give employees practical support to innovate: they accelerate product design and prototyping, enable real-time market insights, and optimize production workflows, freeing employees to focus on higher-value creative activities. By reducing cognitive workload, AI enhances both efficiency and employee well-being. When AI supports employees with repetitive tasks, they report higher job satisfaction and engagement [63]. If employees see AI as a helpful tool, they become more engaged and adaptable [64].

The TAM explains why AI adoption can drive employee innovation. According to TAM, employees are more likely to use new technologies they see as practical and easy to use [65]. In OBM firms, if employees believe AI enhances their effectiveness or creativity, they will integrate it into their workflow, increasing both exploratory (trying new ideas) and exploitative (improving existing ideas) innovation [66]. For example, employees can use generative AI for prototyping and AI analytics to spot market opportunities, boosting innovation overall [67]. Empirical research shows that combining generative AI with human creativity improves innovative performance [41] [68]-[70]. When employees see AI as a partner, they receive better cognitive support and make faster decisions, which enhances innovative behavior [40] [71]. However, AI adoption alone does not guarantee more innovation. If employees view AI as a competitor instead of a collaborator, for instance, when algorithmic decisions override human input, they are less likely to take initiative [33]. This duality underscores the importance of examining AI's concurrent enabling and suppressive effects on employee behavior.

2.3. AI as a Threat to Employee Innovation Behavior in OBM

AI technologies enhance idea development, but over-reliance on them reduces employees' sense of ownership and autonomy, which in turn limits innovation [46]. Heavy dependence on AI also raises job security concerns [72], and shifts how human contributions are valued, directly undermining innovative activity. In OBM firms, employees play a central role in product and brand development. The excessive automation of creative and decision-making processes can make workers feel replaceable and undervalued, a pattern documented across organizational contexts where AI encroaches on human judgment and expertise [73]. When AI determines most product characteristics or heavily influences strategic choices, employees perceive that their expertise is disregarded. Empirical studies

confirm these concerns. Employees exposed to advanced AI and robotics report lower job security, reduced organizational commitment, and heightened anxiety about the future. Brougham and Haar [74] found that greater awareness of STARA was negatively related to organizational commitment and career satisfaction, while positively linked to turnover intentions, cynicism, and depression. Similarly, Bhargava, Bester [33] showed that employees who perceived RAIA implementation in their workplace reported lower job security and reduced confidence in their long-term employability, factors that erode the motivation to take initiative and contribute innovatively.

The COR theory [38] explains why AI-related threats can suppress innovation. Employees seek to protect vital resources such as job security, autonomy, and self-efficacy. When these resources appear at risk, they adopt a defensive posture, prioritizing preservation over exploration. As a result, their willingness to engage in innovative activities declines [45]. Integrating TAM and COR clarifies AI's double-edged effect: TAM highlights the enabling side when AI is embraced as useful, while COR explains the risks when AI is seen as a threat. Recent research supports this duality: Du and Liu [46] found that employees credited AI with improving focus but also felt it reduced their autonomy, showing that AI adoption brings both opportunities and risks. Several psychological mechanisms can explain why AI adoption may dampen innovative behavior in OBM firms.

Given these contrasting dynamics, a critical question arises: Does AI adoption enable or inhibit innovation in OBM firms? If AI supports employees (as TAM suggests), innovation should increase. But if AI causes resource-loss fears (as COR predicts), innovation will decline. Both effects may happen at once. In OBM, where efficiency and creativity must be balanced, understanding this trade-off is essential. Therefore, we argue that AI adoption significantly affects how employees engage in innovation and seek to test this empirically. Accordingly, we propose:

H1: AI adoption has a significant negative impact on employee innovative behavior in OBM firms.

2.4. The Mediating Role of Job Security

Job security generally refers to an employee's confidence in the continued stability of their job and the absence of threats to their position [34]. More specifically, it captures employees' perception of stability and continuity within their roles [75]. Across industries, new technologies like robotics and AI have raised employee concerns about job stability [76]. AI-driven automation has intensified these concerns, as it can replace tasks and create uncertainty about future employment [26]. If organizations do not address these anxieties, employee stress can negatively impact performance [38] [77] [78]. AI adoption may make employees feel insecure and think AI may replace their jobs [74]. Recent surveys and studies confirm this: a 2024 Pew survey found 52% of U.S. workers are concerned about AI's impact on their jobs, and one-third believe AI will lead to fewer job opportunities for them

in the long run [79]. In fast-changing industries, such as OBM, AI adoption has introduced concerns regarding job displacement and role obsolescence [41] [70]. While AI has the potential to enhance productivity and efficiency, it simultaneously raises apprehensions about workforce reductions and shifts in job responsibilities [68] [69]. While most research has examined AI's impact on organizational performance, less attention has been given to its effects on individual employees' job security and innovative behavior. Since job security strongly influences motivation, risk-taking, and creativity, it is essential to understand its mediating role in the AI-innovation relationship.

2.5. AI Adoption and Job Security

AI impacts job security in two major ways. First, by automating routine tasks like design iteration, supply chain forecasting, and optimizing production, AI can make some jobs redundant or outdated [80], fueling worker anxiety. Second, AI adoption demands new skills: employees need digital literacy and the ability to understand algorithmic processes to stay competitive [81]. Without organizational support for upskilling, employees feel more anxious and may resist AI integration [82]. While AI makes workflows more efficient [70], it also increases fears of job loss [41] [68].

COR theory helps to explain how AI adoption can affect employees' sense of job security, and also explains that employees aim to protect valued resources such as job stability [38]. When AI adoption is perceived as a threat to these resources, employees become stressed and defensive [45]. This reduces engagement and commitment at work.

Research in industry fields shows a consistent negative link between AI adoption and job security: in hospitality, for example, AI-induced automation has raised job security concerns, which has introduced lowered job engagement [83]. Efforts to adopt AI and pursue digital transformation have led to job cuts and uncertainty in various industries [82], with manufacturing workers fearing job loss and fewer career opportunities [35]. Overall, AI adoption often weakens employees' sense of job security, leading to increased stress and reduced motivation. Based on this evidence, we propose:

H2a: AI adoption negatively influences job security.

2.6. Job Security and Employee Innovative Behavior

Job security strongly affects employees' willingness to participate in innovation [84] [85]. When employees feel secure in their jobs, they take more risks, explore new ideas, and actively support innovation within their organization [86]. Many researchers have found a clear positive link between job security and employee innovation [87]-[89]. COR theory Hobfoll [38] helps explain this link: employees are more willing to invest time, energy, and creativity in innovation when they feel their jobs are safe [35] [83]. According to the TAM, employees who feel secure see new technologies as opportunities to improve their work, not threats [30] [65]

[68].

Empirical studies confirm that job security encourages creativity, problem-solving, and new idea generation [86] [90]. On the other hand, those who faced job insecurity were less engaged in innovation [83]. Later, Probst, Chizh [91] confirmed that job security helps build a sense of stability and trust in the workplace. In contrast, those who feel insecure are less likely to take risks or innovate. Therefore, these findings suggest that feeling secure in their jobs encourages employees to be more innovative. Based on this, we propose:

H2b: *Job security positively influences employee innovative behavior.*

2.7. Mediating Role of JS between AIA and EIB

Based on these arguments, job security mediates the relationship between AI adoption and innovative behavior. When AI adoption threatens job security, employees feel anxious and avoid risks, which reduces innovation [35] [68] [91]. If organizations use AI to support or enhance job security, such as through upskilling or clarifying AI's supportive role, employees are more likely to adopt AI and innovate [30] [83]. According to TAM, perceived usefulness increases willingness to use new technology, and support from the organization boosts innovative behavior [68] [69]. COR theory also supports this: protecting job stability encourages employees to invest resources in innovation. When job security is lacking, employees focus on managing insecurity instead of being creative. Therefore, job security can transmit the effects of AI adoption to employee innovative behavior, buffering against the negative and allowing the positive potential of AI to be realized. Therefore, we propose:

H2: *Job security mediates the relationship between AI adoption and employee innovative behavior.*

2.8. Moderating Role of Employee Well-Being

Employee well-being refers to the overall mental and emotional condition of an employee, reflecting resilience and the ability to manage workplace stress [20] [92]. It plays a crucial role in shaping how employees perceive and react to AI adoption [93]. AI can serve as both an enabler and a stressor, depending on employees' psychological resources and adaptability [94] [95]. According to the COR theory, individuals strive to preserve valued resources such as job security, psychological well-being, and professional stability [38]. When employees perceive AI as a tool that enhances productivity and autonomy, they view it as a valuable resource. This fosters engagement, creativity, and ultimately greater innovation [50] [96]. In contrast, when AI is seen as a threat to job stability or a source of workload uncertainty, employees feel their resources are being eroded. This perception generates stress and anxiety, reducing their motivation to innovate [97] [98]. In this way, employee well-being moderates the relationship between AI adoption and innovative behavior. Employees with high well-being possess stronger psychological resources, which help them adapt to technological change

and use AI as a tool for innovation [99]. Conversely, employees with lower well-being are more vulnerable to AI-related uncertainty and tend to avoid risks, which limits creativity [74] [100] [101]. COR theory supports this view, explaining that individuals with fewer resources conserve energy by avoiding additional efforts such as innovation [102].

