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Sustainable human resource management: A transformation perspective of human resource management functions through optimised artificial intelligence

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Abstract

Human Resource Management has become an increasing focus of research, especially with to its linkage to sustainability and the integration of Artificial Intelligence in HR practice. This paper explores the transformation potential of AI in HRM, revealing the factors that contribute to successful AI adoption and strategies to overcome adoption barriers within organizations. The paper also provides practical insights into how organisations can effectively limit the role of HRM and AI to prevent undue evictions of HR professionals. In addition, the study emphasises the importance of addressing data quality issues and bias in AI applications within HRM. To perform data analysis and processing, this research uses python analysis with the software used is a Jupyter notebook. To find out how well the model has been designed, it is necessary to test using an evaluation model regression. This approach aims to eliminate bias, ensure competitive salaries, and be in line with market standards.Th is research verified the model of salary determination of new employees. The four main findings addressed in the study were lack of quality data, bias in data, loss of human aspect, and error and uncertainty. To overcome data bias, oversampling and salary comparison are carried out through job portals to see current market trends.

Keywords:
artificial intelligence; balance of HRM and AI; HRM practices; HRM transformation sustainable.

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Introduction

Over the past decade, Human Resource Management (HRM) researchers and practitioners have become increasingly interested in uncovering sustainability in the HRM sector (Budhwar et al., 2023; Chowdury et al., 2023; Diaz-Carrion et al., 2020; Margherita, 2022). Fundamental questions arise that are asked by Budhwar et al. (2023), "Will artificial intelligence replace the role of HRM?". Long before the introduction of sustainability HRM, the concept of contemporary strategic HRM was introduced with the idea that human resources in organisations can be a sustainable competitive advantage (Aust et al., 2020; Deadrick & Gibson, 2007; Ehnert et al., 2016; Guzzo & Noonan, 1994; Poon & Law, 2022a). Creating new value and distinct advantages in front of competitors to be able to create new organisational value. In the last 5 years, research on HRM has increased sharply, especially implementation using AI (Budhwar et al., 2023; Chowdhury et al., 2023a; Margherita, 2022), for example, the emphasis and utilisation of AI/Machine learning in the recruitment process (Pan et al., 2022), increased role of chat bots in employee service (Malik et al., 2022), the role of AI in managing responsibilities, roles, and other duties of employees (Jarrahi et al., 2023). However, the rapid development of AI that continues to evolve, resulting in opportunities and challenges, is not in line with contemporary HRM practices. In line with the impact of welfare, anticipating existing changes, the United Nation formulated 17 Sustainable Development Goals (SDGs), inseparable from the application of SDGs in the human resource sector at every level of the organisation, (Panuluh, & Fitri, 2016).

Sustainability becomes an essential element that can generate value, culture, and long-term competitive advantage that is presented on improving business performance by meeting current needs without sacrificing the future needs of the organisation. Currently, many organisations are competing in implementing economic and environmental sustainability, but sustainability is an element that goes beyond the parameters of economic and environmental performance because, in the social dimension, sustainability will affect the relationship between performance, talent, diversity, and employee attitudes (Ahmad et al., 2022). Lopez & Valle (2020), deliver a unique statement that questions whether the organisation will sacrifice this year's profits to practice sustainability in the hope of getting results in the next five years or focusing on increasing profits at the expense of organisational sustainability. Management and continuous processes are always concentrated on achieving short-term goals such as making profits, ignoring long-term goals such as human resource problems (Maley, 2014). On the other hand, public awareness related to economic, social, and environmental issues is strengthened, which creates more significant scenarios for organisations to demonstrate commitment to sustainability practices (Ehnert et al., 2016). Although the amount of research on sustainability continues to increase, problems regarding sustainability practices in terms of human resources are still often problematic, especially in the all-digital era Simultaneously, over the past three decades, human resources stood out for its importance to implementing the organisation's business strategy (Jackson et al., 2014; Kramar, 2014). The relationship between the concept of sustainability and HRMis shown as an innovative approach that emerges in support of the company's strategy to be adaptive, efficient, and effective (Westerman et al., 2020).

Practitioners and researchers in the field of HRM are increasingly interested and onslaught in developing the concept of sustainable HRM. Sustainability is becoming increasingly important and as a HRM strategy as the left HRM function is expected to play an active role in helping organisations meet demanding interests (Omidi & Dal, 2022; Poon & Law, 2022; Qamar et al., 2023). Sustainable HRM can be defined as implementing HRM strategies and practices that enable achievement in various business, financial, social, and ecological dimensions (Poon & Law, 2022). Most of the research analysing sustainability HRM focuses on studying the practicalities of integrating HRM and sustainability, such as the implementation of using artificial intelligence to increase the economic and financial value of organisations efficiently and effectively (Budhwar et al., 2023; Margherita, 2022). There are three lines of study that discuss sustainability HRM, i.e., the study of results-oriented employee welfare, employee behaviour, and effective HRM strategies (Aust et al., 2020). There are at least four fundamental deficiencies that have been identified beyond regulatory, privacy, and data security issues. First, it lacks quality data. AI in HRM requires high-quality data to train AI models well. One major drawback is that historical HR data in many organisations may be incomplete or of poor quality (Budhwar et al., 2022; Chatterjee et al., 2022; Chowdhury et al., 2023; Jackson et al., 2021; Omidi & Dal Zotto, 2022; Poon & Law, 2022; Prikshat et al., 2023; Qamar et al., 2023; Yadav et al., 2022). This can lead to less accurate results from AI models (Budhwar et al., 2023). Second, there is bias in the data. The data used to train AI models can reflect biases present in that data. This can result in discriminatory or unfair decisions if not handled properly (Budhwar et al., 2023). Third, it found loss of the human aspect. The implementation of AI in HRM can reduce the human aspect in interaction and decision making. This can reduce human sensitivity, empathy, and understanding that are often important in complex HR situations, such as crisis management or negotiation. Fourth, there are several errors and uncertainties. While AI can improve efficiency in many aspects of HR, the technology is not error-free. Errors in algorithms or data can result in inaccurate decisions. In addition, AI models often cannot provide definitive answers in complex or unstructured situations.

This research aims to analyse verified the model of salary determination of new employees. This paper contributes to the literature on sustainable HRM management in several ways. First, this paper wants to provide an in-depth review of the transformation of the HRM function through the application of AI in terms of HRM practices and the role of HR including in analysing what factors contribute to the successful adoption of AI in the work environment and how organisations can overcome potential obstacles in its adoption. The review is necessary because as far as we know, factors that understand the adoption of artificial intelligence including how organisations can draw the line between the roles of HRM and artificial intelligence are less noticed. This could enable the eviction of HRM professionals in their roles. Through this review, researchers hope organisations can manage, establish, and structure specifically in establishing roles between technology and humans. Second, overcoming data bias in sustainable HRM practices using artificial intelligence. Many researchers have focused only on practical, economic-oriented research without regard to how the management of the model might affect the outcomes given to minority groups. For example, Feng (2023) and Ramachandran et al. (2022) examined the application of AI in the HRM sector, but it is not discussed about how the model can overcome the problem of data bias that allows discrimination in minority groups. Third, this study also provides examples of the practice of applying artificial intelligence to the salary of a new employee. The use of AI in new employee payroll focuses on eliminating bias and ensuring that salaries are given fairly and equitably. This should include consideration of factors such as qualifications, experience, performance, and job responsibilities. This research also shows how the modeling process with a competitive salary is in accordance with the current market.

