The Fifth International Conference on Government Education Management and Tourism (ICoGEMT-5)
Bandung, Indonesia, January, 24th, 2026

THE POTENTIAL OF ARTIFICIAL INTELLIGENCE (AI) FOR DEVELOPING AN INTEGRATED EMPLOYEE PLACEMENT MODEL BASED ON PERSON-JOB (P-J), PERSON-ORGANIZATION (P-O), AND PERSON-ENVIRONMENT (P-E) FIT: A SYSTEMATIC LITERATURE REVIEW

[1]**Achmad Andriyanto**,[*2]**Joko Siswanto**

[1]*Doctoral Program of Industrial Engineering and Management, Faculty of Industrial Technology*
Bandung Institute of Technology, Bandung, Indonesia
[1]*Engineering Management, Faculty of Logistics, Technology and Business*
University of Logistics and International Business, Bandung, Indonesia
[2]*Industrial Management Research Group of Industrial Technology Faculty*
Bandung Institute of Technology, Bandung, Indonesia

Author's email:
[1]*33425008@mahasiswa.itb.ac.id; achmadandriyanto@ulbi.ac.id;* [2]*j.siswanto@itb.ac.id*

**Corresponding author: j.siswanto@itb.ac.id*

Abstract. *The integration of artificial intelligence (AI) into human resource management has transformed employee placement practices, yet the systematic examination of AI applications across the person-job (P-J), person-organization (P-O), and person-environment (P-E) fit dimensions remains fragmented. This systematic literature review synthesizes 61 peer-reviewed articles (2015-2025) from the Scopus database that examine how AI technologies facilitate matching across three critical fit dimensions. Analysis reveals P-E Fit Theory as the dominant framework (34.4%), with quantitative methodologies prevailing (80-85%) and structural equation modeling preferred (40%). Geographically, Asian countries, particularly China (27.9%) and Taiwan (9.8%), lead research contributions. Findings demonstrate that AI applications enhance recruitment efficiency by approximately 30% while improving matching accuracy through machine learning algorithms that analyze multidimensional candidate profiles. However, challenges persist regarding algorithmic bias, transparency, and explainable AI systems. This review proposes an Augmented Person-Environment Fit Theory that incorporates person-technology fit as an essential dimension in digital workplace contexts, offering practical implications for organizations implementing AI-enhanced placement systems and identifying critical research gaps, including in the tourism industry.*

Keywords: *Artificial Intelligence; Employee Placement; Human Resource Management; Machine Learning; Person-Environment Fit; Person-Job Fit; Person-Organization Fit; Systematic Literature Review;*

1. INTRODUCTION

Organizations undergoing digital transformation and Industry 4.0 face complex challenges in managing human resources to achieve optimal performance and competitive advantage. AI technology development has brought fundamental paradigm shifts in HR management, including employee placement processes (Malik, Budhwar, Patel, & Srikanth, 2020; Paramita, Okwir, & Nuur, 2024). Employee placement represents a critical strategic decision, as misalignment between individual characteristics and work environment results in decreased productivity, increased turnover, and reduced job satisfaction (Kristof-Brown, Zimmerman, & Johnson, 2005; Rayton, Yalabik, & Rapti, 2019).

Person-environment (P-E) fit has evolved from a static understanding to a dynamic construct considering contextual and temporal changes (Guan, Deng, Fan, & Zhou, 2021; Tims, Derks, & Bakker, 2016). Contemporary research demonstrates P-E fit comprises multiple dimensions, with person-job (P-J) fit and person-organization (P-O) fit being most extensively studied (Kristof, 1996; Edwards J. , 2008). P-J fit refers to compatibility between individual characteristics and job requirements, while P-O fit addresses alignment between personal values and organizational culture (Zeng & Hu, 2024). These dimensions, alongside person-group and person-supervisor fit, form the broader P-E fit construct, which predicts organizational outcomes (Chuang, Shen, & Judge, 2015; Afsar, Badir, & Khan, 2015).

