Influence of Augmented Artificial Intelligence Platforms on Talent Management in Energy Parastatals in Nairobi, Kenya

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ABSTRACT

This purpose of the study was to investigate the influence of augmented artificial intelligence platforms (AAIPs) on talent management in Energy Parastatals in Nairobi, Kenya. The study employed a descriptive research design, in which questionnaires were used to collect data from Human Resource (HR) managers from four energy parastatals, in Nairobi, Kenya. The study target population was 246, from which stratified random sampling was used to obtain a sample size of 152 HR managers. The study employed both descriptive and inferential analysis methods to analyze the data using Statistical Packages for Social Scientists version 25. The statistical method was used to determine measures of central tendencies, data distribution, and descriptive statistics. Inferential analysis including correlation and regression analysis was also done. The study revealed a mean of (M=3.72) and a correlation coefficient of (R=0.75). This statistic indicated that, respondents strongly support the use of AAIPS and recognize their significant influence on talent management. The revealed linear regression and ANOVA values indicated that, AAIPs have the significant contribution to talent management as shown by $\beta= 0.762$ and ($\beta=0.762$, $p<0.05$) scores respectively. These findings highlight the significance and importance of augmented artificial intelligence platforms in enhancing talent management practices within the energy parastatals in Nairobi Kenya. The findings of this study will immensely contribute to the growing body of literature on the impact of artificial intelligence on talent management, particularly in the context of energy parastatals in Nairobi, Kenya. It is also inferred that augmented artificial intelligence platforms, have a positive linear relationship with talent management. Moreover, the findings have revealed that the deployment of augmented artificial intelligence platforms yield significant influence on talent management.

Keywords: Augmented, Artificial, Intelligence, Platforms, Talent, Management

INTRODUCTION

Talent management remains a critical aspect of organizational success, particularly in knowledge-intensive sectors like energy (Gardas et al. 2019). The ability to attract, develop, and retain skilled professionals directly impacts an organization's ability to innovate and adapt to changing market conditions (Gardas et al. 2019; Owino et al. 2016). In the rapidly evolving landscape of the energy sector, the infusion of advanced technologies has become imperative for organizations seeking to optimize their operations and stay competitive (Li et al. 2023). Augmented Artificial Intelligence platforms (AAIPs) have emerged as transfor mative tools with the potential to revolutionize talent management practices within energy parastatals (Chelliah et al., 2023). Nairobi, as the research setting, serves as a microcosm of the larger technological and economic advancements in the region (Li et al. 2023). Energy parastatals in Nairobi operate at the forefront of supplying power to the nation, making them key players in the socio-economic development of

Kenya (Owino et al. 2016). Understanding how AAIPs influence talent management within this dynamic context is not only relevant to the organizations themselves but also to the broader national agenda of fostering innovation and sustainable development (Chelliah et al., 2023).

The selection of AAIPs as the focal point stems from its unique ability to enhance human decision-making processes through the amalgamation of the Artificial intelligence and human talent (Chelliah et al., 2023). According to Pillai and Sivathanu (2020), in the context of talent management, the adoption of AAIPs translates into more informed recruitment processes, efficient performance evaluations, and strategic workforce planning. As the energy sector grapples with the need for precision and efficiency, AAIPs hold the promise of addressing these challenges and unlocking new potentials (Owino et al. 2016).

This research aimed at examining the extent to which the integration of AAIPs in talent management strategies is done within energy parastatals in Nairobi, Kenya. By revealing aspects such as AAIPs adoption levels, the underlying challenges faced by the energy parastatals in the integration of the AI technology in talent management, and evaluating the outcomes of incorporating Augmented AI, the study sought to provide an understanding of the relationship between AAIPs technology and talent management in the energy sector.

Moreover, this research focused on unraveling the intricate dynamics and assessing the impact of Augmented AI on talent management in energy parastatals situated in Nairobi, Kenya. The intersection of technology and talent management in this specific context holds paramount importance given the city's strategic position as a hub for technological innovation and its critical role in shaping Kenya's energy landscape.

LITERATURE REVIEW

Talent management is defined as the efforts made to plan, attract, select and train the talent required to meet current and future human capital needs (Pauli and Pocztowski, 2019). Talent management has also been defined as the systemic, planned effort to attract, retain, develop and motivate highly skilled employees and managers (Michigan State University, 2023). Talent management is a complex system that requires integration with a company's vision and mission statements, objectives, human resources processes and policies, and business operations (Kimanzi and Gamede 2020). Talent management within knowledge-intensive sectors like energy remains pivotal for organizational success and innovation (Whelan et al., 2016). AAIPs have emerged as transformative tools, promising to revolutionize talent management practices within energy parastatals (Chelliah et al., 2023). Initially introduced as a means to enhance human decision-making processes (Chang, 2020), AAIPs have gradually evolved to address various facets of talent management.

