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Use of Predictive Analytics in Human Resource and Employee Turnover in Private Universities in South- South, Nigeria.

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Abstract: *The study examined use of predictive analytics in human resource and employee turnover in private universities in South- South, Nigeria. The accessible population consisted of 6,300 academic staff members from these universities. A sample size of 361 was determined using the Krejcie and Morgan (1970) table. Data were collected through a structured questionnaire, with all items rated on a 4-point Likert scale. Pearson's product-moment correlation coefficient was employed for data analyses. The findings revealed a significant association between use of predictive analytics in human resource and employee turnover. The study concludes that predictive analytics in human resources relates with employee turnover. The study recommends enhancing predictive analytics to reduce turnover rate of employees.*

Keywords: *Employee turnover, Predictive analytics, Predictive model accuracy and validation, Predictive model robustness and stability.*

INTRODUCTION

Employee turnover in private universities presents significant challenges that affect the quality of education, institutional stability, and financial performance. Unlike public universities, private institutions rely heavily on tuition fees and donations, making the costs associated with turnover particularly burdensome (Ramasamy& Abdullah, 2017). Job satisfaction is a primary driver of turnover. Factors such as an unsupportive or toxic work culture, excessive workloads, and job role mismatches can lead to high turnover rates (Stanfast, 2018). Competitive compensation and benefits are crucial for retaining employees, as private universities must offer attractive salaries and comprehensive benefits packages, including health insurance, retirement plans, and professional development opportunities.

Career development opportunities also play a significant role in employee retention. Limited career advancement prospects and lack of support for professional development can cause employees to seek opportunities elsewhere (Adeoye & Egwakhe, 2019). Effective management and leadership are critical; poor management practices and lack of open communication can drive employees away Luthra & Dahiya, 2015). Furthermore, employees who do not feel aligned with the university's values and culture, or who experience a lack of inclusivity and diversity, are more likely to leave (Alshaabani et al., 2021).

The impact of employee turnover on private universities is substantial and financial costs associated with recruiting, hiring, and training new employees are significant, as is the temporary loss of productivity and institutional knowledge when experienced employees leave (De Winne et al., 2019). Frequent turnover among faculty can disrupt the continuity of academic programs, negatively affecting student learning experiences and the university's research output and high turnover rates can also harm the university's reputation, making it less attractive to prospective employees and students, thereby lowering student satisfaction and retention rates.

To mitigate employee turnover, private universities can enhance job satisfaction by fostering a supportive and collaborative work culture and ensuring a balanced workload (Anderson, 2021). Competitive compensation and benefits are essential; regular salary reviews and offering comprehensive benefits packages can address employee needs (Oginni et al., 2023). Providing clear career progression paths and investing in professional development programs can also help retain staff. Effective management practices, including leadership training and promoting open communication, are crucial for creating a supportive work environment (Luthra, 2015). Additionally, promoting diversity and inclusivity within the university can ensure that employees feel aligned with the institution's values and culture.

However, with pressing issues of employee turnover, which disrupt the continuity of academic programs, increase recruitment and training costs, and impact the overall institutional effectiveness, many private universities are turning to predictive analytics, a powerful tool that leverages historical data and statistical techniques to forecast future events and trends. Predictive analytics in human resources (HR) offers a transformative approach to understanding and managing employee turnover turnover (Valecha, 2022). By analyzing vast amounts of data related to employee performance, engagement, and organizational factors, predictive models can identify patterns and predictors of. various outcomes. This allows HR professionals to proactively implement strategies to retain valuable staff and optimize hiring. In the context of private universities, the application of predictive analytics can be particularly beneficial, as these institutions often operate in competitive environments where attracting and retaining talented faculty and staff is crucial for maintaining academic excellence and institutional reputation.

Predictive analytics provides a data-driven foundation for making informed HR decisions, ultimately leading to a more stable and productive workforce. Nyathani (2023). Despite several studies on predictive analytic, the dearth of empirical work on use of predictive analytics in human resource and employee turnover in private universities in South- South, Nigeria motivate this study, this study will bridge the observed gap in knowledge by exploring the applications of predictive analytics in managing human resources and reducing employee turnover within private universities. Delving into the specifics of how predictive analytics can be utilized, will uncover actionable insights that support strategic HR initiatives and foster a more engaged and committed academic community.