Literature review

Transforming HRM into sustainable HRM

Systematic review conducted by Budhwar et al. (2023), voiced concern from artificial intelligence that this technology will replace the current work that was originally done by humans. In a report entitled, key resources are people, acknowledging that AI is "increasingly understood as a strategic technology that governments want to promote domestically and be constrained by advertising". Furthermore, the existing consensus is that "talent" is the most important contributor to "project success", thereby highlighting the important role that talent attraction, motivation, and retention can play in a country's international competitiveness. Since talent is mobile, it contributes to the global war for talent, which is a stable research subject at HRM (Beer et al., 2015; Mariappanadar, 2014). According to Budhwar et al. (2023), offer strategies and scenarios seek to utilise AI to help humans break free from repetitive aspects of work and focus more on human aspects that machines cannot. In generating innovative ideas, because so far, AI can only summarise and analyse data without being able to generate ideas outside the box of thought (Chowdhury et al., 2023b). Therefore, considering the potential that exists, instead of continuing to be in the throes of rejecting the presence of this technology, accepting and coexisting by setting existing boundaries is a wise action. In this way, organisations can channel their workforce in generating ideas and creativity by encouraging AI technology to work on daily and repetitive tasks. This shift in focus could result in new changes to HRM policies and practices (Budhwar et al., 2023; Pan & Froese, 2023).

However, there are still many research agendas that need to be completed by researchers and practitioners before releasing work entirely to AI. Although it has been trained by a very large database, the result is that this technology still often produces issues of discrimination against minority groups. In short, although this technology continues to evolve, in HRM perspective there are still many research agendas that need to be completed (Budhwar et al., 2022; Ren et al., 2023). This paper seeks to answer the research agenda that has been formulated by previous researchers to be able to develop literature on sustainable HRM.

In an era of globalisation and an ever-deepening awareness of environmental and social issues, organisations are facing new demands to pay attention to sustainability in their operations. One innovative and effective way is to change the conventional HRM approach to sustainability HRM, by utilising artificial intelligence as a key tool in this transformation process. Sustainability HRM integrates sustainability principles into the HRMfunction, enabling companies to achieve their sustainability goals while ensuring sustainable efficiency and productivity (Ren et al., 2023).

Fundamental shortcomings of sustainability HRM practices

Previous research has discussed the implementation of sustainable HRM, including in the implementation using artificial intelligence. There are four fundamental shortcomings in the implementation of sustainable HRM transformation, i.e., lack of quality data, bias in data, loss of human aspect, and errors and uncertainties (Budhwar et al., 2022; Chatterjee et al., 2022; Chowdhury et al., 2023; Jackson et al., 2021; Omidi & Dal Zotto, 2022; Poon & Law, 2022; Prikshat et al., 2023; Qamar et al., 2023; Yadav et al., 2022)

Lack of quality data

The lack of quality data is one of the major challenges faced in HRM practices, especially when organisations try to implement AI technology in their HRM processes. High-quality data is critical to support accurate decision making, in-depth analysis, and the development of effective HR strategies (Deadrick & Gibson, 2007; Jackson et al., 2014). In the context of HRM, quality data plays a key role in various aspects, from recruitment to performance management and succession planning. Quality data in HRM refers to accurate, relevant, consistent, and reliable data related to employee aspects, such as personal information, work experience, performance, and training. Quality data also includes data that is free from bias or discrimination and processed properly in accordance with applicable privacy regulations (Najam et al., 2020).

However, the challenges faced by HRM practitioners in fulfilling data completeness are first, data fragmentation. HR data is often spread across different systems, applications, and formats. Relevant information about employees can be stored in human resource management systems (HRIS), performance management systems, payroll systems, and more. This makes it difficult to integrate and manage data well. Second, data incompleteness. Data quality is often affected by incomplete information. For example, some personal data or employment history may be incomplete. This incompleteness can limit the understanding of employees and their performance. Third, data changes. HR data is not static; They change over time. Changes such as promotions, mutations, or changes in marital status can make data outdated or irrelevant if not updated quickly. Fourth, data privacy and security. In the context of increasingly stringent privacy regulations such as GDPR and CCPA, organisations need to ensure that employee data is stored and processed securely and in compliance with applicable regulations. This can restrict data access and use (Yong et al.,2020). The effect that occurs when a lack of quality data occurs is that the decision making made by AI becomes inaccurate (Macke & Genari, 2019; Yong et al., 2020). Unqualified HR data can lead to wrong decision making. For example, performance appraisals that are based on inaccurate data can hurt employees who are performing well. Other impacts include uncertainty in employee planning, inability to analyse employees, and poor employee health experiences (Budhwar et al., 2023; Leidner et al., 2019; Macke & Genari, 2019; Yong et al., 2020).

Bias in data

The potential for bias in data is a serious problem in the use of AI technology, including in the context of sustainability HRM practices. Bias in data refers to imbalances, discrimination, or distortions in datasets used to train AI algorithms. This kind of bias can result in unfair or inaccurate recommendations or decisions in the HRM process (Budhwar et al., 2023). Modeling salary can benefit employees. Unfortunately, modeling salary often causes discrimination to minority groups such as gender and race. This discrimination results in employee dissatisfaction which influences the performance of that group of employees. This bias can creep into decisions or recommendations generated by AI algorithms, which in turn can result in unfair or adverse consequences, especially in the context of sustainability HRM practices. Let's go deeper into the potential for bias in data (Chowdhury et al., 2023).

One of the main sources of potential bias in data is historical data used to train AI algorithms. This data often reflects practices that may already be contaminated by human bias (Keegan & Den Hartog, 2019). For example, in recruitment practice, if organisations previously had a tendency to select candidates from certain groups based on gender or race, the old recruitment data would reflect this bias. AI algorithms trained with such data can inadvertently maintain such biases in the further recruitment process. In other words, algorithms can assume that certain groups are superior without a solid foundation, which results in unfairness in candidate selection. In addition, bias in data can also appear in the process of labeling or classifying data (Budhwar et al., 2022; Pan et al., 2022). In the context of HRM, this bias can affect employee performance appraisals. For example, an employer who has certain preferences or biases may give employees unobjective judgments based on factors irrelevant to actual performance. As a result, such appraisal data will reflect such biases and may interfere with fair decision-making in performance management and career development (Hu & Oh, 2022).

Furthermore, imbalances in group representation in data are another problem that contributes to potential bias. If the dataset does not cover specific groups or represents only a very small number of them, then the AI algorithm may be less able to generate appropriate recommendations for those groups. For example, if a recruitment dataset includes only a small number of employees from minority backgrounds, then the algorithm may not have enough information to identify and recommend employees from that group. In this case, minority groups can experience inequality in employment opportunities. Bias in data can also arise due to a process known as confirmation bias. This happens when AI algorithms confirm or reinforce biases already present in the data (Bagdadli & Gianecchini, 2019).