Since their inception, AAIPs have been deployed to optimize recruitment processes, streamline performance evaluations, and facilitate strategic workforce planning (Bhalgat, 2019). By amalgamating artificial intelligence with human talent, AAIPs offer organizations the ability to make more informed decisions, leading to greater efficiency and precision (Tschang & Almirall, 2021). These platforms leverage advanced algorithms to analyze vast amounts of data, enabling organizations to identify and attract top talent while minimizing biases in the selection process.

Moreover, AAIPs contribute significantly to talent retention and development by providing personalized learning and development opportunities tailored to individual employee needs (Chowdhury et al., 2023). Through continuous monitoring and feedback mechanisms, these platforms assist in identifying skill gaps and offering targeted training interventions, thereby enhancing employee engagement and satisfaction (Chowdhury et al., 2023).

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In the context of energy parastatals in Nairobi, Kenya, the integration of AAIPs in talent management strategies holds immense potential (Atinda et al., 2022). Given Nairobi's position as a hub for technological innovation, the adoption of AAIPs not only enhances organizational efficiency but also contributes to the broader national agenda of fostering innovation and sustainable development (Atinda et al., 2022).

Despite the promising prospects of AAIPs, challenges persist in their implementation within energy parastatals. These challenges include data privacy concerns, technological infrastructure limitations, and resistance to change among employees (Owino et al., 2016). Addressing these challenges requires strategic planning, investment in technological infrastructure, and comprehensive change management strategies to ensure successful integration and adoption of AAIPs in talent management practices.

In general, AAIPs represent a paradigm shift in talent management practices within energy parastatals, offering organizations the opportunity to optimize their operations and stay competitive in an increasingly dynamic market. However, realizing the full potential of AAIPs requires overcoming various challenges and fostering a culture of innovation and collaboration within organizations (Atinda et al., 2022).

EMPIRICAL REVIEW

Artificial Intelligence (AI) is a rapidly advancing field encompassing different applications across different industries (Khan, 2024). AI (Artificial intelligence) has the potential to improve strategies to talent management by implementing advanced automated systems for workforce management (Faqihi & Shah, 2023). According to Kim-Schmid and Raveendhran, (2022) artificial intelligence can help address pain points in each of the three phases of talent management: employee attraction, employee development, and employee retention. Utilizing AI for talent management involves leveraging artificial intelligence techniques and tools to optimize various aspects of the employee lifecycle, from recruitment and selection to employee development and engagement (Khan, 2024). Faqihi and Shah, (2023) did a study is to discover the new requirements for generating a new AI-oriented artefact so that the issues pertaining to talent management are effectively addressed. The study utilized a design science methodology to investigate the use of organized machine learning approaches. From the study it was found that smart technologies have the potential to assist in mentoring both current professionals and future talent. The study shows that AI has the potential to assist career counselors with some of their daily tasks and it can also be used to develop a chatbot that can answer frequently asked questions about careers, job applications, and resumes.

Using both primary and secondary data Khan (2024) did a study to investigate the challenges and opportunities of using AI for talent management within organizations to assist them in making informed decisions and implementing effective strategies to harness the potential of AI in optimizing their talent acquisition and development efforts. Primary data was collected through an interview from different organizations' HR managers while secondary data was gathered from different organizations' published reports and articles along with other academic reliable resources. From the study it was found that AI in talent management can update recruitment processes, enhance decision-making, and enable personalized employee development. AI has the potential to optimize HR operations and improve overall workforce management for organizations. While AI offers numerous benefits in talent management, challenges arise in terms of data quality and privacy, potential lack of human judgment in complex decisions, ethical considerations related to biases in AI algorithms, user acceptance and trust, and the need for a skilled and adaptable workforce. The findings of this research provide valuable insights for companies aiming to apply AI effectively in talent management strategies by overcoming the challenges.

Prikshat, Islam, Patel, Malik, Budhwar and Gupta (2023) did an empirical review analyze the context (i.e., chronological distribution, geographic spread, sector-wise distribution, theories, and methods used) and the theoretical content (key themes) of HRM (AI) research and identify gaps to present a robust multilevel framework for future research. The study was a systematic literature review (SLR) of 56 articles published in 35 peer-reviewed academic journals from October 1990 to December 2021. From the analysis the authors identified noticeable research gaps, mainly stemming from – unequal distribution of previous HRM (AI) research in terms of the smaller number of sector/country-specific studies, absence of sound theoretical base/frameworks, more research on routine HR functions (i.e. recruitment and selection) and significantly less empirical research. They also found minimal research evidence that links HRM (AI) and organizational-level outcomes.

