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THE EFFECT OF AI TOOLS ON TALENT MANAGEMENT PROCESSES

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Abstract

In the current research paper, the researcher will explain the potential of artificial intelligence (AI) capabilities in enhancing talent management practices in organizations. The subjects of the study are perceived AI efficiency, ease of use, AI-generated insights, employee training, overall AI use, and AI-driven talent management results. The quantitative research methodology was followed, and the primary data was collected using a structured questionnaire given to the employees of different organizations. Convenience sampling was applied and 56 valid responses were obtained and analyzed using descriptive statistics, correlation analysis and multiple regression analysis. The results indicate that AI efficiency, usability, and AI-generated insights can be regarded as important predictors of AI-optimized talent management outcomes, and perceived AI efficiency proved to be the most potent predictor. Conversely, the training of employees and the overall use of AI did not prove to be statistically significant in the sample. The regression model elucidates a significant share of the variance in AI-optimized talent management performance, which places the quality of AI systems and functionality in the limelight. Nevertheless, the results must be taken with a grain of salt because of weaknesses that include small sample size, non-probability sampling, and use of cross-sectional and self-reported data. In spite of these shortcomings, the research provides useful information to organizations that aim to improve talent management with the help of effective AI application.

I.INTRODUCTION

The field of talent management has experienced a massive influence of ai in the modern organizations, especially in recruitment, performance management, workforce planning, and development of employees. The recent advances such as generative ai and enhanced machine learning that began in 2022 have opened up the scope of use of ai beyond automation of administrative functions to strategic decision support in human resource management [9], [20]. However, AI talent management is not always effective in any organization because the system might not be efficient, friendly, and capable of developing quality AI-driven insights, and employees might not be well trained. According to previous studies, employee perceptions and usability of the system are regarded as key success factors that can determine the effectiveness of AI-enabled talent management systems [27], [19]. Moreover, raising ethical and regulatory issues show that the responsible adoption of AI is essential in the organizational setting [21].

To address the research question, the proposed study will assume a quantitative survey approach to investigate the role of AI-related factors on AI-optimized talent management performance.

II.RESEARCH HYPOTHESIS

The proposed study will be based on the available literature on technology acceptance and AI-enabled human resource management, whereby a series of hypotheses will be proposed to investigate the connection between the main AI-related variables and the AI-optimised talent management outputs. According to previous research, the efficiency of the system and user-friendliness, as well as the quality of the AI-created insights, serve as the key factors to define the effectiveness of the digital technologies in the organisational environment [27], [19].Also, training of employees and the level of AI application is widely assumed to be an impact in successful technology integration in the talent management processes.

Perceived AI efficiency states how AI systems accelerate, increase the accuracy, and efficiency of talent mana gement operations. The systems that can eliminate the manual workload and enhance the effectiveness of the decision-making process will have a positive effect on the outcomes of the talent management. Thus the hypothesis is the following:

H1: AI-optimised talent management has a positive relation with perceived AI efficiency.

Ease of use is the extent of how AI systems are perceived to be user friendly and intuitive. Easier technologies to use will have higher chances of adoption and successful integration in the everyday HR practices resulting in better talent management results. Based on this, the second hypothesis is the following one:

H 2: AI optimised talent management is positively related to the perceived easiness of the use of AI systems.

The AI-generated insights can be defined as the potential of the AI systems to generate valuable and practical information to aid in making decisions related to talent. On the one hand, AI tools allow improving the quality of workforce planning and talent development decisions when they produce useful insights. According to this reason, the third hypothesis is developed:

H3: AI-formed insights have a positive relationship with AI-optimised talent management.

Employee training is associated with the level to which employees are provided with knowledge and skills to use AI systems efficiently. Proper training is likely to enhance the improved use of AI technologies in the talent management processes. So, the hypothesis below is constructed:

H4: AI-optimised talent management bears a positive relationship with employee training on AI systems.

The application of AI use is the prevalence and extent of AI use in talent management activities. It is assumed that more AI systems will be used, and their role in HR practices will grow, which may result in better talent management outcomes. Thus, the formulated final hypothesis is the following:

H5: AI-optimised talent management has a positive relationship with AI usage.

III.RESEARCH OBJECTIVES

The main aim of this research is to determine the role of artificial intelligence (AI) capabilities in optimising the results of talent management in organisations. Particularly, the research seeks to empirically examine how perceptions of the employees towards AI factors affect AI-optimised talent management.

