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SUSTAINABLE HUMAN RESOURCE MANAGEMENT: A TRANSFORMATION PERSPECTIVE OF HRM FUNCTIONS THROUGH OPTIMIZED ARTIFICIAL INTELLIGENCE

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Abstract:

Background: Nowadays startups are no longer a thing. Startups are mushrooming and attracting much attention both nationally and internationally. Business incubation activities are essential for startups, because many startups that have yet to have time to develop but have to stop running their operations.
Purpose: 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. In addition, the paper addresses important issues related to data bias in sustainable HRM practices when using AI, emphasizing the need to eliminate bias to ensure fairness and equity.
Design/methodology/approach: To perform data analysis and processing, the author uses python with the software used is a Jupyter notebook. The use of Python programming language has gained significant popularity in the world of research. Python's strengths are seen through a variety of research methods that include data and statistical analysis with libraries such as NumPy and Pandas, building machine learning models using TensorFlow and scikit-learn, and mathematical simulation and modeling with the help of Matplotlib and Seaborn
Findings/Result: The paper also provides practical insights into how organizations can effectively limit the role of HRM and AI to prevent undue evictions of HR professionals. In addition, the study emphasizes the importance of addressing data quality issues and bias in AI applications within HRM, with a particular focus on ensuring equal treatment and opportunities for minority groups. As an illustrative example, this paper details a practical approach to AI-powered new employee payroll. This approach aims to eliminate bias, ensure competitive salaries, and be in line with market standards. While embracing AI for HRM, the paper emphasizes the importance of maintaining the human touch in decision-making and maintaining sensitivity, empathy, and understanding, especially in complex HR scenarios.
Conclusion: This research has discussed and contributed to a literature review on the transformation of Human Resource Management (HRM) into sustainable HRM using Artificial Intelligence (AI). 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.

Keywords: artificial intelligence, balance of HRM and AI, HRM transformation, sustainability, sustainable hrm practices

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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; S. Chowdhury, Dey, et al. 2023; Diaz-Carrion et al. 2020; Margherita, 2022; Mayuri Chaudhary, 2023). 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 organizations can be a sustainable competitive advantage (Aust et al. 2020a; Deadrick & Gibson, 2007; Ehnert et al. 2016a; Guzzo & Noonan, n.d.; Poon & Law, 2022a). Creating new value and distinct advantages in front of competitors to be able to create new organizational value. In the last 5 years, research on HRM has increased sharply, especially implementation using AI (Budhwar et al. 2023; S. R. Chowdhury et al. 2023; Margherita, 2022), for example, the emphasis and utilization 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 (Jarrahi et al. 2023), roles, and other duties of employees (Haidari & Chhibber, n.d.). However, the rapid development of AI that continues to evolve resulting in opportunities and challenges is not in line with contemporary HRM practices.

The application of artificial intelligence (AI) in human resource management (HRM) offers significant opportunities and challenges, but it is often not aligned with contemporary HRM dynamics. In terms of opportunities, AI can improve the efficiency of the recruitment process with in-depth data analysis for better and faster candidate selection. AI-based chat bots' systems can also provide more responsive and efficient customer service in the context of HRM. However, challenges arise in the integration of these technologies with human values that are increasingly valued in modern human resource management.

One of the main challenges is the potential for dehumanization in the interaction between employees and the company. Although AI can provide operational efficiencies, the risk of emerging perceptions that employees are perceived as entities that can be replaced by machines also increases. Highly mechanistic and data-driven decision making without considering emotional and human aspects can be detrimental to an inclusive organizational culture and employee happiness.

Misalignment can also arise in terms of inequality and bias. The implementation of AI in employee recruitment and evaluation can create biases in models that influence selection decisions and performance evaluations. If training data contains bias, AI models can reinforce inequalities that may already exist in HRM systems.

While AI promises the automation of routine tasks, some HRM roles that require emotional intelligence, and a deep understanding of human dynamics may be difficult to replace by technology. The importance of human aspects in contemporary HRM, such as conflict management, employee development, and understanding of organizational context, may not be fully covered by AI.