Malik, De Silva, Budhwar and Srikanth, (2021) did an in-depth qualitative interview study to present insights into how a large MNE shared knowledge through artificial intelligence (AI) mediated social exchange using effective global talent management (GTM) strategies. From the study it was found that AI-enabled talent applications improved individual experiences of talents at the MNE pursuing an innovation strategy. The results from the data analysis also suggest that an innovation-led strategy and culture created a social context for sharing of talent-specific knowledge through knowledge-based data systems embedded in talent-focused AI applications and that talent-focused knowledge sharing using AI-mediated social exchange applications resulted in talents experiencing varying personalization levels and positive experience in terms of increased job satisfaction and commitment and reduced turnover intentions.

RESEARCH METHODOLOGY

A descriptive research design was employed in this study. The chosen descriptive research design demonstrated its effectiveness by enabling a comprehensive exploration of employee attitudes, perspectives, habits, and performance. The survey instruments utilized included open-ended questions, which was followed by a quantitative methodology (Nicholas, 2011). Moreover, the study population involved 246 managers from Kenyan energy parastatals, namely: KETRACO, NUPEA, EPRA, and KPLC, as shown in Table 1. This is due to the fact that managers play a crucial role in implementing AI strategies and supervising talent management within the parastatals. Some of the roles include; developing practical strategies, allocating budgets, and exerting influence over whether technologies such as AI and different aspects of talent management result in improved employee and organizational performance.

Table 1: Target Population of the Energy Sector Companies

Energy Parastatal	**Total Managers**
KPLC	105
KETRACO	53
NUPEA	26
EPRA	64
Total	**246**

Ministry of Energy 2023

The sampling frame which included managers from various organizational levels, spanning from lower-level to middle-level and top-level management was developed (Shields & Rangarajan, 2013). The details of the sampling frame are outlined in the table below.

Table 2: Sampling frame

Energy Parastatal	**Low-Level Management**	**Middle-Level Management**	**High-Level Management**	**Total Managers**
KPLC	70	25	10	**105**
KETRACO	30	15	8	**53**
NUPEA	15	8	3	**26**
EPRA	32	20	12	**64**
Total	**147**	**68**	**33**	**246**

Ministry of Energy 2023

The sample was selected using stratified random sampling techniques. The population was first divided into distinct strata corresponding to various management levels: low, middle, and top management. These strata were delineated based on shared characteristics or attributes among their members (Singh & Mangat, 1996). Subsequently, representative participants were randomly selected from each stratum, involving managers drawn at random.

The Yamane formula (1967) (equation 1) was used to determine the sample size from the resulting population (Chaokromthong & Sintao, 2021).

$$n = \frac{N}{1 + Ne^2} = \frac{246}{1 + 246(0.05^2)} = 152 \; \dots\dots\dots\dots\dots\dots\dots 3.1$$

Where n is the sample size, N is the target population in each parastatal, and e is an error value determined from the confidence level adopted in the study. Here, the confidence level is 95%. Therefore e = 5% = 0.05 (Chaokromthong & Sintao, 2021).

Since this study had one independent variable, as described by Campbell (2023), the linear regression equation was of the form:

$$Y = \beta 0 + \beta_1 X + \varepsilon \; \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots 3.2$$

Where Y is the dependent variable, X is the independent variable, β_0 is the intercept, β_1 is the slope for the independent variable, and ε is the error term. In this study, Y represented talent management, and X represented AAIPs

Data collection involved administering questionnaires to participants. The choice of using questionnaires is grounded in their extensive application in business research. These questionnaires were in a paper-based format and featured a combination of open-ended, close-ended, and Likert-type questions, as recommended by Mugenda and Mugenda (2003). The questionnaire encompassed various aspects, including queries about the implementation of AAIPs in the company, the impact of AAIPs in the company and its components on talent attraction and retention, the participants' managerial experience before and after AAIPs implementation, and other relevant aspects.

The research procedure involved obtaining research permits from the National Commission for Science Technology and Innovation (NACOSTI) and the Institutional Review Board (IRB) at USIU Africa. A pilot study was conducted to validate the feasibility and manageability of the process, along with assessing the practicality and efficacy of the questionnaire. During the pilot study, a stratified random sampling was conducted where 10% of the sample size participated. Notably, during the actual study, respondents from the pilot study were excluded (Lowe, 2019). This precaution was taken to mitigate sampling bias. Additionally, the trial data underwent statistical analysis to confirm its compatibility with the intended analytical approach (Hazzi & Maldaon, 2015).