Well-being also shapes how employees connect job security with AI adoption. Concerns about automation, job loss, or increased digital-skill demands heighten insecurity for employees lacking psychological support [103]. From the COR perspective, low well-being amplifies these threats, leading to anxiety and resistance to AI-driven change [104]. In contrast, employees with higher well-being are more likely to interpret AI as an opportunity for growth, adjust their skills, and embrace AI integration without feeling undermined [93]. Thus, employee well-being serves as a protective buffer, softening the negative effects of AI adoption on job security. From this perspective [65], while COR explains how employees protect personal resources [38]. As a result, employees with higher well-being are less threatened by AI and better positioned to leverage it as a resource for growth. Based on these arguments, we propose:

H3: *Employee well-being moderates the relationship between AI adoption and employee innovative behavior, such that the negative relationship is weaker (i.e., less harmful to innovation) when employee well-being is high, and stronger (i.e., more harmful) when well-being is low.*

H4: *Employee well-being moderates the relationship between AI adoption and job security, such that higher well-being reduces the negative impact of AI adoption on job security.*

Despite growing interest in AI and innovation, few studies have empirically examined these mediated (job security) and moderated (employee well-being) mechanisms in manufacturing contexts where both creative agility and operational precision are essential. This study addresses this gap in the OBM industry, where understanding these dynamics is critical to leveraging AI in an innovation-driven environment.

3. Methodology

3.1. Research Design and Data Collection Approach

This study used a quantitative research design to examine the relationship between AI adoption (AIA) and employee innovative behavior (EIB), with job security (JS) as a mediator and employee well-being (EWB) as a moderator. To reduce common method bias [105] [106], data were collected in a two-wave online survey from employees within OBM industry in China. Participants were drawn from R&D, product management, marketing, and project management teams, key functions in AI-driven innovation [107]-[109]. Prior studies show AI in these roles enhances forecasting, automation, market insights, and collaboration [110]-[112], though concerns over job security remain [113]. Data were collected via Credamo, which offers high-quality recruitment, data cleaning, and secure ad-

ministration. The study adhered to strict ethical guidelines, including informed consent, anonymity, confidentiality, voluntary participation, and verification that respondents were members of product innovation teams to ensure eligibility and data accuracy. This approach aligns with best practices by ensuring diversity, reducing geographic limitations, and maintaining cost efficiency [114]. In the first wave, we collected responses on AI adoption (IV) and job security (mediator). Four weeks later, the same participants completed employee well-being (moderator) and employee innovative behavior (DV) measures. This temporal separation helped reduce potential common method bias between the predictor and outcome variables [105] [115].

3.2. Population and Sample

We targeted employees in OBM firms who worked in innovation-driven roles. To verify eligibility, respondents were first required to confirm that their employer manufactured products under its own brand and was responsible for marketing or commercializing that brand, rather than operating exclusively as an OEM or ODM firm. Respondents were also asked whether they were currently part of a product innovation team, such as R&D, design, product management, marketing management, or project management. Only respondents who satisfied both criteria were allowed to proceed with the survey. A total of 400 survey invitations were distributed, resulting in 330 valid responses in the first wave (82.5% response rate). After four weeks, we sent the questionnaire to the same 330 participants contacted in the first wave, and we received 290 valid responses, resulting in a retention rate of 87.88%. After checking for logic and quality, 39 invalid questionnaires were removed. These included responses with unusually short completion times, failed screening questions, or repetitive answer patterns. A total of 251 valid questionnaires were retained for analysis. The effective response rate was 86.55%. Demographic details are shown in **Table 1**. The final dataset met the recommended sample size thresholds for PLS-SEM [116].

3.3. Measurement of Variables

All variables were measured using validated multi-item scales from previous studies. Responses were recorded on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Compared to a seven-point scale, a five-point format reduces confusion over small differences between options. This improves response quality [117] [118].

AI adoption: The AI adoption scale was adapted from [119] measure of computer use. We replaced “computer” with “AI” and revised the items based on expert input and the specific goals of this study. In this study, AI adoption refers to the degree to which employees integrate and depend on AI tools in their day-to-day work tasks, a usage-centered conceptualization reflecting how deeply AI has been embedded into each employee’s working practice, rather than a binary indicator of whether AI exists in the organization. This operationalization captures

the employee's lived experience of AI at the task level, consistent with how job-level AI exposure has been measured in prior individual-level studies [68] [97]. The measurement scales used were originally developed in English, we conducted a commonly used translation and back-translation procedure for the items to ensure the equivalency of meaning in the Chinese version. The final version includes eight items. One example is, "I need AI to help me do my job." The Cronbach's alpha is 0.927.

Job security: The JS was measured using a 10-item scale developed by [75]. An example item is: "I'll be able to keep my present job as long as I wish." The Cronbach's alpha is 0.848.

Employee well-being was assessed using the well-being scales proposed by [92], which measure five key dimensions: meaning, positive relationships, engagement, positive emotions, and accomplishment. These dimensions were operationalized in an employee well-being questionnaire, as demonstrated in a study conducted by [120]. Example statements from the scale include: *"My job has significance. In most cases, I can count on my colleagues. My job makes me happy."* and *"My job inspires me. I look to the future with optimism. I will achieve what I want against all odds."* The Cronbach's alpha is 0.897.

Employee innovative behavior: We applied the scales developed by [20] to measure EIB. The scale consists of six items, a sample item is "I often use new processes, techniques, and methods in my work." The Cronbach's alpha is 0.873.

3.4. Data Analysis

We used SPSS 26 and SmartPLS 4.1.1.1 for the statistical analysis. PLS-SEM was selected because the model includes multiple latent constructs, indirect effects, and interaction effects, and because the study aims to estimate both the measurement and structural models simultaneously. PLS-SEM is also appropriate for examining complex predictive relationships with a moderate sample size [121]. The analysis proceeded in two stages. First, the measurement model was assessed for reliability and convergent and discriminant validity. Second, the structural model was evaluated by examining path coefficients, indirect effects, interaction effects, explanatory power, and collinearity. Mediation and moderation effects were tested using bootstrapping with 5,000 resamples, as illustrated in **Figure 2**.

4. Result

4.1. Descriptive Statistics

Our sample included 251 OBM professionals occupying diverse roles within product innovation teams. **Table 1** summarizes demographic and professional characteristics. The Participants were 58.6% male and 41.4% female. Most participants were between the ages of 26 and 35, with 23.5% aged 26 - 30 and 25.5% aged 31 - 35. A majority held advanced degrees, including 41.8% with a Master's, and participants reported a range of work experience, with most falling within the 1 - 4 years range.

Table 1. Sample demographics (n = 251).

Demographics	Items	Frequency	Percentage
Gender	Male	147	58.6
	Female	104	41.4
Age	20 - 25	33	13.1
	26 - 30	59	23.5
	31 - 35	64	25.5
	36 - 40	38	15.1
	Above 40	57	22.7
Experience	1 - 2 Years	66	26.3
	2 - 3 Years	65	25.9
	3 - 4 Years	59	23.5
	>4 Years	61	24.3
Education Level	Diploma	12	4.8
	Bachelor	93	37.1
	Master	105	41.8
	PhD	41	16.3
Role in the Product Innovation Team	R&D	47	18.7
	Designer	50	19.9
	Product Manager	48	19.1
	Marketing Manager	54	21.5
	Project Manager	52	20.7

Source(s): Created by authors.

4.2. Measurement Model

To validate our research model, we examined reliability, convergent validity, and discriminant validity, with results presented in **Tables 2-4**. Reliability was assessed at both the item and construct levels. Item reliability was evaluated using outer loadings, all of which exceeded 0.5, with most above 0.7. These values indicate that the questionnaire items strongly reflect their intended constructs [122] [123]. Construct reliability was further tested using Cronbach's alpha (α) and composite reliability (CR). Both measures surpassed the accepted threshold of 0.70 [122] [124], and in this study, both Cronbach's alpha and CR values for all variables were above 0.80. This demonstrates strong internal consistency and supports the reliability of the measurement model. Convergent validity was also established. All factor loadings exceeded 0.5, and the average variance extracted (AVE) values for each construct were greater than 0.5 [125]. These findings confirm that each construct accounts for a meaningful proportion of variance in its indicators. We assessed discriminant validity using the Fornell-Larcker criterion [126], and the heterotrait-monotrait (HTMT) ratio [127]. These methods were tested to verify

the correlation among latent variables. The HTMT is widely regarded as the most robust method for testing discriminant validity [122]. As shown in **Table 3**, all HTMT values ranged from 0.067 to 0.453, well below the recommended threshold of 0.85 [127]. Thereby confirming strong discriminant validity among the constructs. Additionally, **Table 4** shows that the square root of the AVE for each construct is higher than its correlations with other variables. This confirms that the measurement model meets the standard for discriminant validity [127] [128].