Statement of the Problem

High turnover rates typically indicate underlying issues within the company. These problems may include deficiencies in the recruiting process, a negative workplace culture, inadequate compensation and benefits, poor management practices, insufficient training programs, and limited opportunities for career advancement (Holliday, 2021).. Such issues can drive employees to seek employment elsewhere, reflecting broader organizational challenges that need to be addressed. The integration of predictive analytics into human resources (HR) practices within private universities aims to enhance improve decision-making, recruitment processes, and resource allocation. However, this integration also presents several challenges that often lead to increased employee turnover. One primary issue is resistance to change, where employees fear job losses due to automation of HR tasks and exhibit skepticism towards the accuracy and fairness of predictive analytics tools (Fountaine, et al. 2019; Raghavan et al., 2020). Additionally, cultural misalignment can occur, disrupting established HR practices and causing frustration among employees who are accustomed to traditional methods (Van Aken, et al., 2020). Ineffective communication about the benefits and implementation of these tools exacerbates resistance and misunderstandings. Moreover, perceived inequity and bias in predictive models, particularly when historical data reflecting discriminatory practices are used, can erode trust and lead to dissatisfaction (O'Neil, 2016; Barocas, et al., 2019).

Privacy concerns also play a significant role in the challenges associated with integrating predictive analytics. Extensive collection and analysis of employee data raise significant privacy issues, leading to discomfort and mistrust among employees, especially when there is a lack of transparency about data usage (Newell & Marabelli, 2015; Binns, 2018). An overemphasis on quantitative metrics can overlook important qualitative aspects of employee performance and satisfaction, leading to disengagement and turnover (Davenport & Harris, 2017; Mehta et al., 2020). Furthermore, the pressure to meet targets set by predictive analytics can increase stress and job dissatisfaction. Implementation challenges, such as insufficient training on predictive analytics tools and complex integration with existing HR systems, can result in misuse, misunderstanding, and operational disruptions, contributing to frustration and higher turnover rates (King & Steffen, 2017). Understanding these challenges is crucial for the effective implementation of predictive analytics in HR practices.

Aim and Objectives of the Study

The aim of the study is to assess the influence of predictive analytics into human resources (HR) practices on employee turnover within private universities in South- South, Nigeria. The specific objectives are to:

1. Determine the relationship between predictive model accuracy and validation and functional turnover in private universities in South- South, Nigeria.
2. Examine the relationship between predictive model accuracy and validation and dysfunctional turnover in private universities in South- South, Nigeria.
3. Assess the relationship between predictive model robustness and stability and functional turnover in private universities in South- South, Nigeria.
4. Determine the relationship between predictive model robustness and stability and dysfunctional turnover in private universities in South- South, Nigeria.

Research Questions

1. What is the relationship between predictive model accuracy and validation and functional turnover in private universities in South- South, Nigeria?
2. What is the relationship between predictive model accuracy and validation and dysfunctional turnover in private universities in South- South, Nigeria?
3. How does predictive model robustness and stability relate to functional turnover in private universities in South- South, Nigeria?
4. How does predictive model robustness and stability relate to dysfunctional turnover in private universities in South- South, Nigeria?

Research Hypotheses

Ho_1: There is no significant relationship between predictive model accuracy and validation and functional turnover in private universities in South- South, Nigeria.

Ho_2: There is nosignificant relationship between predictive model accuracy and validation and dysfunctional turnover in private universities in South- South, Nigeria.

Ho_3: There is no significant relationship between predictive model robustness and stability and functional turnover in private universities in South- South, Nigeria.

Ho_4: There is no significant relationship between predictive model robustness and stability and dysfunctional turnover in private universities in South- South, Nigeria.

LITERATURE REVIEW

Theoretical Foundation

This study is anchored on the human capital theory.