The pilot study was followed by primary data collection using a self-administered questionnaire. Prior to questionnaire administration, informed consent was obtained as a critical step in ethical research. This involved explaining the study's nature, participants' roles, and associated risks or benefits. Comprehensive information, encompassing the study's purpose, procedures, and the right to withdraw at any time, was communicated to participants (Rasi-Heikkinen, 2022).

Moreover, ethical considerations including confidentiality, anonymity, and data protection was explained to the participants. Participants were apprised of their right to privacy, with assurances regarding the safeguarding of personal information (Rasi-Heikkinen, 2022). After allowing participants a one-week period, the questionnaires were collected for analysis. During this process, a debriefing session was conducted, providing additional information, addressing questions or concerns, and offering gratitude for participants' contributions. The debriefing also served to furnish participants with feedback on the study's results, inform them of any implications, and provide a platform for them to share their experiences and for researchers to reflect on ethical considerations (Hodson, 2022).

Finally, the collected data was analyzed utilizing Statistical Package for the Social Sciences (SPSS) version 25. Additionally, data entry involved inputting information, followed by thorough checks for accuracy and completeness. Descriptive statistics were employed to determine the mean and standard deviation, while inferential statistics facilitated the execution of linear correlation and regression analysis, accommodating both quantitative and qualitative data (Etchegaray & Fischer, 2009).

RESULTS AND FINDINGS

Before conducting the primary survey, a preliminary study was carried out to assess the reliability and validity of the study instrument. This involved the random selection of a sample of 25 participants, constituting 10% of the total population of 246 (Noor et al., 2022). The reliability results indicated that Augmented Artificial Intelligence Platforms (AAIPs) exhibited Cronbach's Alpha values of 0.843. This suggests that the measurement scales used to evaluate the variable are reliable and consistent.

Analysis of the filled questionnaires from the final study showed that out of the 152 participants selected and given the questionnaire, 128 responded to the questionnaires, yielding a response rate of 84.21%. According to Lund (2023), a response rate exceeding 50% is considered sufficient, 60% is deemed good, and 70% is regarded as very good for conducting a study's analysis. Therefore, the response rate of 84.21% in this study was considered very good, indicating a dependable representation of the target population.

The study revealed a gender distribution of 44% and 56% for male and female respondents, respectively. This signifies the inclusion of both genders in the study, thereby seeking diverse information regarding the utilization of artificial intelligence in talent management. Additionally, concerning years of work experience, the study found that 52 respondents had 5 years or less of work experience, 43 respondents had work experience ranging between 6-10 years, 22 respondents had work experience between 11-20 years, 10 respondents had work experience ranging between 21-30 years, and 1 respondent had work experience of over 30 years (Figure 1). This implies that participants in the study were generally young (1-10 years) in their jobs, thus possessing relevant information on artificial intelligence as they had firsthand experience in the field.

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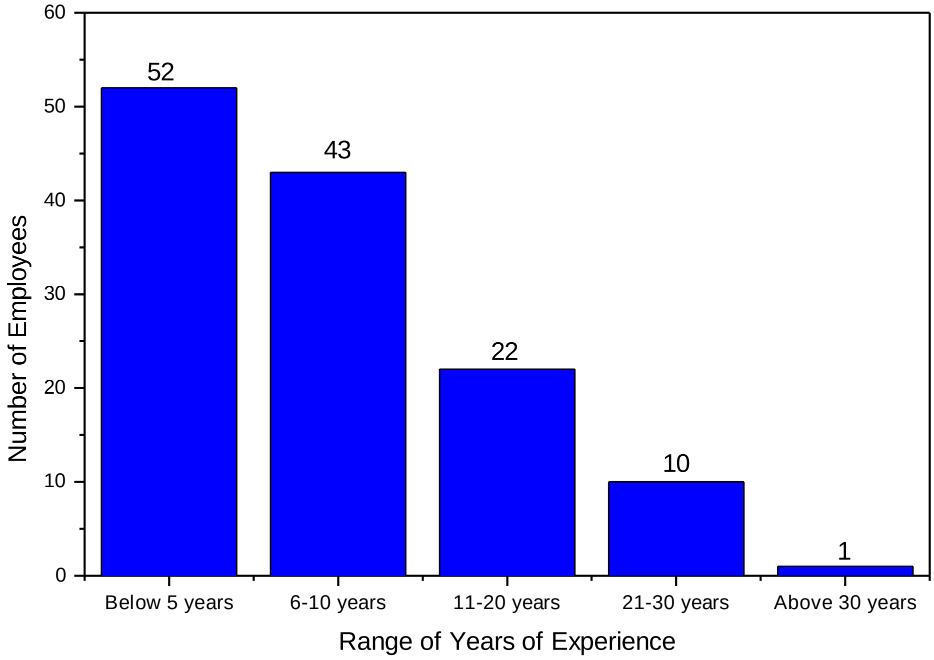

