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The Nexus Between Human Capital Analytics and Human Resource Information Systems (HRIS) in Zimbabwean State Universities

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Abstract

Using the quantitative research strategy, the paper sought to investigate the relationship between adoption of human capital analytics and the release of HRIS. A sample of 419 respondents from three categories of senior management, HRM professionals, and HR service consumers from five Zimbabwean state universities was utilised. Stratified random sampling method and a structured questionnaire were used as sampling technique and data collection tool respectively. Findings revealed that the level of HR Analytics maturity was significantly correlated with the period since the introduction of HRIS and that there was little negative correlation. The study rejected the alternative hypothesis that the length of time using HRIS influences the level of HCA adoption in organizations. The study is unique in that it investigates level of human capital analytics adoption and the unveiling of HRIS in state universities, which has not been extensively studied in Zimbabwe. Furthermore, the study provides valuable insights to university and government policymakers and practitioners as they develop policies and interventions for data-driven human resource management in tertiary institutions.

Keywords: *Human Capital Analytics; Human Resource Information Systems; Adoption; Zimbabwean State Universities; Descriptive; Predictive; Prescriptive Analytics*

1. Introduction

Human resource analytics basically refers to the process of managing an organisation's workforce using artificial intelligence. In essence, the process involves the use of various statistical techniques to predict the future of the organisation in terms of achieving strategic human resource management and overall business goals (Marler & Boudreau, 2017). According to the preceding account, the strategic role of HR Analytics goes beyond reporting HR metrics to connect human resource management resolutions and procedures to organizational performance (Belizón & Kieran, 2021a). These HR decisions are based on data from both internal and external environment of the organisation. In contemporary research and practice, human capital analytics has a variety of labels and forms, indicating that the topic is still evolving (Boudreau & Cascio, 2017). Talent analytics (CIPD, 2013), workforce analytics (Lawler, 2015), people analytics (Waxer, 2013), and human resource intelligence are some other terms (Falleta, 2014). Mishra and Lama (2016) and Marler and Boudreau (2017) used human capital analytics and human resource analytics, respectively. The researchers in this study adopted the term "human capital analytics." The history of human capital analytics dates back to the Industrial Revolution (1760-1913) when Frederick Winslow Taylor developed a scientific management methodology based on four guiding principles in order to optimize work output (Chartered Institute of Personnel Development (CIPD), 2015). Analytics in human resources can be descriptive, predictive, or prescriptive (Narula, 2015). Descriptive analytics is a type of data analysis that collects, organizes, and presents historical data in an understandable manner (McCartney & Fu, 2021). In contrast, descriptive analytics is a basic starting point for preparing data for further analysis. The predictive analytics level is the second level of analysis. Predictive analytics, as the name suggests, is concerned with predicting and comprehending what may happen in the future. Analyzing past data patterns and trends with historical data and customer insights can predict what will happen in the future and thus inform many aspects of a business, such as setting realistic goals, effective planning, managing performance expectations, and avoiding risks (Green, 2017). Predictive analytics forecasts potential future outcomes and the likelihood of events using a variety of techniques such as statistical modeling (mathematical relationships between variables to predict outcomes) and machine learning algorithms (classification, regression, and clustering techniques). The third level of analysis, prescriptive analytics, takes predictive data to the next level. This includes not only producing the best results with limited resources.It entails using linear programming, simulations, mathematical modeling, and implementation to determine the most cost-effective alternative training investment for organizational effectiveness (Collmann &Matei, 2016). HRIS are critical tools for human capital analytics. These systems automate many core HR functions, such as benefit management, time and attendance, and applicant tracking. It works in the same way as a company's employee database. The major HR analytics vendors include Oracle (USA), SAP (Germany), Infor (USA), Workday (USA), Sage Software (UK), Kronos (USA), MicroStrategy (USA), and IBM (USA) (Bennett & Lemoine,2014). Extant literature (Pongpisutsopa et al., 2020; Vargas et al., 2018; Malini, 2018; Hulised, 2018) reveal the adoption of Human capital analytics by different organisations world over. However, empirical evidence on the full adoption of HRA is limited, both personal and organisational factors were identified as impeding full adoption of human capital analytics in organisations (Vargas et al.,2018). Although the majority of Zimbabwean public universities have implemented human resource information systems, they primarily employ descriptive analytics, which focuses on reactive data presentations on tables, reports, and metrics (Hughes, 2018). In the circumstances, the goal of this study was to determine the relationship between the level of human capital analytics and the time since state universities implemented HRIS.