Algorithms tend to pay attention to patterns present in training data and use those patterns to make decisions or recommendations. If the pattern already reflects bias, then the algorithm will maintain that bias in the results, even if the pattern is incorrect or unfair. Confirmation bias can result in increasingly inaccurate and unfair decision-making over time. It's important to remember that potential bias in data isn't an inevitable or insurmountable problem. Identification, understanding, and reduction of bias in data requires serious and sustained effort. This involves auditing data to detect existing biases, expanding datasets to cover greater diversity, using anti-bias data processing techniques, and actively monitoring the output of AI algorithms to detect and address biases that may arise. With these measures, the potential for bias in data can be reduced, and AI technology can be used more fairly and effectively in sustainability HRM practices (Christensen et al., 2022).

Loss of human aspect

Losing the human aspect is one of the challenges that need to be considered in the application of artificial intelligence technology and automation in various aspects of life, including in the context of AI and HRM. This refers to a shift or reduction in human interaction, involvement, and understanding in processes and decisions that previously involved more humanitarian aspects. The potential that can arise are reduced human-human interaction, limitations in understanding, and the loss of ethical abilities and human decisions (Cachón-Rodríguez et al., 2022).

First, reduced human-human interaction. One of the main impacts of automation and the use of AI technology in HRM is the decrease in direct interaction between individuals. At various stages of the human resources cycle, such as recruitment, performance management, or training, human interaction tends to decline. Previously, job interviews, performance appraisal meetings, or mentoring interactions could involve humans more often. However, with the adoption of technology, some of these stages can be automated or done through digital platforms. This can result in the loss of personal relationships and togetherness that are often important in career development and employee management (Katou et al., 2014; Poon & Law, 2022).

Second, limitations in understanding nuances. Humanity also includes the ability to understand nuances and contexts in complex situations. HRMs often deal with problems that cannot be fully explained by data or algorithms. HRM professionals have the ability to read facial expressions, interpret tone of voice, and feel the atmosphere in a meeting. This ability to understand and handle nuances and contexts cannot be replaced by technology. Therefore, the use of AI technology in HRM should strive to maintain and enhance understanding of these nuances and contexts (Poon & Law, 2022).

Third, the loss of ethical abilities and human decisions. HRM also often involves making decisions that require deep ethical considerations. Decisions such as performance appraisals, firings, or conflict management often require ethical considerations that cannot be fully automated. HRM professionals are responsible for ensuring that organisational policies and actions conform to the company's values and ethics. They also serve as ethical leaders who develop policies that support justice and sustainability (Bush, 2020).

In the use of AI technology in HRM, it is important to maintain a balance between automation and human presence. HRM professionals are still needed for aspects of humanity that cannot be automated, such as interpersonal communication, understanding nuances, ethical decisions, and emotional support. Therefore, their role will not be replaced by technology, but will complement and increase the efficiency of HRM processes. In the context of sustainable HRM practices, HRM professionals also have an important role to play in ensuring that the values of fairness, inclusion, and sustainability wich are integrated in all aspects of human resource management.

Errors and uncertainties

In today's digital age, artificial intelligence has become one of the most dominating aspects in various aspects of human life, including business, medicine, transportation, and even human resources. Although AI has provided significant advances and provided great benefits, it is undeniable that this technology also brings errors and uncertainties that need to be seriously faced and addressed.

One of the most important aspects of using AI is the errors that may occur. Errors in the context of AI can come from a variety of sources, including human error in collecting and processing data, errors in the algorithms used, as well as errors in the interpretation of results. Even with excellent data and sophisticated algorithms, AI is not error-free. These mistakes can have serious repercussions in many areas, including HRM. For example, in the recruitment process using AI, errors in candidate performance measurement algorithms can result in unfair rejections or improper selection. This kind of mistake can be detrimental to both parties, namely the company and the candidate. On the other hand, uncertainty is an intrinsic characteristic in AI. AI models often cannot provide definitive answers or accurate predictions in very complex or unstructured situations. This is because AI works based on existing data and mathematical processing, so uncertainty becomes an inevitable part (Pan et al., 2022). This uncertainty can be a significant challenge in HRM when it comes to making critical decisions relating to employee management, compensation, promotion, and talent development. Uncertainty can result in decisions that are not always satisfactory or cannot be explained unequivocally. Inadequate AI-based HRM policies can affect employee motivation, retention, and overall job satisfaction.

To address errors and uncertainties in the use of AI, organisations must take a cautious and proactive approach. This includes continuous monitoring of AI system performance, continuous improvements to algorithms and data used, and a human-based approach to sensitive decision making. In addition, organisations need to understand that AI is a tool that can improve human decisions, not replace them entirely. Thus, collaboration between humans and AI is key to mitigate errors and uncertainties in the use of this technology (Yadav et al., 2022). In sustainability HRM practices, AI technology can be a very powerful tool, but it must be wisely integrated and closely monitored to ensure that the values of fairness, inclusion, and sustainability are maintained.

Contributing factors to the successful application of AI in sustainability HRM

The successful application of artificial intelligence in sustainable HRM is a highly desired goal by many organisations in this era. AI can play an important role in supporting sustainable HRM practices, which include equity, corporate social responsibility, environmental impact reduction, and sustainable human capital development (Budhwar et al., 2023). This research explores the factors that contribute to the successful application of AI in sustainable HRM.

Leadership and organisational commitment

Strong leadership and organisational commitment are key factors in the successful application of AI in sustainable HRM. Organisational leaders must support and encourage the use of AI technology to achieve sustainable goals. They must communicate the vision and values associated with sustainable HRM to the entire organisation. Without the support of the right level of leadership, the implementation of AI in sustainable HRM may face significant obstacles (Qamar et al., 2023).

Clear sustainable HRM goals

Organisations need to have a clear understanding of the ongoing HRM goals they want to achieve. Whether the goal is to create an inclusive culture, reduce environmental impact, or increase equity in HR practices, those goals must be well identified. AI should be used as a tool to achieve this end and not as an end in itself (Ren et al., 2023).

High-quality data

Data is the raw material for AI. Organisations need to ensure that HR data such as employee data, performance records, and recruitment data are accurate, relevant, and complete. Lack of high-quality data can result in inaccurate or biased AI results (Ren et al., 2023).

Regulatory compliance and data security

The implementation of AI in HRM must comply with applicable data privacy regulations, such as General Data Protection Regulation (GDPR) in the European Union or California Consumer Privacy Act (CCPA) in California. This compliance is important to protect employees' personal data. In addition, data protection and security must take precedence (Yong et al., 2020).

Performance measurement and continuous evaluation

Organisations must have appropriate metrics to measure the impact of AI use on sustainable HRM. This includes measuring operational efficiency, increasing productivity, increasing fairness in HR policies, and reducing environmental impact. AI performance evaluation should be an ongoing process, and organisations should be prepared to make improvements based on evaluation findings (Ren et al., 2023).

Alignment with organisational strategy
The integration of AI in HRM should align with the general strategy of the organisation. It should be an integral part of the organisation's overall efforts to achieve sustainable goals, which may include corporate social responsibility, achievement of environmental targets, and sustainable management of human resources (Qamar et al., 2023).