Figure 1: Range of years of work experience

Considering that a notable proportion of study participants had substantial experience within the organization, it can be deduced that they harbored a significant information on the influence of artificial intelligence on talent management in the energy sector. Furthermore, the study analyzed the managerial positions held by the diverse respondents in their respective parastatals, as illustrated in table 3.

Table 3: Level of management

Level of management	**Frequency**	**Percentage**
High Level Management	9	7.03
Medium Level Management	32	25.00
Low Level Management	87	67.97
Total	**128**	**100**

As shown in Table 3, 7.03% of the participants were categorized as high-level managers, while middle-level managers constituted 25.00%, and low-level managers represented 67.97%. Additionally, factor analysis and reliability analysis of AAIPs employed the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity, along with the examination of total variance. The KMO measure and Bartlett's Test aimed at determining the suitability of the data.

Typically ranging between 0 and 1, the KMO value serves as an indicator of data adequacy for factor analysis, with a value closer to or equal to 1 signifying suitability (Parsakia et al., 2023). As observed in Table 4, the computed KMO value of 0.794, indicated that the sample size employed in the study was suitable for conducting meaningful factor analysis. Moreover, the p-value derived from Bartlett's test of sphericity was 0.000 ($p<0.05$), signifying a significant departure of the correlation matrix from an identity matrix. Notably, a KMO value exceeding 0.7 and a Bartlett's Test of ($p < 0.05$) affirmed the appropriateness of the dataset for factor analysis. These findings suggest that the interrelationships and dependencies among these variables are sufficient to proceed with factor analysis.

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Table 4: KMO and Bartlett's Test for AAIPs

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		**0.794**
Bartlett's Test of Sphericity	Approx. Chi-Square	305.116
	Df	54
	Sig.	0.000

Researcher Computation 2024

Furthermore, the findings regarding the total variance are outlined in Table 5. The findings reveal that the 13 items associated with Augmented Artificial Intelligence Platforms (AAIPs) were amalgamated into 9 components, collectively representing 93.135% of the variance in the utilization of AAIPs in talent management. This signifies a comprehensive comprehension of the pivotal factors influencing the adoption of AAIPs, facilitating organizations in enhancing talent management strategies through the application of Artificial Intelligence.

Table 5: Total Variance Explained on AAIPs and Talent Management

Component	**Initial Eugenvalue**			**Extraction of squared loadings**			**Rotation sums of Squared Loadings**		
	Total	% Variance	Cumulative %	Total	% Variance	Cumulative %	Total	% Variance	Cumulative %
1	2.332	19.445	19.445	2.332	19.445	19.445	1.812	19.758	19.758
2	2.014	16.131	35.576	2.014	16.131	35.576	1.764	15.535	35.293
3	1.924	15.124	50.700	1.924	15.124	50.700	1.683	14.097	49.39
4	1.617	11.163	61.863	1.617	11.163	61.863	1.475	11.561	60.951
5	1.432	9.581	71.444	1.432	9.581	71.444	1.399	9.753	70.704
6	1.405	8.734	80.178	1.405	8.734	80.178	1.376	8.780	79.484
7	1.403	5.813	85.991	1.403	5.813	85.991	1.308	5.606	85.09
8	1.392	3.859	89.850	1.392	3.859	89.850	1.298	4.253	89.343
9	1.199	3.285	93.135	1.199	3.285	93.135	1.202	3.792	93.135
10	0.921	2.568	95.703						
11	0.837	1.562	97.265						
12	0.795	1.429	98.694						
13	0.626	1.306	100.00						

Extraction Method: Principal Component Analysis 2024

After conducting descriptive statistics on Augmented Artificial Intelligence Platforms (AAIPs), the overall results revealed a consensus among respondents regarding the positive contribution of AAIPs to talent management in their respective organizations. This is evident in the mean and standard deviations of (M=3.72, SD=0.96) for AAIPs. The descriptive statistics suggest a prevailing belief among respondents that AAIPs play significant roles in the talent management practices of their organizations, as reflected in the mean value of 3.72. These findings imply a greater confidence in the efficacy of AAPs technology for talent management compared to conventional manual solutions.