Table 2. Constructs reliability and (AVE) for reflective constructs.

Variables/Items	Loadings	Cronbach α	rho_A	CR	AVE
AI Adoption		0.927	0.932	0.940	0.661
AIA_1	0.792				
AIA_2	0.822				
AIA_3	0.843				
AIA_4	0.814				
AIA_5	0.775				
AIA_6	0.810				
AIA_7	0.843				
AIA_8	0.802				
Job Security		0.914	0.929	0.929	0.572
JS_17	0.837				
JS_18	0.862				
JS_19	0.591				
JS_20	0.831				
JS_21	0.843				
JS_22	0.856				
JS_23	0.679				
JS_24	0.721				
JS_25	0.628				
JS_26	0.646				
Employee Well-being		0.897	0.904	0.924	0.708
EWB_27	0.823				
EWB_28	0.827				
EWB_29	0.856				
EWB_30	0.873				
EWB_31	0.828				
Employee Innovative Behavior		0.873	0.879	0.905	0.616
EIB_11	0.878				
EIB_12	0.744				
EIB_13	0.878				
EIB_14	0.713				
EIB_15	0.765				
EIB_16	0.711				

Source(s): Created by authors.

Table 3. HTMT.

Variables	AIA	EIB	EWB	JS
AIA				
EIB	0.329			
EWB	0.067	0.095		
JS	0.175	0.453	0.313	

Note: Created by authors.

Table 4. Fornell and Larkers criterion.

Variables	AIA	EIB	EWB	JS
AIA	0.813			
EIB	−0.302	0.785		
EWB	0.005	0.065	0.842	
JS	−0.167	0.410	0.297	0.756

Note: Created by authors.

4.3. Structural Model

Before examining the structural relationships hypothesized in this study, we examined the potential collinearity issues among constructs, in order to ensure accuracy and reliability in results interpretation. We used the Variance Inflation Factor (VIF) analysis to check for multicollinearity in the structural model. All VIF values ranged from 1.005 to 1.175, well below the threshold of 5 [122]. As shown in **Table 5**, the results confirm that multicollinearity is not a concern. This supports the model's stability and reliability for testing the hypotheses. Following the collinearity assessment, we evaluated the path coefficients to test the proposed hypothesized relationships outlined in **Figure 2**.

Table 5. Collinearity assessment (inner VIF values).

Constructs	EIB	JS
AIA	1.044	1.005
EWB	1.120	1.006
JS	1.175	
EWB x AIA	1.050	1.011

Note: Created by authors.

We tested the structural model using SmartPLS with a bootstrapping procedure of 5000 resamples. This approach evaluated the hypothesized relationships based on significance, path strength, and explanatory power [122] [129]. **Table 6** shows the path coefficients and their significance levels. The results show that five out of six proposed hypotheses are statistically supported. One hypothesis did not meet the significance criteria and was not supported. The model demonstrated accepta-

ble explanatory power: the R^2 value for employee innovative behavior was 0.232 and for job security was 0.066, indicating that the predictors account for a meaningful share of variance in the outcome variables and are consistent with ranges reported in comparable behavioral PLS-SEM studies (Hair *et al.*, 2019). The analysis began by testing the direct relationships in the conceptual framework. It first assessed the effect of AI adoption on employee innovative behavior to establish a baseline before exploring mediation and moderation effects.

Table 6. Results of the hypotheses testing.

Hypothesis	Relationships	β	STDEV	T-value	p-value	Remarks
Direct effect						
H1	AIA $\rightarrow$ EIB	-0.232	0.057	4.099	0.000***	Supported
H2a	AIA $\rightarrow$ JS	-0.182	0.068	2.678	0.007**	Supported
H2b	JS $\rightarrow$ EIB	0.394	0.059	6.648	0.000***	Supported
H2 (Mediation)	AIA $\rightarrow$ JS $\rightarrow$ EIB	-0.072	0.026	2.713	0.007**	Supported
H3 (Moderation)	EWB $\times$ AIA $\rightarrow$ EIB	-0.051	0.056	0.914	0.361	Not Supported
H4 (Moderation)	EWB $\times$ AIA $\rightarrow$ JS	0.195	0.059	3.278	0.001***	Supported

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

First, we explored the direct relationships between variables. We found that AI adoption has a significant negative impact on employee innovative behavior ($\beta = -0.232$, $t = 4.099$, $p < 0.01$), which supports our H1. In examining further hypotheses, the impact of AI adoption on job security was assessed. AI adoption showed a significant negative effect on job security ($\beta = -0.182$, $t = 2.678$, $p < 0.01$), which supports H2a. Conversely, job security significantly and positively impacted employee innovative behavior ($\beta = 0.394$, $t = 6.648$, $p < 0.01$), which supports our H2b. Secondly, we calculated the indirect relationship between AI adoption and employee innovative behavior through job security. The mediation analysis shows that job security partially mediated the negative relationship between AI adoption and employee innovative behavior ($\beta = -0.072$, $t = 2.713$, $p < 0.01$). Thus, H2 was significantly supported. Thirdly, the moderated effects were explored by analyzing whether employee well-being could buffer or amplify the direct relationships examined earlier. Interestingly, the moderation analysis results revealed a non-significant moderation effect of employee well-being on the direct association between AI adoption and employee innovative behavior ($\beta = -0.051$, $t = 0.914$, $p > 0.05$), thus not supporting H3. The interaction between AI adoption and employee well-being was significantly associated with job security ($\beta = 0.195$, $t = 3.278$, $p = 0.001$). Conditional-effect analysis showed that when employee well-being was low (-1 SD), AI adoption was negatively associated with job security ($\beta = -0.377$, 95% CI $[-0.509, -0.211]$). At the mean level of employee well-being, the negative association remained significant ($\beta = -0.182$, 95% CI $[-0.307, -0.039]$). At a high level of employee well-being ($+1$ SD), the association became small and non-sig-

nificant ($\beta = 0.013$, 95% CI $[-0.176, 0.208]$). These findings indicate that higher employee well-being substantially weakens the negative association between AI adoption and job security, consistent with H4.

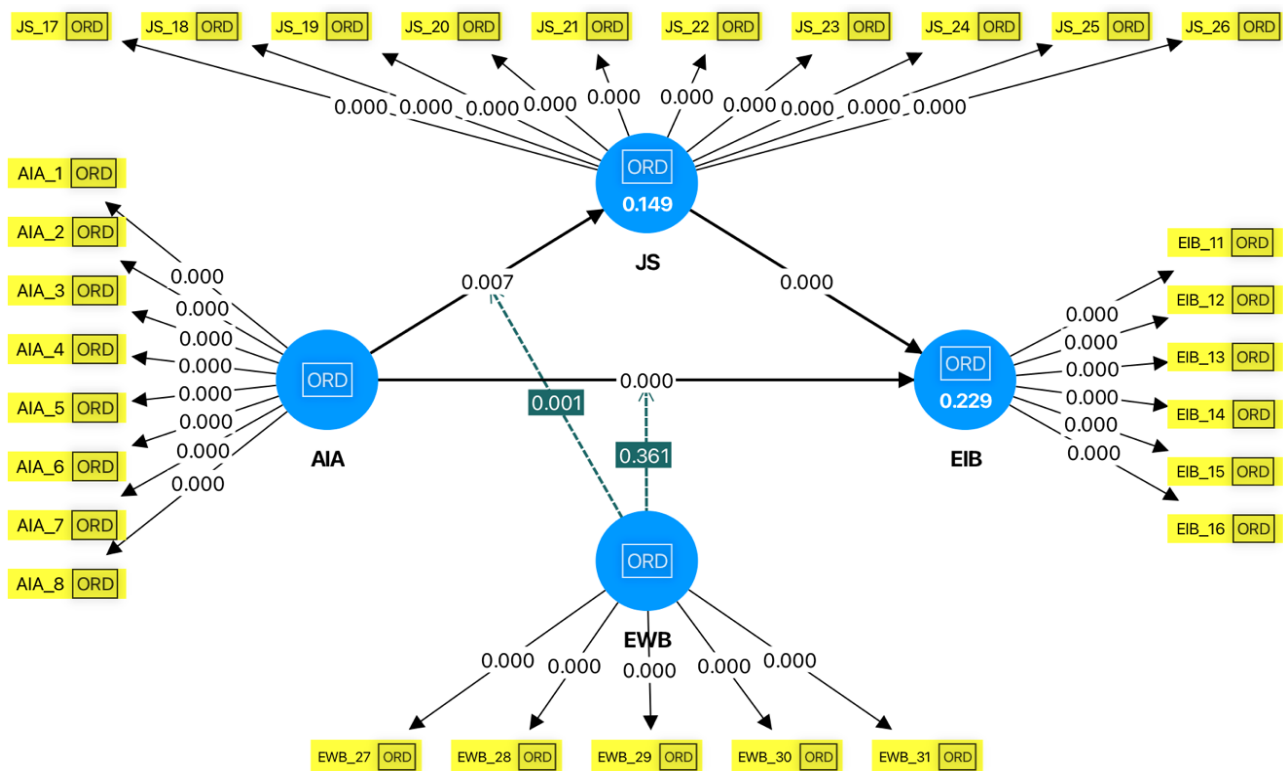


Figure 2. Structural model.