Sustainability in development and innovation
Sustainability in the context of sustainable AI and HRM includes continuous development and innovation. Organisations need to invest in the development of better and more advanced AI technologies and always look for ways to integrate AI in HRM more effectively (Leidner et al., 2019).

By considering and implementing the above factors, organisations can maximise their chances of achieving success in the application of AI in sustainable HRM. This can help organisations achieve their sustainability HRM goals more efficiently, make HR practices fairer, and create a more positive impact on their sustainability and corporate social responsibility.

AI and implication for HRM

Creating smart integration of AI technology or systems and HRM is an important step in entering the HRM dimension of sustainability. This balancing is important because it reflects a fundamental transformation in the way organisations perceive, manage, and interact with their human assets, namely employees (Prikshat et al., 2023). At least, there are several reasons why it is necessary to align, such as, first, the HRM paradigm shift. The use of AI technology has fundamentally changed the HRM paradigm. In traditional HRM, the primary roles are administrative and operational, such as employee data management, payroll, and performance management. However, with the advent of AI, HRM has become more strategic, focusing on data analysis, data-driven decision making, and the use of technology to understand, manage, and optimise human potential in organisations (Budhwar et al., 2022). Second, data-driven decision making. One of the main roles of AI in HRM is to transform decision making to be more data driven. AI can analyse employee data deeply to provide valuable insights into employee behaviour, tendencies, and needs. It helps organisations develop HR strategies that are smarter and responsive to environmental changes, including sustainability-related changes (Diaz-Carrion et al., 2018). Third, more effective performance management. AI can be used in performance management to provide faster and accurate feedback to employees. This can assist employees in understanding how they are performing and where they need to improve, which in turn can contribute to continued growth and development. In addition, AI can assist HR in identifying high and potential performers, who can be provided with greater development opportunities (Prikshat et al., 2023). Fourth, reduction of bias and injustice. Bias is one of the major problems in HRM, and AI can help in reducing it. AI systems can be trained to make decisions based on facts and objective data, without taking into account factors such as gender, race, or background. This ensures that existing HR policies and practices support fairness and equity within the organisation, which is a critical component of sustainability (Budhwar et al., 2022).

HRM professionals remain indispensable despite the growing role of AI in the world of business and human resource management. Despite technological advancements, there are several reasons why the role of humans in HRM is still vital and cannot be completely replaced by AI (Budhwar et al., 2023), such as complex human relationships (Chillakuri & Vanka, 2021), the role of ethics and leadership (Chillakuri & Vanka, 2021), healthy organisational culture (Aust et al., 2020), understanding context and nuance (Aust et al., 2020), conflict management and team development, and strategic decision making (Mariappanadar, 2014). With the reasons mentioned earlier, it is necessary to form a role alignment between AI and HRM practitioners. This process is an important step to be able to utilise AI effectively without losing the essence of HRM and employee well-being. This alignment can help organisations improve operational efficiency, optimise decision-making, and improve employee experience.

Research method

Data analysis

To perform data analysis and processing, this research uses python with the software used is a Jupyter notebook. By modeling the salary determination of new employees, this research provides an example of implementing sustainable HRM by designing a new employee salary determination model without causing data bias so that there is discrimination against minority groups and building models and compare machine learning/deep learning algorithms in determining the salary of new employees.

Bias data

The use of artificial intelligence technology in HRM has changed the HRM landscape significantly. AI has enabled organisations to take more efficient and effective HRM decisions, from the recruitment process to performance evaluation. However, as is the case in various other AI applications, data bias is a serious problem that can affect fairness and equity in sustainable HRM (Budhwar et al., 2023). Data bias is a problem that can arise in HRM practices that use AI and machine learning technologies. Data bias occurs when the training data used to train an AI model contains preferences or imbalances that should not be present in HRM decisions (Budhwar et al., 2023; Margherita, 2022). In the context of HRM, data bias can have a serious impact on human resource policies and decisions, including in recruitment, promotion, and performance evaluation, etc. (Margherita, 2022). There are many researchers who try to address data through data preprocessing, such as data cleansing, data stratification, weight adjustment, and other stages. In the context of sustainable HRM, the use of AI has many potential benefits. AI can speed up the recruitment process, identify high-performing employees, manage diverse workgroups, and provide valuable insights to HRM management. However, when AI models are used in HRM decisions, they must decide based on historical data that may contain bias. This can result in unfair decisions, such as discrimination in recruitment or promotion (Kim et al., 2022).

A concrete example is gender bias in the recruitment process. If a recruitment model's training data contains a preference for male candidates over female candidates, then the model will be more likely to choose male candidates, even if female candidates have similar qualifications. This means that women may be ignored or not invited for interviews, which can result in unintentional gender discrimination. Likewise with the determination of new employee salary. In addition, data bias can also affect diversity and inclusion in organisations. If AI models tend to prioritise certain groups, such as graduates from certain universities, then other groups may be overlooked. This can result in less diverse and less inclusive organisations (Ehnert, 2014; Fu et al., 2020).

Model evaluation

To find out how well the model has been designed, it is necessary to test using an evaluation model where in the case of this study is a regression evaluation model. A regression evaluation model is a process for assessing the performance and accuracy of a regression model (Swamynathan, 2017). The performance metrics used in this study are Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Coefficient of Determination R^2-Score (Swamynathan, 2017).

MAE is the average of the absolute difference between the actual value (observed) and the predicted value (predicted). The formula of this metric is available in formula (1).

$$MAE = \frac{1}{N}\sum(y - \hat{y})^{2} \quad (1)$$

Mean Squared Error (MSE) is one of the commonly used metrics in statistics, data analysis, and machine learning to measure the quality or accuracy of regression or prediction models. MSE measures the degree to which the model's predicted value approaches the actual value in squared form, and it pays more attention to large errors (Chen et al., 2023; Farzana et al., 2023; Haq et al., 2023; Khairan et al., 2023). MSE measures the mean of squares the difference between actual (observed) and predicted values (predicted) in a regression or prediction model. The formula of this metric is available in formula (2).

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(y_i - \hat{y}_i) \quad (2)$$

RMSE is a statistical metric that measures the accuracy of a prediction model by calculating the square root of the mean of the squared difference between the actual value (observed) and the predicted value (predicted) in a regression or prediction model (Chen et al., 2023; Farzana et al., 2023; Haq et al., 2023; Khairan et al., 2023). The formula of this metric is available in formula (3).