Despite developments in the P-E fit literature and AI applications, research gaps remain. First, previous research predominantly examined single fit dimensions in isolation, with limited integration in comprehensive frameworks (Padmasiri, Kailasapathy, & Jayawardana, 2019). Second, while AI adoption accelerated, systematic understanding of how technologies facilitate P-E fit matching remains limited (Zhang, Pan, Tang, & Yao, 2025). Third, most studies focus on Western contexts, leaving cross-cultural dynamics underexplored. Finally, ethical implications, including algorithmic bias, transparency, and fairness, require systematic examination (Goodman & Flaxman, 2017).

This systematic review addresses gaps by comprehensively examining the use of AI for P-J, P-O, and P-E matching. It offers theoretical contributions by integrating the P-E fit literature with AI developments, establishing connections between traditionally separate domains. It proposes a classification framework that incorporates three factors into a superordinate model to explain dynamic interactions (Guan, Deng, Fan, & Zhou, 2021; Milliman, Ausar, & Bradley-Geist, 2017), develops a thematic taxonomy that groups findings into antecedents, mediators/moderators, and outcomes, and explores AI-P-E fit linkages, including their impacts on job satisfaction, turnover, and organizational performance.

Practically, this research provides strategic implications across sectors. In technology industries, AI integration must consider technical efficiency and psychological/cultural impacts (Wu, Zhang, & Zhang, 2025; Ali, 2017). In traditional sectors transforming, implementation should be gradual, with comprehensive change management (Zacher, 2015; Rattanapon, Jorissen, Jones, & Ketkaew, 2023). For public organizations, adoption must prioritize transparency, accountability, and fairness while accommodating regulatory constraints (Cai, Wu, Xin, Chen, & Wu, 2020). The research scope is limited to peer-reviewed journals indexed in Scopus (2015-2025). It focuses on AI applications for employee placement and P-E fit matching, with a focus on the tourism industry.

2. LITERATURE REVIEW

2.1. Theoretical Framework of Person-Environment Fit

P-E fit has developed as a central construct in organizational psychology since the mid-20th century. Holland proposed that career satisfaction depends on congruence between personality types and work environment characteristics (Amalianita & Putri, 2020), establishing that individuals thrive when personal attributes align with environmental demands.

Kristof (1996) advanced the field by distinguishing between P-O fit (compatibility between individual values and organizational culture) and P-J fit (alignment between capabilities and job requirements, needs, and job supplies). P-O fit predicts organizational commitment, citizenship behavior, and retention (Chen, Yen, & Tsai, 2014), while P-J fit predicts task performance, job satisfaction, and engagement (Edwards J. R., 1991; Lu, Wang, Lu, Du, & Bakker, 2014). Edwards (2008) introduced distinctions between supplementary fit (individuals possess characteristics similar to others) and complementary fit (characteristics fill gaps or complete the environment).

Researchers developed comprehensive measurement instruments, including the Perceived Person-Environment Fit Scale (PPEFS), measuring five factors: person-job, person-organization, person-group, person-supervisor, and person-vocation fit (Chuang, Shen, & Judge, 2015). These factors exhibit differential predictive validity, suggesting the importance of examining multiple dimensions simultaneously (Andela, Doef, & Lheureux, 2019).

2.2. Artificial Intelligence in Human Resource Management

AI encompasses the ability of computer systems to perform tasks that require human intelligence, including visual perception, speech recognition, decision-making, and language translation (Russell & Norvig, 2020). In organizational contexts, AI includes machine learning, natural language processing, computer vision, and predictive analytics (Jordan & Mitchell, 2015), enabling systems to learn from data, identify patterns, and make predictions with minimal intervention.