5. Discussion and Implications

This study investigated how AI adoption influences employee innovative behavior in OBM firms and how job security and employee well-being shape this relationship. Grounded in TAM [39] [130] and COR theory [38] [102], we show that AI adoption is not merely a technical transformation but a psychological shift that alters how employees approach innovation [20]. Empirically, AI adoption suppressed innovative behavior; job security mediated this effect, such that protecting employees' sense of job security partially attenuated the harm, consistent with COR's resource-loss logic [90] [91]. Employee well-being did not moderate the direct AI-innovation path, but it buffered the negative effect of AI on job security, positioning well-being as a protective resource within COR. These findings nuance the predominantly efficiency-focused AI discourse and align with emerging evidence that role insecurity can undercut technology-enabled innovation [30] [68] [69].

5.1. Theoretical Implications

We advance organizational behavior and technology-management scholarship by identifying the psychological pathway through which AI adoption influences in-

novative behavior in OBM firms, and by offering a theoretically integrated account of why that pathway operates. A recurrent critique of AI-and-work research is that TAM and COR do not individually address innovation. In this study, TAM is used as a contextual theoretical lens rather than as a fully tested explanatory model. Specifically, TAM helps explain why employees may respond differently to AI depending on whether they perceive it as useful and supportive in their work. However, perceived usefulness and perceived ease of use were not directly measured in the present study. Therefore, we do not test the core TAM mechanisms empirically. Instead, TAM provides a broader conceptual context for understanding employees' responses to AI adoption, while COR theory directly explains the resource-related mechanisms involving job security, well-being, and innovative behavior.

This synthesis provides a more complete model than either theory offers independently. Prior TAM-based research emphasizes perceived usefulness and efficiency gains of AI [39] [130], but our evidence shows that innovation declines when employees experience role uncertainty and resource threat [20] [90] [91]. Theoretically, we extend TAM by showing that perceived usefulness is not sufficient for positive behavioral outcomes when job-related concerns are salient. Integrating COR, we position job security as a central psychological resource; its erosion under AI implementation prompts withdrawal from discretionary, innovation-oriented behaviors. This expands COR's application into technology-induced workplace transitions and emphasizes the need to address the emotional and psychological costs embedded in digital transformation, costs that efficiency-centered AI literature has largely set aside. It is worth noting, however, that job security perceptions are not shaped by AI alone. Macro-level factors, including economic volatility, industry restructuring, labor market tightness, and organizational culture, all influence baseline levels of perceived security. Our model captures the AI-specific contribution to these perceptions after controlling for individual characteristics, but future work should examine how contextual factors condition the AI-job security relationship. We also contribute by introducing employee well-being as a moderating factor. Although it does not buffer the direct effect of AI on innovation, it does reduce the negative impact of AI on job security, consistent with COR's resource-buffer logic [102]. The lack of moderation at the innovation level suggests that resilience alone cannot offset structural concerns about role stability. Even so, well-being functions as a protective factor, enriching theorizing on psychological resources in disrupted work contexts [30]. Our research model, connecting AI adoption, job security, well-being, and innovative behavior, captures AI's double-edged nature by shifting focus from system-level benefits to employee-level responses in innovation-intensive settings such as OBM. Finally, AI's impact is contingent on how organizations manage employee perceptions during technological change. By combining TAM and COR and validating this integrated model in a high-stakes industry, we provide a lens for understanding the socio-psychological dynamics of AI in the workplace in OBM firms.

5.2. Practical Implications

Our findings translate into four interconnected and directly evidence-based recommendations for OBM managers implementing AI. First, signal job security throughout the change process. Communicate the augmentation intent (not replacement), map how tasks will shift, and provide reskilling and internal-mobility pathways. These actions protect the psychological resource of job security and sustain discretionary innovation, consistent with COR and evidence that insecurity suppresses innovative effort. Second, design AI for augmentation using work-design principles, preserve autonomy, control, and skill variety in AI-enabled workflows and decision rights [50]. Adopt “collaborative intelligence” practices that keep people in the loop [100] and pursue human-machine complementarity rather than substitution [1]. These practices align with TAM by increasing perceived usefulness and adoption quality [39] [130]. Third, invest in employee well-being as a buffer against AI-related threats. Provide mental-health resources, manageable workload norms, supportive leadership, and flexible work where feasible, interventions that enlarge resource reserves and mitigate insecurity [93] [102] [103]. Our results show that well-being attenuates AI’s negative effect on job security, creating the conditions for innovation to thrive. Fourth, establish structured AI onboarding and change management: AI literacy training, safe sandboxes for experimentation, transparent decision-logic briefings, and rapid feedback channels. These steps enhance perceived usefulness and ease of use (core TAM constructs) TAM and reduce threat perceptions [24] [131]. Across all four recommendations, firms should additionally commit to transparent, human-centered AI governance: communicating clearly how AI decisions are made, conducting fairness checks, and maintaining proportionate oversight that protects both performance goals and employee dignity [132]–[134]. Together, these practices enable firms to realize AI’s efficiency gains without eroding the climate for employee innovation.

5.3. Limitations and Future Research

We acknowledge that this research has limitations that need to be addressed in future studies. The first limitation is that our model considered only two psychological variables: job security and well-being. Future research should consider additional factors, such as leadership style, team support, and trust in AI, that may shape these outcomes. Moreover, the indirect effect of well-being suggests more complex underlying mechanisms (e.g., stress coping, organizational trust), which longitudinal or multi-level designs could further uncover. Second, this study does not account for macro-level factors such as broader economic conditions, organizational culture, or national labor-market context, all of which may independently shape perceived job security. Future research should examine whether the AI-job security relationship is moderated by organizational climate (e.g., psychological safety) or labor-market tightness, which may strengthen or attenuate the effects observed here. Third, while the current PLS-SEM model demonstrates

strong reliability and validity, future studies would benefit from complementary robustness checks such as alternative model specifications, holdout sample validation, or the inclusion of additional control variables (e.g., firm AI maturity, tenure) to further confirm the stability of the structural estimates. Finally, our study focuses on the OBM, where innovation is a core value. The findings may not generalize to low-innovation sectors or jobs with routine tasks. Replication in other contexts, such as healthcare, logistics, or education, could validate and refine the model's boundaries.

Despite these limitations, the study makes significant contributions by bridging psychological insights with the predominantly technical discourse on AI. It provides both practical and theoretical frameworks that are valuable for academics and professionals. To strengthen and generalize these findings, future studies should explore new variables, apply the framework across diverse industries, and examine how cultural context shapes the AI-employee dynamic. These efforts will contribute to a deeper understanding of how AI affects human behavior and organizational dynamics. This research enhances our understanding of the psychological processes that link AI adoption to employee innovation, and identifies meaningful directions for future inquiry.

6. Conclusion

Based on TAM and COR theory, this study explored how AI adoption influences employee innovative behavior in OBM firms. The results show that AI adoption has a negative impact on employee innovative behavior. A key finding is the mediating role of job security: by threatening this critical resource, AI adoption sets off a chain that ultimately suppresses employees' motivation to innovate. The study also identifies employee well-being as an important factor. Although well-being does not directly moderate the link between AI adoption and innovative behavior, it significantly attenuates AI's negative effect on job security, a finding that highlights the protective value of organizational investment in employee well-being. Together, these results offer a comprehensive account of how AI adoption influences innovation through both direct and resource-mediated pathways, and point to actionable levers for organizations seeking to sustain employee creativity in AI-intensive environments.

