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Enhancing Employee Performance through AI-Enabled HR Analytics: Exploring the Roles of Job Crafting, Perceived Risk, and Employee Engagement

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Abstract

This study investigates the significant impact of AI-enabled HR analytics on employee and sustainable performance, highlighting the mediating role of job crafting and the moderating effects of perceived risk and employee engagement in manufacturing organisations in Bandung, Indonesia. Drawing on cross-sectional data from 349 employees in manufacturing firms in Bandung, Indonesia, this study provides empirical evidence of the positive influence of AI-enabled HR analytics on long-term employee performance. The research utilises JD-R theory to validate the mediating role of job crafting in this relationship. Partial Least Square (PLS) analysis, conducted using SMART PLS 3.0 software, was applied to test the model. The results demonstrate that AI-enabled HR analytics significantly impacts job crafting. Additionally, job crafting mediates the relationship between AI-enabled HR analytics and both sustainable performance and employee performance. Perceived risk moderates the relationship between job crafting and both performance outcomes. Similarly, employee engagement moderates the relationship between job crafting and both sustainable and employee performance. This study is among the first to empirically examine the use of AI-enabled HR analytics in the context of job crafting and its effects on sustainable and employee performance. It provides valuable insights for managers and business leaders seeking to leverage AI to enhance employee sustainability and performance in diverse organizational settings.

Keywords

AI-enabled HR Analytics, Job Crafting, Perceived Risk, Employee Engagement, Employee Performance, Sustainable Performance, JD-R Theory

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1. Introduction

In today's competitive business environment, enhancing employee performance is a critical priority for organizations seeking to remain productive (Arora et al., 2024). One of the most promising approaches involves leveraging artificial intelligence (AI) in human resource analytics. AI-enabled HR analytics has revolutionized human resource practices, enabling companies to collect and analyze employee data (Huang et al., 2023). These advanced tools help interpret employee attitudes, work patterns, and performance metrics. Despite the progress in understanding how AI-enabled HR analytics can enhance employee performance, increasing employee productivity and promoting a sense of belonging remain central to motivation efforts (Arora et al., 2024). Performance, of same citation (Sugiarti et al., 2021), is essentially a reflection of an employee's performance appraisal. However, unlocking an employee's full potential requires an understanding of how the dynamic relationships between job crafting, perceived risk, and employee engagement impact sustainable employee performance. In the face of increasing competition, organizations must continuously devise new

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strategies to maximize human capital, which is seen as a crucial driver of long-term success (Mousa & Othman, 2020). As nations advance in a fast-paced economy, demands on energy and sustainability become more pressing. This growing motorization and urbanization present further challenges to environmental sustainability (Malik et al., 2021).

Technological advances, such as AI, machine learning, deep learning, chatbots, and big data, have been key drivers of transformation in human resource management during the Fourth Industrial Revolution (Xiao et al., 2023). The widespread use of these technologies has dramatically reshaped HR analytics, workplace communication, job design, employee engagement, and decision-making processes (Jangbahadur et al., 2024; Teune, 2023). Although different terminologies are used to describe these concepts, such as people analytics (Shahzad et al., 2023), HR analytics (Yusliza et al., 2020), and human capital analytics (Cavanagh et al., 2021), they all refer to AI-enabled techniques aimed at improving employee management through data-driven HR decisions. Previous research highlights how AI-enabled HR analytics can provide advanced diagnostic and predictive functions that enhance both employee and organizational performance (Chatterjee et al., 2022). Businesses often use AI-enabled HR analytics to gather and analyze large volumes of real-time data, offering a comprehensive understanding of the workforce (Cavanagh et al., 2023; Cavanagh et al., 2021; Xiao et al., 2023). Job crafting—employees' proactive efforts to modify task, relational, or cognitive aspects of their job—has been a focal point in the literature on job design (Harju et al., 2021). Studies have shown positive correlations between job crafting and employee health, job satisfaction, work engagement, and overall performance (Zhang et al., 2021). Organizations also benefit from these behaviors through enhanced team and organizational outcomes. For example, job crafting is linked with positive personality traits (Tims et al., 2012), self-esteem (Kuijpers et al., 2020), and regulatory focus (Hu et al., 2020), as well as workplace autonomy (Zhang & Liu, 2021) and workplace resources (Wang et al., 2020). Approach crafting, which involves proactive job modification, improves employee (Tims & Parker, 2020; Wang et al., 2020; Xiao et al., 2023; Zhang & Liu, 2021; Zhang et al., 2021) and engagement (Kuijpers et al., 2020; Lazazzara et al., 2020), while avoidance crafting has been associated with negative outcomes, such as poorer performance and increased employee fatigue (Harju et al., 2021).

Perceived risk has also been identified as a key factor influencing sustainable employee performance (Almaiah et al., 2022). Workers may experience uncertainty or apprehension when making technology-related decisions, which can impact long-term performance. Risk perception involves both the likelihood of harm and the extent of its potential consequences (Jeon et al., 2020). It is a multifaceted concept shaped by psychological, social, and cultural factors (Kaur & Arora, 2020); (Lăzăroiu et al., 2020). Employee engagement, another critical aspect, has emerged as an essential factor in shaping organizational outcomes (Chandni & Rahman, 2020). Engagement has been shown to interact with variables like employee voice and performance management, contributing significantly to employee performance (Rattrie et al., 2020). This study examines the impact of AI-enabled HR analytics on employee performance, with a focus on job crafting, perceived risk, and employee engagement. Using cross-sectional data from a range of organizations, this research employs structural equation modeling through partial least squares (PLS-SEM). The study's background and hypothesis development are presented in Section 2 and 3, followed by the methodology in Section 4. Data analysis and findings are discussed in Sections 5 and 6, and the implications for theory and practice are outlined in Section 7. The paper concludes with a discussion of limitations and directions for future research.