Human Capital Theory

Human Capital Theory, proposed by economists Gary Becker and Theodore Schultz (Becker,1993; Schultz, 1961), posits that employees are valuable assets due to their skills and knowledge. Predictive analytics in HR can enhance this value in private universities by improving talent acquisition, development, and retention. By analyzing hiring data, universities can recruit candidates more likely to stay and excel. Identifying skill gaps and predicting training needs ensures continuous employee development, leading to higher job satisfaction and reduced turnover. Additionally, predictive analytics aids in forecasting turnover and planning workforce needs. By identifying turnover predictors and engagement levels, HR can implement targeted retention strategies. Effective workforce planning ensures a steady talent pipeline, aligning with the theory's emphasis on maximizing human capital. Ultimately, these analytics-driven approaches help private universities retain skilled employees and achieve their strategic goals.

Predictive Analytics

Human Capital Theory, proposed by economists Gary Becker and Theodore Schultz, posits that employees are valuable assets due to their skills and knowledge (Becker, 1993; Schultz, 1961).

Predictive analytics in human resource (HR) management can enhance this value in private universities by improving talent acquisition, development, and retention. For instance, by analyzing hiring data, universities can recruit candidates more likely to stay and excel. According to a recent study by Marr (2020), organizations that leverage predictive analytics in their recruitment processes have seen a significant reduction in turnover rates. This approach ensures continuous employee development, leading to higher job satisfaction and reduced turnover.

Furthermore, predictive analytics aids in forecasting turnover and planning workforce needs. By identifying turnover predictors and engagement levels, HR departments can implement targeted retention strategies. For example, a study by Jain et al. (2021) demonstrated that predictive models could accurately forecast employee turnover, allowing for proactive interventions. Effective workforce planning, facilitated by predictive analytics, ensures a steady talent pipeline, aligning with Human Capital Theory's emphasis on maximizing human capital. Ultimately, these analytics-driven approaches help private universities retain skilled employees and achieve their strategic goals.

Predictive Model Accuracy and Validation:
Predictive model accuracy and validation are essential for ensuring that predictive analytics provide reliable and actionable insights for Human Resources (HR) practices. Accuracy measures how closely a model's predictions align with actual outcomes. It is a fundamental aspect of model performance, typically evaluated using metrics such as precision, recall, and the F1 score (Chicco & Jurman, 2020). High accuracy in predictive models is crucial for HR professionals, as it enables them to make informed decisions and implement effective strategies to manage employee turnover.

Validation of predictive models is equally important, as it assesses the model's ability to generalize to new, unseen data, rather than just the data on which it was trained. Common validation techniques include cross-validation, where the dataset is divided into training and testing subsets to evaluate model performance (Kuhn & Johnson, 2013). This approach helps ensure that the model does not overfit the training data and performs well on independent data, thereby enhancing its reliability and robustness.

To maintain high accuracy and validate predictive models effectively, it is essential to regularly calibrate them to reflect changes in organizational data and dynamics. This process involves adjusting model parameters and retraining the model with updated data (Cleveland, 2019). Advanced validation techniques, such as k-fold cross-validation and bootstrap methods, should also be employed to robustly assess model performance and prevent overfitting (Hastie, Tibshirani, & Friedman, 2009). Additionally, continuous monitoring of model performance using real-time data and feedback mechanisms is crucial for identifying and correcting any deviations or inaccuracies (Friedman, Hastie, & Tibshirani, 2001). HR professionals should ensure that their predictive models are both accurate and validated, leading to more effective management of employee turnover and other HR-related challenges.

Predictive Model Robustness and Stability

Robustness and stability are crucial attributes for predictive models, ensuring that they deliver consistent and reliable performance across varying conditions and datasets. Robustness refers to a model's ability to handle variations in input data, such as noise and outliers, without a significant drop in performance. Jain et al. (2021) highlight that robust models can handle diverse data inputs effectively, including employee demographics, performance metrics, and organizational factors, to predict turnover with high accuracy. This capability is crucial for universities seeking to proactively manage talent retention strategies amidst changing economic and organizational landscapes (Marr, 2020).

Stability, on the other hand, pertains to a model's ability to produce consistent predictions despite minor changes in data or model parameters. A stable model is crucial for dependable decision-making, as instability can lead to varying results with slight perturbations in input data (Zhang & Zhao, 2020). Assessing model stability involves techniques such as bootstrap aggregating (bagging) and cross-validation. These methods evaluate how performance metrics fluctuate with different subsets of data and parameter settings, thereby providing insights into model reliability.