The application of artificial intelligence (AI) in human resource management (HRM) presents significant opportunities and challenges, but they often do not keep pace with the dynamics of contemporary HRM. AI can improve the efficiency of recruitment and customer service of HRM through data analysis and chat bot's systems. However, the risk of dehumanization and potential bias in employee evaluation are challenges that must be overcome. The role of HRM that requires emotional intelligence, and a deep understanding of human dynamics is still difficult to replace by technology. In the context of sustainable development, the implementation of AI in HRM must integrate the principles of the Sustainable Development Goals (SDGs), maintaining a balance between operational efficiency and human values and social justice.

In line with the impact of welfare, anticipating existing changes, the UN formulated 17 Sustainable Development Goals (SDGs), inseparable from the application of SDGs in the human resource sector at every level of the organization.

Sustainability becomes an important 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 organization. Currently, many organizations 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). There is a unique statement delivered by (Lopez-Cabrales & Valle-Cabrera, 2020), will the organization sacrifice this year's profits to practice sustainability in the hope of getting results in the next 5 years, or will the organization focus on increasing profits at the expense of organizational sustainability in the future. 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 larger scenarios for organizations to demonstrate commitment to sustainability practices (Ehnert et al. 2016a). 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 organization's business strategy (S. E. Jackson et al. 2014; Kramar, 2014). The relationship between the concept of sustainability and human resource management 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).

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 human resource management (HRM) strategy as the left HRM function is expected to play an active role to help organizations meet demanding interests (Omidi & Dal Zotto, 2022; Poon & Law, 2022a; Qamar et al. 2023). Sustainable HRM can be defined as the implementation of HRM strategies and practices that can enable achievement in various lines such as business, financial, social, and ecological (Poon & Law, 2022a). Most of the research analyzing 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 organizations efficiently and effectively (Budhwar et al. 2023; Margherita, 2022). There are three lines of study that discuss sustainability HRM, namely the study of results-oriented employee welfare, employee behavior, and effective HRM strategies (Aust et al. 2020b). Although the study of the field of HRM has valuable insights, at least through our analysis through several articles like (Budhwar et al. 2022, 2023; Chatterjee et al. 2022; S. Chowdhury, Dey, et al. 2023; N. C. Jackson & Dunn-Jensen, 2021; Mayuri Chaudhary, 2023; Omidi & Dal Zotto, 2022; Poon & Law, 2022a; Prikshat et al. 2023; Qamar et al. 2023; Susanti et al. 2020; Yadav et al. 2022), there are at least 4 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 organizations may be incomplete or of poor quality. This can lead to less accurate results from AI models (Budhwar et al. 2023). Second, 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, 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, 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.

To fill this gap, this paper seeks to be able to contribute 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 Artificial Intelligence in terms of HRM practices and the role of HR including in analyzing what factors contribute to the successful adoption of Artificial Intelligence in the work environment and how organizations 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 organizations 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 organizations can manage, establish, and structure specifically in establishing roles between technology and humans. Second, overcoming data bias in sustainable HRM practices using Artificial Intelligence. Through the various papers we reviewed, 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 like When in 1 team, 80% of workers are men while the rest are women, or workers in a company are dominated by certain groups. For example, (Feng, 2023; Ramachandran et al. 2022) which discusses the application of AI in the HRM sector, but in the discussion process, it is not discussed about how the model can overcome the problem of data bias that allows discrimination in minority groups. Third, we also provide 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. In the modeling that we provide, we will also show how the modeling process with a competitive salary is in accordance with the current market.

METHODS

To perform data analysis and processing, the author uses python with the software used is a Jupyter notebook. The use of Python programming language has gained significant popularity in the world of research. Python's strengths are seen through a variety of research methods that include data and statistical analysis with libraries such as NumPy and Pandas, building machine learning models using TensorFlow and scikit-learn, and mathematical simulation and modeling with the help of Matplotlib and Seaborn. Python libraries such as OpenCV also provide strong support in image processing and computer vision research. Meanwhile, Python is used in web scraping research and data mining by using tools like Beautiful Soup and Scrapy. In the security domain, Python is used for malware analysis and network security, while in natural language processing (NLP), NLTK and spaCy are the top choices. Python's diverse functionality makes it easy for researchers from different disciplines to integrate this programming language into their research methodology, making it a highly relevant and popular choice in modern research contexts. By modeling the salary determination of new employees, the author will provide an example of implementing Sustainable HRM by answering 2 questions. First, designing a new employee salary determination model without causing data bias so that there is discrimination against minority groups. Second, build models and compare machine learning/deep learning algorithms in determining the salary of new employees.