2. Literature Review

2.1. Background

2.1.1. Sustainable performance and employee performance

Sustainable performance and employee performance are crucial for the long-term success of organizations (Piwowar-Sulej & Iqbal, 2023). Employee performance refers to the quality and quantity of work produced in fulfilling assigned responsibilities (Phina et al., 2018). Sustainable performance, on the other hand, is the organization's ability to achieve its goals over time while balancing economic, social, and environmental outcomes (Mousa & Othman, 2020). "The primary guidance emerging from changing working conditions is that a business's social responsibility is to manage its resources efficiently and engage in profitable ventures that contribute to long-term success (Udin, 2024). Achieving sustainable performance requires creating an environment where employees are engaged and aligned with the company's objectives (Chowdhury et al., 2022). Organizations are increasingly driven to adopt sustainable practices to gain long-term economic benefits (Chowdhury et al., 2022). There is growing pressure from stakeholders to meet not only financial targets but also voluntary environmental and social goals (Mousa & Othman, 2020). Sustainable business practices are closely linked to corporate social responsibility, integrating ecological, environmental, and social aspects (Iqbal et al., 2021; Iqbal et al., 2020). Companies that reduce their environmental and societal impact can sustain themselves over time (Yusliza et al., 2020). Sustainable organizations prioritize reducing resource consumption, emissions, and environmental impact while delivering value to various stakeholders (Chowdhury et al., 2022). Systemic thinking and management development are critical for achieving sustainable performance, similar to the approach taken by sustainable leaders who consider long-term outcomes (Piwowar-Sulej & Iqbal, 2023).

2.1.2. AI-enabled HR analytics

AI-enabled HR analytics marks a significant shift in human resource management, revolutionizing how organizations manage and develop their workforce. These analytics enable companies to gather and analyze employee data, offering predictive capabilities to anticipate employee needs, forecast turnover, and identify skill gaps (Cavanagh et al., 2023; Danilwan et al., 2020). An increasing number of organizations are utilizing AI in HR analytics to manage workforce data and optimize HR functions, including employee performance management, recruitment, retention, and training (Jangbahadur et al., 2024). The adoption of AI-enabled HR analytics has led to improvements in business performance, financial outcomes, and return on investment (Teune, 2023). By leveraging advanced data analysis techniques, HR analytics can drive positive workplace changes (Xiao et al., 2023). Furthermore, the growing use of AI in HR opens new opportunities to enhance the employee experience (Papa et al., 2020). As technology continues to evolve, AI's role in workforce management will expand, enabling organizations to build a more resilient, engaged, and adaptable workforce, ultimately improving performance (Jangbahadur et al., 2024).

2.1.3. Job crafting

Job crafting refers to the actions employees take to modify or reframe their roles, allowing them to find new meaning and satisfaction in their work (Tims et al., 2012). It is an employee-driven process, giving individuals the autonomy to reshape job elements to enhance their sense of purpose and fulfillment. This may involve taking on new tasks, changing how work is performed, or altering relationships with colleagues. By tailoring their jobs to align with their skills and goals, employees experience greater job satisfaction, engagement, and improved performance. Job crafting involves altering task and relational resources and job demands based on well-established situational theoretical frameworks (Tims & Parker, 2020; Zhang & Liu, 2021). A self-aware approach is required for employees to interpret the motivational benefits of redesigning work. Researchers have further advanced the concept of job crafting by linking it with role identity formation in the workplace. Encouraging job crafting helps organizations stay competitive by assisting adaptability and creativity among employees. Studies have shown that when employees are empowered to design their roles, they are more engaged and motivated, leading to increased productivity and organizational commitment

(Harju et al., 2021; Tims et al., 2012; Zhang & Liu, 2021). However, it is essential to ensure that job crafting aligns with organizational goals to prevent role ambiguity or conflict (Zhang et al., 2021).

3. Hypothesis Development

3.1. AI-enabled HR Analytic and Job Crafting

The study explores how AI-enabled HR analytics influences employee outcomes through job crafting using an HR process framework (Teune, 2023). AI-driven HR analytics offers organisations data-driven insights that help understand employees' strengths, preferences, and areas for development (Xiao et al., 2023). These insights allow managers and employees to adjust job roles, aligning them with individual skills and goals. Research highlights how AI-powered solutions can provide tailored career advice, promoting skill development and enabling employees to reshape their roles to enhance performance and engagement. Effective adoption of AI in HR systems depends on consistent employee perceptions. The communication of HR activities significantly shapes employees' understanding and perception of HRM systems (Wang et al., 2020). This study examines how collective employee perceptions of AI-enabled HR systems influence job crafting, contributing to existing research on the subject. While HR analytics is viewed as a critical workplace tool, less attention has been given to how personal resources may moderate the relationship between HR analytics and employee outcomes (Jangbahadur et al., 2024; Malik et al., 2021; Mousa & Othman, 2020; Paais & Pattiruhu, 2020). AI tools assist employees in identifying inefficiencies and suggesting optimisations, motivating individuals to reinterpret their roles to promote both personal and professional development. This feedback loop enhances employees' control and autonomy, key components of job crafting (Xiao et al., 2023). Furthermore, AI-enabled HR analytics creates a structured environment for employees to experiment with role configurations, reducing risks associated with job crafting, such as ambiguity or misalignment with organisational goals (Lazazzara et al., 2020; Tims & Parker, 2020). AI ensures that role modifications remain aligned with broader organisational objectives (Wang et al., 2020).