Employee Turnover

Employee turnover is a critical concern for organizations, impacting productivity, continuity, and overall organizational effectiveness. Defined as the rate at which employees leave an organization over a specified period, turnover rates can significantly affect operational costs and morale (Holliday, 2021). Research by Jain et al. (2021) emphasizes that high turnover rates can disrupt team dynamics, lower morale, and increase recruitment costs. Their study highlights the importance of predictive analytics in understanding turnover predictors, such as job satisfaction, career development opportunities, and organizational culture. By identifying these factors, organizations can implement targeted retention strategies to reduce turnover and enhance employee engagement as turnover, particularly voluntary turnover, significantly affects a company's ability to meet its business goals and is a major concern since the reasons for employee departures are diverse, and companies often find it challenging to completely prevent it (Holliday, 2021).

Marr (2020) discusses how predictive analytics can transform HR practices by predicting turnover trends and enabling proactive interventions. This approach not only helps in retaining key talent but also in optimizing workforce planning and resource allocation. By leveraging data-driven insights, organizations can foster a supportive work environment that aligns with employees' career aspirations and organizational goals. In addressing turnover challenges, organizations benefit from adopting comprehensive retention strategies informed by predictive analytics. These strategies not only mitigate turnover risks but also contribute to long-term organizational sustainability and growth, supporting the principles of Human Capital Theory (Becker, 1993; Schultz, 1961).

Functional Turnover

Functional turnover occurs when employees leave an organization in a manner that benefits the organization. This type of turnover is considered positive as it often involves the departure of underperforming employees, those who do not fit well with the company culture, or those whose roles are no longer necessary due to organizational changes (Allen et al., 2010). Functional turnover can lead to increased productivity, better team dynamics, and the opportunity to bring in new talent that is a better fit for the organization’s needs (Griffeth & Hom, 2001). One key characteristic of functional turnover is improved performance. The departure of underperforming employees can result in a more efficient and effective workforce. Additionally, when employees who do not align with the company's values and culture leave, it can enhance team cohesion and overall morale. Better cultural fit among remaining employees can lead to a more harmonious work environment (Ostroff, 1992).

Cost savings is another benefit of functional turnover. Removing employees who are not contributing effectively can reduce costs associated with poor performance, such as decreased productivity and the potential for mistakes or errors. Furthermore, functional turnover presents the opportunity for fresh talent. New hires can bring in fresh perspectives, innovative ideas, and up-to-date skills that can drive the organization forward (Holtom et al., 2008). Managing functional turnover involves identifying which departures are beneficial and ensuring that recruitment and retention strategies align with the organization’s goals and culture. By doing so, organizations can leverage functional turnover to enhance their workforce and achieve their strategic objectives (Morrell, et al., 2001).

Dysfunctional Turnover

Dysfunctional turnover refers to the situation where employees leave an organization, but their departure has a negative impact on the organization. This can happen when valuable employees with critical skills or knowledge leave, causing disruptions, increased workload on remaining staff, or loss of institutional knowledge (Hancock et al., 2013). It's often contrasted with functional turnover, where employees leaving actually benefit the organization by removing poor performers or those who are not a good fit (Griffeth & Hom, 2001). Addressing dysfunctional turnover typically involves improving retention strategies, enhancing workplace culture, and ensuring that employees feel valued and supported (Hausknecht et al., 2009).

Empirical Review

Robinson and Sethukarasi (2024) examine HR analytics' role in improving employee retention, highlighting technological advancements and the use of statistical tools for sustainable strategies. The study emphasizes HR analytics' importance in informed decision-making and predictive strategies for enhancing retention rates.

Adeusi et al. (2024) investigate using machine learning to predict employee turnover in high-stress sectors. By analyzing employee demographics, job satisfaction, performance metrics, and stress levels, the research employs logistic regression, decision trees, random forests, and neural networks. Results show that random forests and neural networks are particularly effective in predicting turnover.

Valecha (2022) explores the evolution and challenges of human resource management through HR analytics, enhancing decision-making regarding human and organizational capital. A survey of 217 HR team members reveals that HR analytics significantly improves HR management.