We used 2 data sources in this study. Job Description and Salary data which is employee recruitment information data, description, KSAO skills, and salaries obtained through the Jobstreet Job Portal. Researchers conducted Web scraping to be able to pull data sourced from Job Street with the amount of data obtained was 23,561 employee recruitment data in various positions. In addition, we use employee data which contains information data about employees of a company that contains information about general data such as name, education, position, employee performance data, training history, career data, and others. Data obtained from PT. Telkom Indonesia which has been modified to maintain the company's internal confidentiality with a total of 3,412 data.

The use of artificial intelligence (AI) technology in human resource management (HRM) has changed the HRM landscape significantly. AI has enabled organizations 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 Human Resource Management (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).

The tendency for bias in data is often a challenge in research and can stem from a variety of factors such as unrepresentative data sources, data collection errors, and subjective analyst prejudices. Previous research has tried to address this issue with a variety of approaches. For example, (McCarthy et al. 2013) has emphasized the importance of more representative sample selection and using more thorough data collection methods to reduce errors. In addition, there are efforts to leverage technologies, such as specialized algorithms, to detect and reduce bias in machine learning models.

However, although many of these efforts have made a positive contribution in reducing data bias, further emphasis on the humanitarian side is still needed. More holistic solutions must consider the social and ethical impact of data use. Some research also such as (Barrick & Zimmerman, 2009; Boselli et al. 2018; McCarthy et al. 2013) highlights the need to involve a broader human perspective in data analysis, by encouraging the participation of groups that may be underrepresented. For example, the implementation of culturally responsive and participatory design can help ensure that data collection and analysis do not overlook or disadvantage specific groups (Grechanuk et al. 2018; Schwartz et al. 2022).

In addition, several studies such as (Newman et al. 2020) have explored ways to increase transparency and accountability in the data analysis process, as well as put forward documentation that is clear and understandable to all stakeholders. Awareness of social impact and equity in the use of data must also be improved. The integration of ethics and human values in the entire research cycle, from planning to interpretation, becomes very important. This side of humanity not only includes ethical and justice perspectives, but also involves decision-making that is responsive to human values to reduce inequality and care for diversity. These solutions reflect a holistic approach geared towards more comprehensive and inclusive improvements in the use of data in research.

In the context of HRM, data bias can have a serious impact on human resource policies and decisions, including in recruitment, promotion, performance evaluation, etc. (Margherita, 2022). Sure, 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 organizations. If AI models tend to prioritize certain groups, such as graduates from certain universities, then other groups may be overlooked. This can result in less diverse and less inclusive organizations (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 (R2-Score) (Nelli, 2015; 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 as follows:

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

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 as follows:

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

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 as follows:

$$\mathrm{RMSE} = \sqrt{}1/N \sum_{k=1}^{n}(y_k\text{-}\hat{y}_k)$$

The Coefficient of Determination, often referred to as the R-squared or R2-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. R2-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:

- R2-Score = 0: This 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.
- R2-Score = 1: This indicates that the model is perfect and able to explain all variations in the data correctly.
- 0 < R2-Score value < 1: This 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 as follows:

$$R^2=1-\frac{1/N \sum_n^{k=1}(y_k\text{-}\hat{y}_k)}{1/N \sum_n^{k=1}(y_k\text{-}\hat{y}_k)}$$

RESULTS

We have explained how the transformation of HRM into HRM continues, we also conduct 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 Neurul Network), we gain insight into model performance which can be seen in the following Table 1.

In our research, we used 2 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. Through the table, most models show values close to 1, which means that the model has a high level of match and accuracy in predicting the salary of new employees. We also analyzed error metrics such as MAE, MSE, and RMSE, values close to 0 are models that use LSTM, Neural Network, and linear regression algorithms. That is, 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.