H1: AI-enabled HR analytics significantly influences job crafting.

3.2. Mediating Role of Job Crafting

AI-enabled HR analytics provides valuable insights that improve organisational processes and employee performance. Job crafting acts as a mediator in this process by enhancing employee engagement, adaptability, and creativity. This link bridges the technological capabilities of AI-driven analytics with long-term organisational sustainability (Iqbal et al., 2021; Xiao et al., 2023). Employees who actively engage in job crafting demonstrate higher commitment, which increases motivation and job satisfaction—key factors for long-term success. Motivated employees are more productive, experience less burnout, and contribute positively to achieving long-term business goals, promoting sustained success (Almaiah et al., 2022). Numerous studies highlight the potential benefits AI and HR analytics offer to both employees and organisations (Iqbal et al., 2021). With access to extensive employee data and real-time insights, organisations can gain a deeper understanding of their workforce, leading to improved performance outcomes (Jangbahadur et al., 2024). While research on the impact of AI-HR analytics on organisational performance is growing, there has been less focus on its effects on employee well-being. Few studies have explored the mechanisms through which AI-HR analytics shapes both employee and organisational performance (Teune, 2023; Xiao et al., 2023). An employee's performance is determined by the quality and amount of work that he or she produces in fulfilling their assigned obligations (Danilwan et al., 2020; Jangbahadur et al., 2024). Job crafting enables employees to manage the continuous feedback provided by AI-enabled HR analytics, allowing them to adjust their roles as needed. This adaptability is critical for long-term performance improvements. By integrating AI insights into their daily responsibilities, employees gain control and ownership over their work, rather than feeling overwhelmed by the data. This proactive approach encourages employees to innovate and take initiative in addressing workplace challenges, whereby enhancing their overall performance (Chandni & Rahman, 2020; Harju et al., 2021). The theoretical and empirical evidence supports the connection between HR analytics and job crafting, as well as job crafting's role in AI-HR analytics' impact on performance.

H2: Job crafting mediates the relationship between AI-enabled HR analytics and sustainable performance.

H3: Job crafting mediates the relationship between AI-enabled HR analytics and employee performance.

3.3. Moderating Role of Perceived Risk

Perceived risk refers to the potential loss employees may face when pursuing desired goals, such as fear of job loss, career failure, or organisational instability (Almaiah et al., 2022). Employees exposed to high levels of risk may be less inclined to engage in job crafting due to concerns that modifying work tasks or responsibilities could result in negative consequences, such as appearing incompetent or becoming less relevant in a changing workplace (Lăzăroiu et al., 2020). In high-risk environments, employees often adopt a defensive approach, avoiding proactive efforts to enhance their roles, which can limit their contributions to sustainable performance. Since job crafting plays a critical role in furthering creativity, engagement, and long-term adaptability, this hesitation can hinder both individual and organisational growth. Employees who are restricted from modifying their jobs in alignment with organisational goals are less likely to make meaningful contributions (Ventre & Kolbe, 2020). Conversely, in low-risk environments, where employees perceive greater job security, they are more likely to feel empowered to engage in job crafting. In such contexts, employees are more inclined to experiment, take initiative, and align their roles with both their personal strengths and the organisation's sustainability objectives. This leads to higher levels of engagement, creativity, and innovation—key components of sustainable performance. In these low-risk environments, job crafting creates a positive cycle where employees continuously adapt to changing conditions, enhancing both organisational and individual resilience.

Job crafting behaviours can be categorised into two higher-order constructs: approach and avoidance crafting (Hu et al., 2020). These categories reflect whether employees make behavioural or cognitive changes and whether they focus on altering job demands or job resources (Lazazzara et al., 2020). Approach crafting involves proactive efforts to increase job resources and enhance work roles, while avoidance crafting relates to efforts aimed at reducing job demands. These different crafting strategies influence performance outcomes depending on the level of perceived risk in the workplace. Economic sustainable performance of same citation (Paais & Pattiruhu, 2020), focuses on market share growth, return on assets, and organisational cost reduction and profit within the context of income development (Piwowar-Sulej & Iqbal, 2023). By reducing uncertainty, promoting psychological safety, and promoting experimentation, organisations can create an environment where employees feel comfortable modifying their roles to improve both individual and organisational performance.

H4: Perceived risk moderates the relationship between job crafting and sustainable performance.

H5: Perceived risk moderates the relationship between job crafting and employee performance.

3.4. Moderating Role of Employee Engagement

Employee engagement refers to the psychological state in which employees invest their mental, emotional, and physical energy into their work, resulting in varying performance outcomes depending on the level of effort (Chandni & Rahman, 2020). A high level of commitment, enthusiasm, and passion reflects employee engagement, which plays a crucial role in enhancing the effectiveness of job crafting (Rattrie et al., 2020). Engaged employees are more likely to take proactive steps to modify their roles in ways that align better with their skills and interests, contributing to the organisation's long-term success. Through job crafting, employees adjust their responsibilities, relationships, and work environments to increase job satisfaction and better align with their strengths (Nienaber & Martins, 2020). The level of employee engagement significantly influences the extent to which individuals engage in job crafting. Highly engaged employees are more motivated and enthusiastic about their work, prompting them to seek opportunities to craft their roles, in that way improving productivity and meeting organisational goals (Riyanto et al., 2021). Job crafting, in this context, becomes a tool for enhancing employee engagement as workers actively reshape their work environments in meaningful ways. However, when engagement is low, the relationship between job crafting and employee performance weakens. Disengaged employees may lack the motivation to invest the time and effort required for role modifications. This lack of engagement may lead to adherence to rigid job structures that stifle potential, resulting in missed opportunities for performance improvement (Jangbahadur et al., 2024).