Nyathani (2023) emphasizes the importance of comprehensive employee data management and the role of AI in HR analytics. The paper discusses AI-driven workflows, ethical considerations, and the transformative potential of AI in HR, advocating for strategic and responsible adoption.

Methodology

This study used a cross-sectional survey to examine the role of predictive analytics in human resource management and employee turnover of private universities in South-South Nigeria. The accessible population consisted of 6,300 academic staff members from these universities. A sample size of 361 was determined using the Krejcie and Morgan (1970) table. Data were collected through a structured questionnaire, with all items rated on a 4-point Likert scale. Pearson's product-moment correlation coefficient was employed for data analysis.

RESULT

Out of the 361 distributed copies, 335 (92.8%) were retrieved and well-filled. However, 15 copies were either incorrectly filled or incomplete due to non-adherence to stipulated instructions, accidental omissions, and the selection of multiple options for a single item, rendering them invalid for the study. Consequently, 320 (88.6%) of the mobilized questionnaire copies were deemed valid and utilized in the study. The hypotheses were tested at a 95% confidence interval, with the decision rule as follows:

- Reject the null hypothesis if $P < 0.05$
- Accept the null hypothesis if $P > 0.05$

Table 1: Predictive Model Accuracy and Validation and Employee Turnover

Correlations

		Predictive Model Accuracy and Validation	Functional Turnover	Dysfunctional Turnover
Predictive Model Accuracy and Validation	Pearson Correlation	1	.673**	.700**
	Sig. (2-tailed)		.000	.000
	N	320	320	320
Functional Turnover	Pearson Correlation	.673**	1	.606**
	Sig. (2-tailed)	.000		.000
	N	320	320	320
Dysfunctional Turnover	Pearson Correlation	.700**	.606**	1
	Sig. (2-tailed)	.000	.000	
	N	320	320	320

**. Correlation is significant at the 0.01 level (2-tailed).

Source: SPSS Output, 2024.

The analysis in Table 1 indicates a significant relationship ($p< 0.05$) between predictive model accuracy and validation and functional turnover. The correlation coefficient is 0.673 suggesting a strong positive relationship between predictive model accuracy and validation and functional turnover. Furthermore, the outcome depicts a significant relationship ($p < 0.05$) between predictive model accuracy and validation and dysfunctional turnover. The correlation coefficient is 0.700, indicating a strong positive relationship between predictive model accuracy and validation and dysfunctional turnover.

Table 2: Predictive Model Robustness and Stability and Employee Turnover

Correlations

		Predictive Model Robustness and Stability	Functional Turnover	Dysfunctional Turnover
Predictive Model Robustness and Stability	Pearson Correlation	1	.667**	.668**
	Sig. (2-tailed)		.000	.000
	N	320	320	320
Functional Turnover	Pearson Correlation	.667**	1	.611**
	Sig. (2-tailed)	.000		.000
	N	320	320	320
Dysfunctional Turnover	Pearson Correlation	.668**	.611**	1
	Sig. (2-tailed)	.000	.000	
	N	320	320	320

**. Correlation is significant at the 0.01 level (2-tailed).

Source: SPSS Output, 2024.

The analysis in Table 2 reveals a significant relationship ($p < 0.05$) between predictive model robustness and stability and dysfunctional turnover, with a correlation coefficient of 0.667, indicating a strong positive relationship. Additionally, the results show a significant relationship ($p < 0.05$) between predictive model robustness and stability and dysfunctional turnover, with a correlation coefficient of 0.668, suggesting a strong positive relationship between these variables.

Discussion of Findings

Predictive Model Accuracy and Validation and Functional Turnover

The analysis on predictive model accuracy and validation, as well as functional turnover, yielded a correlation value of 0.673 with a p-value of 0.000. This indicates a strong, positive, and significant relationship between the two variables. The coefficient of determination (R^2) value of 0.452 signifies that 45.2% of the total variation in functional turnover can be explained by changes in predictive model accuracy and validation. This implies that a substantial portion of the variability in functional turnover is influenced by how accurately and effectively the predictive model is validated. This result aligns with the findings of Marr (2020) that leveraged predictive analytics in recruitment processes enhances a significant reduction in turnover rates, and Ikegwuru and Acee-Eke (2020) whose finding reveal that predictive data analytics contribute significantly to performance of retail supply chains in Rivers State