Author Contributions

Sangar Wahidullah, Ren Hualiang: Conceptualization, Validation, Visualization, Writing-Original Draft, Writing-Review & Editing, Methodology, Investigation, Data curation. **Ren Hualiang:** Supervision. **Sangar Wahidullah:** Formal analysis. **Yihao Su:** Investigation, Data curation. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

References

- [1] Brynjolfsson, E. and McAfee, A. (2014) *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. WW Norton & Company.
- [2] Philbeck, T. and Davis, N. (2018) The Fourth Industrial Revolution Shaping a New Era. *Journal of International Affairs*, **72**, 17-22.
- [3] Makridakis, S. (2017) The Forthcoming Artificial Intelligence (AI) Revolution: Its Impact on Society and Firms. *Futures*, **90**, 46-60.
<https://doi.org/10.1016/j.futures.2017.03.006>
- [4] Melanie, A., Terry, G. and Ulrich, Z. (2016) The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis. OECD Social, Employment and Migration Working Papers. 189 p.
- [5] PwC (2020) Sizing the Prize: What's the Real Value of AI for Your Business and How Can You Capitalise?
- [6] Bughin, J., *et al.* (2017) Artificial Intelligence the Next Digital Frontier. McKinsey Global Institute.
- [7] Davenport, T.H. and Ronanki, R. (2018) Artificial Intelligence for the Real World. *Harvard Business Review*, **96**, 108-116.
- [8] Tambe, P., Cappelli, P. and Yakubovich, V. (2019) Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. *California Management Review*, **61**, 15-42. <https://doi.org/10.1177/0008125619867910>
- [9] De Cremer, D., Narayanan, D., Nagpal, M., McGuire, J. and Schweitzer, S. (2023) AI Fairness in Action: A Human-Computer Perspective on AI Fairness in Organizations and Society. *International Journal of Human-Computer Interaction*, **40**, 1-3.
<https://doi.org/10.1080/10447318.2023.2273673>
- [10] Russell, S.J. and Norvig, P. (2016) *Artificial Intelligence: A Modern Approach*. Pearson, 2-3.
- [11] Ghobakhloo, M., Fathi, M., Iranmanesh, M., Maroufkhani, P. and Morales, M.E. (2021) Industry 4.0 Ten Years On: A Bibliometric and Systematic Review of Concepts, Sustainability Value Drivers, and Success Determinants. *Journal of Cleaner Production*, **302**, Article ID: 127052. <https://doi.org/10.1016/j.jclepro.2021.127052>
- [12] Xie, K., *et al.* (2024) Artificial Intelligence, Product Innovation, and Adaptive Transformation in Manufacturing. *Journal of Beijing Jiaotong University (Social Sciences Edition)*, **23**, 84-95.
- [13] Zheng, P., Wang, H., Sang, Z., Zhong, R.Y., Liu, Y., Liu, C., *et al.* (2018) Smart Manufacturing Systems for Industry 4.0: Conceptual Framework, Scenarios, and Future Perspectives. *Frontiers of Mechanical Engineering*, **13**, 137-150.
<https://doi.org/10.1007/s11465-018-0499-5>
- [14] Brynjolfsson, E., Rock, D. and Syverson, C. (2019) Artificial Intelligence and the Modern Productivity Paradox. In: Agrawal, A., Gans, J. and Goldfarb, A., Eds., *The Economics of Artificial Intelligence*, University of Chicago Press, 23-60.
<https://doi.org/10.7208/chicago/9780226613475.003.0001>
- [15] Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., *et al.* (2021) Artificial Intelligence (AI): Multidisciplinary Perspectives on Emerging Challenges, Opportunities, and Agenda for Research, Practice and Policy. *International Journal of Information Management*, **57**, Article ID: 101994.
<https://doi.org/10.1016/j.ijinfomgt.2019.08.002>
- [16] Thomas, A., Duggal, H.K., Khatri, P. and Corvello, V. (2024) ChatGPT Appropriation: A Catalyst for Creative Performance, Innovation Orientation, and Agile Lead-

- ership. *Technology in Society*, **78**, Article ID: 102619. <https://doi.org/10.1016/j.techsoc.2024.102619>
- [17] Joksimovic, S., Ifenthaler, D., Marrone, R., De Laat, M. and Siemens, G. (2023) Opportunities of Artificial Intelligence for Supporting Complex Problem-Solving: Findings from a Scoping Review. *Computers and Education: Artificial Intelligence*, **4**, Article ID: 100138. <https://doi.org/10.1016/j.caeai.2023.100138>
 - [18] Amabile, T.M. (1996) Creativity in Context: Update to the Social Psychology of Creativity. Taylor & Francis Group.
 - [19] Janssen, O. (2000) Job Demands, Perceptions of Effort-Reward Fairness and Innovative Work Behaviour. *Journal of Occupational and Organizational Psychology*, **73**, 287-302. <https://doi.org/10.1348/096317900167038>
 - [20] Scott, S.G. and Bruce, R.A. (1994) Determinants of Innovative Behavior: A Path Model of Individual Innovation in the Workplace. *Academy of Management Journal*, **37**, 580-607. <https://doi.org/10.2307/256701>
 - [21] De Jong, J. and Den Hartog, D. (2010) Measuring Innovative Work Behaviour. *Creativity and Innovation Management*, **19**, 23-36. <https://doi.org/10.1111/j.1467-8691.2010.00547.x>
 - [22] Wu, L., Liu, H. and Bao, Y. (2021) Outside-in Thinking, Value Chain Collaboration and Business Model Innovation in Manufacturing Firms. *Journal of Business & Industrial Marketing*, **37**, 1745-1761. <https://doi.org/10.1108/jbim-03-2021-0189>
 - [23] Tsai-Lin, T., Chi, H. and Chang, Y. (2021) The Business Model and Innovation Mix in the Transition of Contract Manufacturers in the Greater China Region. *Asia Pacific Business Review*, **27**, 444-469. <https://doi.org/10.1080/13602381.2021.1894844>
 - [24] Raisch, S. and Krakowski, S. (2021) Artificial Intelligence and Management: The Automation-Augmentation Paradox. *Academy of Management Review*, **46**, 192-210. <https://doi.org/10.5465/amr.2018.0072>
 - [25] Wang, Y., Kung, L. and Byrd, T.A. (2018) Big Data Analytics: Understanding Its Capabilities and Potential Benefits for Healthcare Organizations. *Technological Forecasting and Social Change*, **126**, 3-13. <https://doi.org/10.1016/j.techfore.2015.12.019>
 - [26] Frey, C.B. and Osborne, M.A. (2017) The Future of Employment: How Susceptible Are Jobs to Computerisation? *Technological Forecasting and Social Change*, **114**, 254-280. <https://doi.org/10.1016/j.techfore.2016.08.019>
 - [27] Peng, Y.Y. and Wang, X.Y. (2020) Research on the Influence of Artificial Intelligence on Employment in Manufacturing Industry: Based on the Survey of Total Employment and Structure of Manufacturing Enterprises in Guangdong Province, China. *Journal of Beijing University of Technology (Social Sciences Edition)*, **20**, 68-76.
 - [28] Huang, M. and Rust, R.T. (2020) Engaged to a Robot? The Role of AI in Service. *Journal of Service Research*, **24**, 30-41. <https://doi.org/10.1177/1094670520902266>
 - [29] Zhou, Y., Wang, L. and Chen, W. (2023) The Dark Side of Ai-Enabled HRM on Employees Based on AI Algorithmic Features. *Journal of Organizational Change Management*, **36**, 1222-1241. <https://doi.org/10.1108/jocm-10-2022-0308>
 - [30] Chatterjee, S., Rana, N.P., Dwivedi, Y.K. and Baabdullah, A.M. (2021) Understanding AI Adoption in Manufacturing and Production Firms Using an Integrated TAM-TOE Model. *Technological Forecasting and Social Change*, **170**, Article ID: 120880. <https://doi.org/10.1016/j.techfore.2021.120880>
 - [31] Acemoglu, D. and Restrepo, P. (2020) Robots and Jobs: Evidence from US Labor Markets. *Journal of Political Economy*, **128**, 2188-2244. <https://doi.org/10.1086/705716>

