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Examining Effects of Human Resource Analytics in Decision Making: A Case Study Ministry of Health HQ in Lusaka

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Abstract

Data Analytics has potential to change how companies compete through new business models, where decisions are automated in a way that guarantees speed, quality and flexibility. Despite this rush and the push to have enterprises embrace BDA, empirical evidence shows that majority of the firms have not benefited from their investments in DA. Despite the potential benefits of HRA, it has not received adequate attention from management researchers. The general objective of the study is to examine the effects of Human Resource Analytics on decision-making processes in the Ministry of Health. Research design is defined as the general plan of how the researcher goes about answering the research questions. A descriptive case study approach will be adopted to match the nature of the topic. The study will use open ended questionnaires and guided oral interviews. A sample will be drawn from HRM personnel to generate inferences about the target population. This helps in saving time and resources it would otherwise have taken to meet every individual in the entire population. Target population in this research comprises of all those potential participants that could make up the study group. In this research, the target population was 50. Purposive sampling of respondents was carried out. The respondents will be picked from various departments involved in various activities. This will be done in order to extract correct and accurate information because the problem at hand required such consideration. The basic idea of sampling is by selecting some of the elements in a population, we may draw conclusions about the entire population The reason why sampling is necessary is because of lower costs, greater accuracy of results, and greater speed of data collection and availability of population elements. The sample size refers to the number of elements or units that the researcher draws from the population of respondents for research exercise. In this study, the sample size of 50 respondents will be picked. And all 50 questionnaires will be distributed. These respondents will be purposely chosen by the researcher Data collection consisted of interviews from the selected HRM personnel both male and female. Data analysis is the process of editing and reducing accumulated data to a manageable size, developing summaries, looking for patterns and applying statistical techniques. The data collected will be analyzed using tables, figures. The researcher used both qualitative and quantitative method. According to the results in (Table 5.7), several limiting factors to the effective use of Human Resource Analytics (HRA) were identified. The highest reported constraint was poor system integration, with a mean score of 3.80 (±0.99), followed closely by lack of staff technical skills at 3.68 (±1.12). Lack of appropriate tools/software was also noted as a major barrier, scoring a mean of 3.62 (±1.16). Other relevant constraints included privacy and security concerns (3.54 ±1.18), infrastructure constraints (3.50 ±1.06), and inadequate training on HRA among staff, which was the least reported limitation, with a mean of 3.18 (±0.90). The results demonstrate varied levels of Human Resource Analytics (HRA) usage across core HR functions within the Ministry of Health in Lusaka. Among the four key areas assessed, the highest level of application was noted in monitoring employee performance, with 68% of the maximum possible score (Mean = 3.40). Similarly, the use of analytics to identify training needs followed closely with a mean of 3.38 (67.6%), reflecting a relatively strong uptake of HRA in skills development and capacity-building initiatives. Workforce planning recorded a moderate mean of 3.32 (66.4%). Conversely, tracking attrition was the least utilized function, with only 50% of the maximum score (Mean = 2.50). The crosstabulation results reveal substantial differences in the use of Human Resource Information Systems (HRIS) across various job roles within the Ministry of Health. HR Officers, Planners, and Administrators all reported 100% usage of HRIS in their roles. Among Analysts, 71.4% indicated use of HRIS, while 28.6% did not. Notably, respondents categorized under "Other" reported 0% usage, highlighting potential exclusion or limited exposure to HRIS tools in that category. The recommendations are that there is a need for an integrated system that will bring all areas of HR on board and also a need for capacity building HR.

Keywords: Personnel, Big Data Analytics, Human Resource

1. Introduction

1.1 Background

Human resources (HR) analytics, is defined as "using descriptive, visual, and statistical analyses of data related to HR

processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making" (Marler & Boudreau, 2017, p. 15), and has gained increasing attention among HR researchers and HR practitioners (Angrave *et al*., 2016, Bartram and Cooke, 2022, Huselid, 2018, Minbaeva, 2018). Effective HR analytics implementation is viewed as a vital organizational capability (Davenport *et al*., 2010) that enhances HR operations (Holwerda, 2021, Leonardi and Contractor, 2018), identifies HR-related business challenges (Levenson, 2018, McCartney and Fu, 2022, Tambe *et al*., 2019), and positions the HR department as a strategic business partner (Lawler, 2014).