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{n}(y_k - \hat{y}_k)} \quad (3)$$

The coefficient of determination, often referred to as the R-squared or R^2-Score, is an evaluation metric that measures the extent to which variations in actual data can be explained or predicted by regression models. This provides insight into how well the model matches the actual data. R^2-Score ranges from 0 to 1 (Chen et al., 2023; Farzana et al., 2023; Haq et al., 2023; Khairan et al., 2023), with the following interpretation. R^2-Score = 0 indicates that the model cannot explain the variation at all and is no better than a model that only uses the average of the data as a prediction. R^2-Score = 1 indicates that the model is perfect and able to explain all variations in the data correctly. 0 < R^2-Score value < 1 indicates the extent to which the model can account for variations in the data. The higher the R2-Score, the better the model is at explaining variations. The formula of this metric is available in formula (4).

$$R^2 = 1 - \frac{\frac{1}{N}\sum_{k=1}^{n}(y_k - \hat{y}_k)}{\frac{1}{N}\sum_{k=1}^{n}(y_k - \hat{y}_k)} \quad (4)$$

Results

This research conducted data analysis including overcoming data bias by providing examples of modeling processes in determining employee salaries. By comparing modeling using machine learning (linear regression, lasso regression, random forest regressor, gradient boosting regressor, and SVM) and deep learning (LSTM and Neural Network), an insight into model performance is gained.

Table 1.
Comparison of algorithm modeling results

Algorithm	MAE	MSE	RMSE	R2
Regress Linier	0,663	0,691	0,881	0,992375
Regress Lasso	0,766	0,901	0,941	0,991242
Random Forest Regressor	2,978	4,857	1,321	0,967382
Gradient Boosting Regressor	2,876	6,798	2,317	0,826736
SVM	0,999	1,012	1	0,988851
LSTM	0,0181	0,0167	0,0450	1
Neural Network	0,0497	0,0672	0,0601	0,998407

In this research, there are two types of accuracy parameters in regression (machine learning) and deep learning. R2 – Score and Accuracy values close to 1 indicate strong model suitability and accuracy from the data set used in this study. Values close to 1 or equal to 1 are LSTM. Table 1 shows that most models values close to 1, which means that the model has a high level of match and accuracy in predicting the salary of new employees. This research also analysed error metrics such as MAE, MSE, and RMSE; values close to 0 are models that use LSTM, Neural Network, and linear regression algorithms. The algorithm shows a high match in the learning model process to create a new employee salary prediction model. Through the evaluation of error metrics and accuracy, the LSTM model provides the smallest accuracy and error metrics so that this algorithm is determined as the algorithm that has the best performance in predicting the salary of new employees by paying attention to the salary range according to the current market.

The utilisation of AI models in sustainable HRM brings a number of significant benefits. First, it increases transparency in payroll because AI models can account for the factors used in determining salaries. Second, it helps reduce bias in payroll by using objective data and impartial analysis. Third, the use of AI models allows organisations to respond quickly to job market changes, ensuring that salaries offered remain competitive and in line with industry trends.

Discussion

This article seeks to introduce a literature review in the process of transforming HRM into sustainable HRM. Although research on sustainable HRM continues to evolve to expand and synchronise with business and organisational strategies, there are many conceptual processes and findings that can be developed (Aust et al., 2020; Budhwar et al., 2022 ; Chowdhury et al., 2023; Chowdhury, Joel et al., 2023; Chowdhury et al., 2023; Deadrick &

Gibson, 2007; Diaz-Carrion et al., 2018; Ehnert et al., 2016; Guzzo & Noonan, 1994; Poon & Law, 2022). This research introduced findings of deficiencies in sustainable HRM practices. This research highlighted four shortcomings that we managed to identify beyond regulatory, privacy, and data security issues. These shortcomings are lack of quality data, biased data, loss of human aspects, and uncertainty.

Sustainable HRM is an approach that emphasises the importance of treating employees as valuable and sustainable resources for the organisation (Macke & Genari, 2019). Sustainable HRM has become a key focus for modern companies that want to create an inclusive work environment, value employee well-being, and achieve their long-term goals. Amidst dynamic changes in the world of business and technology, sustainable HRM faces great challenges to meet these expectations (Qamar et al., 2023). One increasingly important tool in this change is artificial intelligence (Budhwar et al., 2022; Jarrahi et al., 2023; Ramachandran et al., 2022). However, it is important to recognise the benefits provided by the integration of AI in continuous HRM. AI can encounter a number of paradoxes and problems that require serious attention. AI can not only provide various benefits in managing human resources, but also present significant risks related to human aspects, bias, data privacy, and many other things (Budhwar et al., 2022; Poon & Law, 2022). One of the major paradoxes in the implementation of sustainable HRM with AI is that the focus on the human aspect can be eroded. Sustainable HRM is supposed to bring values like employee happiness, career development, and an inclusive organisational culture into the limelight. However, when companies rely too much on AI, the risk of dehumanisation in the relationship between employees and companies arises (Budhwar et al., 2023; Pellegrini et al., 2018). Employees may feel ignored or perceived as entities that can be replaced by machines. Highly mechanistic and data-driven decision making without consideration of emotional and human aspects may result in an inadequate work environment and impaired employee well-being (Pellegrini et al., 2018).

Another problem that arises in the implementation of continuous HRM with AI is related to bias. AI algorithms tend to learn from historical data, and if this data contains gender, racial, or ethnic biases, they might reinforce these biases in HRM decision-making. For example, in recruitment or promotion, AI can inadvertently amplify existing inequalities. This is contrary to the goal of sustainable HRM which should create a fair and inclusive work environment (Budhwar et al., 2023; Poon & Law, 2022; Prikshat et al., 2023). It is important to understand that bias in AI is not an intentional problem but is often the result of data devices used to train AI models. Training data may reflect existing inequalities and biases in society. When AI models study this data, AI users can internalise and reinforce those biases in their decision-making.

However, in machine learning model development, one of the serious challenges that is often faced is imbalances in datasets. This imbalance occurs when the number of samples among the various classes in a dataset is highly unbalanced, with one or more classes having a significantly smaller number of samples than others. This can lead to biased results in the model, where the model tends to overpredict the majority class and pay less attention to the minority class (Chowdhury et al., 2023a). In addressing this issue, this research strongly recommend the use of oversampling. Oversampling is a technique in data processing that involves making copies or replicating samples from minority classes so that the number of samples in that class becomes more balanced with the majority class. In other words, oversampling increases the proportion of minority classes in the dataset, allowing machine learning models to have more data to understand and model the characteristics of those classes. In some cases, practitioners may use external data such as support in decision making.

The practice of sustainable HRM in determining the salary of new employees with the principle of providing salaries is in accordance with the skills, experience, and salary range in the market. Job portals data can be used to get salary ranges according to the current market (Budhwar et al., 2023). AI has become a powerful ally in ensuring fairness, transparency, and efficiency in sustainable HRM processes, including payroll management processes. In predicting the salary of new employees, employer can follow these following steps. (1) Pulling salary data through job portals and analysing the salaries of old employees. (2) Analysing salary data and recruitment requirements from job portals. (3) Collect and analysing salary data available on job portals to understand the various factors that influence payroll and gain a better understanding of the relevant compensation structures in specific industries. (4) Analysing the salaries of old employees already in the organisation. This model is used to identify factors that affect the salary of old employees such as company strength, experience, level of education, length of work at the company and certain positions. (5) Building a salary prediction model by combining salary data from job portals and old employee salary analysis. The model can be used to predict the appropriate salary range for new hires based on specific job profiles and requirements. Naturally, data balancing through oversampling is useful to prevent data bias in our study. The results of our model show contrast performance across the various algorithms used in this study. Our deep learning approach in modeling dominates in predicting employee salaries by paying attention to accuracy on the R2 score. In particular, the LSTM algorithm shows the best performance model with an R2 score of 1 and RMSE 0.0450 and overtakes other algorithm models. In error metrics analysis there is a considerable gap between machine learning and deep learning approaches. This may be because LSTM has a neural network structure that allows it to recall information from the past over long periods of time. This allows LSTM to handle long-term dependencies in data, which may be missed by linear regression or lasso regression that only considers linear or small relationships between variables. However, what is surprising is that the gradient boosting regressor algorithm has the most fractional level of accuracy. Our basic hypothesis is that because this algorithm has a robust nature against outliers, it means that gradient boosting regress uses decision trees as basic estimators, which can divide data into different groups. It is possible that when doing this modeling is not suitable for numerical data that provides salary recommendations with the basis for decision making is a decision tree. Finally, the last part of the study highlights that the use of LSTM algorithms by oversampling and using salary data from job portals results in a high level of accuracy in the salary decision-making process of new employees.