In modeling to avoid data bias, we apply careful strategies in data collection and handling. For example, in this study, we ensured that the dataset used included balanced representations of different job categories and education levels, to prevent biases that might arise from imbalances in group representations. In addition, we normalize salary data based on factors such as education level, work experience, and geographic location, to reduce potential bias that may arise due to differences in worker characteristics.

Next, we use oversampling techniques on minority categories to ensure that the model does not discriminate against specific groups with a smaller number of samples. This technique helps improve the model's accuracy in predicting salaries for minority groups that may be underrepresented in training data.

The importance of bias mitigation is also reflected in the selection of algorithms. We chose machine learning and deep learning algorithms that have been proven to address bias well, such as LSTM (Long Short-Term Memory) and Neural Network. LSTM's excellence in handling data sequences helps overcome potential biases that may arise in the order of work experience or career growth, which can greatly affect salary predictions.

Table 4. Comparison of algorithm modeling results

Algorithm	MAE	MSE	RMSE	R^2
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

Through these measures, we strive to ensure that the models built not only have a high level of accuracy but are also free from biases that can affect fairness and objectivity in salary predictions for new employees. By carefully organizing data and selecting appropriate algorithms, we hope to minimize the impact of bias and ensure fairer and more accurate prediction results. The utilization 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 organizations to respond quickly to job market changes, ensuring that salaries offered remain competitive and in line with industry trends.

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 synchronize with business and organizational strategies, there are some many conceptual processes and findings that can be developed (Aust et al. 2020b, 2020a; Budhwar et al. 2022, 2023; S. Chowdhury, Dey, et al. 2023; S. Chowdhury, Joel-Edgar, et al. 2023; S. R. Chowdhury et al. 2023; Deadrick & Gibson, 2007; Diaz-Carrion et al. 2018, 2020; Ehnert et al. 2016b, 2016a; Guzzo & Noonan, n.d.; Mayuri Chaudhary, 2023; Poon & Law, 2022b, 2022a). We introduced findings of deficiencies in sustainable HRM practices, we highlighted 4 shortcomings that we managed to identify beyond regulatory, privacy, and data security issues. These shortcomings are a lack of quality data, biased data, loss of human aspects, and uncertainty.

In this paper, we propose a literature review and continuous HRM processes using AI, specifically regarding solution solving in our findings. We have summarized an in-depth review analysis of the transformation of the HRM function towards sustainable HRM with Artificial Intelligence practices. Sustainable Human Resource Management (HRM) is an approach that emphasizes the importance of treating employees as valuable and sustainable resources for the organization (Macke & Genari, 2019). However, when we discuss the implementation of sustainable HRM then the AI approach is inevitable. Sustainable Human Resource Management (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 (AI) (Budhwar et al. 2022; Jarrahi et al. 2023; Ramachandran et al. 2022). However, it is important to recognize the benefits provided by the integration of AI in continuous HRM. Using AI, we encounter several paradoxes and problems that require serious attention. AI can provide various benefits in managing human resources, but it can also present significant risks related to human aspects, bias, data privacy, and many other things (Budhwar et al. 2022, 2023; Poon & Law, 2022a).

The significance of risks related to human aspects, bias, data privacy, and other matters has been recognized in research by Budhwar et al. (2022, 2023) and Poon & Law (2022a). To overcome this risk and prevent the system from prioritizing certain groups over others, careful measures need to be taken. Even if unintentional or unprogrammed, these risks can arise because of unbalanced policies or data.

One way to avoid the system giving certain priorities to certain groups is to apply filters that consider the needs of users thoroughly. This can be done by ensuring that the algorithms and models used in the system are given special attention not to discriminate or give more advantages to certain groups, such as based on gender, ethnicity, or other factors. The implementation of this filter must consider justice and humanity so that every group has an equal chance of being accommodated by the system.

In addition, to avoid group bias, the data used in system development must be monitored and evaluated continuously. If indications of bias are found in the data, corrective steps should be taken to ensure that the model does not reinforce or exploit any inequalities that may exist in the training data.