Although previous research indicates that HR analytics has the potential for positive organizational outcomes, in some organizations, HR analytics has not delivered on this expectation (Holland & Bardoel, 2016). The HR Technology Market 2021 Report by Josh Bersin highlights a significant gap between anticipated and realized value in HR technology projects, with 42% of such projects proving either partially successful or failing within two years (Bersin, 2021, p. 19). Even large organizations that have heavily invested in HR analytics struggle to fully harnessing its benefits (Angrave *et al*., 2016). Therefore, the implementation of HR analytics, a dynamic process involving key HRM actors (such as line managers, HR specialists, and user employees) interacting with technology to tailor it to their needs (Trullen *et al*., 2020), encounters specific hurdles. For example, two key challenges noted in HR analytics literature point to the general lack of individual knowledge, skills, and capabilities to successfully interact with the technology, as well as the ability to formulate business-relevant research questions and construct and run analytical models (Minbaeva, 2017, Minbaeva, 2021).

1.2 Statement of the Problem

Data Analytics has potential to change how companies compete through new business models, where decisions are automated in a way that guarantees speed, quality and flexibility (Bughin, Catlin, Hirt, & Willmott, 2018) [10]. Despite this rush and the push to have enterprises embrace BDA, empirical evidence shows that majority of the firms have not benefited from their investments in DA (Bughin *et al*., 2018 [10]; Manyika, *et al*., 2015). Despite the potential benefits of HRA, it has not received adequate attention from management researchers (Marler & Boudreau, 2016). This is because very little information is available about the process through which HRA influences organizations and their performance (Huselid, 2018, Schiemann *et al*., 2017). HRA adoption is defined as the process through which an organization invests in, operationalizes, and assimilates HRA into the workforce's decision-making process. This includes envisioning the decisions they want to be driven by data, assessing the resources required to support the decision-making, building the case for HRA adoption and making relevant investments, prioritizing the design and delivery of such supporting resources, enabling stakeholders in their decision-making process, and driving the usage of HRA in the entire organization. However, the adoption of HRA by an organization is marred by several challenges. In addition, it is also not completely clear how organizations should use HRA to achieve important organizational outcomes (Mclver, Lengnick-Hall & Lengnick-Hall, 2018). Organizations need to overcome several challenges before they can adopt HRA in their processes. They need to review how analytics can be employed to capture, organize, and leverage the HR data to derive value. For this to happen, HRA needs to move from the existing descriptive models to the predictive ones to understand human capital's strategic impact (Boudreau and Lawler, 2015, Boudreau and Cascio, 2017). Therefore, more structured solutions to these issues are needed before analytics can be adopted in the HRM of an organization. Despite the apparent benefits of Human Resource Analytics in decision-making processes, the Ministry of Health in Zambia suffers from a lack of effective data utilization, leading to low productivity and inefficiencies. Empirical evidence shows that only a small fraction of health professionals utilize technological innovations, resulting in persistent challenges in health service delivery.

1.3 General Objective

The general objective of the study is to examine the effects of Human Resource Analytics on decision-making processes in the Ministry of Health.

1.3.1 Specific Objectives

1. To establish Human Resource Analytics used at the ministry of health in Lusaka.
2. To examine how Human Resource Analytics is used enhancing decision-making in enhancing performance.
3. To ascertain factors limiting the effective use of Human Resource Analytics in the Ministry of Health.

1.4 Theoretical Frameworks

This research anchors on the Knowledge Based View (RBV) theory which was arrived at upon reviewing three theories that are relevant to the topic of study. The theories are: Prospect theory (Kahneman & Tversky, 1974), Dynamic Capabilities theory (Teece, Pisano & Shuen, 1997), Knowledge Based View theory (Grant, 1996). A KBV approach holds the view that data is a critical resource in operation decisions as articulated in the resource based view (RBV) theory. The RBV theory underscores the criticality of inside resources to an operation. Operations optimize their internal resources which are of value, scarce, and difficult to substitute (Barney, 1991) [3]. In the context of BDA knowledge or information is viewed as resource, which however keeps changing in volume, velocity, value, veracity and variety (Verschiedene, 2014). Therefore, in terms of approach, the researcher is influenced by McAfee and Brynjolfsson (2012) who characterize big data as possessing volume, velocity and variety attributes.