The research has the following objectives:

- *To ascertain the correlation of perceived AI-efficiency with AI-optimised talent management results.*

To identify the effects of the perceived ease of use of AI systems on the AI-optimised talent management.

- *To assess the effect of AI-generated insights on talent management practice optimisation.*

To examine the correlation between employee training on AI systems and AI-optimised talent management.

Alternatively, it is possible to explore the relationship between AI usage and AI-optimised talent management results.

IV.SIGNIFICANCE OF RESEARCH

The current literature on artificial intelligence (AI) and its use in human resource management is based on the overall digital transformation or HR functions, including recruitment. The lack of empirical data investigating the overall effect of AI capabilities in the whole talent management cycle is especially observed in emerging economies such as Pakistan [16].

This paper fills this gap by offering empirical understanding of the relationship between AI efficiency, ease of use, AI-generated insights, training, and usage with regard to AI-optimised talent management outcomes. The results have practical implications to organisations that aim to apply AI systems in a more efficient way in the talent management practices.

V.LITERATURE REVIEW

The increased use of artificial intelligence (AI) within the organisational environment has resulted in a great number of scholarly studies on the role of AI in the talent management (TM) processes. Past literature has revealed that various organisational factors such as organisational environment and managerial practices have a great impact on employee performance outcomes, proving that technological interventions do not exist in isolation and they are rather embedded in wider organisational systems [29].

The available literature analyses the use of AI in recruitment, learning and development, performance management, employee engagement, and retention, and the organisational and environmental aspects that affect the performance of AI-promoting TM systems. In this section, the main literature reviewing is focused on the problems of AI tools that can make talent management practices effective[30-34].

Leadership style and workplace culture have been identified as organisational factors that are important to employee performance outcomes, and technological interventions have been shown to interact with the broader managerial dynamics [28]

ARTIFICIAL INTELLIGENCE AND THE IMPACT OF AI ON TALENT MANAGEMENT PROCESSES

The application of AI to recruitment has drawn a lot of scholarly interest, where researchers have shown that AI can potentially increase the pace, accuracy, and objectivity of recruitment activities [1]. AI systems enhance objective candidate selection and make initial screening automated and minimize redundant administrative functions. Nonetheless, the issues of algorithmic bias and transparency have been raised, and it is important to note that the quality of AI results depends on the quality of inputs and how the system is formed.

Particularly, HireVue and Pymetrics are used to screen candidates with the help of AI-based tools, LinkedIn Talent Insights are used to analyze the workforce, and Eightfold is used to match candidates by their skills. These tools represent the way AI functions mentioned in the literature are realised in the real-world situation of talent management to enhance the efficiency of recruitment and accuracy of decision-making [4], [7]. Though the current research does not consider concrete software solutions, these illustrations prove that AI-enhanced hiring became a feasible solution.

These facts are further supported by empirical evidence. According to Johnson et al., AI can enhance the accuracy of predictions and time-to-hires, but there are still doubts about the trustworthiness of applicants as far as the lack of transparency of algorithmic decision-making procedures is concerned [14]. This points to the trade-off between efficiency incentives and ethical in AI-based recruitment.

In addition to the recruitment sphere, AI is increasingly involved in the employee learning and development. Learning systems that are powered by AI would facilitate individualised training according to the identified skill gaps, facilitating ongoing reskilling and organisational competitiveness [17]. Nevertheless, the digital maturity among developing economies could be different, and the ability of such systems to scale up might be constrained.

Performance management is also becoming an area where AI is being used. The organisational functions of algorithmic management systems involve using real time performance statistics, behavioural tracking and predictive evaluation to make organisations more objective and predictable [15]. However, the acceptance of employees is a very important consideration of the effectiveness of these systems.

In terms of retaining employees, predicting analytics powered by AI have been applied to determine the risks of turnover and facilitate proactive employee retention. Studies suggest that these systems are able to lower the rates of employee turnover, despite the fact that issues of data privacy and the ethical governance still exist [18].

Last but not least, technological maturity, labour market, and regulatory environments are external factors that can profoundly impact the use and performance of AI in talent management. Most organisations are beginning to consider AI as a source of strategic value, though it is implemented in different regions in different ways [24].