Low engagement can lead to decreased job satisfaction and overall productivity, as disengaged employees may feel demoralised or indifferent toward their roles, further limiting their participation in job crafting activities. This inertia can negatively impact performance, reducing both job satisfaction and overall organisational productivity. High employee performance is crucial for delivering quality services and boosting profitability, which in turn generates a sustainable competitive advantage (Khan, 2022). Sustainable business practices, closely linked to corporate social responsibility, create opportunities for businesses to thrive by balancing environmental, social, and organisational considerations (Malik et al., 2021; Sugiarti et al., 2021). By integrating ecological and social performance, businesses can achieve long-term sustainability. Corporate organisations face increasing pressure from various stakeholders to meet both financial objectives and voluntary environmental and social goals. Sustainable performance is measured by considering the company's impact on the environment, society, and economy, as well as its ability to address the needs of all stakeholders (Paais & Pattiruhu, 2020; Yusliza et al., 2020).

H6: Employee engagement moderates the relationship between job crafting and sustainable performance.

H7: Employee engagement moderates the relationship between job crafting and employee performance.

The suggested study model and hypotheses based on the foregoing explanation are presented as follows:

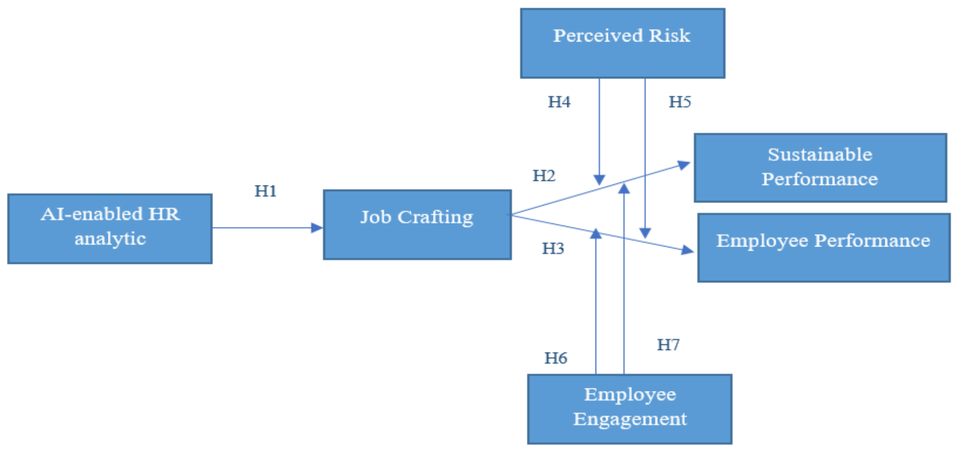

Figure 1: Conceptual Framework

4. Methodology

4.1. Instrument Development

The instruments employed in this study are well-established, with a strong track record of validity, ensuring the reliability of the results.

4.1.1. Research constructs

The constructs measured in this study were based on the following scales:

A. AI-Enabled HR Analytics (Cavanagh et al., 2023)

- AIHR1: "I intend to use HR analytics applications for different purposes."
- AIHR2: "I am comfortable using different HR analytics applications."
- AIHR3: "It is easy to use HR analytics applications."
- AIHR4: "People should be trained to use HR analytics applications appropriately."
- AIHR5: "Different authentication levels (guidelines) should be established for using HR analytics applications."

B. Job Crafting (Tims et al., 2012)

- JC1: "I try to develop my capabilities."
- JC2: "I try to develop myself professionally."
- JC3: "I try to learn new things at work."
- JC4: "I make sure my work is mentally less intense."
- JC5: "I try to ensure that my work is emotionally less intense."
- JC6: "I ask my supervisor for coaching."
- JC7: "When an interesting project arises, I proactively offer myself as a co-worker."

C. Perceived Risk (Falco et al., 2021)

- PR1: "When AI is used, my data may fall into the wrong hands."
- PR2: "I have reservations when computers examine scans without human intervention."
- PR3: "AI makes healthcare staff lazy."
- PR4: "The replacement of doctors by AI will happen in the far future."
- PR5: "AI should only support human judgment."

D. Employee Engagement (Soane et al., 2012)

- EE1: "I focus hard on my work."

- EE2: "I concentrate on my work."
- EE3: "I pay close attention to my work."
- EE4: "I share the same work values as my colleagues."
- EE5: "I share the same work goals as my colleagues."
- EE6: "I share the same work attitudes as my colleagues."
- EE7: "I feel positive about my work."
- EE8: "I feel energetic in my work."
- EE9: "I am enthusiastic in my work."

E. Sustainable Performance (Iqbal et al., 2020)

- SP1: "Increase the volume of recycled materials and reduce waste."
- SP2: "Commitment to separating medical waste from the public sewage system."
- SP3: "Increase the rate of purchasing environmentally friendly goods."
- SP4: "Reduce the cost of energy use."
- SP5: "Reduce processing fees and waste disposal."
- SP6: "Develop economic activities in the community and provide more job opportunities."
- SP7: "Reduce the impact of the organization's waste on the community."
- SP8: "Improve the quality of service provided, adhering to the code of ethics."