2. Literature Review

2.1 Human Resource Analytics used at the ministry of health in Lusaka

There are five approaches of making decisions; the rational approach, satisficing approach, personal approach, procedural approach and political approach (Keen & Morton, 1978). Big Data Analytics is founded on the basis of rational models of decision making. A rational model assumes that operations are deterministic and produces error-free results (Boudreau, *et al*., 2003) [8]. A rational model employs a stepwise approach of data collection, weighing and analyzing evidence then choosing among many alternatives that emerge (Crozier, Ranyard, & Svenson, 2002).

Data Analytics facilitates decision-making, by providing a choice of actions to take from an array of possibilities. Big Data Analytics is the source of insight, knowledge, information and insights that reduces uncertainty in decision making (Chiang & Abbasi, 2016). Insights refer to deep and intuitive comprehension of constructs and phenomena that can be leveraged by practitioners (Sharma, Reynolds, Scheepers, Seddon, & Shanks, 2010; Lycett, 2013) leading to better decisions (Storey, Chen, & Chiang, 2012).

2.2 How Human Resource Analytics is used enhancing decision-making in enhancing performance

Data Analytics had been used to enhance operations efficiency, customer satisfaction and new product development (Jeseke, Grüner, & Wei, 2013). New product development is a series of steps that a firm takes in turning ideas into products and eventually deciding to commercialize them (Cooper, 2010). Furthermore, BDA can be used to analyze consumer behavior so as to know what products to launch (Yu & Yang, 2016). Big Data Analytics can enable an operation to be efficient and effective which can confer competitive advantages (Prahalad & Hamel, 1990).

Data Analytics may help in market discovery which is at the end of the products chain where value is being generated. The smiling curve is a tool that can assist to identify activities along the value chain which may add more value to customers and help the firm grow quickly. Examples of these activities are research and development (R&D), standardized services, advertising, brand management, logistics and after sale services. (Shih, 1996). Although it was initially applied in a manufacturing context, it has could have applications in the services industry as well. An operation's core competence can be used to inform the decision on the choice of activities that can add value in any industry. This means if an activity fits a firm's core competence, it can be done in-house. If it is not a core activity, it can be done by another firm (Sanchez & Mahoney, 1996).

2.3 Limiting the effective use of Human Resource Analytics in the Ministry of Health

The DA constructs are operationalized through variables that are categorized into tangible resources, intangible resources and human skills. Tangible resources are those which can be traded in a market like data, technology and time. Data collected by banks is both in structured and unstructured format. Structured data is internal and firm-specific and can be measured by customer transactions, number loans and human resources. Unstructured data is external to the firm and may not have a relationship with firm's business but can provide additional insight about customers. Examples of external data are websites, internet searches, social media and calling records. The existence of technologies to process big data are like data warehouses, data marts, Hadoop and Spark can be measured. In addition, time devoted to big data initiatives can be measured as resource.

3. Methodology

3.1 Research Design

Research design is defined as the general plan of how the researcher goes about answering the research questions (Saunders *et al* (2007). A descriptive case study approach will be adopted to match the nature of the topic. The study will use open ended questionnaires and guided oral interviews. A sample will be drawn from HRM personnel to generate inferences about the target population. This helps in saving time and resources it would otherwise have taken to meet every individual in the entire population.

3.2 Target Population

According to Shajahan (2004) the term population refers to the set of all elements of interest in a particular study. Target population in this research comprises of all those potential participants that could make up the study group. In this research, the target population will be 50.

3.3 Sampling Design

Purposive sampling of respondents will be carried out. The respondents will be picked from various departments involved in various activities. This will be done in order to extract correct and accurate information because the problem at hand required such consideration.

3.4 Sample Size Determination

The basic idea of sampling is by selecting some of the elements in a population, we may draw conclusions about the entire population [Cooper and Schindler (2001)]. The reason why sampling is necessary is because of lower costs, greater accuracy of results, and greater speed of data collection and availability of population elements.

The sample size refers to the number of elements or units that the researcher draws from the population of respondents for research exercise. In this study, the sample size of 50 respondents will be picked. And all 50 questionnaires will be distributed. These respondents will be purposely chosen by the researcher.

