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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 research which links to sustainability and the integration of artificial intelligence (AI) in HR practice has been increased. This paper explores the potential transformation of AI in HRM, revealing the factors that contribute to successful AI adoption and strategies to overcome adoption barriers within organisations. This research aims to verify a model for determining salaries for new employees that is competitive and in line with market standards. This paper also provides practical insights regarding how organisations can effectively analysis the role of HRM and AI to prevent undue evictions of HR professionals. To perform data analysis and processing, this research uses python analysis, with Jupyter notebook software and continues with model testing using regression evaluation model such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and coefficient of determination R^2-Score. The four main findings addressed in this study are lack of quality data, bias in data, loss of human aspect, and error and uncertainty. Furthermore, this research provides managerial implications for sustainable HRM practices in overcoming the main problem, namely determining new employee salaries using AI with the best accuracy by oversampling and comparing salaries through job portals to see current market trends.

Keywords:
artificial intelligence; HRM practices; HRM sustainable; HRM transformation.

JEL Code: E2; L2

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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), if artificial intelligence (AI) will replace the role of HRM. Long before the introduction of sustainable 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 can create new organisational value. In the last five years, research on HRM has increased sharply, especially in implementation of 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), and the role of AI in managing employees' responsibilities and roles (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 (Ferranti, 2019).

Sustainability becomes an essential element that can generate value, culture, and long-term competitive advantage that is presented in improving business performance by achieving 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 influences 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 to get results in the next five years or focus on increasing profits at the expense of organisational sustainability. When an organisation are concentrated on achieving short-term goals such as making profits, it will ignore 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 sustainability practices commitment (Ehnert et al., 2016). Although the amount of research on sustainability continues to increase, problems regarding sustainability practices in terms of human resources are often problematic, especially in the all-digital era. Over the past three decades, human resources stood out for its importance to implement the organisation's business strategy (Jackson et al., 2014; Kramar, 2014). The relationship between the concept of sustainability and HRM is shown as an innovative approach that emerges in support of the company's strategy to be adaptive, efficient, and effective (Westerman et al., 2020).

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 research analysing sustainabile 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 sustainable HRM, i.e., the study of results-oriented employee welfare, employee behaviour, and effective HRM strategies (Aust et al., 2020).

This research aims to analyse the salary determination model of new employees. This paper contributes to the literature on sustainable HRM 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 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. Second, overcoming data bias in sustainable HRM practices using artificial intelligence needs more discussion. A lot of research focus only on practical and economic-oriented without regard to how the management of the model might affect the outcomes given to minority groups (Feng, 2023). For example, 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. Furthermore, the use of AI in new employee payroll focuses on eliminating bias and ensuring that salaries are given fairly and equitably which includes consideration of factors such as qualifications, experience, performance, and job responsibilities. This research also shows how the modeling process of competitive salary is in accordance with the current market.

Literature review

Transforming HRM into sustainable HRM

Systematic review conducted by Budhwar et al. (2023) concerned that AI will replace the current work that was originally done by humans. However, human is key resources in AI, 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). 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, 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 rejecting the presence of AI, accepting and coexisting by setting existing boundaries of AI 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, which resulting new changes in HRM policies and practices (Budhwar et al., 2023; Pan & Froese, 2023).

However, there are still many research agendas that need to be completed before releasing work entirely using AI. Although AI has been tested using a very large database, this technology still often produces issues of discrimination against minority groups. In short, although this technology continues to evolve, there are still many research agendas in HRM perspective that need to be completed (Budhwar et al., 2022; Ren et al., 2023).

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

Fundamental shortcomings of sustainable 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 which creates difficulties to integrate and manage data well. Relevant information about employees can be stored in human resource management systems (HRIS), performance management systems and payroll systems. 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; it changes over time. Changes such as promotions, mutations, or 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 general data protection regulation and consumer protection privacy act, organisations need to ensure that employee data is stored and processed securely and in compliance with applicable regulations. These regulations can restrict data access and use (Yong et al., 2020). The effect that occurs when quality data is lack is an inaccurate decision making made by AI (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 sustainable 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 employees group. 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 sustainable HRM practices (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, appraisal data will reflect 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 is important to remember that potential bias in data is not an inevitable or insurmountable problem. Identification, understanding, and reduction of bias in data requires serious and sustained effort, which 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 sustainable 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 AI. Human aspect 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 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. Automated technology 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. 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 ensure that the values of fairness, inclusion, and sustainability which are integrated in all aspects of human resource management.

Errors and uncertainties

In today's digital age, AI has become one of the most dominating aspects in human life, including business, medicine, transportation, and even human resources. Although AI has provided significant advances and great benefits, it is undeniable that this technology also brings errors and uncertainties that need to be seriously faced and addressed (O'Neil & Denke, 2016).

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 (Gal & Ghahramani, 2016). This kind of mistake can be detrimental to both parties, which are 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. AI works based on existing data and mathematical processing, so uncertainty becomes an inevitable part. 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 (Pan et al., 2022).