In addition to using filters and keeping an eye on data, system programming can ignore data that has significant group bias. This can be achieved by actively identifying those variables that have the potential to cause bias and determining policies to ignore or give lesser weight to those variables during the system's decision-making process.

In this context, it is important to develop and implement policies and ethics of system use that reflect the values of fairness and inclusivity. Considering the perspective of diversity and equity in system development and maintenance is a key step to prevent automated systems from giving preference to one group. With this approach, it is hoped that risks related to bias, inequality, and data privacy can be minimized, and the system can operate more fairly and sustainably.

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 organizational culture into the limelight. However, when companies rely too much on AI, the risk of dehumanization 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. We have proposed a literature review of the middle line between the role of AI and HRM practitioners (Pellegrini et al. 2018). We also provide a summary and analysis of the contributing factors and potential in adopting AI in the HRM dimension.

The above statement highlights the main paradox in the implementation of Sustainable Human Resource Management (HRM) with artificial intelligence (AI), namely that the focus on the human aspect can be eroded. Sustainable HRM should bring values such as employee happiness, career development, and inclusive organizational culture into the spotlight. However, when companies rely too heavily on AI, the risk of dehumanization in the relationship between employees and companies arises (Budhwar et al. 2023; Pellegrini et al. 2018). Employees can feel ignored or perceived as entities that can be replaced by machines. Highly mechanistic and data-driven decision making without considering emotional and human aspects can result in an inadequate work environment and disrupt employee well-being.

In digging deeper into the statement, it is necessary to clarify which HRM tasks AI can perform and which tasks require a human touch so that HR governance remains meaningful. Can AI effectively manage administrative and routine tasks in HRM, such as payroll data processing and employee administration, or does it have the capability to understand and respond to employees' emotional needs and manage aspects of career development that require a deep understanding of human individuality?

These questions raise important concepts about sustainable and ethical HRM policies in integrating technology. Developing a clear understanding of the task boundary between AI and human touch can help create a framework that ensures that the implementation of artificial intelligence in HRM does not sacrifice critical aspects of sustainable human resource management. By answering these questions, companies can steer their HRM policies towards balanced and sustainable integration of technology, while still prioritizing employee well-being and maintaining a balance between operational efficiency and human care. 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, 2022a; 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, they can internalize and reinforce those biases in their decision-making. When we talk about 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 (S. Chowdhury, Dey, et al. 2023). In addressing this issue, we provide a literature review on handling data bias. In general cases, we 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. However, in some cases, practitioners may use external data such as support in decision making.

In this paper, we provide examples of how to practice sustainable HRM in determining the salary of new employees with the principle of providing salaries in accordance with the skills, experience, and salary range in the market. We use data from job portals to get salary ranges according to the current market. of course, the application of sustainable HRM in this case will use AI as the research agenda that has been proposed by previous research (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, we pull salary data through job portals and analyze the salaries of old employees. We analyze salary data and recruitment requirements from job portals. We collect and analyze 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. Then, we analyze the salaries of old employees already in the organization. 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. Finally, we built 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, we do data balancing through oversampling to prevent data bias in our study. The results of our model show contrast performance across the various algorithms we 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. Of course, 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.

Managerial Implications

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, we strongly encourage further researchers to answer and resolve the limitations in this paper to be able to complete this paper and literature review. 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. We encourage further researchers to be able to 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 organization, and how organizations can measure and evaluate these effects. The use of Artificial Intelligence (AI) in Human Resource Management (HRM) has entered an increasingly mature stage, providing great potential to improve efficiency, accuracy, and fairness in managing human resources in various organizations. 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 organizations 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 organizational 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 organizational 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 Chaudhary, 2023).

In addition to the impact on organizational 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 minimizing 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. Organizations 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 organizational 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 organizations 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 organizations to plan their long-term investments in AI technology and optimize its benefits.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

This research has discussed and contributed to a literature review on the transformation of Human Resource Management (HRM) into sustainable HRM using Artificial Intelligence (AI). 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 several 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.

Recommendations

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 organizational 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, organizations can optimize 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.

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