3.5 Data Collection Methods

The main instruments to be used are questionnaires and personal interviews. The questionnaires will comprise closed and open ended questions. Questionnaires will either be administered or handed out to the respondents depending on their business operating schedules. Qualitative and quantitative data analysis will be done. Quantitative data will be used because it is easier to present using tables and qualitative data helped express the data collected.

Data collection consisted of interviews from the selected HRM personnel both male and female.

3.6 Data Analysis

Data analysis is the process of editing and reducing accumulated data to a manageable size, developing summaries, looking for patterns and applying statistical techniques [Cooper and Schindler (2008). The data collected will be analyzed using tables, figures. The researcher used both qualitative and quantitative method.

For the qualitative data, the researcher used descriptive method, while for quantitative data will be analyzed using Microsoft Word and Excel to generate tables and other graphic illustrations.

3.7 Ethical Considerations

The researcher will ensure that no respondents are forced to give information concerning the subject matter but allowed them to give information out of their own convenience and free will. The researcher will also ensure the information

obtained from respondents remain confidential, and that information obtained is purely for academic purposes. Anonymity will be taken into account by not disclosing names of the respondents. The research will not use arm twisting tactics such as embarrassing questions or threats when collecting data. The study will get informed consent from all the respondents.

4. Presentation of Data and Discusions

Objective 1: To establish Human Resource Analytics used at the ministry of health in Lusaka.

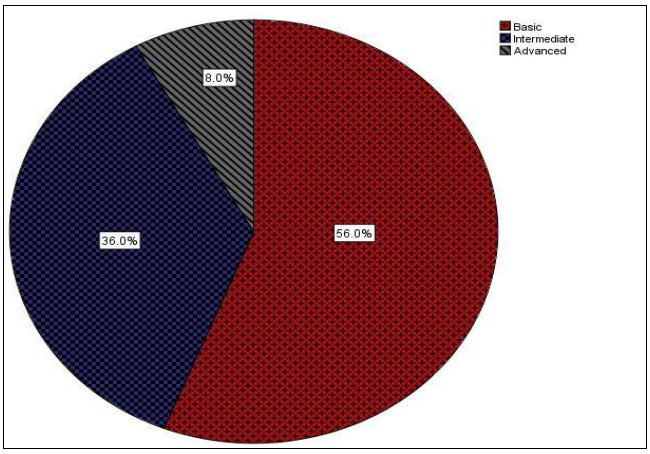

Fig 5.1: Knowledge of Human Resource Analytics among Respondents at the Ministry of Health, Lusaka

In exploring the extent of human resource analytics (HRA) knowledge among staff at the Ministry of Health in Lusaka, results reveal that a majority of respondents (56.0%) reported having only basic knowledge of HRA.

A further 36.0% of participants reported having intermediate knowledge, suggesting a modest proportion of staff are conversant with moderately technical aspects or have some applied exposure to HRA tools and techniques. Only a small segment (8.0%) of the workforce indicated possessing advanced knowledge of HRA, pointing to a significant skills gap at higher analytical levels. One respondent remarked during the interviews, "*We mostly use Excel and some basic tools, but a deeper understanding of predictive analytics is still lacking across departments*."

Table 5.2: Utilization of Human Resource Analytics in Core HR Functions at the Ministry of Health, Lusaka

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Use of analytics for workforce planning	50	1	5	3.32	1.151
Use of analytics to track attrition	50	1	5	2.50	.763
Use of analytics to monitor employee performance	50	1	5	3.40	.782
Use of analytics to identify training needs	50	2	5	3.38	.923
Valid N (listwise)	50				

The descriptive statistics reveal varying degrees of Human Resource Analytics (HRA) utilization across key HR functions within the Ministry of Health in Lusaka. The use of analytics to monitor employee performance recorded the highest mean score (M = 3.40, SD = 0.782). This was closely followed by the application of analytics to identify training needs, which also showed a moderately high mean (M = 3.38, SD = 0.923). Analytics use for workforce planning was slightly lower but still meaningful, with a mean of 3.32 (SD = 1.151). In contrast, the least utilized area was analytics for tracking attrition, with a notably lower mean score of 2.50 (SD = 0.763).