Future research directions

With great attention to HRM transformation, especially the issue of sustainable and artificial intelligence, new approaches can be introduced in different and unique dimensions. With the presence of limitations in this study, this study strongly encourages further research to answer and resolve. Our limitations regarding context and non-salary factors. Relying too heavily on AI in sustainable HRM management can also eliminate the critical human element in decision-making and inter-employee relationship management. AI should be used as a tool that supports, not replaces, decisions and actions made by HR professionals. Further researchers can also discuss non-salary factors in conceptual and practical that can explain how the essence of humans remains in AI practice.

Future research may be able to focus on the long-term effects of AI use practices in the workplace or organisation, and how organisations can measure and evaluate these effects. The use of artificial intelligence in human resource management has entered an increasingly mature stage, providing great potential to improve efficiency, accuracy, and fairness in managing human resources in various organisations. However, while the use of AI in HRM has proven its benefits in terms of smarter and more efficient decision making, future research in this area may have to focus on understanding the long-term effects of these practices and how organisations can thoroughly measure and evaluate their impact. One important aspect to investigate is the long-term impact of the use of AI in HRM on organisational productivity. While AI can improve operational efficiency and aid in the decision-making process, more in-depth research is needed to understand how long-term use of AI affects organisational productivity and competitiveness. It includes an analysis of company growth and profits that may relate to the application of AI in HRM

(Budhwar et al., 2023; Cachón-Rodríguez et al., 2022; Marchington, 2015; Margherita, 2022; Mayuri, 2023).

In addition to the impact on organisational productivity, future research should examine the impact of AI use on employee well-being and satisfaction in the long term. The use of AI in HRM can affect various aspects, from workload to work-life balance. Research could focus on whether the use of AI positively or negatively affects employees' quality of work life and their level of satisfaction, which is an important factor in retaining talent and improving employee retention.

Furthermore, the effect of using AI in HRM on equality and fairness in the workplace is a critical aspect that requires further research. AI has the potential to amplify or dampen inequalities in career, payroll, and promotion opportunities. In-depth studies can identify the impact of using AI in minimising or possibly widening this gap in the long term. In addition, the evaluation of policies and guidelines related to the use of AI in HRM is very important. Organisations need to develop appropriate ethical and regulatory frameworks to govern the use of AI. Research can assess the effectiveness of such policies in ensuring sustainability and fairness in HRM practices. Measuring the impact of the use of AI in HRM on organisational innovation and adaptability is also a relevant focus. AI can influence innovation in a company's products or services as well as adaptability to market changes. This research will help organisations to understand how the use of AI can help or hinder innovation and adaptation in the long term. Lastly, it is important to develop long-term studies involving data collection over several years to provide better insight into the long-term impact of using AI in HRM. This will help organisations to plan their long-term investments in AI technology and optimise its benefits.

Conclusion

This research verified the model of salary determination of new employees. The four main findings addressed in the study were lack of quality data, bias in data, loss of human aspect, and error and uncertainty. To overcome data bias, oversampling and salary comparison are carried out through job portals to see current market trends. Furthermore, the study provides examples of sustainable HRM practices using AI with a focus on setting new employee salaries. The models generated from salary data in the job portal and old employee salary data are compared, and the model with the best accuracy is selected.

However, this study also has a number of limitations that must be considered. First, there is no validity between modeling that oversamples and those that do not, so it is necessary to understand the impact and difference between the two. Secondly, attention is given only to salary as a compensation factor, while non-salary factors are also important in sustainable HRM. Future research directions could focus on the long-term effects of using AI in HRM, including its impact on productivity, employee well-being, equality in the workplace, innovation, and organisational adaptation. In addition, research should go more in-depth on non-salary factors in the context of sustainable HRM and how AI can support the human element in decision making. With a better understanding of the long-term impact and factors that influence sustainable HRM, organisations can optimise the use of AI to achieve more efficient, equitable, and productive HRM goals. This research is an important first step in exploring the role of AI in creating sustainable HRM that is responsive and employee oriented.

Author contribution

Arif Furqon Nugraha Adz Zikri: Conceptualisation, Data curation, Methodology, Writing–original draft. **Sunu Widianto and Rita Komaladewi:** Validation, Writing–review and editing.

Declaration of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Ahmad, I., Ullah, K., & Khan, A. (2022). The impact of green HRM on green creativity: mediating role of pro-environmental behaviours and moderating role of ethical leadership style. *International Journal of Human Resource Management*, *33*(19), 3789–3821. https://doi.org/10.1080/ 09585192.2021.1931938

Aust, I., Matthews, B., & Muller-Camen, M. (2020a). Common Good HRM: A paradigm shift in Sustainable HRM? *Human Resource Management Review*, *30*(3).1–11 https://doi.org/10.1016/j.hrmr.2019.100705

Bagdadli, S., & Gianecchini, M. (2019). Organisational career management practices and objective career success: A systematic review and framework. *Human Resource Management Review*, *29*(3), 353–370. https://doi.org/10.1016/j.hrmr.2018.08.001

Beer, M., Boselie, P., & Brewster, C. (2015). Back to the Future: Implications for the Field of HRM of the Multistakeholder Perspective Proposed 30 Years Ago. *Human Resource Management*, *54*(3), 427–438. https://doi.org/10.1002/hrm.21726

Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Lee Cooke, F., Decker, S., DeNisi, A., Dey, P. K., Guest, D., Knoblich, A. J., Malik, A., Paauwe, J., Papagiannidis, S., Patel, C., Pereira, V., Ren, S., Varma, A. (2023). Human resource management in the age of generative artificial intelligence: Perspectives and research directions on ChatGPT. In *Human Resource Management Journal*. John Wiley and Sons Inc, 33(3), 606-659. https://doi.org/10.1111/1748-8583.12524

Budhwar, P., Malik, A., De Silva, M. T. T., & Thevisuthan, P. (2022). Artificial intelligence–challenges and opportunities for international HRM: a review and research agenda. In *International Journal of Human Resource Management* (Vol. 33, Issue 6, pp. 1065–1097). Routledge. https://doi.org/10.1080/09585192.2022.2035161