To explore potential linear correlations between the AAIPs and talent management, the study employed Pearson correlation analysis. This analytical approach was instrumental in determining the strength of associations within the model. That is, it helped reveal whether AAIPs and Talent management have weak or strong linear relationship, as determined by the Pearson correlation coefficient (R-coefficient). A comprehensive summary of the correlation results and analysis findings is presented in Table 6.

Table 6: Pearson's Correlation analysis

Variable/R-Coefficient		**AAIPs**	**Talent Management**
AAIPs	R-Coefficient	1	
	(p-value)	0.0	
Talent Management	R-Coefficient	0.75	1
	(p-value)	0.015	0.0

Researcher Computation 2024

The table displaying Pearson's correlation coefficient (Table 6) above illustrates the extent of linearity, between AAIPs and Talent management. Notably, the findings reveal a linear relationship with an R-coefficient of 0.75. Furthermore, the p-values are notably below 0.05.

The goodness of fit for the regression model is presented in Table 7. Additionally, an F-significance from ANOVA was conducted to determine the error term (ε).

Table 7: Regression Model Goodness of Fit

R	**R-square**	**Adjusted R-Square**	**Sum of Squared Residues**	**Standard Error of the Estimate**	**Durbin-Watson**
0.794	0.630	0.631	189	1.12	0.724

Researcher Computation 2024

Table 7 reveals a noticeable positive auto correlation between the variables, indicating that residuals exhibit a tendency to be positively correlated with their lagged values, as evidenced by the Durbin-Watson value being less than 2. Furthermore, the table demonstrates that 68.30% of the variance in talent management within energy parastatals is collectively explained by the utilization of AAIPs. Table 8 provides the data from the regression analysis regarding the application of AAIPs in talent management by energy parastatals in Nairobi, Kenya. The table presents the regression coefficients, their beta values, standard errors, and the significance level of the independent variable.

Table 8: Regression Coefficient

Variable/Constant	**Regression Coefficients**		**Sig.**
	Beta	**Std. Error**	
Constant	4.660	2.002	0.021

AAIPs	0.762	0.196	0.014

Researcher Computation 2024

As shown in Table 8, a derived regression model can be expressed as Y = 4.660 + 0.762X, where Talent Management = 4.660 + 0.762*(AAIPs). The constant value (β_0=4.660) signifies that Talent Management is at 4.660 when the energy parastatals do not utilize AAIPs at all. Importantly, the results suggest that Talent Management would increase to 5.422 units with the deployment of one unit of AAIPs. Furthermore, this study employed analysis of variance (ANOVA) in the regression analysis to assess the significance of the regression model. Table 9 presents the ANOVA, conducted to evaluate the appropriateness of the regression model.

Table 9: Analysis of Variance (ANOVA)

	Sum of Squares	degrees of freedom (df)	Mean Square	F	Sig
Regression	301.184	1	301.184	860.527	0.000
Residual	48.616	139	0.350		
Total	349.800	140			

Researcher Computation 2024

The ANOVA findings (Table 9) indicate a highly significant relationship between AAIPs and talent management. The regression analysis shows a substantial F-statistic (860.527) with a p-value (Sig) of 0.000, suggesting that the model is statistically significant. The regression sum of squares (301.184) demonstrates the explained variation in talent management due to AAIPs. Additionally, the residual sum of squares (48.616) represents unexplained variation. The overall model, with a total sum of squares (349.800), suggests that AAIPs play a crucial role in influencing talent management practices within the studied context.

DISCUSSION OF RESULTS

The research investigated the influence AAIPs on talent management within energy parastatals in Nairobi, Kenya. Upon analyzing the results, it was evident that AAIPs exert a positive influence on talent management. This was substantiated by a mean value of (M=3.72) and a standard deviation of (SD=0.96), indicating a substantial consensus among respondents regarding the deployment of AAIPs in talent management within their organizations. Specifically, respondents affirmed the presence of AAIPs in talent management, acknowledged their influence on talent management practices, and highlighted the regular use of AAIPs by employees in talent management processes.

Moreover, respondents expressed that AAIPs have played a constructive role in enhancing talent acquisition, retention, and development. They conveyed that the utilization of AAIPs has led to improvements in training and development programs, contributing to more effective talent forecasting and succession planning. These findings align with the observations of Raisch and Krakowski (2021), who emphasized the critical role of AAIPs in talent management and organizational performance, particularly in the context of automation applications.