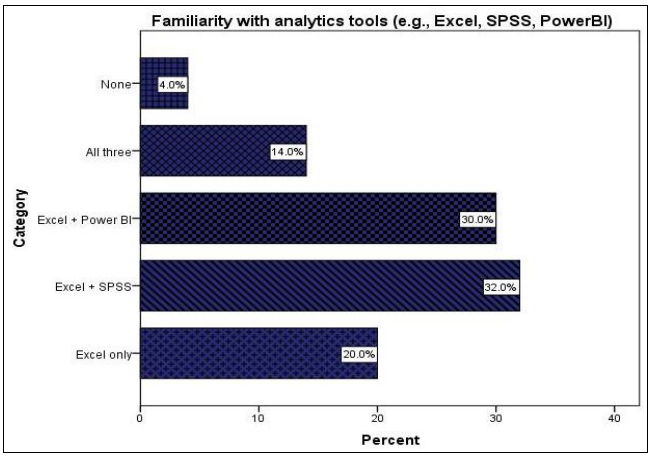

Fig 5.2: Utilization of Human Resource Analytics at the Ministry of Health in Lusaka

The results demonstrate varied levels of Human Resource Analytics (HRA) usage across core HR functions within the Ministry of Health in Lusaka. Among the four key areas assessed, the highest level of application was noted in monitoring employee performance, with 68% of the maximum possible score (Mean = 3.40). Similarly, the use of analytics to identify training needs followed closely with a mean of 3.38 (67.6%), reflecting a relatively strong uptake of HRA in skills development and capacity-building initiatives. Workforce planning recorded a moderate mean of 3.32 (66.4%). Conversely, tracking attrition was the least utilized function, with only 50% of the maximum score (Mean = 2.50).

Table 5.3: Utilization of Human Resource Information Systems (HRIS) by Job Role within the Ministry of Health in Lusaka

Job Role * Use of HR Information Systems (HRIS) Crosstabulation				
Count				
		Use of HR Information Systems (HRIS)		Total
		Yes	No	
Job Role	HR Officer	7	0	7
	Planner	12	0	12
	Administrator	13	0	13
	Analyst	10	4	14
	Other	0	4	4
Total		42	8	50

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	28.741[a]	4	.000
Likelihood Ratio	27.215	4	.000
Linear-by-Linear Association	16.719	1	.000
N of Valid Cases	50		
a. 6 cells (60.0%) have expected count less than 5. The minimum expected count is .64.			

The crosstabulation results reveal substantial differences in the use of Human Resource Information Systems (HRIS) across various job roles within the Ministry of Health. HR Officers, Planners, and Administrators all reported 100% usage of HRIS in their roles. Among Analysts, 71.4% indicated use of HRIS, while 28.6% did not. Notably, respondents categorized under "Other" reported 0% usage, highlighting potential exclusion or limited exposure to HRIS tools in that category. The Pearson Chi-Square test yielded a statistically significant result ($\chi^2 = 28.741$, $p = .000$).

Table 5.4: Familiarity with Analytics Tools by Years of Experience – Ministry of Health, Lusaka

Years of Experience * Familiarity with analytics tools (e.g., Excel, SPSS, PowerBI) Crosstabulation							
Count							
		Familiarity with analytics tools (e.g., Excel, SPSS, PowerBI)					Total
		Excel only	Excel + SPSS	Excel + Power BI	All three	None	
Years of Experience	0–2 years	1	0	0	1	2	4
	3–5 years	7	0	0	0	0	7
	6–10 years	2	16	5	0	0	23
	10+ years	0	0	10	6	0	16
Total		10	16	15	7	2	50

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	89.216[a]	12	.000
Likelihood Ratio	79.040	12	.000
Linear-by-Linear Association	4.518	1	.034
N of Valid Cases	50		
a. 17 cells (85.0%) have expected count less than 5. The minimum expected count is .16.			

The results show a clear pattern between years of professional experience and familiarity with analytical tools such as Excel, SPSS, and Power BI. Among respondents with 0–2 years of experience, only 25% reported familiarity with Excel alone, and another 25% were familiar with all three tools. Notably, 50% in this group reported no familiarity with any of the listed tools. Respondents with 3–5 years of experience showed 100% reliance on Excel only, with no reported use of other tools. Among those with 6–10 years of experience, 69.6% reported familiarity with Excel and SPSS, 21.7% with Excel and Power BI, and 8.7% with Excel only. Those with over 10 years of experience demonstrated the most diversified tool use: 62.5% were familiar with Excel and Power BI, while 37.5% reported familiarity with all three tools (Excel, SPSS, and Power BI). None in this group reported using Excel alone or having no familiarity with analytics tools. Statistically, the Pearson Chi-Square test was significant ($\chi^2 = 89.216$, $p = .000$).