AI applications have transformed talent management from recruitment to development. Professional platforms leverage AI algorithms to match job seekers with opportunities, analyze skill gaps, and provide career recommendations (Chiang & Suen, 2015). Applicant tracking systems employ natural language processing for resume screening, candidate ranking, and position matching. Chatbots handle HR inquiries, schedule interviews, and guide applicants through the application process (Paramita, Okwir, & Nuur, 2024). Predictive analytics forecast turnover, identify high-potential individuals, and recommend retention interventions in the hotel sector (Bakir, Ayoun, Wei, & Bilgihan, 2025).

In recruitment specifically, AI revolutionized each stage. Matching algorithms analyze candidate profiles and job requirements across multiple factors, considering skills, qualifications, cultural compatibility, career aspirations, and learning potential (Zhang, Pan, Tang, & Yao, 2025). These algorithms process vast datasets, including resumes and social media profiles, for comprehensive assessments. AI-based assessment tools evaluate candidates through gamified simulations that measure cognitive abilities, personality traits, and competencies (Paramita, Okwir, & Nuur, 2024).

As AI complexity increases, particularly with deep learning as a ‘black box,’ explainable AI (XAI) has emerged in recruitment. XAI refers to methods that make AI decisions transparent and interpretable (Zhang, Pan, Tang, & Yao, 2025). Techniques include Local Interpretable Model-agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP), providing feature importance scores, attention mechanisms that highlight prioritized information, and rule extraction, translating model behaviors into human-readable rules; however, implementation challenges persist regarding accuracy-interpretability trade-offs (Goodman & Flaxman, 2017).

2.3. Integration of AI with Person-Environment Fit

AI integration created new paradigms in human-technology relationships, known as human-AI collaboration, which affects hotel employees' quality of work life and work engagement (Wu, Zhang, & Zhang, 2025). This collaboration represents synergistic relationships where AI augments human capabilities while humans provide contextual judgment, ethical oversight, and creative problem-solving. In P-E fit contexts, individuals must not only fit with jobs and organizations but also adapt to working alongside AI systems.

Research indicates that AI awareness influences perceptions of P-E fit. When employees understand AI's capabilities and limitations, they experience less uncertainty about adopting technology (Liu, Lin, Tu, & Xu, 2025), facilitating realistic expectations about human-AI collaboration and reducing mismatches. AI awareness enables employees to identify opportunities to leverage technology to enhance performance, improving the demands-abilities fit through AI augmentation.

Trust in AI determines successful collaboration and the impact of P-E fit. Employees who trust AI are more willing to delegate tasks, accept recommendations, and engage collaboratively (Kong, Yin, Baruch, & Yuan, 2023). Trust develops through consistent performance, transparent explanations, and positive experiences. Conversely, trust erosion from errors, biases, or unexplainable decisions disrupts P-E fit.

AI has substantial potential to facilitate P-E fit matching, particularly P-J and P-O fit. In P-J contexts, machine learning algorithms analyze skill profiles and career trajectories to identify optimal matches, accounting for current capabilities and learning potential. (Zhang, Pan, Tang, & Yao, 2025). In P-O contexts, AI identifies value alignment through social media profiles, online activities, and personality assessments (Malik, Budhwar, Patel, & Srikanth, 2020).

3. RESEARCH METHODS

3.1. Research Design and Protocol

This study employed a systematic literature review methodology to identify, evaluate, and synthesize scientific literature on AI utilization for P-J, P-O, and P-E fit matching. A systematic review was chosen for rigorous, transparent, and replicable knowledge synthesis (Tranfield, Denyer, & Smart, 2003; Kitchenham & Charters, 2007). Unlike narrative reviews, systematic reviews follow structured protocols, minimizing bias and ensuring comprehensive coverage, enhancing reliability and validity for evidence-based conclusions (Lincoln & Guba, 1985).

The review followed Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher, Liberati, Tetzlaff, Altman, & The PRISMA Group, 2009), providing standardized approaches for conducting and reporting reviews through four phases: identification, screening, eligibility assessment, and inclusion. PRISMA checklist and flow diagram documented the process, identifying records at each stage (Page, et al., 2021; Siddaway, Wood, & Hedges, 2019).