The evidence was further substantiated by a Pearson’s correlation coefficient of ($R=0.75$, $p<0.05$), underscoring a linear correlation between AAIPs and talent management. The study reveals a positive and robust relationship between the AAIPs and talent management. The significant Pearson’s correlation coefficient (R=0.75) implies that there exist a meaningful association, suggesting that enhanced deployment of AAIPs corresponds to improved talent management practices. These findings reveal the crucial role of AAIPs in advancing talent attraction, retention and development in the Kenyan energy parastatals. As reported by Malik et al. (2021), this study reports that AAIPs elevate the overall talent experience, fostering innovation in talent management and ultimately enhancing the human resource experience.

Finally, the influence of AAIPs on talent management was observed through linear regression analysis. The results of the analysis revealed a beta value of ($\beta = 0.762$, $p<0.05$), indicating a positive and statistically significant relationship between AAIPs and talent management. The beta value of ($\beta = 0.762$) with a significance level of ($p<0.05$) in the linear regression analysis signifies a favorable influence of AAIPs on talent management. This implies that an enhancement in the deployment and utilization of AAIPs corresponds to improvement in talent management practices. The linear regression analysis findings reveal that AAIPs exert a tangible impact on talent attraction, retention and development among the Kenyan energy parastatals. The regression analysis corresponds to the findings of Yorks et al. (2022), who reported a positive impact and improved process execution in human resource management through the deployment of AAIPs, expediting decision-making in talent attraction, retention, and development.

CONCLUSION AND RECOMMENDATIONS

From the study, it is concluded that AAIPs has a positive influence on talent management. This was supported by a mean of ($M=3.72$), indicating that are highly practiced as aspects of talent management. The findings of the study also revealed a correlation coefficient of ($R=0.75$, $p<0.05$), indicating that AAIPs have a strong and positive relationship with talent management. Finally, the study revealed a beta value of ($\beta =0.762$, $p<0.05$). This means that AAIPs have a significant influence on talent management in the energy parastatals within Nairobi, Kenya.

The adoption of AAIPs has a positive influence on talent management. Organizations should leverage AAIPs to enhance talent identification, skills assessment, and employee development. Utilizing AAIPs for data-driven decision-making in talent attraction, retention and development would lead to improved talent pipeline and organizational performance. For further studies, this study suggests conducting of comparative studies to assess the influence of AAIPs on Talent management. The study also recommends investigation of long-term effects of integrating AAIPs in talent management, including talent attraction, retention and career progression, to assess sustained impact.

The study provides valuable insights into the impact and influence of AAIPs on talent management in energy parastatals within Nairobi, Kenya. Building upon these findings, a recommendation for further studies emerges. This study recommends a comparative analysis of AAIPs. To gain a comprehensive understanding, future research should conduct comparative studies between organizations that fully adopt AAIPs and those that do not. This would help measure the extent of influence on talent management practices and provide insights into the factors contributing to effective AAIP utilization.

REFERENCES

1. Atinda, T. E. (2022). Blockchain Technology and Operational Efficiency in Kenya's Power Sector (Doctoral dissertation, University of Nairobi).
2. Bhalgat, K. H. (2019). An exploration of how Artificial Intelligence is impacting Recruitment and Selection process (Doctoral dissertation, Dublin Business School).
3. Campbell, H. (2023). Equivalence testing for linear regression. Psychological Methods.
4. Chang, K. (2020). Artificial intelligence in personnel management: the development of APM model. The Bottom Line, 33(4), 377-388.
5. Chaokromthong, K., & Sintao, N. (2021). Sample size estimation using Yamane and Cochran and Krejcie and Morgan and green formulas and Cohen statistical power analysis by G* Power and

comparisions. Apheit International Journal, 10(2), 76-86.