Objective 2 – Script

Objective 2: To examine how Human Resource Analytics is used enhancing decision-making in enhancing performance.

Effectiveness of Human Resource Analytics in Enhancing Decision-Making and Performance

Figure 5.3 presents respondent perceptions on whether Human Resource (HR) analytics contributes to improved decision-making and performance enhancement at the Ministry of Health in Lusaka.

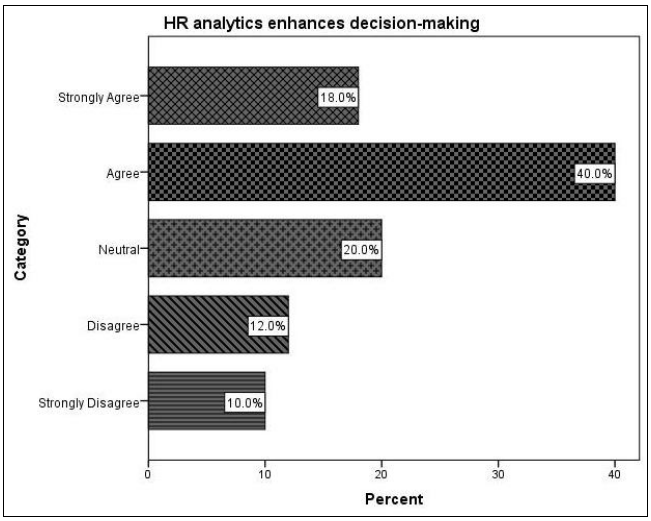

Fig 5.3: HR Analytics Enhances Decision-Making

The majority of respondents (40.0%) agreed that HR analytics enhances decision-making, while a further 18.0% strongly agreed, bringing the total positive affirmation to 58.0%. A significant proportion (20.0%) remained neutral, indicating a moderate level of uncertainty or mixed experiences regarding its role. On the other hand, 12.0% disagreed and 10.0% strongly disagreed, cumulatively 22.0%.

Utilization of Human Resource Analytics in Enhancing Decision-Making and Performance

Table 5.5: Ranks – Human Resource Analytics Applications

Ranks	
	Mean Rank
HR analytics used to monitor performance	2.92
Integration of HR data improves decisions	2.62
HR analytics supports policy-making	3.32
Analytics enables timely reporting	2.77
Evidence-based planning improved by HR analytics	3.37

Test Statistics[a]	
N	50
Chi-Square	34.077
df	4
Asymp. Sig.	.000
a. Friedman Test	

According to the Likert scale, 1 represented the highest level of agreement, while 5 represented the lowest. Therefore, variables with lower mean ranks were ranked higher in importance.

Among the five dimensions assessed, integration of HR data to improve decisions was ranked first with the lowest mean rank of 2.62, indicating it was the most acknowledged use of HR analytics in enhancing decision-making. This was followed by HR analytics used to monitor performance (mean rank = 2.92) and analytics enabling timely reporting (mean rank = 2.77). HR analytics supporting policy-making and evidence-based planning improved by HR analytics received higher mean ranks of 3.32 and 3.37 respectively. The Friedman Test revealed a statistically significant difference in the rankings ($\chi^2 = 34.077$, $df = 4$, $p < 0.001$).

Relationship between Human Resource Analytics and Evidence-Based Planning in Enhancing Decision-Making

Table 5.6: Correlations between HR Analytics and Evidence-Based Planning

Correlations			
		HR analytics enhances decision-making	Evidence-based planning improved by HR analytics
HR analytics enhances decision-making	Pearson Correlation	1	.932**
	Sig. (2-tailed)		.000
	N	50	50
Evidence-based planning improved by HR analytics	Pearson Correlation	.932**	1
	Sig. (2-tailed)	.000	
	N	50	50
**. Correlation is significant at the 0.01 level (2-tailed).			

The results indicate a strong positive relationship between the use of HR analytics to enhance decision-making and evidence-based planning improved by HR analytics, as reflected by a Pearson correlation coefficient of 0.932. This correlation is statistically significant at the 0.01 level ($p = .000$).