THEORETICAL AND CONCEPTUAL MODELS ASSOCIATED WITH AI IN TALENT MANAGEMENT

Various theoretical frameworks are used to support research on AI-enabled talent management. According to the Technology Acceptance Model (TAM), user acceptance of the new technologies is determined by perceived usefulness and perceived ease of use [8]. When applied to talent management, TAM means that AI-based systems will work better in the case when the HR professionals think of them as trustworthy, easy-to-use, and conducive to human judgment [22].

Resource-based View (RBV) of the firm is an argument that the organisations can gain competitive advantage based on valuable and inimitable resources [1]. In this view, AI-based TM systems are potential strategic resources, as long as they are accompanied by the digital infrastructure and human capacities.

The Human-AI Collaboration Model also focuses on the notion that AI supports the human decision-making but does not substitute it. AI complements the results of TM with analytical information, whereas human managers can offer context and their understanding, reasoning, and judgement [13].

Last but not least, the algorithmic decision-making theory lays emphasis on the efficiency versus fairness of AI-driven HR systems. Algorithms bias can also lead to the failure and loss of effectiveness and credibility of talent management practices without proper governance and transparency [5].

I.RESEARCH METHODOLOGY

VI.DATA ANALYSIS

The survey data were analysed using quantitative statistical methods to explore the association between the artificial intelligence (AI) capabilities and the AI-optimised talent management results. The descriptive statistics, Pearson correlation coefficients and multiple regression results generated in spreadsheet-based analysis are extensively employed in research in business and management to test hypotheses [25].

1) Descriptive statistics

The main characteristics of the data were summarised with the help of descriptive statistics. All the study variables were measured by their means and standard deviations to determine the perceptions of respondents to AI efficiency, ease of use, AI-generated knowledge, employee training, AI usage, and AI-optimised talent management [10].

2) Correlation analysis

Pearson correlation was performed to provide the strength and direction of the relationships between independent variables and the dependent variable. This analysis gave some early information of associations between variables not with the implication of causation [2]. Correlation coefficients were also evaluated to test whether there was a possibility of multicollinearity and the data showed that the issue of multicollinearity was not in question [10].

3) Multiple Regression Analysis.

To test the hypotheses and assess the combined and individual impacts of the independent variables on AI-optimised talent management, the multiple linear regression analysis test was used. The independent variables were perceived AI efficiency, ease of use, AI-generated insights, employee training and AI usage whereas the dependent variable was AI-optimised talent management [11]. The results of the regression were interpreted using standardised and unstandardised coefficients, significance values, and coefficient of determination (R 2). Since the study is cross-sectional, the results refer to levels of association and not levels of causality [6].

***4)* Demographic Respondent Characteristics.**

The sample of the survey was 56 people who work in various organisational positions and in organisations of various sizes. The participants were divided into interns, employees, HR professionals and managers with the latter making the majority of the sample group. The organisations of less than 50 employees, 50 to 200 employees, 200 to 500 employees and above were used to sample the respondents so as to have representative sample of small organisations, medium organisations and large organisations.

VII. DESCRIPTIVE STATISTICS OF IMPORTANT VARIABLES

The descriptive statistics helped summarize the central features of the data and give the first idea of how the respondents think about the possibilities of artificial intelligence (AI) and AI-optimized talent management. All variables of the study were measured using the means and the standard deviations of central tendency and dispersion. Furthermore, minimum, and maximum values were also analyzed to determine the number of responses and any anomalies in the data (Field, 2018).

Table 1 shows the descriptive statistics of the perceived AI efficiency, ease of use, AI generated insights, employee training, AI use, and AI optimized talent management. In the results, the general reports of respondents are that they have moderate to high perceptions of efficiency, ease of use, and AI-generated insights. This implies that in general, the employees perceived AI systems as adding value to their talent management activities in their respective organizations.

The standard deviation values presented in Table 1 reflect a decent degree of variation in the responses, meaning that although the overall perceptions of the AI systems were positive, there were dissimilarities in the experiences and perception of the respondents. Such difference proves the appropriateness of additional inferential analysis because there is enough dispersion within the data (Bryman, 2016).