3.2. Inclusion and Exclusion Criteria

Articles were included if: published in peer-reviewed journals indexed in Scopus; published 2015-2025, ensuring relevance with AI developments; written in English; focused on AI integration in P-J, P-O, or P-E fit matching; provided substantial theoretical/empirical contributions; and published in Q1-Q4 journals (González-Pereira, Guerrero-Bote, & Moya-Anegón, 2010).

Articles were excluded if: duplicates; lacked accessible abstracts/full texts; were not journal articles; did not directly address AI-P-E fit relationships; focused on contexts outside HR management; or were published in predatory journals (Grudniewicz, et al., 2019).

3.3. Literature Search Strategy

Scopus was selected for its comprehensive coverage across disciplines, indexing thousands of peer-reviewed journals, and offering advanced search capabilities and bibliometric tools (Baas, Schotten, Plume, Côté, & Karimi, 2020; Bergman, 2012; Rocha, Fialho, & Mendonça, 2020).

Search strings captured terminological variations in AI (artificial intelligence, machine learning, deep learning, intelligent systems) and P-E fit concepts (person-job fit, person-organization fit, person-environment fit, P-J fit, P-O fit, P-E fit, employee placement, talent matching, recruitment, selection). Boolean operators AND/OR combine terms, with searches limited to title, abstract, and keyword fields.

3.4. Article Selection Process

Initial Scopus searches yielded 174 articles. After removing duplicates, 109 unique articles remained for screening. Two independent researchers evaluated titles and abstracts, with disagreements resolved through discussion. Articles that were clearly irrelevant were excluded, leaving 88 for retrieval.

Full texts of 88 articles were obtained through institutional subscriptions, open access repositories, and author contacts. Twenty-seven articles were inaccessible. Through snowballing, 10 additional articles were identified, leaving 61 for eligibility assessment. Two independent researchers assessed full texts using standardized forms. All 61 articles met the inclusion criteria for final analysis.

3.5. Data Extraction and Synthesis

Data were extracted using standardized forms capturing bibliographic information, methodological characteristics, theoretical frameworks, findings, implications, and limitations (Aria & Cuccurullo, 2017). Two researchers independently conducted extraction for subsets, ensuring consistency, with discrepancies resolved through consensus (van Eck & Waltman, 2010).

Data synthesis used thematic analysis to identify patterns and themes (Braun & Clarke, 2006) Through six steps: familiarization through repeated reading; generating initial codes; searching for themes, organizing codes; reviewing themes, checking validity; defining and naming themes; and producing reports, selecting compelling examples. This iterative process enabled comprehensive synthesis (Rodgers, et al., 2006).

4. RESULTS AND DISCUSSION

4.1. Overview of Search Results

Initial Scopus searches yielded 174 articles. After identification, screening, and eligibility phases, 61 articles (51 from Scopus, 10 from other sources) were included in the final analysis. This rigorous PRISMA-guided process demonstrates strict application of inclusion criteria. The 65% exclusion rate reflects substantive focus requirements on AI-P-E fit integration and methodological quality standards.

Table 1. Summary of Article Selection Process Based on PRISMA

Stages	Number of Articles	Remarks
Identification	174	Initial search results in Scopus
After deduplication	142	32 duplicate articles deleted
After the period filter	120	22 articles outside the period 2015-2025
After the quartile filter	109	11 non-Q1-Q4 articles
Screening	88	21 irrelevant articles
Full text retrieval	51	37 articles are not accessible
Additional articles from other sources	10	Through snowballing
Total articles analyzed	**61**	**51 from Scopus + 10 from other sources**

Source: (Prisma, 2025)

4.2. Bibliometric Analysis

Publication trends reveal interesting dynamics in AI utilization for P-J, P-O, and P-E fit from 2015 to 2025. Publication numbers fluctuated, with the highest peak in 2020 (8 articles). Overall upward trends from 2015 to 2020 reflect growing scholarly interest following significant advances in machine learning and deep learning (Jordan & Mitchell, 2015). The 2020 peak is associated with COVID-19 and accelerated digital transformation, including AI adoption in remote recruitment (Malik, Budhwar, Patel, & Srikanth, 2020).