F. Employee Performance (Phina et al., 2018)

- EP1: "To what extent can you perform effectively and understand your job description?"
- EP2: "To what extent do you understand job performance requirements and the standards expected?"
- EP3: "To what extent does your superior review your job description and performance requirements?"
- EP4: "To what extent is your job performance reviewed and rescheduled?"
- EP5: "To what extent does your job description reflect the reality of your position?"

All constructs were measured using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Demographic information was collected in a separate section.

4.2. Instrument Validity and Reliability

To ensure content validity, the survey instrument was developed following expert recommendations and existing validated research scales (Cooper & Schindler, 2014; Staub et al., 2004). Several reflective items from prior research were selected based on their relevance and clarity.

- Four academic experts evaluated the questionnaire's length, relevance, and layout. While the measures captured the key variables, the panel suggested minor adjustments to align with the study objectives.

- A pilot study was conducted with a small group of employees, resulting in minor revisions to survey length and formatting.

4.3. Data Collection and Adequacy

A total of 450 questionnaires were distributed among employees working in manufacturing organisations in Bandung, Indonesia. Of these, 340 questionnaires were returned, yielding a response rate of over 75%. These surveys were conducted through direct interaction with the employees, providing explanations where necessary. Respondents were assured that their information would remain confidential. This research employed a quantitative approach. Convenience sampling was used, targeting available employees willing to complete the questionnaire.

5. Analysis and Results

5.1. Sample Profile

Table 1 outlines the demographics of the respondents. The majority were male (72.7%), while 27.3% were female. The largest age group was between 20 and 30 years (32.6%), followed by those aged 30-40 years (27.3%), more than 40 years (20.5%), and less than 20 years (19.4%). Most respondents had 4-8 years of experience (39.7%), and the largest share of respondents worked in the managers/marketing/sales department (35.2%)

Table1: Sample Profile

Demographics	Responses	Percentages %
Gender		
Male	247	72.7
Female	93	27.3
Age		
Less than 20 Years	66	19.4
20-30 Years	111	32.6
30-40 Years	93	27.3
More than 40 Years	70	20.5
Experience		
Less than 3 Years	115	33.8
4-8 Years	135	39.7
More than 10 Years	90	26.4
Department		
CEO/Director	20	5.8
Manager/Marketing/Sales	120	35.2
IT/MIS	105	30.8
HR/ Finance	70	20.5
Others	45	13.2

5.2. Assessment of Measurement Model

Model measurement and assessment were conducted using Structural Equation Modeling (SEM). This methodology is favored in research that predicts correlations between variables in theoretical models, as it accounts for measurement error when analyzing statistical data (Hair et al., 2024). Both variance-based and covariance-based SEM approaches are available. For data analysis, the Partial Least Squares (PLS) approach with variance-based SEM is employed. Originally developed for predictive purposes, PLS-SEM can be utilized for both formative and reflective measurement models (Hair et al., 2024). Additionally, PLS-SEM does not always necessitate multivariate normal sample data, as it operates as a component-based method (Hair et al., 2024). The resampling methods employed in PLS-SEM are not restricted to meeting parametric assumptions (Hair et al., 2024). This method also demonstrates less sensitivity to sample size compared to covariance-based approaches, permitting the use of smaller samples (Hair et al., 2024). Furthermore, PLS-SEM can validate exploratory models for theory development and estimate both hidden and manifest variables in complex models. As indicated in Table 2, all measurement items exhibit standardized factor loadings close to -1 or 1, signifying a substantial influence of the factor on the variable. Loadings near zero suggest that the factor has minimal effect on the variable.

Table 2: Cross-Loading

	AIHR	EE	EP	JC	PR	SP
AIHR1	.753	-.550	.537	.538	.525	.610
AIHR2	.815	-.539	.541	.430	.461	.557
AIHR3	.864	-.594	.611	.546	.541	.632
AIHR4	.770	-.440	.467	.445	.553	.549
AIHR5	.823	-.511	.567	.611	.542	.631
EE1	-.596	.814	-.639	-.541	-.697	-.639
EE2	-.451	.794	-.532	-.416	-.590	-.501
EE3	-.529	.744	-.492	-.357	-.559	-.536
EE4	-.475	.780	-.475	-.495	-.597	-.555
EE5	-.440	.788	-.522	-.431	-.580	-.557
EE6	-.460	.810	-.491	-.451	-.551	-.540
EE7	-.484	.829	-.516	-.529	-.630	-.569
EE8	-.566	.715	-.522	-.482	-.605	-.553
EE9	-.642	.855	-.632	-.647	-.688	-.653
EP1	.481	-.556	.823	.528	.642	.713
EP2	.624	-.628	.819	.529	.622	.754
EP3	.552	-.607	.848	.531	.708	.758
EP4	.589	-.450	.775	.549	.535	.678
EP5	.443	-.429	.682	.560	.456	.610
JC1	.462	-.466	.530	.693	.508	.547
JC2	.486	-.455	.493	.783	.564	.474
JC3	.551	-.514	.580	.782	.494	.669
JC4	.506	-.449	.540	.809	.501	.581
JC5	.447	-.485	.435	.756	.475	.493
JC6	.529	-.492	.522	.763	.494	.552
JC7	.378	-.330	.405	.626	.361	.432
PR1	.589	-.772	.571	.621	.752	.637
PR2	.601	-.728	.566	.551	.854	.646
PR3	.583	-.695	.606	.589	.883	.692
PR4	.482	-.518	.693	.463	.838	.701