Bush, J. T. (2020). Win-Win-Lose? Sustainable HRM and the promotion of unsustainable employee outcomes. *Human Resource Management Review*, *30*(3). 1-10 https://doi.org/10.1016/j.hrmr.2018.11.004

Cachón-Rodríguez, G., Blanco-González, A., Prado-Román, C., & Del-Castillo-Feito, C. (2022). How sustainable human resources management helps in the evaluation and planning of employee loyalty and retention: Can social capital make a difference? *Evaluation and Program Planning*, *95(3)*. 1-10 https://doi.org/10.1016/j.evalprogplan.2022.1021 71

Chatterjee,S., Chaudhuri, R., Vrontis, D., & Jabeen, F. (2022). Digital transformation of organisation using AI-CRM: From microfoundational perspective with leadership support. *Journal of Business Research*, *153(2)*, 46–58. https://doi.org/10.1016/j.jbusres.2022.08.019

Chen, F., Xu, W., Wen, Q., Zhang, G., Xu, L., Fan, D., & Yu, R. (2023). Advancing Concrete Mix Proportion through Hybrid Intelligence: A Multi-Objective Optimization Approach. *Materials*, *16*(19), 48–64. https://doi.org/10.3390/ma16196448

Chillakuri, B., & Vanka, S. (2021). Examining the effects of workplace well-being and high-performance work systems on health harm: a Sustainable HRM perspective. *Society and Business Review*, *16*(1), 71–93. https://doi.org/10.1108/SBR-03-2020-0033

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human Resource Management Review*, *33*(1). 1–21 https://doi.org/10.1016/j.hrmr.2022.100899

Chowdhury, S., Joel-Edgar, S., Dey, P. K., Bhattacharya, S., & Kharlamov, A. (2023). Embedding transparency in artificial intelligence machine learning models: managerial implications on predicting and explaining employee turnover. *The International Journal of Human Resource Management*, *34*(14), 2732–2764. https://doi.org/10.1080/09585192.2022.2066981

Chowdhury, S. R., Mendy, J., & Rahman, M. (2023). A Systematic Literature Review of GHRM: Organisational Sustainable Performance Reimagined Using a New Holistic Framework. In *Sustainability (Switzerland)* (Vol. 15, Issue 9) 1-15. MDPI. https://doi.org/10.3390/su15097513

Christensen, J. F., Guschke, B. L., Storm, K. I. L., & Muhr, S. L. (2022). The norm of norms in HRM research: A review and suggestions for future studies. *Human Resource Management Review*, *32*(4). 1-23 https://doi.org/10.1016/j.hrmr.2021.100859

Deadrick, D. L., & Gibson, P. A. (2007). An examination of the research-practice gap in HR: Comparing topics of interest to HR academics and HR professionals. *Human Resource Management Review*, *17*(2), 131–139. https://doi.org/10.1016/j.hrmr.2007.03.001

Diaz-Carrion, R., López-Fernández, M., & Romero-Fernandez, P. M. (2018). Developing a sustainable HRM system from a contextual perspective. *Corporate Social Responsibility and Environmental Management*, *25*(6), 1143–1153. https://doi.org/10.1002/csr.1528

Diaz-Carrion, R., López-Fernández, M., & Romero-Fernandez, P. M. (2020). Sustainable human resource management and employee engagement: A holistic assessment instrument. *Corporate Social Responsibility and Environmental Management*, *27*(4), 1749–1760. https://doi.org/10.1002/csr.1921

Ehnert, I. (2014). Paradox as a Lens for Theorizing Sustainable HRM: Mapping and Coping with Paradoxes and Tensions. In *CSR, Sustainability, Ethics and Governance* (pp. 247–271). Springer Nature. https://doi.org/10.1007/978-3-642-37524-8_11

Ehnert, I., Parsa, S., Roper, I., Wagner, M., & Muller-Camen, M. (2016). Reporting on sustainability and HRM: a comparative study of sustainability reporting practices by the world's largest companies. *International Journal of Human Resource Management*, *27*(1), 88–108. https://doi.org/10.1080/09585192.2015.1024157

Farzana, S. Z., Paudyal, D. R., Chadalavada, S., & Alam, M. J. (2023). Prediction of Water Quality in Reservoirs: A Comparative Assessment of Machine Learning and Deep Learning Approaches in the Case of Toowoomba, Queensland, Australia. *Geosciences*, *13*(10), 293–315. https://doi.org/10.3390/geosciences13100293

Feng, S. (2023). Job satisfaction, management sentiment, and financial performance: Text analysis with job reviews from indeed.com. *International Journal of Information Management Data Insights*, *3*(1). 1–10 https://doi.org/10.1016/j.jjimei.2023.100155

Fu, N., Flood, P. C., Rousseau, D. M., & Morris, T. (2020). Line Managers as Paradox Navigators in HRM Implementation: Balancing Consistency and Individual Responsiveness. *Journal of Management*, *46*(2), 203–233. https://doi.org/10.1177/0149206318785241

Guzzo, Richard A, & Noonan, K. A. (1994). Human Resource Practices as Communications and the Psychological Contract. *Human Resource Management*, *33*(3), 447-462. https://doi.org/10.1002/hrm.3930330311

Haidari, M., & Chhibber, P. (2022). *ARTIFICIAL INTELLIGENCE AND HUMAN RESOURCE MANAGEMENT: A CONCEPTUAL FRAMEWORK Workplace Mentoring and Skill Gap in Retail Sector View project*. 45(3)43-50 https://www.researchgate.net/publication/360079890

Haq, Y. U., Shahbaz, M., Asif, S., Ouahada, K., & Hamam, H. (2023). Identification of Soil Types and Salinity Using MODIS Terra Data and Machine Learning Techniques in Multiple Regions of Pakistan. *Sensors*, *23*(19), 1-19. https://doi.org/10.3390/s23198121

Hu, D., & Oh, I.-S. (2022). *The "Why" and "How" of Human Resource (HR) Practices: A Critical Review of the Antecedents and Consequences of Employee HR Attributions Research* 40(3) pp. 157–204. https://doi.org/10.1108/S0742-730120220000040006

Jackson, N. C., & Dunn-Jensen, L. M. (2021). Leadership succession planning for today's digital transformation economy: Key factors to build for competency and innovation. *Business Horizons*, *64*(2), 273–284. https://doi.org/10.1016/j.bushor.2020.11.008

Jackson, S. E., Schuler, R. S., & Jiang, K. (2014). An Aspirational Framework for Strategic Human Resource Management. *Academy of Management Annals*, *8*(1), 1–56. https://doi.org/10.1080/19416520. 2014.872335

Jarrahi, M. H., Askay, D., Eshraghi, A., & Smith, P. (2023). Artificial intelligence and knowledge management: A partnership between human and AI. *Business Horizons*, *66*(1), 87–99. https://doi.org/10.1016/j. bushor.2022.03.002

Katou, A. A., Budhwar, P. S., & Patel, C. (2014). Content vs. process in the hrm-performance relationship: An empirical examination. *Human Resource Management*, *53*(4), 527–544. https://doi.org/10.1002/ hrm.21606