The geographical distribution shows that research is predominantly conducted in Asian countries, with China as the most significant contributor. Among 61 articles, China contributed 17 studies (27.9%), reflecting high AI R&D investment (Liao, 2022; Yang, Wang, & Bell, 2024; Wu, Zhang, & Zhang, 2025). Taiwan follows with six studies (9.8%), demonstrating East Asian concentration (Kim, Shin, Kim, Jun, & Wreen, 2023; Chuang, Shen, & Judge, 2015). Other contributors include India, South Korea, and European nations. Distribution reflects the technological infrastructure and cultural contexts in which AI adoption gained traction (Carstens, Koekemoer, & Masenge, 2021).

Table 2. Ten Countries with the Most Research Contributions

Ranking	Country	Number of Articles	Percentage
1	China	17	27,9%
2	India	6	9,8%
3	Taiwan	4	6,6%
4	South Korea	3	4,9%
5	Nigeria	2	3,3%
6	Thailand	2	3,3%
7	United States	2	3,3%
8	Belgium	2	3,3%
9	Portugal	1	1,6%
10	Poland	1	1,6%

Source: (Prisma, 2025)

Publication distribution by journal shows approximately 60% (37 articles) published in Q1 journals, indicating high quality. Leading journals include Journal of Vocational Behavior, Current Psychology, Journal of Managerial Psychology, and Computers in Human Behavior, reflecting an interdisciplinary nature integrating computer science, psychology, management, and organizational behavior. High Q1 representation suggests AI applications for P-E fit are recognized as significant research topics.

4.3. Methodological Characteristics

Quantitative approaches dominate with 80-85% (48 of 61 articles) employing this method. Cross-sectional surveys account for approximately 65% of quantitative studies examining relationships between variables at specific time points. Longitudinal studies account for 15% and provide insights into temporal dynamics (Soares, Rodrigues, & Rebelo, 2024; Tong, Wang, & Peng, 2015). Quantitative dominance reflects a preference for testing causal relationships and for statistical generalization.

Self-report questionnaires are most widely used (approximately 75%) and measure personality, job satisfaction, organizational commitment, turnover, and perceptions of P-E fit using established scales (Liao, 2022; Kim, Shin, Kim, Jun, & Wreen, 2023; Ugwu & Onyishi, 2020). Some use multi-source data from supervisors/colleagues, reducing common-method bias (Yang, Wang, & Bell, 2024; Chuang, Shen, & Judge, 2015). Secondary data from organizational systems appear in 15% of studies.

Structural Equation Modeling (SEM) dominates analysis techniques (approximately 40% or 22 articles) for testing complex relationships, including mediation/moderation, and assessing measurement/structural models simultaneously (Ghetta, Hirschi, Wang, Rossier, & Herrmann, 2020; Liao, 2022; Yang, Wang, & Bell, 2024; Kong, Yin, Baruch, & Yuan, 2023). Regression analysis (25%) examines predictive relationships, while Hayes PROCESS macro (10%) tests mediation/moderation (Rayton, Yalabik, & Rapti, 2019; Xu, Liu, Chen, & Feng, 2023). Advanced techniques like hierarchical linear modeling and machine learning appear in 10% of the papers, reflecting increasing analytical sophistication.