PR5	.490	-.557	.707	.522	.852	.702
SP1	.516	-.562	.802	.545	.711	.784
SP2	.656	-.658	.818	.554	.698	.834
SP3	.573	-.617	.797	.521	.774	.821
SP4	.593	-.452	.717	.529	.597	.744
SP5	.476	-.444	.643	.549	.543	.698
SP6	.647	-.569	.563	.545	.543	.762
SP7	.432	-.433	.394	.495	.430	.646
SP8	.566	-.547	.520	.641	.496	.698

Note: EE="Employee Engagement", AIHR="AI-Enabled HR Analytics", EP="Employee Performance", JC="Job Crafting", PR="Perceived Risk", SP="Sustainable Performance".

All variables demonstrated acceptable composite reliability (CR) values ranging from 0.60 to 0.70, while Cronbach's alpha (α) values varied between 0.850 and 0.926. The rule of thumb suggests that a Cronbach's alpha value of 0.70 or higher is considered satisfactory (Hair et al., 2024). Additionally, the average variance extracted (AVE) values should not fall below 0.5 to indicate an acceptable level of convergent validity.

Table 3: Discriminant Validity

	α	**Rho-A**	**CR**	**AVE**	**AIHR**	**EE**	**EP**	**JC**	**PR**	**SP**
AI HR	0.865	0.874	0.902	0.650	0.806					
EE	0.926	0.929	0.938	0.629	0.656	0.793				
EP	0.850	0.858	0.893	0.627	0.680	0.681	0.792			
JC	0.867	0.873	0.898	0.558	0.648	0.616	0.677	0.747		
PR	0.892	0.895	0.921	0.700	0.652	0.774	0.756	0.653	0.837	
SP	0.888	0.895	0.911	0.564	0.744	0.719	0.790	0.726	0.810	0.751

Note: CA="Cronbach Alpha", CR="Composite Reliability", AVE="Average Variance Extracted", EE="Employee Engagement", AIHR="AI-Enabled HR Analytics", EP="Employee Performance", JC="Job Crafting", PR="Perceived Risk", SP="Sustainable Performance".

Subsequently, the HTMT criterion proposed by Hair et al. (2024) was employed to evaluate discriminant validity. Measures were deemed discriminant if the ratios were below the HTMT threshold of 0.85, as shown in Table 4. Furthermore, (Hair et al., 2024) noted that measures are considered discriminant if the upper limit of the HTMT bootstrapping value does not include 1. All ratios were below the cut-off value of 0.85, as indicated in Table 3, confirming that the measurements are distinct.

Table 4: HTMT

	AIHR	**EE**	**EP**	**JC**	**PR**	**SP**
AIHR						
EE	0.725					
EP	0.789	0.756				
JC	0.732	0.678	0.789			
PR	0.745	0.817	0.850	0.745		
SP	0.843	0.784	0.841	0.824	0.847	

Note: EE="Employee Engagement", AIHR="AI-Enabled HR Analytics", EP="Employee Performance", JC="Job Crafting", PR="Perceived Risk", SP="Sustainable Performance".

5.3. Testing the Structural Model

The overall impact of the endogenous latent variable is assessed using the coefficient of determination, known as R-square. This metric elucidates the variation introduced by the model. R-square represents the squared correlation between the actual and anticipated values of a given endogenous construct, indicating the model's predictive accuracy. It demonstrates the influence of the exogenous latent variable on the endogenous latent variable. R-square values range from 0 to 1, with a value of 1 indicating high predictive accuracy. To evaluate the proposed path coefficients—covering direction, strength, and significance—the bootstrap method with 1,000 resamples is applied (Hair et al., 2024). The results of the hypothesis testing for each relationship in the model, along with significance levels, t-statistics, and path coefficients (β), are presented in Table 5. The structural model with path coefficients and corrected R^2 values is illustrated in Figure 2. The adjusted R^2 values in the structural model suggest a medium to large variance explained of same citation (Hair et al., 2024).

Table 5 demonstrates that AI-enabled HR analytics has a positive and significant impact on job crafting (β=0.648, $p < 0.001$). The mediating role of job crafting significantly influences the relationship between AI-enabled HR analytics and sustainable performance (β=0.284, $p < 0.001$). Furthermore, the mediating role of job crafting also significantly impacts the connection between AI-enabled HR analytics and employee performance (β=0.291, $p < 0.001$). In addition, the moderating role of perceived risk significantly affects both job crafting and sustainable performance (β=-0.155, $p < 0.001$). Likewise, the moderating role of perceived risk significantly influences the relationship between job crafting and employee performance (β=-0.225, $p < 0.001$). The moderating role of employee engagement also has a significant impact on the relationship between job crafting and sustainable performance (β=0.147, $p < 0.001$). Lastly, the moderating role of employee engagement significantly affects the relationship between job crafting and employee performance (β=0.127, $p < 0.001$).