Keegan, A., & Den Hartog, D. (2019). Doing it for themselves? Performance appraisal in project-based organisations, the role of employees, and challenges to theory. *Human Resource Management Journal*, *29*(2), 217–237. https://doi.org/10.1111/1748-8583.12216

Khairan, H. E., Zubaidi, S. L., Al-Mukhtar, M., Dulaimi, A., Al-Bugharbee, H., Al-Faraj, F. A., & Ridha, H. M. (2023). Assessing the Potential of Hybrid-Based Metaheuristic Algorithms Integrated with ANNs for Accurate Reference Evapotranspiration Forecasting. *Sustainability*, *15*(19), 1-19. https://doi.org/10.3390/su151914320

Kim, S., Vaiman, V., & Sanders, K. (2022). Strategic human resource management in the era of environmental disruptions. *Human Resource Management*, *61*(3), 283–293. https://doi.org/10.1002/hrm.22107

Kramar, R. (2014). Beyond strategic human resource management: Is sustainable human resource management the next approach? *International Journal of Human Resource Management*, *25*(8), 1069–1089. https://doi.org/10.1080/09585192.2013.816863

Leidner, S., Baden, D., & Ashleigh, M. J. (2019). Green (environmental) HRM: aligning ideals with appropriate practices. *Personnel Review*, *48*(5), 1169–1185. https://doi.org/10.1108/PR-12-2017-0382

Lopez-Cabrales, A., & Valle-Cabrera, R. (2020). Sustainable HRM strategies and employment relationships as drivers of the triple bottom line. *Human Resource Management Review*, *30*(3). 1–11 https://doi.org/10.1016/j.hrmr.2019.100689

Macke, J., & Genari, D. (2019). Systematic literature review on sustainable human resource management. *Journal of Cleaner Production*, *20(8)*, 806–815. https://doi.org/10.1016/j.jclepro.2018.10.091

Maley, J. (2014). Sustainability: The missing element in performance management. *Asia-Pacific Journal of Business Administration*, *6*(3), 190–205. https://doi.org/10.1108/APJBA-03-2014-0040

Malik, A., Budhwar, P., Patel, C., & Srikanth, N. R. (2022). May the bots be with you! Delivering HR cost-effectiveness and individualised employee experiences in an MNE. *International Journal of Human Resource Management*, *33*(6), 1148–1178. https://doi.org/10.1080/09585192.2020.1859582

Marchington, M. (2015). Human resource management (HRM): Too busy looking up to see where it is going longer term? *Human Resource Management Review*, *25*(2), 176–187. https://doi.org/10.1016/j.hrmr.2015.01.007

Margherita, A. (2022). Human resources analytics: A systematization of research topics and directions for future research. *Human Resource Management Review*, *32*(2).1–13 https://doi.org/10.1016/j.hrmr.2020.100795

Mariappanadar, S. (2014). Stakeholder harm index: A framework to review work intensification from the critical HRM perspective. *Human Resource Management Review*, *24*(4), 313–329. https://doi.org/10.1016/j.hrmr.2014.03.009

Najam, U., Ishaque, S., Irshad, S., Salik, Q. U. A., Khakwani, M. S., & Liaquat, M. (2020). A Link Between Human Resource Management Practices and Customer Satisfaction: A Moderated Mediation Model. *SAGE Open*, *10*(4).1-15 https://doi.org/10.1177/2158244020968785

Omidi, A., & Dal Zotto, C. (2022). Socially Responsible Human Resource Management: A Systematic Literature Review and Research Agenda. In *Sustainability (Switzerland)* (Vol. 14, Issue 4). Pp 1-12 MDPI. https://doi.org/10.3390/su14042116

Panuluh, S., & Fitri, M. R. (2016). Perkembangan Pelaksanaan Sustainable Development Goals (SDGs) di Indonesia. Biefing Paper, 20 (2), 1-25.

Pan, Y., & Froese, F. J. (2023). An interdisciplinary review of AI and HRM: Challenges and future directions. *Human Resource Management Review*, *33*(1).1-22 https://doi.org/10.1016/j.hrmr.2022.100924

Pan, Y., Froese, F., Liu, N., Hu, Y., & Ye, M. (2022). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. *International Journal of Human Resource Management*, *33*(6), 1125–1147. https://doi.org/10.1080/09585192.2021.1879206

Pellegrini, C., Rizzi, F., & Frey, M. (2018). The role of sustainable human resource practices in influencing employee behaviour for corporate sustainability. *Business Strategy and the Environment*, *27*(8), 1221–1232. https://doi.org/10.1002/bse.2064

Poon, T. S. C., & Law, K. K. (2022). Sustainable HRM: An extension of the paradox perspective. *Human Resource Management Review*, *32*(2).1-12 https://doi.org/10.1016/j.hrmr.2020.100818

Prikshat, V., Islam, M., Patel, P., Malik, A., Budhwar, P., & Gupta, S. (2023). AI-Augmented HRM: Literature review and a proposed multilevel framework for future research. *Technological Forecasting and Social Change*, *193(3)*.1-19 https://doi.org/10.1016/j.techfore.2023.122645

Qamar, F., Afshan, G., & Rana, S. A. (2023). Sustainable HRM and well-being: systematic review and future research agenda. *Management Review Quarterly*. https://doi.org/10.1007/s11301-023-00360-6

Ramachandran, K. K., Apsara Saleth Mary, A., Hawladar, S., Asokk, D., Bhaskar, B., & Pitroda, J. R. (2022). Machine learning and role of artificial intelligence in optimizing work performance and employee behaviour. *Materials Today: Proceedings*, *51(3)*, 2327–2331. https://doi.org/10.1016/j.matpr.2021.11.544

Ren, S., Cooke, F. L., Stahl, G. K., Fan, D., & Timming, A. R. (2023). Advancing the sustainability agenda through strategic human resource management: Insights and suggestions for future research. *Human Resource Management*, *62*(3), 251–265. https://doi.org/10.1002/hrm.22169

Swamynathan, M. (2017). Mastering Machine Learning with Python in Six Steps. In *Mastering Machine Learning with Python in Six Steps*. Ed 1 Apress Berkeley, CA: Apress. https://doi.org/10.1007/978-1-4842-2866-1

Westerman, J. W., Rao, M. B., Vanka, S., & Gupta, M. (2020). Sustainable human resource management and the triple bottom line: Multi-stakeholder strategies, concepts, and engagement. In *Human Resource Management Review* (Vol. 30, Issue 3). 1-4 Elsevier Ltd. https://doi.org/10.1016/j.hrmr.2020.100742

Yadav, R., Chaudhary, N. S., Kumar, D., & Saini, D. (2022). Mediating and moderating variables of employee relations and sustainable organisations: a systematic literature review and future research agenda. In *International Journal of Organisational Analysis*. Emerald Group Holdings Ltd. Vol. 31 No. 7, pp. 3023-3050 https://doi.org/10.1108/IJOA-12-2021-3091

Yong, J. Y., Yusliza, M. Y., & Fawehinmi, O. O. (2020). Green human resource management: A systematic literature review from 2007 to 2019. In *Benchmarking* (Vol. 27, Issue 7, pp. 2005–2027). Emerald Group Holdings Ltd. https://doi.org/10.1108/BIJ-12-2018-0438