4.4. Substantive Findings

The theoretical framework analysis shows that P-E Fit Theory is the most widely used, appearing in 21 studies (34.4%), underscoring the importance of individual-environment fit (Kristof, 1996; Edwards J. , 2008). The Job Demands-Resources Theory appears in 8 studies

(13.1%), framing AI as a resource or a demand (Bakker & Demerouti, 2007). Self-Determination Theory was used in 6 studies (9.8%) examining AI effects on autonomy, competence, and relatedness. Other theories include Social Exchange Theory, specific P-J/P-O Fit variants, and emerging frameworks such as the Technology Acceptance Model and Human-AI Collaboration Theory, reflecting an interdisciplinary nature.

Variable analysis indicates that P-O and P-J fit are the most frequently studied (10 and 9 studies, respectively, with 294 and 282 citations) (Kristof-Brown, Zimmerman, & Johnson, 2005; Cable & DeRue, 2002). Job satisfaction is the most common outcome across 12 studies, followed by organizational commitment and turnover (Rayton, Yalabik, & Rapti, 2019; Amarneh, Raza, Matloob, Alharbi, & Abbasi, 2021). Antecedent variables include proactive personality, psychological capital, career calling, and self-efficacy (Liao, 2022; Xu, Liu, Chen, & Feng, 2023). Mediators include job crafting, work engagement, and trust in AI (Lu, Wang, Lu, Du, & Bakker, 2014; Kong, Yin, Baruch, & Yuan, 2023). Moderators include job autonomy, organizational support, and AI awareness.

Findings demonstrate that AI integration with P-E fit enhances HR process effectiveness. AI is utilized across employee lifecycles from recruitment to development and retention. In recruitment, AI-powered screening analyzes thousands of applications quickly, identifying the highest P-E fit potential candidates (Chiang & Suen, 2015; Zhang, Pan, Tang, & Yao, 2025). Algorithms consider technical skills, qualifications, cultural compatibility, values alignment, and personality to predict successful integration (Malik, Budhwar, Patel, & Srikanth, 2020).

Research by Wu et al. (2025) demonstrates that human-AI collaboration improves the quality of work life when P-J fit is high, indicating AI effectiveness in contexts where employees already feel compatible with AI. When P-J fit is low, AI introduction may exacerbate problems by adding complexity without addressing fundamental mismatches, underscoring the importance of P-E fit as a foundation for successful AI implementation rather than viewing AI as a solution to poor fit (Kong, Yin, Baruch, & Yuan, 2023; Bakir, Ayoun, Wei, & Bilgihan, 2025).

4.5. Interpretation and Implications

Findings indicate P-E Fit Theory dominates (21 of 61 studies, 34.4%), explaining that fit impacts job satisfaction, commitment, and performance (Kristof, 1996). In AI contexts, P-E fit provides a valuable lens for understanding how technology changes work environment characteristics and individual needs. However, traditional theory requires expansion to accommodate technological dimensions, specifically person-technology fit as an additional dimension, recognizing that individuals must fit with jobs, organizations, and AI systems that mediate work activities (Guan, Deng, Fan, & Zhou, 2021).

AI has dual roles as both a facilitator and a potential disruptor. As a facilitator, AI enhances recruitment efficiency by automating screening and analyzing data, reducing recruitment time by up to 30% while improving matching accuracy (Paramita, Okwir, & Nuur, 2024). Machine learning identifies patterns human recruiters might overlook, potentially reducing hiring errors and increasing retention (Chiang & Suen, 2015). However, challenges include algorithmic bias, transparency concerns, and the need for explainable AI. Algorithms trained on historical data may perpetuate biases, potentially discriminating against underrepresented groups (Zhang, Pan, Tang, & Yao, 2025), necessitating careful design, ongoing bias monitoring, and accountability mechanisms (Goodman & Flaxman, 2017).

Quantitative approaches dominate (80-85%), particularly cross-sectional designs with SEM. This reflects preferences for testing causal relationships and generalization. However, cross-sectional designs limit understanding of temporal dynamics, and reliance on self-report increases the risk of common method bias. The field would benefit from longitudinal studies examining the evolution of AI-mediated P-E fit (Soares, Rodrigues, & Rebelo, 2024), qualitative research providing contextual understanding of individual experiences (Malik, Budhwar, Patel,

& Srikanth, 2020; Paramita, Okwir, & Nuur, 2024), and mixed-methods approaches combining quantitative rigor with qualitative depth.