The analysis of the lowest and highest values showed that the range of responses was exhausted, which was on both ends of the Likert scale, and this means that the questionnaire has indeed managed to represent the varied opinions. None of the extreme or unrealistic values were present, which indicated that the data were suitable in the further correlation and regression studies. Overall, the descriptive statistics are strong to continue testing and hypothesis testing using the further statistics.

use of AI in organisation		*ease of using AI tools*		*Efficiency result of AI tools*		*talent identification and management insights*		*AI-Optimised Talent*	
Mean	2.89	Mean	3.57	Mean	2.84	Mean	3.30	Mean	3.04
Standard Error	0.19	Standard Error	0.19	Standard Error	0.19	Standard Error	0.21	Standard Error	0.21
Median	3	Median	4	Median	3	Median	4	Median	3
Mode	3	Mode	5	Mode	1	Mode	5	Mode	5
Standard Deviation	1.41	Standard Deviation	1.44	Standard Deviation	1.45	Standard Deviation	1.55	Standard Deviation	1.58
Sample Variance	1.99	Sample Variance	2.07	Sample Variance	2.10	Sample Variance	2.40	Sample Variance	2.51
Kurtosis	-1.20	Kurtosis	-0.81	Kurtosis	-1.29	Kurtosis	-1.40	Kurtosis	-1.53
Skewness	0.08	Skewness	-0.68	Skewness	0.10	Skewness	-0.38	Skewness	-0.03
Range	4	Range	4	Range	4	Range	4	Range	4
Minimum	1	Minimum	1	Minimum	1	Minimum	1	Minimum	1
Maximum	5	Maximum	5	Maximum	5	Maximum	5	Maximum	5
Sum	162	Sum	200	Sum	159	Sum	185	Sum	170
Count	56	Count	56	Count	56	Count	56	Count	56

VIII.CORRELATION ANALYSIS

Pearson correlation analysis was applied to test the level and direction of the relationship between the independent variables, including perceived AI efficiency, ease of use, AI-generated insights, employee training, and AI usage and the dependent variable, AI-optimized talent management. Correlation analysis gives a rough evaluation of relationships between variables without an assumption of causality (Bryman, 2016).

The Pearson correlation coefficients between all the variables of the study are given in Table 2. The findings show that AI-optimized talent management is positively related to the perceived AI efficiency, ease of use, and AI-generated insights. These associations indicate that the better the perceptions of system effectiveness, usability, and insight generation are, the better the talent management outcomes are.

Positive relationships can also be observed between employee training and the use of AI, but they are lower than the data discussed in relation to AI-optimized talent management. It means that training and usage are correlated with the outcome of talent management, but its correlation can be less significant compared to the efficiency, ease of use, and AI-generated insights.

Correlation coefficients between the independent variables were also analyzed to determine the possibilities of occurrence of multicollinearity. The values of all correlations were below standard accepted values ($r < 0.80$), which implied that the likelihood of the multicollinearity to bias the regression outcomes was minimal (Field, 2018). This justifies the fact that all independent variables will be included in the following multiple regression analysis.

Overall, the analysis of correlation gives the initial results that support the hypotheses that were formulated and warrant additional investigation using a multiple regression analysis to determine the individual contribution of each of the predictors.

	use of AI in organisation	ease of using AI tools	Efficiency result of AI tools	talent identification and management insights	training for AI tools
use of AI in organisation	1	0.60	0.68	0.72	0.36
ease of using AI tools	0.60	1	0.52	0.43	0.52
Efficiency result of AI tools	0.68	0.52	1	0.75	0.36
talent identification and management insights	0.72	0.43	0.75	1	0.41
training for AI tools	0.36	0.52	0.36	0.41	1

IX.REGRESSION MODEL RESULT

Regression Statistics	
Multiple R	0.87
R Square	0.76
Adjusted R Square	0.74
Standard Error	0.81
Observations	56

The multiple linear regression analysis was used to determine the degree to which perceived AI efficiency, ease of use, AI-generated insights, employee training, and AI use forecast AI-optimized talent management, holding the impact of the other independent variables constant. Multiple regression is suitable when it is necessary to evaluate the individual contribution of a few predictors to one dependent variable (Hair et al., 2019).

Although the regression model demonstrates strong explanatory power, a portion of the variance in AI-optimized talent management remains unexplained, suggesting that additional organizational or behavioral factors may influence outcomes beyond the current framework.

Table 3 shows the regression output, the unstandardized coefficients (B), the standardized coefficients (B) and the standard errors, t-values, level of significance (p), variance inflation factors (VIF), and the measure of the effect size. The entire regression model was statistically significant and accounted significant percentage of the variance in AI-optimized talent management results as the coefficient of determination (R 2) shows. It implies that the chosen variables in AI context will be a robust explanatory scheme that can be used to comprehend the variation in AI-optimized talent management.