6. Chelliah, P. R., Jayasankar, V., Agerstam, M., Sundaravadivazhagan, B., & Cyriac, R. (2023). The Power of Artificial Intelligence for the Next-Generation Oil and Gas Industry: Envisaging AI-inspired Intelligent Energy Systems and Environments. John Wiley & Sons.
7. Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. Human Resource Management Review, 33(1), 100899.
8. Etchegaray, J. M., & Fischer, W. G. (2009). Understanding evidence-based research methods: Descriptive statistics. HERD: Health Environments Research & Design Journal, 3(1), 111-117.
9. Faqihi, A. and Shah, J. M. (2023). “Artificial Intelligence-Driven Talent Management System: Exploring the Risks and Options for Constructing a Theoretical Foundation” Journal of Risk and Financial Management 16, no. 1: 31. https://doi.org/10.3390/jrfm16010031
10. Gardas, B. B., Mangla, S. K., Raut, R. D., Narkhede, B., & Luthra, S. (2019). Green talent management to unlock sustainability in the oil and gas sector. Journal of Cleaner Production, 229, 850-862.
11. Hazzi, O., & Maldaon, I. (2015). A pilot study: Vital methodological issues. Business: Theory and Practice, 16(1), 53-62.
12. Hodson, G. (2022). Reconsidering reconsent: Threats to internal and external validity when participants reconsent after debriefing. British Journal of Psychology, 113(3), 853-871.
13. Khan, M. (2024). Application of Artificial Intelligence for Talent Management: Challenges and Opportunities. In: Tareq Ahram, Waldemar Karwowski, Dario Russo and Giuseppe Di Bucchianico (eds) Intelligent Human Systems Integration (IHSI 2024): Integrating People and Intelligent Systems. AHFE (2024) International Conference. AHFE Open Access, vol 119. AHFE International, USA. http://doi.org/10.54941/ahfe1004496
14. Kimanzi, M. K. & Gamede, V.W. (2020). Embracing the role of finance in sustainability for SMEs. International Journal of Economics and Finance 12: 453–68.
15. Kim-Schmid, J. & Raveendhran, R. (2022). Where AI Can — and Can’t — Help Talent Management. https://hbr.org/2022/10/where-ai-can-and-cant-help-talent-management. October 13, 2022
16. Li, J., Herdem, M. S., Nathwani, J., & Wen, J. Z. (2023). Methods and applications for Artificial Intelligence, Big Data, Internet of Things, and Blockchain in smart energy management. Energy and AI, 11, 100208.
17. Lowe, N. K. (2019). What is a pilot study?. Journal of Obstetric, Gynecologic & Neonatal Nursing, 48(2), 117-118.
18. Lund, B. (2023). The questionnaire method in systems research: An overview of sample sizes, response rates and statistical approaches utilized in studies. VINE Journal of Information and Knowledge Management Systems, 53(1), 1-10.
19. Malik, A., De Silva, M. T., Budhwar, P., & Srikanth, N. R. (2021). Elevating talents’ experience through innovative artificial intelligence-mediated knowledge sharing: Evidence from an IT-multinational enterprise. Journal of International Management, 27(4), 100871.
20. Michigan State University (2023). https://www.michiganstateuniversityonline.com/resources/leadership/human-resources-management-vs-talent-management/
21. Mugenda, O. & Mugenda, A. (2003). Research methods. Nairobi: Acts Press.
22. Noor, S., Tajik, O., & Golzar, J. (2022). Simple random sampling. International Journal of Education & Language Studies, 1(2), 78-82.
23. Owino, T., Kamphof, R., Kuneman, E., van Tilburg, X., van Schaik, L., & Rawlins, J. (2016). Towards a” green” trajectory of economic growth and energy security in Kenya? (p. 7). Petten: Clingendael; ECN.
24. Parsakia, K., Rostami, M., & Saadati, S. M. (2023). Validity and reliability of digital self-efficacy scale in Iranian sample. Journal of Adolescent and Youth Psychological Studies (JAYPS), 4(4), 152-

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XI Issue IV April 2024

158.
25. Pauli, U. & Pocztowski, A. (2019). Talent management in SMEs: An exploratory study of polish companies. Entrepreneurial Business and Economics Review 7: 199–218.
26. Pillai, R., & Sivathanu, B. (2020). Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations. Benchmarking: An International Journal, 27(9), 2599-2629.
27. Prikshat, V., Islam, M., Patel, P., Malik, A., Budhwar, P., & Gupta, S. (2023). AI-Augmented HRM: Literature review and a proposed multilevel framework for future research. Technological Forecasting & Social Change 193 (2023) 122645
28. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. Academy of management review, 46(1), 192-210.
29. Rasi-Heikkinen, P. (2022). Ethical Considerations. In Older People in a Digitalized Society (pp. 101-103). Emerald Publishing Limited.
30. Singh, S. K., & Park, J. H. (2022). TaLWaR: Blockchain-Based Trust Management Scheme for Smart Enterprises With Augmented Intelligence. IEEE Transactions on Industrial Informatics, 19(1), 626-634.
31. Tschang, F. T., & Almirall, E. (2021). Artificial intelligence as augmenting automation: Implications for employment. Academy of Management Perspectives, 35(4), 642-659.
32. Whelan, E., Collings, D. G., & Donnellan, B. (2010). Managing talent in knowledge-intensive settings. Journal of knowledge Management, 14(3), 486-504.
33. Yorks, L., Abel, A. L., & Rotatori, D. (2022). Digitalization, Artificial Intelligence, and Strategic HRD. In Strategic Human Resource Development in Practice: Leveraging Talent for Sustained Performance in the Digital Age of AI (pp. 69-80). Cham: Springer International Publishing.