Table 5: Hypothesis Testing

Path	Path Coefficient	T Value	P Values	Results
H1:AIHR -> JC	0.648	22.568	0.000	Supported
H2: AIHR -> JC -> SP	0.284	5.445	0.000	Supported
H3: AIHR -> JC -> EP	0.291	3.956	0.000	Supported
H4:JC *PR -> SP	-0.155	2.144	0.005	Supported
H5:JC *PR -> EP	-0.225	3.399	0.012	Supported
H6:JC *EE -> SP	0.147	2.131	0.009	Supported
H7:JC *EE -> EP	0.127	2.056	0.040	Supported

Note: EE="Employee Engagement", AIHR="AI-Enabled HR Analytics", EP="Employee Performance", JC="Job Crafting", PR="Perceived Risk", SP="Sustainable Performance".

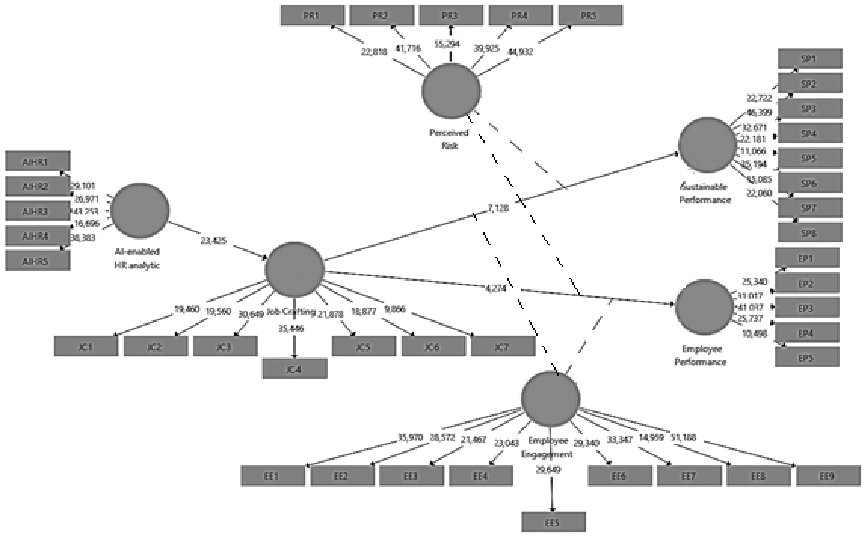

Figure 2: Structural Model

5. Discussion

The first hypothesis demonstrates that AI-enabled HR analytics has a significant impact on job crafting. Organisations have increasingly relied on HR analytics to gain deeper insights into their workforce, which allows employers to address workforce-related inquiries more effectively (Danilwan et al., 2020). Despite the benefits of HR analytics, it has also introduced complex challenges. Previous studies (Cavanagh et al., 2023; Cavanagh et al., 2021; Iqbal et al., 2021; Teune, 2023) support these findings. This study highlights the influence of perceived risks and benefits on the use of HR analytics, aligning with the concept of job crafting. While this paper explores the advantages of HR analytics in organisations, the focus remains on addressing potential drawbacks. Organisations can mitigate the misuse of HR analytics applications by implementing well-structured policies and leadership support. Job crafting involves employees actively reshaping their tasks to align with their preferences, skills, and job requirements (Xiao et al., 2023). Three forms of job crafting—relational, cognitive, and task crafting—have been identified (Jangbahadur et al., 2024). The theory suggests that employees enhance their performance by taking initiative and expanding their responsibilities. Employees are also likely to receive support from peers based on ability similarity, helping them perform tasks more effectively.

The second and third hypotheses suggest that job crafting mediates the relationship between AI-enabled HR analytics, sustainable performance, and employee performance. Early perspectives on work design maintained that managers should have exclusive control over job changes (Kuijpers et al., 2020; Lazazzara et al., 2020; Tims & Parker, 2020). Job crafting, however, presents a departure from this view, as it positions employees as the key agents in redefining their work.(Tims et al., 2012) further developed the idea by highlighting how employees modify their jobs through increased resources, enhanced challenges, or reduced demands that hinder their work (Xiao et al., 2023; Zhang & Liu, 2021; Zhang et al., 2021). We argue that approach crafting—represented by increased task complexity and effort—relates to challenge demands using the approach-avoidance paradigm. (Harju et al., 2021) contends that approach behaviors aim to achieve mastery or performance objectives. Demonstrating competence through hard work and busyness is linked to higher status and performance in contemporary work environments (Chen et al., 2020). Consequently, approach crafting can increase an individual's workload. The pursuit of mastery goals, which is linked to efforts to develop competence and ability, aligns with the notion of approach crafting (Yusliza et al., 2020). Therefore, focusing on approach crafting may elevate job complexity by increasing responsibility and learning demands. This is consistent with the JD-R model, which frames employment as an exchange of labor for material and social resources (Mousa & Othman, 2020). Frontline employees who receive valuable AI-enabled HR insights may feel a greater sense of obligation to support the organisation. As a result, they may invest more effort in developing new skills and working proactively to improve performance.