Predictive Model Accuracy and Validation and Dysfunctional Turnover

The analysis of predictive model accuracy and validation and dysfunctional turnover revealed a correlation coefficient of 0.700 with a p-value of 0.000, indicating a significant and positive, strong relationship between these variables. The correlation determination (R2) value of 0.490 suggests that 49% of the total variation in dysfunctional turnover can be explained by changes in predictive model accuracy and validation. This implies that a considerable portion of the variation in dysfunctional turnover is influenced by the effectiveness and accuracy of the predictive model's validation. The findings conform with Robinson and Sethukarasi (2024) that HR analytics improve employee retention.

Predictive Model Robustness and Stability and Functional Turnover

The analysis of predictive model robustness and stability and functional turnover revealed a correlation coefficient of 0.667 with a p-value of 0.000, indicating a positive, strong and significant relationship between the two variables. The coefficient of determination (R^2) value of 0.445 signifies that 44.5% of the total variation in functional turnover can be explained by changes in predictive model robustness and stability. This implies that a substantial portion of the variability in functional turnover is influenced by the robustness and stability of the predictive model. This aligns with Adeusi et al. (2024) that predictive analytics are effective in predicting turnover.

Predictive Model Robustness and Stability and Dysfunctional Turnover

The analysis of predictive model robustness and stability and dysfunctional turnover revealed a correlation coefficient of 0.668 with a p-value of 0.000, indicating a significant and positive, strong relationship between these variables. The correlation determination (R2) value of 0.446 suggests that 44.6% of the total variation in dysfunctional turnover can be explained by changes in Predictive Model Robustness and Stability. This implies that a significant portion of the variability in dysfunctional turnover is associated with the robustness and stability of the predictive model. This conform with the findings of Valecha (2022) reveals that HR analytics significantly improves HR management.

Conclusion

The study on the impact of predictive analytics on HR practices and employee turnover in private universities in South-South, Nigeria, highlights the significant role of predictive model accuracy, validation, robustness, and stability. The findings indicate a strong positive relationship between predictive model accuracy and validation and both functional and dysfunctional turnover, with correlation coefficients of 0.673 and 0.700, respectively, and p-values of 0.000. This demonstrates that accurate and well-validated predictive models are associated with lower rates of functional and dysfunctional turnover.

Similarly, the analysis shows that predictive model robustness and stability are significantly related to turnover, with correlation coefficients of 0.667 for functional turnover and 0.668 for dysfunctional turnover, both with p-values of 0.000. This suggests that robust and stable predictive models are vital in managing turnover rates effectively. The study emphasises the importance of using accurate, validated, and stable predictive models in HR practices. Such models enhance the understanding of turnover factors and support proactive management strategies. By integrating predictive analytics, private universities in South-South, Nigeria can refine their HR strategies, reduce turnover, and create a more stable and productive work environment.

Recommendations

Based on the study of predictive analytics in relation to employee turnover in private universities in South-South, Nigeria, the following recommendations are made:

1. Universities should routinely calibrate and test their predictive models to ensure high accuracy and effective validation.
2. Invest in training for HR professionals to enhance their understanding of predictive analytics tools and techniques, to ensure they can effectively utilize these models for better decision-making.
3. Focus on developing predictive models that are not only accurate but also robust and stable across various scenarios, using diverse datasets and incorporating various factors that may influence turnover.
4. Conduct periodic reviews and updates of predictive models to ensure their stability over time, to help in adapting to any changes in organizational dynamics or external factors that might affect turnover.
5. Utilize insights gained from predictive models to drive HR strategies and implement targeted interventions based on the predictions to address potential issues related to both functional and dysfunctional turnover.
6. Use predictive analytics to anticipate turnover trends and proactively address potential causes of turnover before they become significant issues, by improving employee engagement, refining recruitment processes, or enhancing job satisfaction.
7. Work closely with data scientists and analysts to enhance the quality and effectiveness of predictive models, as collaborative efforts can lead to better model development and application.
8. Engage with other institutions or organizations to share best practices and experiences related to predictive analytics in HR to enhance valuable insights and help in adopting successful strategies.

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