Objective 3 – Script

Objective 3: To ascertain factors limiting the effective use of Human Resource Analytics in the Ministry of Health.

Factors Limiting the Effective Use of Human Resource Analytics in the Ministry of Health

Table 5.7: Descriptive Statistics on Barriers to Effective Use of HR Analytics

Descriptive Statistics					
	N	Mean	Std. Deviation	Minimum	Maximum
Lack of staff technical skills limits use of HRA	50	3.68	1.115	1	5
Poor system integration limits HRA	50	3.80	.990	1	5
Lack of appropriate tools/software limits HRA	50	3.62	1.159	1	5
Inadequate training on HRA among staff	50	3.18	.896	1	5
Privacy/security concerns restrict HRA adoption	50	3.54	1.182	1	5
Infrastructure constraints limit HRA usage	50	3.50	1.055	1	5

According to the results in (Table 5.7), several limiting factors to the effective use of Human Resource Analytics (HRA) were identified. The highest reported constraint was poor system integration, with a mean score of 3.80 (±0.99), followed closely by lack of staff technical skills at 3.68 (±1.12). Lack of appropriate tools/software was also noted as a major barrier, scoring a mean of 3.62 (±1.16). Other relevant constraints included privacy and security concerns (3.54 ±1.18), infrastructure constraints (3.50 ±1.06), and inadequate training on HRA among staff, which was the least reported limitation, with a mean of 3.18 (±0.90).

Factors Limiting the Effective Use of Human Resource Analytics in the Ministry of Health

Table 5.8: Ranking of Limiting Factors Based on Friedman Test

Ranks	
	Mean Rank
Lack of staff technical skills limits use of HRA	3.85
Poor system integration limits HRA	4.22
Lack of appropriate tools/software limits HRA	3.68
Inadequate training on HRA among staff	2.47
Privacy/security concerns restrict HRA adoption	3.44
Infrastructure constraints limit HRA usage	3.34

Test Statistics[a]	
N	50
Chi-Square	63.069
df	5
Asymp. Sig.	.000
a. Friedman Test	

According to the Likert scale where 1 was the highest priority and 5 the lowest, the mean rank scores were used to determine the relative importance of factors limiting the effective use of Human Resource Analytics (HRA). In this ranking, a lower mean rank indicates a higher perceived impact.

Among the six identified factors, inadequate training on HRA among staff ranked first, with the lowest mean rank of 2.47. This was followed by infrastructure constraints (mean rank = 3.34) and privacy/security concerns (3.44). Lack of appropriate tools/software and lack of staff technical skills received mean ranks of 3.68 and 3.85, respectively. Poor system integration was ranked the least limiting factor, with the highest mean rank of 4.22. The Friedman test yielded a Chi-square value of 63.069 ($df = 5$, $p = .000$), indicating that the differences in rankings among the six limiting factors were statistically significant.

4.1 Discussions

Objective 1: To establish Human Resource Analytics used at the ministry of health in Lusaka.

Figure 5.1: Knowledge of Human Resource Analytics among Respondents at the Ministry of Health, Lusaka

In exploring the extent of human resource analytics (HRA) knowledge among staff at the Ministry of Health in Lusaka, results reveal that a majority of respondents (56.0%) reported having only basic knowledge of HRA.

A further 36.0% of participants reported having intermediate knowledge, suggesting a modest proportion of staff are conversant with moderately technical aspects or have some applied exposure to HRA tools and techniques. Only a small segment (8.0%) of the workforce indicated possessing advanced knowledge of HRA, pointing to a significant skills gap at higher analytical levels. One respondent remarked during the interviews, “We mostly use Excel and some basic tools, but a deeper understanding of predictive analytics is still lacking across departments.”

Table 5.2: Utilization of Human Resource Analytics in Core HR Functions at the Ministry of Health, Lusaka

The descriptive statistics reveal varying degrees of Human Resource Analytics (HRA) utilization across key HR functions within the Ministry of Health in Lusaka. The use of analytics to monitor employee performance recorded the highest mean score ($M = 3.40$, $SD = 0.782$). This was

closely followed by the application of analytics to identify training needs, which also showed a moderately high mean (M = 3.38, SD = 0.923). Analytics use for workforce planning was slightly lower but still meaningful, with a mean of 3.32 (SD = 1.151). In contrast, the least utilized area was analytics for tracking attrition, with a notably lower mean score of 2.50 (SD = 0.763).