At the level of individual predictors, the perceived AI efficiency, ease of use, and AI-generated insights were statistically significant predictors of AI-optimized talent management. In this set of variables, perceived AI efficiency showed the largest standardized effect, which implies that the most important fulfillment in the effectiveness and performance of the system is linked to talent management results. The results are consistent with the previous studies that state the significance of system capability and usability in technology-enabling HR practices [27]

Conversely, the relationships between employee training and AI usage and AI-optimized talent management in this sample were not statistically significant. Although their direction was positive, the fact that these coefficients were not statistically significant indicates that they did not have a strong effect to be noticed with the size of the sample. This result might be due to a lack of statistical strength or difference in the implementation of training and AI use in different organizations, as opposed to the lack of practical relevance.

The diagnostics of multicollinearity were measured by the values of variance inflation factor (VIF). The VIFs of all values were less than commonly accepted values, which meant that multicollinearity was not an urgent issue and that regression coefficients could be viewed with confidence (Field, 2018).

In general, the results of the regression analysis confirm several hypotheses suggested and show that certain attributes of AI systems, such as efficiency, usability, and generation of insights, are significant in the prediction of AI-optimized talent management. Nevertheless, due to the cross-sectional research and convenience sampling method, the outcome is understood as associative as opposed to causal.

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower
	-0.29	0.33	-0.87	0.39	-0.94	0.37	
	-0.19	0.13	-1.52	0.14	-0.45	0.06	
	0.32	0.11	3.03	0.00	0.11	0.54	
	0.59	0.12	4.81	0.00	0.34	0.83	
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	

A. **Significant Predictors**

1) *Efficiency of AI tools ($\beta = 0.59$, $p < .001$)*

- Strongest predictor.

The higher the optimization of AI talent score of the employees the more they consider AI as making the tasks more efficient.

2) *Ease of using AI tools ($\beta = 0.32$, $p < .001$)*

- Implicates that usability has a significant role in talent optimization.

3) *Talent insights ($\beta = 0.27$, $p = .03$)*

Suggests that through AI generated insights organizations can be in a better position to identify, manage, and develop talent.

B. **Non-Significant Predictors**

1) *Use of AI in organization ($\beta = -0.19$, $p = .14$)*

- The overall adoption of AI does not necessarily entail better talent results, rather success is pegged into the usage of AI.

2) *Training for AI tools ($\beta = 0.35$, $p = .19$)*

- Training does not have any significant impact on talent optimization, presumably because of quality, relevance, or depth of training.

C. **Statistical Findings Summary**

The AIs Efficiency, Ease of AI Tools and Talent Insights are highly predictive of AI-Optimized Talent.

- The overall use and training by AI do not have a significant impact on talent outcomes.

People will be surprised to see that the regression model is strong, with R 2 = 0.76, as it shows that there is strong correlation between the characteristics of AI tools and talent optimization.

X. RESEARCH OBJECTIVE-RELATED FINDINGS

Objective 1: To explore the perception of the employees in terms of AI usage, ease, efficiency, insights, and training.

As descriptive statistics indicate:

Employees find AI to be perceived as easy and usable.

- There is a divided opinion regarding AI-driven talent insights.
- Training levels vary widely.

Purpose 2: To evaluate the correlation between AI-related aspects and talent outcome.

Analyses of correlation revealed:

- Positive relationships between most variables which are moderate and strong.
- No multicollinearity issues.

The closest relations were between insights and efficiency.

Objective 3: To identify the AI dimensions that are associated with talent optimization to a significant extent.

The results of the regression fulfilled:

- Predictors of efficiency, ease and insights are important.
- Training and general Use of AI are Negligible.

It means that AI tools enhance talent results effectively and simply when they are efficient, easy to work with, and yield meaningful information, not just because they have been adopted or taught.

XI.DISCUSSION

This study was aimed at analyzing the role of artificial intelligence (AI) capabilities and their effect on AI-optimized talent management in organizations. The results support the hypotheses that certain attributes of the AI systems, specifically perceived efficiency, easiness of use, and AI-generated insights, improve the effect of talent management. Meanwhile, the findings indicate significant subtleties connected to the functions of employee training and AI usage that did not become statistically significant predictors in this sample.

Despite high perceived accountability scores, lower confidence in using AI for recruitment tasks may reflect ethical concerns, perceived risk of algorithmic bias, or hesitation toward automated hiring decisions.