- [32] Autor, D.H. (2015) Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives*, **29**, 3-30.
<https://doi.org/10.1257/jep.29.3.3>
- [33] Bhargava, A., Bester, M. and Bolton, L. (2020) Employees' Perceptions of the Implementation of Robotics, Artificial Intelligence, and Automation (RAIA) on Job Satisfaction, Job Security, and Employability. *Journal of Technology in Behavioral Science*, **6**, 106-113. <https://doi.org/10.1007/s41347-020-00153-8>
- [34] Burchell, B. (2020) Job Security. In: Maggino, F., Ed., *Encyclopedia of Quality of Life and Well-Being Research*, Springer, 1-3.
- [35] Ghorbanzadeh, D., Kumar, S.P., Mahmood, A.H., Prasad, K.D.V., Alkhayyat, A. and Rahehagh, A. (2026) Examining the Impact of Artificial Intelligence on Physicians' Performance: Mediating Effects of Innovative Work Behavior and Skills Enhancement. *Journal of Health Organization and Management*, 1-26.
<https://doi.org/10.1108/JHOM-03-2025-0150>
- [36] Tarafdar, M., Cooper, C.L. and Stich, J. (2017) The Technostress Trifecta—Techno Eustress, Techno Distress and Design: Theoretical Directions and an Agenda for Research. *Information Systems Journal*, **29**, 6-42. <https://doi.org/10.1111/isj.12169>
- [37] Wamba-Taguimdje, S., Fosso Wamba, S., Kala Kamdjoug, J.R. and Tchatchouang Wanko, C.E. (2020) Influence of Artificial Intelligence (AI) on Firm Performance: The Business Value of AI-Based Transformation Projects. *Business Process Management Journal*, **26**, 1893-1924. <https://doi.org/10.1108/bpmj-10-2019-0411>
- [38] Hobfoll, S.E. (1989) Conservation of Resources: A New Attempt at Conceptualizing Stress. *American Psychologist*, **44**, 513-524.
<https://doi.org/10.1037/0003-066x.44.3.513>
- [39] Davis, F.D. (1989) Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, **13**, 319-340.
<https://doi.org/10.2307/249008>
- [40] Wilkens, U. (2020) Artificial Intelligence in the Workplace—A Double-Edged Sword. *The International Journal of Information and Learning Technology*, **37**, 253-265.
<https://doi.org/10.1108/ijilt-02-2020-0022>
- [41] Sah, T., Purwati, D., Reniati, and Valeriani, D. (2024) The Double-Edge Sword Impact of Artificial Intelligence Support on Employee Innovation Behavior. *1st International Conference of Economics, Management, Accounting, and Business Digital*, Pangkalpinang, 15 October 2024 133-140.
https://doi.org/10.2991/978-94-6463-614-7_18
- [42] Venkatesh, V., Thong, J. and Xu, X. (2016) Unified Theory of Acceptance and Use of Technology: A Synthesis and the Road Ahead. *Journal of the Association for Information Systems*, **17**, 328-376. <https://doi.org/10.17705/1jais.00428>
- [43] Halbesleben, J.R.B., Neveu, J., Paustian-Underdahl, S.C. and Westman, M. (2014) Getting to the “Cor”. *Journal of Management*, **40**, 1334-1364.
<https://doi.org/10.1177/0149206314527130>
- [44] Lee, M.K., Kusbit, D., Metsky, E. and Dabbish, L. (2015) Working with Machines. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, Seoul, 18-23 April 2015, 1603-1612.
<https://doi.org/10.1145/2702123.2702548>
- [45] Chiu, Y., Zhu, Y. and Corbett, J. (2021) In the Hearts and Minds of Employees: A Model of Pre-Adoptive Appraisal toward Artificial Intelligence in Organizations. *International Journal of Information Management*, **60**, Article ID: 102379.
<https://doi.org/10.1016/j.ijinfomgt.2021.102379>

- [46] Du, P. and Liu, S. (2024) The Double-Edged Impact of Artificial Intelligence Use on Employee Psychology. *Operations Research and Fuzziology*, **14**, 541-547. <https://doi.org/10.12677/orf.2024.144422>
- [47] Brynjolfsson, E., Rock, D. and Syverson, C. (2021) The Productivity J-Curve: How Intangibles Complement General Purpose Technologies. *American Economic Journal: Macroeconomics*, **13**, 333-372. <https://doi.org/10.1257/mac.20180386>
- [48] Viskova-Robertson, A. (2024) Investigating the Impacts of AI Integration on Workplace Well-Being, an Exploratory Case Study. Ph.D. Thesis, Western Michigan University.
- [49] Brynjolfsson, E. and McAfee, A. (2017) The Business of Artificial Intelligence. *Harvard Business Review*, **7**, 1-2.
- [50] Parker, S.K. and Grote, G. (2020) Automation, Algorithms, and Beyond: Why Work Design Matters More than Ever in a Digital World. *Applied Psychology*, **71**, 1171-1204. <https://doi.org/10.1111/apps.12241>
- [51] Espina-Romero, L., Gutiérrez Hurtado, H., Ríos Parra, D., Vilchez Pirela, R.A., Talavera-Aguirre, R. and Ochoa-Díaz, A. (2024) Challenges and Opportunities in the Implementation of AI in Manufacturing: A Bibliometric Analysis. *Sci*, **6**, Article 60. <https://doi.org/10.3390/sci6040060>
- [52] Yan, H. (2012) Entrepreneurship, Competitive Strategies, and Transforming Firms from OEM to OBM in Taiwan Region. *Journal of Asia-Pacific Business*, **13**, 16-36. <https://doi.org/10.1080/10599231.2012.629877>
- [53] Yang, C.H. and Wang, Y.L. (2014) Determinants Affecting the Transformational Process from OEM to OBM in Creative Design Industry. International Symposium on Business and Social Sciences. NCKU. <https://researchoutput.ncku.edu.tw/en/publications/determinants-affecting-the-transformational-process-from-oem-to-o/>
- [54] Zhang, Q., Liao, G., Ran, X. and Wang, F. (2025) The Impact of AI Usage on Innovation Behavior at Work: The Moderating Role of Openness and Job Complexity. *Behavioral Sciences*, **15**, Article 491. <https://doi.org/10.3390/bs15040491>
- [55] Holzner, N., Maier, S. and Feuerriegel, S. (2025) Generative AI and Creativity: A Systematic Literature Review and Meta-Analysis. arXiv: 2505.17241.
- [56] Bessen, J. (2018) AI and Jobs: The Role of Demand. Social Science Electronic Publishing.
- [57] Anantrasirchai, N. and Bull, D. (2021) Artificial Intelligence in the Creative Industries: A Review. *Artificial Intelligence Review*, **55**, 589-656. <https://doi.org/10.1007/s10462-021-10039-7>
- [58] Brynjolfsson, E. (2022) The Turing Trap: The Promise & Peril of Human-Like Artificial Intelligence. *Daedalus*, **151**, 272-287. https://doi.org/10.1162/daed_a_01915
- [59] De Cremer, D. and Kasparov, G. (2021) AI Should Augment Human Intelligence, Not Replace It. *Harvard Business Review*, **18**, 1-8.
- [60] Jarrahi, M.H. (2018) Artificial Intelligence and the Future of Work: Human-AI Symbiosis in Organizational Decision Making. *Business Horizons*, **61**, 577-586. <https://doi.org/10.1016/j.bushor.2018.03.007>
- [61] Wan, J., Li, X., Dai, H., Kusiak, A., Martinez-Garcia, M. and Li, D. (2021) Artificial-Intelligence-Driven Customized Manufacturing Factory: Key Technologies, Applications, and Challenges. *Proceedings of the IEEE*, **109**, 377-398. <https://doi.org/10.1109/jproc.2020.3034808>
- [62] Jackson, I., Ivanov, D., Dolgui, A. and Namdar, J. (2024) Generative Artificial Intel-

- ligence in Supply Chain and Operations Management: A Capability-Based Framework for Analysis and Implementation. *International Journal of Production Research*, **62**, 6120-6145. <https://doi.org/10.1080/00207543.2024.2309309>
- [63] Soulam, M., Benchechrone, S. and Galiulina, A. (2024) Exploring How AI Adoption in the Workplace Affects Employees: A Bibliometric and Systematic Review. *Frontiers in Artificial Intelligence*, **7**, Article 1473872. <https://doi.org/10.3389/frai.2024.1473872>
- [64] Zang, J., Shao, Q. and Li, H. (2024) Challenge and Hindrance: Yin and Yang Paths of AI Usage's Effects on Chinese Employee Innovative Behaviour. *Asia Pacific Business Review*. <https://doi.org/10.1080/13602381.2024.2367526>
- [65] Davis, F.D., Bagozzi, R.P. and Warshaw, P.R. (1989) User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*, **35**, 982-1003. <https://doi.org/10.1287/mnsc.35.8.982>
- [66] Singh, K., Chatterjee, S. and Mariani, M. (2024) Applications of Generative AI and Future Organizational Performance: The Mediating Role of Explorative and Exploitative Innovation and the Moderating Role of Ethical Dilemmas and Environmental Dynamism. *Technovation*, **133**, Article ID: 103021. <https://doi.org/10.1016/j.technovation.2024.103021>
- [67] Khan, S., Mehmood, S. and Khan, S.U. (2024) Navigating Innovation in the Age of AI: How Generative AI and Innovation Influence Organizational Performance in the Manufacturing Sector. *Journal of Manufacturing Technology Management*, **36**, 597-620. <https://doi.org/10.1108/jmtm-06-2024-0302>
- [68] Yin, M., Jiang, S. and Niu, X. (2024) Can AI Really Help? The Double-Edged Sword Effect of AI Assistant on Employees' Innovation Behavior. *Computers in Human Behavior*, **150**, Article ID: 107987. <https://doi.org/10.1016/j.chb.2023.107987>
- [69] Ahn, S., Park, J. and Ye, S. (2025) How AI Enhances Employee Service Innovation in Retail: Social Exchange Theory Perspectives and the Impact of AI Adaptability. *Journal of Retailing and Consumer Services*, **84**, Article ID: 104207. <https://doi.org/10.1016/j.jretconser.2024.104207>
- [70] Farhan, A. (2023) The Impact of Artificial Intelligence on Human Workers. *Journal of Communication Education*, **17**, 93-104. <https://doi.org/10.58217/joce-ip.v17i2.350>
- [71] Zong, Z. and Guan, Y. (2024) AI-Driven Intelligent Data Analytics and Predictive Analysis in Industry 4.0: Transforming Knowledge, Innovation, and Efficiency. *Journal of the Knowledge Economy*, **16**, 864-903. <https://doi.org/10.1007/s13132-024-02001-z>
- [72] Chui, M., Manyika, J. and Miremadi, M. (2015) Four Fundamentals of Workplace Automation. *McKinsey Quarterly*, **29**, 1-9.
- [73] Bankins, S., Ocampo, A.C., Marrone, M., Restubog, S.L.D. and Woo, S.E. (2023) A Multilevel Review of Artificial Intelligence in Organizations: Implications for Organizational Behavior Research and Practice. *Journal of Organizational Behavior*, **45**, 159-182. <https://doi.org/10.1002/job.2735>
- [74] Brougham, D. and Haar, J. (2017) Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STARA): Employees' Perceptions of Our Future Workplace. *Journal of Management & Organization*, **24**, 239-257. <https://doi.org/10.1017/jmo.2016.55>
- [75] Oldham, G.R., Kulik, C.T., Stepina, L.P. and Ambrose, M.L. (1986) Relations between Situational Factors and the Comparative Referents Used by Employees. *Academy of Management Journal*, **29**, 599-608. <https://doi.org/10.2307/256226>
- [76] Nam, T. (2019) Technology Usage, Expected Job Sustainability, and Perceived Job