Research focuses on Asia, particularly China (27.9%) and Taiwan (9.8%), reflecting substantial AI investment driven by supportive government policies and robust technological infrastructure. However, this limits generalization as AI perceptions and P-E fit priorities may differ across cultures. Individualistic Western cultures may prioritize P-J fit, emphasizing individual achievement, while collectivistic Eastern cultures may emphasize P-O and person-group fit, reflecting harmony and belongingness values (Kim, Shin, Kim, Jun, & Wreen, 2023). Future research should include diverse geographical contexts and cross-cultural comparative studies examining how cultural values moderate AI adoption-P-E fit relationships.

CONCLUSION

Based on the Theory, Context, Methodology framework analysis, the findings indicate that research on AI for P-J, P-O, and P-E matching has developed significantly over the past decade, with P-E Fit Theory dominating. Theoretically, P-E fit-AI integration opened new avenues for understanding how technology facilitates precise and efficient matching (Zhang, Pan, Tang, & Yao, 2025). Emerging concepts, including person-technology fit, AI awareness, and trust in AI, mark necessary conceptual transformations in understanding fit in the digital era (Kong, Yin, Baruch, & Yuan, 2023; Liu, Lin, Tu, & Xu, 2025). However, theoretical development requires further advancement to address the complexities of human-AI collaboration and the long-term impacts of AI-mediated matching on career development and organizational performance (Wu, Zhang, & Zhang, 2025).

In this context, extensive research in Asian countries, particularly China, indicates a strong interest in integrating technology into HR management (Liao, 2022; Yang, Wang, & Bell, 2024). Studies from developed countries provide significant contributions regarding ethical considerations and AI regulation (Goodman & Flaxman, 2017). This geographical diversity enriches the understanding of AI implementation variations across legal, cultural, and institutional environments. However, gaps remain in developing-country contexts, SMEs, and public-sector organizations, where AI adoption patterns may differ from those of large private-sector organizations that dominate the current literature.

Methodologically, quantitative approaches dominate (approximately 80%), employing cross-sectional/longitudinal surveys and SEM testing complex relationships. While quantitative methods provide rigor and generalizability, qualitative methods gain attention by providing deeper contextual understanding (Malik, Budhwar, Patel, & Srikanth, 2020; Paramita, Okwir, & Nuur, 2024). Future research would benefit from mixed-methods approaches combining quantitative hypothesis testing with qualitative exploration of mechanisms and contextual factors (Tracy, 2010).

Overall, the findings demonstrate that research on AI for P-J, P-O, and P-E matching remains highly relevant and addresses digital transformation challenges. Future challenges include addressing algorithmic bias, enhancing AI transparency, and integrating technology intelligently with individual and organizational needs (Zhang, Pan, Tang, & Yao, 2025; Bakir, Ayoun, Wei, & Bilgihan, 2025). In practice, organizations implementing AI-enhanced placement systems should prioritize explainability and transparency, invest in AI literacy programs, establish mechanisms for bias detection and mitigation, adopt hybrid human-AI approaches that leverage complementary strengths, and maintain a holistic P-E fit focus rather than a narrow technical match. This review proposes Augmented Person-Environment Fit Theory, incorporating person-technology fit as an essential dimension, recognizing that successful contemporary organizational functioning requires alignment between people and jobs/organizations and technological systems mediating work activities (Guan, Deng, Fan, & Zhou, 2021). This research can also be applied in the tourism industry (hotels, restaurants, tour operators, attractions) in

Indonesia and across countries, thereby advancing theoretical literature on P-J, P-O, P-E Fit, and the application of AI in HR management.

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