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 a key to mitigate errors and uncertainties in the use of this technology (Yadav et al., 2022). In sustainable 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 sustainable HRM

The successful application of AI 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).

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. Organisational leaders 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). 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).

Moreover, since data is the raw material for AI, high-quality data is a must. 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). Regarding regulatory compliance and data security, the implementation of AI in HRM must comply with applicable data privacy regulations, this compliance is important to protect employees' personal data. In addition, data protection and security must take precedence (Yong et al., 2020).

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). 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).

Furthermore, 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. By considering and implementing the above factors, organisations can maximise their chances of achieving success in the application of AI in sustainable HRM. Thus, organisations can achieve their sustainable HRM goals more efficiently, make HR practices fairer, and create a more positive impact on their sustainability and corporate social responsibility (Leidner et al., 2019).

BISMA (Bisnis dan Manajemen) Volume 16 Issue 2, April 2024 Page 167–189
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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. The primary roles of traditional HRM 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. AI 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 fair 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 such as complex human relationships, the role of ethics and leadership, healthy organisational culture understanding context and nuance, conflict management and team development, and strategic decision making 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 (Budhwar et al., 2023; Chillakuri & Vanka, 2021; Aust et al., 2020; Mariappanadar, 2014).

Research method

Data analysis

To perform data analysis and processing, this research uses python with Jupyter notebook software. 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.

Data bias

Addressing data through data preprocessing, such as data cleansing, data stratification, and weight adjustment can help to prevent data bias. Data bias is a serious problem that can affect fairness and equity in sustainable HRM. Data bias is a problem that can arise in HRM practices that use AI and machine learning technologies. Data bias occurs when the data used to train an AI model contains preferences or imbalances that should not be present in HRM decisions. 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 (Margherita, 2022; Budhwar et al., 2023). 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, other groups may be overlooked. This can result in less diverse and less inclusive organisations (Ehnert, 2014; Fu et al., 2020).

BISMA (Bisnis dan Manajemen) Volume 16 Issue 2, April 2024 Page 167–189
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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. 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. 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) (Swamynathan, 2017).

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

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. 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) (Chen et al., 2023; Farzana et al., 2023; Haq et al., 2023; Khairan et al., 2023).

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

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. The formula of this metric is available in formula (3) (Chen et al., 2023; Farzana et al., 2023; Haq et al., 2023; Khairan et al., 2023).

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

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 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 R^2-Score, the better the model is at explaining variations. The formula of this metric is available in formula (4) (Chen et al., 2023; Farzana et al., 2023; Haq et al., 2023; Khairan et al., 2023).

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

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 regress, lasso regress, random forest regressor, gradient boosting regressor, and SVM) and deep learning (Long Short-Term Memory "LSTM" and neural network), Comparison of algorithm model performance is shown in Table 1.

Table 1
Comparison of algorithm modeling results

Algorithm	MAE	MSE	RMSE	R^2
Linier Regress	[illegible]63	0.691	0.881	0.992375
Regress Lasso	0.766	0.901	0.941	0.991242
Random Forest Regressor	2.[illegible]78	4.857	1.321	0.967382
Gradient Boosting Regressor	2.87[illegible]	6.798	2.317	0.826736
SVM	0.999	1.0[illegible]	1	0.988851
LSTM	0.0181	0.[illegible]167	0.0450	1
Neural Network	0.0497	0.0672	0.0601	0.998407

Source: Authors' work (2024)

In this research, there are two types of accuracy parameters in regression, machine learning and deep learning. R^2-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. This algorithm is determined as the model 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, the utilisation of AI models 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). Sustainable HRM practices in this research there are four shortcomings that 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 important challenge in this change is the use of AI (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 (Poon & Law, 2022).

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). 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. 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 previous practices. When AI models study this data, AI users can internalise and reinforce those biases in their decision-making (Budhwar et al., 2023; Poon & Law, 2022; Prikshat et al., 2023).

Developing machine learning models is also a serious challenge that is often faced, caused by imbalanced data sets. This imbalance occurs when the number of samples in one or more classes has a much smaller number of samples than other classes. 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 recommends 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. In some cases, practitioners use external data support in determining salaries for new employees with the principle of providing salaries according to skills and experience based on market salary ranges. Job portal data can be used to get salary ranges according to the current market (Budhwar et al., 2023).

AI has become a powerful tool in ensuring fairness, transparency, and efficiency in sustainable HRM processes, including payroll management processes. In predicting the salary of new employees, employer can follow three steps. First, 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. Second, 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, and length of work at the company and certain positions. Third, 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. 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

BISMA (Bisnis dan Manajemen) Volume 16 Issue 2, April 2024 Page 167–189
E-ISSN 2549-7790, P-ISSN 1979-7192

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.

Conclusion, limitations, and future research

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, and Writing–Original Draft. **Sunu Widianto:** Validation, Writing–Review and Editing. **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.

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