Objective 2: To examine how Human Resource Analytics is used enhancing decision-making in enhancing performance.

Effectiveness of Human Resource Analytics in Enhancing Decision-Making and Performance

Figure 5.3: HR Analytics Enhances Decision-Making

Figure 5.3 presents respondent perceptions on whether Human Resource (HR) analytics contributes to improved decision-making and performance enhancement at the Ministry of Health in Lusaka.

The majority of respondents (40.0%) agreed that HR analytics enhances decision-making, while a further 18.0% strongly agreed, bringing the total positive affirmation to 58.0%. A significant proportion (20.0%) remained neutral, indicating a moderate level of uncertainty or mixed experiences regarding its role. On the other hand, 12.0% disagreed and 10.0% strongly disagreed, cumulatively 22.0%.

According to the Likert scale, 1 represented the highest level of agreement, while 5 represented the lowest. Therefore, variables with lower mean ranks were ranked higher in importance.

Among the five dimensions assessed, integration of HR data to improve decisions was ranked first with the lowest mean rank of 2.62, indicating it was the most acknowledged use of HR analytics in enhancing decision-making. This was followed by HR analytics used to monitor performance (mean rank = 2.92) and analytics enabling timely reporting (mean rank = 2.77). HR analytics supporting policy-making and evidence-based planning improved by HR analytics received higher mean ranks of 3.32 and 3.37 respectively. The Friedman Test revealed a statistically significant difference in the rankings ($\chi^2 = 34.077$, df = 4, $p < 0.001$).

Relationship between Human Resource Analytics and Evidence-Based Planning in Enhancing Decision-Making

Table 5.6: Correlations between HR Analytics and Evidence-Based Planning

The results indicate a strong positive relationship between the use of HR analytics to enhance decision-making and evidence-based planning improved by HR analytics, as reflected by a Pearson correlation coefficient of 0.932. This correlation is statistically significant at the 0.01 level (p = .000).

Objective 3 – Script

Objective 3: To ascertain factors limiting the effective use of Human Resource Analytics in the Ministry of Health.

Factors Limiting the Effective Use of Human Resource Analytics in the Ministry of Health

Table 5.7: Descriptive Statistics on Barriers to Effective Use of HR Analytics

According to the results in (Table 5.7), several limiting factors to the effective use of Human Resource Analytics (HRA) were identified. The highest reported constraint was poor system integration, with a mean score of 3.80 (±0.99), followed closely by lack of staff technical skills at 3.68 (±1.12). Lack of appropriate tools/software was also noted as a major barrier, scoring a mean of 3.62 (±1.16). Other relevant constraints included privacy and security concerns (3.54 ±1.18), infrastructure onstraints (3.50 ±1.06), and inadequate training on HRA among staff, which was the least reported limitation, with a mean of 3.18 (±0.90).

5. Conclusions and Recommendations

5.1 Conclusions

In exploring the extent of human resource analytics (HRA) knowledge among staff at the Ministry of Health in Lusaka, results reveal that a majority of respondents (56.0%) reported having only basic knowledge of HRA.A further 36.0% of participants reported having intermediate knowledge, suggesting a modest proportion of staff are conversant with moderately technical aspects or have some applied exposure to HRA tools and techniques. Only a small segment (8.0%) of the workforce indicated possessing advanced knowledge of HRA, pointing to a significant skills gap at higher analytical levels. One respondent remarked during the interviews, “We mostly use Excel and some basic tools, but a deeper understanding of predictive analytics is still lacking across departments. “The descriptive statistics reveal varying degrees of Human Resource Analytics (HRA) utilization across key HR functions within the Ministry of Health in Lusaka. The use of analytics to monitor employee performance recorded the highest mean score (M = 3.40, SD = 0.782). This was closely followed by the application of analytics to identify training needs, which also showed a moderately high mean (M = 3.38, SD = 0.923). Analytics use for workforce planning was slightly lower but still meaningful, with a mean of 3.32 (SD = 1.151). In contrast, the least utilized area was analytics for tracking attrition, with a notably lower mean score of 2.50 (SD = 0.763).

5.2 Recommendations

- Need for an integrated system that will bring all areas of HR on board
- Need for capacity building HR

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