The fourth and fifth hypotheses examine the moderating role of perceived risk between job crafting and both sustainable performance and employee performance. Research has established a link between perceptions of risk and behavioral and environmental uncertainty, which shapes individuals' cognitive assessments of the value of a product or service (Almaiah et al., 2022). Individuals who perceive higher risk may view the benefits of certain actions or innovations as limited, and vice versa. Findings from (Lăzăroiu et al., 2020; Ventre & Kolbe, 2020), and (Xia et al., 2020) support this argument. Employee performance, when paired with job crafting, can lead to heightened perceptions of risk. Overqualified workers, in particular, are more likely to feel authentic and energized when their job roles align with their capabilities, which increases their focus and effectiveness. Such workers also create opportunities to better meet job requirements by tailoring their roles to fit their strengths. The quality and effectiveness of employees' performance are closely linked to their ability to craft their jobs. As organisations face increasing pressure to meet stakeholder demands and operate sustainably, they require proactive employees who can drive innovation. (Falco et al., 2021) and (Qalati et al., 2021) explain how work demands and job resources influence outcomes. Risk-taking and performance are considered elements of job crafting (Jeon et al., 2020), while autonomy and self-efficacy are viewed as job resources. Sustainable performance research increasingly focuses on the role of multiple organisational stakeholders. Organisations aim to integrate sustainable practices into their core strategy to maintain long-term advantages (Kaur & Arora, 2020).

The sixth and seventh hypotheses suggest that employee engagement moderates the relationship between job crafting, sustainable performance, and employee performance. Employment resources such as autonomy, decision-making involvement, training, and job attributes have been shown to positively influence employee engagement. AI-enabled HR analytics further strengthens this connection. Care is also regarded as a resource that provides employees with tools to manage their workload and sustain performance (Nienaber & Martins, 2020). To better understand job crafting, (Rattrie et al., 2020) utilized a regulatory focus perspective to refine earlier job crafting conceptualizations. Regulatory focus theory is often used to explain employees' proactive work adjustments and motivation. When employees modify their job roles and responsibilities to align with their interests, abilities, and preferences, they experience greater job satisfaction and performance. Motivated employees tend to invest more effort into their work, which further enhances productivity. However, the potential benefits of job crafting on employee and sustainable performance may not materialize if engagement levels are low. This suggests that job crafting can be a useful strategy for improving performance, but its effectiveness depends significantly on employee engagement. Therefore, it is crucial for organisations to cultivate an engaged work culture to fully leverage the benefits of job crafting.

6. Conclusion and Implications of Study

This study represents an early exploration of the causes and effects of AI-enabled HR analytics on employee performance, particularly focusing on long-term sustainable performance using PLS-SEM. The findings provide significant insights into how AI-enabled analytics contribute to employee performance and sustainable outcomes, expanding on previous research. One of the study's key objectives was to explore how HR analytics applications in organisations may raise concerns about employee privacy and the handling of personal information. The JD-R theory has been effectively applied in this study to construct a theoretical framework that demonstrates how employees can customize their work to align with their interests and needs. The results indicate that organisational leadership should prioritize safeguarding employee privacy and establishing protections to prevent the misuse of HR analytics. The study also suggests that implementing strict and consistent regulations may encourage employees to embrace technology in HR management.

This research offers empirical evidence of the positive effects of AI-enabled HR analytics on employee performance, based on data collected from 349 employees in manufacturing organisations in Bandung, Indonesia. Through the application of the JD-R model, the study further validates the mediating role of job crafting in the relationship between AI-enabled HR analytics and employee performance. Additionally, the HR process approach was used to examine how job crafting interacts with AI-enabled HR analytics. These findings highlight several managerial implications for HR practitioners and managers aiming to enhance employee sustainable performance through AI-enabled HR analytics. While job crafting is generally understood to influence performance, it is important for managers to communicate to employees that empirical evidence supports this connection. To fully realize the benefits of sustainable performance, companies must also improve job crafting elements that facilitate connections between employees and external partners, such as suppliers and customers. However, it is also important to note that job crafting may increase the complexity of tasks, potentially offsetting the positive effects on performance. From an HR process perspective, the research clarifies the efficacy of AI-enabled HR analytics. HR systems become more effective when both the content of HR practices and employees' collective attitudes toward these activities are aligned. It was found that positive effects of AI-enabled HR analytics on employee resilience, mediated by job crafting, are amplified by employees' perceptions of HR practices. While HR analytics can support data-driven decision-making for managers, these tools will not yield optimal results if employees do not have a consistent understanding of how the technology is applied. Additionally, the study found that employee perspectives on AI-enabled HR analytics can vary, and these responses are key in determining the overall success of AI-driven HR processes. The moderated mediation model results suggest that the effectiveness of AI-enabled HR analytics is enhanced by factors such as employee engagement, perceived risk, and the collective attitudes toward AI. Employees can leverage both personal and organisational resources, such as AI-enabled HR analytics and job crafting, to manage work demands, alleviate stress, and navigate uncertainty and adversity.

7. Limitations and Future Research

While this cross-sectional study offers valuable theoretical and practical insights, the findings should be interpreted with caution. First, the data collection was limited to organisations in Bandung, Indonesia. Future research could expand the model by exploring other countries to enhance the generalisability of the findings. Second, the research sample comprised only 340 employees from various manufacturing sectors. To ensure the robustness of the results, future studies should consider larger SEM sample sizes for validation. Third, the study did not differentiate between specific job crafting behaviors in the context of AI-enabled HR analytics. Future research could explore the variations between AI and HR functions in relation to job crafting to better understand their impact on employee and sustainable performance. Fourth, as this study employed a cross-sectional design, future researchers could adopt a longitudinal approach to gain more comprehensive insights over time. Fifth, investigating the moderating effects of variables such as personality traits, demographic factors, and company size could enhance the depth of the findings, especially in cross-sectional research. Additionally, further research is needed to better understand the relationship between AI-enabled HR analytics and the organisational environment. Finally, this study relied on data collected through an online structured survey from self-reported participants at a single point in time. Conducting longitudinal studies across different time periods could strengthen the conclusions and offer more robust results.

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