The observation that perceived AI efficiency is an important predictor of AI-optimized talent management is closely correlated with the previous studies that highlight the role of performance-enhancing technologies in the HR environment. As soon as AI systems can be seen as enhancing the speed, accuracy, and efficiency of talent-related processes, employees will be more willing to consider these systems as an important contributor to the organizational results. This reinforces the views of the Resource-Based View (RBV) that propose that technologies with the capacity to augment the organizational capabilities might produce value upon successful implementation [19]. Talent management AI efficiency can be observed to act as a crucial ability in enhancing the quality of decision-making and operational efficiency.

Likewise, the high correlation between the ease of use and AI-optimized talent management can be attributed to the Technology Acceptance Model (TAM) and its derivatives. TAM assumes that perceived easy-to-use technologies will be more accepted and become part of work-based practices [27]. The current results indicate that user-friendly AI systems eliminate cognitive and operational barriers that make employees interact more effectively with AI-driven talent management procedures. This supports the significance of the intuitiveness of the system design to make the AI tools effective into tangible organizational gains.

The role of AI in human resource management is also changing as the importance of the AI-generated insights illustrates. In addition to automation, the new generation AI systems is becoming useful in strategic decision-making by deriving actionable insights with complex data. The fact that AI generated insights have been positively linked to talent management optimization is an indication that employees appreciate AI systems that optimize understanding and facilitate judgment as opposed to those which substitute human input. This observation is consistent with the novel studies about collaboration between humans and AI that highlight the importance of AI as a decision-support system as opposed to the managerial skills (Dwivedi et al., 2023).

Conversely, AI-optimized talent management was not statistically significantly related to employee training and AI usage. These findings cannot be regarded as a sign that training and use are not important. Rather, the non-significant results might indicate inadequate statistical power because of the small sample size and differences in various implementation of training and application of AI systems in different companies. According to what previous studies show, training is only effective in case of its availability; it must be relevant, of excellent quality, and in compliance with the job roles [25]. In the same vein, frequency of AI use may not necessarily result into optimized results unless the use is intentional and quality of the system supports the use.

Combined, the results imply that the quality of AI systems and their performance in helping to make decisions is of greater importance than their frequency of application. It has significant implications on organizations that are interested in utilizing AI in talent management. Instead of working only on improving AI adoption or adoption rates, organizations might gain more by investing in system efficiency and usability and improving the quality of offered insights.

Lastly, the results must be discussed within the context of methodological weaknesses of the study, such as the cross-sectional nature of the research and the use of self-reports. Consequently, the associations that are found are relationships and not a cause. Longitudinal studies and bigger sample sizes may give insights into the future research on how AI capabilities can impact talent management in the long term.

XII.LIMITATIONS

Although this study offers valid insights into the connection between the abilities of artificial intelligence (AI) and AI- streamlined talent management, it can be affected by several limitations that are to be taken into account when approaching the findings.

First, the research uses an exceedingly small sample (n = 56), which restricts the statistical strength of the tests. Although the sample was adequate to concur on the exploratory correlation and regression analysis, a bigger sample would enhance the strength of the results and the generalizability of findings (Bryman, 2016). The limited sample size can also have played the role in the non-significant findings as on the case of some of the predictors including employee training and the use of AI.

Second, the sample is not as representative as it could have been because non-probability convenience sampling was used. The participants did not get selected randomly but rather by accessibility and create a risk of sampling bias. Subsequently, the results might not be representative of other population groups of employees who use AI-enhanced talent management systems [25]

Thirdly, the research design adopted in the study was cross-sectional research design, where the data was observed at a point in time. Although this design can be used to establish relationships between variables, it is not possible to draw a causal conclusion or study how these factors can vary across time. To determine the development of AI adoption and talent management outcomes as systems grow and organizations gain experience, longitudinal research would be needed (Creswell and Creswell, 2018).

Fourth, the self-reported questionnaire data was used to measure all the variables, and this increases the likelihood of common method bias. When the same respondents are asked to give predictor and outcome data at the same time, the observed relationships will be inflated by the response consistency or social desirability effect [24]. Even though it was done via the established measurement scales, future studies can address this shortcoming with objective performance measures or multi-source data.

Fifth, the study examines the perceptions of the employees towards AI capabilities instead of objective performance of the AI systems. Although all perceptions matter towards the perception of technology acceptance and usage, they are not necessarily consistent with the actual system effectiveness. It might be more effective to include the system level or organizational performance data to offer a more detailed analysis of AI-optimized talent management.