- Insecurity. *Technological Forecasting and Social Change*, **138**, 155-165.
<https://doi.org/10.1016/j.techfore.2018.08.017>
- [77] Hu, S. and Li, C.B. (2010) An Empirical Analysis of Job Insecurity of Enterprise Employees. *Psychological Insights*, **30**, 79-85.
- [78] Liu, R. and Zhan, Y. (2020) The Impact of Artificial Intelligence on Job Insecurity: A Moderating Role Based on Vocational Learning Capabilities. *Journal of Physics: Conference Series*, **1629**, Article ID: 012034.
<https://doi.org/10.1088/1742-6596/1629/1/012034>
- [79] Lin, L. and Parker, K. (2025) U.S. Workers Are More Worried than Hopeful about Future AI Use in the Workplace. Pew Research Center.
- [80] Rodríguez-Espíndola, O., Chowdhury, S., Dey, P.K., Albores, P. and Emrouznejad, A. (2022) Analysis of the Adoption of Emergent Technologies for Risk Management in the Era of Digital Manufacturing. *Technological Forecasting and Social Change*, **178**, Article ID: 121562. <https://doi.org/10.1016/j.techfore.2022.121562>
- [81] Dabbous, A., Aoun Barakat, K. and Merhej Sayegh, M. (2021) Enabling Organizational Use of Artificial Intelligence: An Employee Perspective. *Journal of Asia Business Studies*, **16**, 245-266. <https://doi.org/10.1108/jabs-09-2020-0372>
- [82] Suseno, Y., Chang, C., Hudik, M. and Fang, E.S. (2023) Beliefs, Anxiety and Change Readiness for Artificial Intelligence Adoption among Human Resource Managers: The Moderating Role of High- Performance Work Systems. In: *Artificial Intelligence and International HRM*, Routledge, 144-171.
<https://doi.org/10.4324/9781003377085-6>
- [83] Koo, B., Curtis, C. and Ryan, B. (2021) Examining the Impact of Artificial Intelligence on Hotel Employees through Job Insecurity Perspectives. *International Journal of Hospitality Management*, **95**, Article ID: 102763.
<https://doi.org/10.1016/j.ijhm.2020.102763>
- [84] Bos-Nehles, A., Renkema, M. and Janssen, M. (2017) HRM and Innovative Work Behaviour: A Systematic Literature Review. *Personnel Review*, **46**, 1228-1253.
<https://doi.org/10.1108/pr-09-2016-0257>
- [85] Sauermann, H. and Cohen, W.M. (2010) What Makes Them Tick? Employee Motives and Firm Innovation. *Management Science*, **56**, 2134-2153.
<https://doi.org/10.1287/mnsc.1100.1241>
- [86] Ma, B., Zhou, Y., Lassleben, H., Ma, G. and Yang, R. (2023) Examining the Mediating Effects of Motivation between Job Insecurity and Innovative Behavior Using a Variable-Centered and a Person-Centered Approach. *Frontiers in Psychology*, **14**, Article 1284042. <https://doi.org/10.3389/fpsyg.2023.1284042>
- [87] Durrah, O. and Kahwaji, A. (2022) Chameleon Leadership and Innovative Behavior in the Health Sector: The Mediation Role of Job Security. *Employee Responsibilities and Rights Journal*, **35**, 247-265. <https://doi.org/10.1007/s10672-022-09414-5>
- [88] Chen, C., Chen, Y., Hsu, P. and Podolski, E.J. (2016) Be Nice to Your Innovators: Employee Treatment and Corporate Innovation Performance. *Journal of Corporate Finance*, **39**, 78-98. <https://doi.org/10.1016/j.jcorpfin.2016.06.001>
- [89] Lee, W., Jeon, Y., Kim, J. and Jung, C. (2014) Effects of Job Security and Psychological Ownership on Turnover Intention and Innovative Behavior of Manufacturing Employees. *Journal of the Korea Safety Management and Science*, **16**, 53-68.
<https://doi.org/10.12812/ksms.2014.16.1.53>
- [90] Probst, T.M., Stewart, S.M., Gruys, M.L. and Tierney, B.W. (2007) Productivity, Counterproductivity and Creativity: The Ups and Downs of Job Insecurity. *Journal*

- of *Occupational and Organizational Psychology*, **80**, 479-497.
<https://doi.org/10.1348/096317906x159103>
- [91] Probst, T., Chizh, A., Hu, S., Jiang, L. and Austin, C. (2019) Explaining the Relationship between Job Insecurity and Creativity. *Career Development International*, **25**, 247-270. <https://doi.org/10.1108/cdi-04-2018-0118>
 - [92] Seligman, M.E.P. (2011) *Flourish: A Visionary New Understanding of Happiness and Well-Being*. Simon and Schuster.
 - [93] Cramarencu, R.E., Burcă-Voicu, M.I. and Dabija, D.C. (2023) The Impact of Artificial Intelligence (AI) on Employees' Skills and Well-Being in Global Labor Markets: A Systematic Review. *Oeconomia Copernicana*, **14**, 731-767.
<https://doi.org/10.24136/oc.2023.022>
 - [94] Luthans, F., Avolio, B.J., Avey, J.B. and Norman, S.M. (2007) Positive Psychological Capital: Measurement and Relationship with Performance and Satisfaction. *Personnel Psychology*, **60**, 541-572. <https://doi.org/10.1111/j.1744-6570.2007.00083.x>
 - [95] Ruiz-Vanoye, J.A., Fuentes-Penna, A., Barrera-Cámara, R.A., Díaz-Parra, O., Trejo-Macotela, F.R., Gómez-Pérez, L.J., et al. (2025) Artificial Intelligence and Human Well-Being: A Review of Applications and Effects on Life Satisfaction through Synthetic Happiness. *International Journal of Combinatorial Optimization Problems and Informatics*, **16**, 14-37. <https://doi.org/10.61467/2007.1558.2025.v16i1.932>
 - [96] Xavier, D.F. and Korunka, C. (2025) Integrating Artificial Intelligence across Cultural Orientations: A Longitudinal Examination of Creative Self-Efficacy and Employee Autonomy. *Computers in Human Behavior Reports*, **18**, Article ID: 100623.
<https://doi.org/10.1016/j.chbr.2025.100623>
 - [97] Dong, X., Tian, Y., He, M. and Wang, T. (2024) When Knowledge Workers Meet AI? the Double-Edged Sword Effects of AI Adoption on Innovative Work Behavior. *Journal of Knowledge Management*, **29**, 113-147.
<https://doi.org/10.1108/jkm-02-2024-0222>
 - [98] Ali, T., Hussain, I., Hassan, S. and Anwer, S. (2024) Examine How the Rise of AI and Automation Affects Job Security, Stress Levels, and Mental Health in the Workplace. *Bulletin of Business and Economics (BBE)*, **13**, 1180-1186.
<https://doi.org/10.61506/01.00506>
 - [99] Daugherty, P.R. and Wilson, H.J. (2024) *Human + Machine, Updated and Expanded: Reimagining Work in the Age of AI*. Harvard Business Review Press.
 - [100] Wilson, H.J. and Daugherty, P.R. (2018) Collaborative Intelligence: Humans and AI Are Joining Forces. *Harvard Business Review*, **96**, 114-123.
 - [101] Chhatre, R. and Singh, S. (2024) AI and Organizational Change: Dynamics and Management Strategies. *Journal of Emerging Trends and Novel Research*, **2**, a148-a159.
 - [102] Hobfoll, S.E. (2001) The Influence of Culture, Community, and the Nested-Self in the Stress Process: Advancing Conservation of Resources Theory. *Applied Psychology*, **50**, 337-421. <https://doi.org/10.1111/1464-0597.00062>
 - [103] Gupta, A., Pranathy, R.S., Binny, M., Chellasamy, A., Nagarathinam, A., Pachiyappan, S., et al. (2024) Voices of the Future: Generation Z's Views on AI's Ethical and Social Impact. In: El Khoury, R., Ed., *Technology-Driven Business Innovation*, Springer, 367-386. https://doi.org/10.1007/978-3-031-51997-0_31
 - [104] Hobfoll, S.E., Halbesleben, J., Neveu, J. and Westman, M. (2018) Conservation of Resources in the Organizational Context: The Reality of Resources and Their Consequences. *Annual Review of Organizational Psychology and Organizational Behavior*, **5**, 103-128. <https://doi.org/10.1146/annurev-orgpsych-032117-104640>