Lastly, the research fails to factor in contextual aspects of industry type, the size of an organization or national regulatory settings that could affect the use of AI and talent management practices. These aspects might be the moderating factors of the observed relationships, and they need to be investigated in a future study.

XIII.CONCLUSION

The research analyzed the connection between artificial intelligence (AI) capabilities and artificial intelligence-optimized talent management in companies by adopting a quantitative in a cross-sectional research design. Based on employee perceptions, the results show that the perception of AI efficiency, ease of use, and AI-generated insights are related with AI-optimized talent management results in a positive way. These findings underscore the fact that the usefulness of AI in talent management is not as much to do with the existence of AI systems but rather with the capability of these systems and their user-friendliness and quality of the insights that the systems can offer to make a decision.

Conversely, the process of employee training and AI use were not found to be statistically significant predictors in this research. These results indicate that training and use on their own might not be adequate to result in optimized talent management without being complemented by effective user-friendly systems that lead to insights of value. Notably, these findings ought to be viewed with reservations owing to the methodological shortcomings of the research such as small sample size, convenience sampling, and cross-sectional design that limit causal generalization and generalizability.

However, employee training showed a moderate positive correlation in earlier analysis, indicating that its effect may be indirect rather than predictive once other variables are controlled in the regression model.

In general, the research is a contribution to the expanding literature regarding AI-based human resource management, as it offers empirical evidence about the factors related to AI that are connected to the optimization of talent management to the highest extent. The results support the theoretical views on technology acceptance and HR analytics by highlighting the role of the system quality and perceived value in influencing the organizational outcomes.

XIV.RECOMMENDATIONS

On the basis of the results of the current research the following recommendations can be offered to organizations aimed at optimizing talent management with the usage of AI:

1) Focus on the efficiency of AI systems

The implementation of AI systems that prove to be faster, more accurate, and efficient in terms of speed and accuracy should be prioritised by organisations in the talent management processes. The presence of AI-based recruitment and workforce analytics systems, including HireVue, Pymetrics, and Eightfold AI, demonstrates the ability of machine learning to automate the candidate screening process, increase job-candidate fit, and eliminate manual work. Developing effective AI systems that can generate tangible performance gains is also likely to bring more benefits in talent management than merely raising the rate of AI implementation within HR functions (Davenport and Ronanki, 2018; Chamorro-Premuzic et al., 2019). Increase usability by user-centered design.

The use of AI should be simple and user-friendly to facilitate resistance to change. The resistance can be mitigated through involvement of end-users in system selection and design which enhances integration in daily HR practices.

2)* Dwelling on practical AI-generated *intelligence

Instead of only doing automation, organizations ought to make sure that AI systems report easy to understand and interpret as well as actionable insights that can aid in talent-related decision-making. Workforce analytics applications based on AI like LinkedIn Talent Insights, Visier, and Workday People Analytics show the ways in which AI-based insights can be utilized to make workforce planning decisions, skills gap analysis, and predict the risk of employee turnover. The systems facilitate a human-AI partnership model, in which AI supplements managerial judgment rather than substitutes it, and therefore increase human talent management practice strategic worth [24].

***3)* Reconsider AI training guidelines**

Training did not prove to be an important predictor in this research, but the organizations must evaluate the relevance and quality of the AI training programs. Role-specific training which is also based on real system usage can have a more powerful effect than general training.

***4)* Make the AI use aligned with strategy**

The use of AI may not enhance talent management just because it has been used more. It is important to emphasize that organizations must pay attention to intentional and value-driven application of AI systems and make sure general HR, and organizational objectives are implemented.

XV.SELF-REFLECTION

This scientific study has taught me a lot both academically and practically by enhancing my knowledge of the quantitative research design, data collection, and statistical analysis in the framework of AI based talent management. Among the most important learning outcomes was the ability to create a structured questionnaire, to calculate numerical data with the help of descriptive statistics, correlation, and regression methods and to interpret the results critically without exaggerating the causality. The value of methodological rigor, especially concerning the size of the sample, sampling strategy, and the constraints of the cross-sectional, self-reported data, were also brought to the fore by the project. In retrospect, I would consider that future research might be enhanced in terms of bigger and more heterogenous samples, longitudinal designs, and objective measures of performance to add to the generalizability and analysis level. The experience has improved my critical thinking, ability to interpret data as well as solve problems and better understand how theoretical constructs in AI and talent management apply to empirical research practice.

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