- [105] Podsakoff, P.M., MacKenzie, S.B., Lee, J. and Podsakoff, N.P. (2003) Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *Journal of Applied Psychology*, **88**, 879-903. <https://doi.org/10.1037/0021-9010.88.5.879>
- [106] Podsakoff, P.M., MacKenzie, S.B. and Podsakoff, N.P. (2012) Sources of Method Bias in Social Science Research and Recommendations on How to Control It. *Annual Review of Psychology*, **63**, 539-569. <https://doi.org/10.1146/annurev-psych-120710-100452>
- [107] Cooper, R.G. (2024) The AI Transformation of Product Innovation. *Industrial Marketing Management*, **119**, 62-74. <https://doi.org/10.1016/j.indmarman.2024.03.008>
- [108] Mehta, A.M., Rauf, A. and Senathirajah, A.R.B.S. (2024) Achieving World Class Manufacturing Excellence: Integrating Human Factors and Technological Innovation. *Sustainability*, **16**, Article 11175. <https://doi.org/10.3390/su162411175>
- [109] Haefner, N., Wincent, J., Parida, V. and Gassmann, O. (2021) Artificial Intelligence and Innovation Management: A Review, Framework, and Research Agenda. *Technological Forecasting and Social Change*, **162**, Article ID: 120392. <https://doi.org/10.1016/j.techfore.2020.120392>
- [110] Füller, J., Hutter, K., Wahl, J., Bilgram, V. and Tekic, Z. (2022) How AI Revolutionizes Innovation Management—Perceptions and Implementation Preferences of AI-Based Innovators. *Technological Forecasting and Social Change*, **178**, Article ID: 121598. <https://doi.org/10.1016/j.techfore.2022.121598>
- [111] Bouschery, S.G., Blazevic, V. and Piller, F.T. (2023) Augmenting Human Innovation Teams with Artificial Intelligence: Exploring Transformer-Based Language Models. *Journal of Product Innovation Management*, **40**, 139-153. <https://doi.org/10.1111/jpim.12656>
- [112] Mesa Fernández, J.M., González Moreno, J.J., Vergara-González, E.P. and Alonso Iglesias, G. (2022) Bibliometric Analysis of the Application of Artificial Intelligence Techniques to the Management of Innovation Projects. *Applied Sciences*, **12**, Article 11743. <https://doi.org/10.3390/app122211743>
- [113] Sońta-Drączkowska, E. and Mrożewski, M. (2019) Exploring the Role of Project Management in Product Development of New Technology-Based Firms. *Project Management Journal*, **51**, 294-311. <https://doi.org/10.1177/8756972819851939>
- [114] Gosling, S.D. and Mason, W. (2015) Internet Research in Psychology. *Annual Review of Psychology*, **66**, 877-902. <https://doi.org/10.1146/annurev-psych-010814-015321>
- [115] Podsakoff, P.M. and Organ, D.W. (1986) Self-Reports in Organizational Research: Problems and Prospects. *Journal of Management*, **12**, 531-544. <https://doi.org/10.1177/014920638601200408>
- [116] Sarstedt, M., Ringle, C.M. and Hair, J.F. (2021) Partial Least Squares Structural Equation Modeling. In: Homburg, C., Klarmann, M. and Vomberg, A., Eds., *Handbook of Market Research*, Springer, 587-632. https://doi.org/10.1007/978-3-319-57413-4_15
- [117] Babakus, E. and Mangold, W.G. (1992) Adapting the SERVQUAL Scale to Hospital Services: An Empirical Investigation. *Health Services Research*, **26**, 767-786.
- [118] Sachdev, S.B. and Verma, H.V. (2004) Relative Importance of Service Quality Dimensions: A Multisectoral Study. *Journal of Services Research*, **4**, 93.
- [119] Medcof, J.W. (1996) The Job Characteristics of Computing and Non-Computing Work Activities. *Journal of Occupational and Organizational Psychology*, **69**, 199-212. <https://doi.org/10.1111/j.2044-8325.1996.tb00610.x>

- [120] Kun, Á., Balogh, P. and Krasz, K.G. (2016) Development of the Work-Related Well-Being Questionnaire Based on Seligman's PERMA Model. *Periodica Polytechnica Social and Management Sciences*, **25**, 56-63. <https://doi.org/10.3311/ppso.9326>
- [121] Astrachan, C.B., Patel, V.K. and Wanzenried, G. (2014) A Comparative Study of CB-SEM and PLS-SEM for Theory Development in Family Firm Research. *Journal of Family Business Strategy*, **5**, 116-128. <https://doi.org/10.1016/j.jfbs.2013.12.002>
- [122] Hair, J.F., Risher, J.J., Sarstedt, M. and Ringle, C.M. (2019) When to Use and How to Report the Results of PLS-SEM. *European Business Review*, **31**, 2-24. <https://doi.org/10.1108/eb-11-2018-0203>
- [123] Chin, W.W. (1998) The Partial Least Squares Approach to Structural Equation Modeling. In: Marcoulides, G.A., Ed., *Modern Methods for Business Research*, Psychology Press, 295-336.
- [124] Sarstedt, M., Hair, J.F., Cheah, J., Becker, J. and Ringle, C.M. (2019) How to Specify, Estimate, and Validate Higher-Order Constructs in PLS-SEM. *Australasian Marketing Journal*, **27**, 197-211. <https://doi.org/10.1016/j.ausmj.2019.05.003>
- [125] Hair, J.F., Howard, M.C. and Nitzl, C. (2020) Assessing Measurement Model Quality in PLS-SEM Using Confirmatory Composite Analysis. *Journal of Business Research*, **109**, 101-110. <https://doi.org/10.1016/j.jbusres.2019.11.069>
- [126] Fornell, C. and Larcker, D.F. (1981) Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, **18**, 39-50. <https://doi.org/10.1177/002224378101800104>
- [127] Henseler, J., Ringle, C.M. and Sarstedt, M. (2014) A New Criterion for Assessing Discriminant Validity in Variance-Based Structural Equation Modeling. *Journal of the Academy of Marketing Science*, **43**, 115-135. <https://doi.org/10.1007/s11747-014-0403-8>
- [128] Ab Hamid, M.R., Sami, W. and Mohmad Sidek, M.H. (2017) Discriminant Validity Assessment: Use of Fornell & Larcker Criterion versus HTMT Criterion. *Journal of Physics: Conference Series*, **890**, Article ID: 012163. <https://doi.org/10.1088/1742-6596/890/1/012163>
- [129] Streukens, S. and Leroi-Werelds, S. (2016) Bootstrapping and PLS-SEM: A Step-by-Step Guide to Get More Out of Your Bootstrap Results. *European Management Journal*, **34**, 618-632. <https://doi.org/10.1016/j.emj.2016.06.003>
- [130] Venkatesh, V. and Davis, F.D. (2000) A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, **46**, 186-204. <https://doi.org/10.1287/mnsc.46.2.186.11926>
- [131] Tarafdar, M., Beath, C.M. and Ross, J.W. (2019) Using AI to Enhance Business Operations. *MIT Sloan Management Review*, **60**, No. 4.
- [132] Floridi, L. and Cowls, J. (2022) A Unified Framework of Five Principles for AI in Society. In: Carta, S., Ed., *Machine Learning and the City*, Wiley-Blackwell, 535-545.
- [133] Jobin, A., Ienca, M. and Vayena, E. (2019) The Global Landscape of AI Ethics Guidelines. *Nature Machine Intelligence*, **1**, 389-399. <https://doi.org/10.1038/s42256-019-0088-2>
- [134] Sigfrids, A., Leikas, J., Salo-Pöntinen, H. and Koskimies, E. (2023) Human-Centricity in AI Governance: A Systemic Approach. *Frontiers in Artificial Intelligence*, **6**, Article 976887. <https://doi.org/10.3389/frai.2023.976887>