Human capital analytics are underutilized in Zimbabwean state universities. Human resources staff in many of these institutions tend to use only descriptive analytics in their reports to top management. Human capital analytics is currently mostly used for standard HR accounting and reporting (Pape, 2016). Human resource practitioners' failure to tell the story behind the numbers has failed to depict the logical relationships between people's strategies and business strategies in state universities. As such, the purpose of this study was to assist state universities by answering the following research question: what is the nexus between level of human capital analytics adoption and the period since state universities implemented HRIS? Researchers collected data from five state universities between 2021 and 2022 to answer this question. The findings revealed that HR Analytics maturity level was significantly correlated with the period since the introduction of HRIS, with a scant negative relationship. In the following ways, the paper adds to the existing literature: The study will help to advance the conversation about human capital analytics in Zimbabwean tertiary institutions. The study significantly contributes to the methodology for future human capital analytics studies.

The findings presented here have policy implications for university and government policymakers and practitioners developing data-driven human resource management policies and interventions in tertiary institutions. There haven't been many studies that look into the level of human capital analytics adoption in Zimbabwe's state universities. This study attempted to bridge that gap to contribute to the advancement of a scientific discipline that is underutilized in Zimbabwean state universities.The paper was divided into five sections: introduction, literature review, research methodology, findings and discussion, and conclusions.

2. Theoretical Analysis and Research Hypothesis

According to resource-based view theory, both tangible and intangible resources and capabilities (such as management abilities, organizational procedures, and the information and knowledge under its control) can be a source of long-term competitive advantage if they are uncommon, valuable, difficult to duplicate, and non-substitutable (Barney, 1991; Barney et al., 2001). The strengths found in previous studies (Ranjan & Basak, 2013; Vargas, 2015; Godwin-Opara, 2016; Mbarki, 2017) combined with the absence of other researchers who applied this theory locally in state universities, particularly in examining the level of adoption of human capital analytics, made the RBV theory more applicable to this study on the adoption of human capital analytics.The theory provides a framework for understanding the importance of organizational resources and explains how the resources that an organization owns and controls influence its performance and sustainability. The RBV theory was also chosen due to its empirical testing, validation, application, and replication (Schaup et.al. 2010; Lee 2010). The resource-based view theory is one of the most powerful, robust, and simple theories for predicting the level of adoption of human capital analytics, which is the focus of this research. The RBV model is applicable to any industry or organization, regardless of its structure, orientation, components, or scope. Human resource analytic is a very important tool that adds value to organisations by lowering operational costs and improving quality in day to day decision making. Various factors aligned to individual employees and organisational factors were identified as stumbling blocks to the proper implementation of HRA (Etukudo,2019). Despite the fact that HR analytics has been associated with successful companies such as Google, Apple, Disney, Amazon, and Microsoft (Bock, 2015; Morgan, 2017), some business organisations are still very hesitant to fully embrace the benefits of artificial intelligence (Lydgate, 2018). A previous study (Bersin 2017) found that impressive HRA is associated with good talent management and achievement of strategic business goals. Boakye and Lamptey's (2020) Ghanaian research study revealed an improvement in recruitment and selection and performance managements functions of the host organisations. At Zimbabwe's ZETDC, ZIMRA, and Tel-One, Makwinja (2015) identified barriers to successful HCIS implementation and use. Makwinja study basically discovered personal and organisation factors as the stumbling blocks to the successful implementation of HCIS. Despite the availability of similar studies, only a few aspects exist in the Zimbabwean context. From the foregoing, a research hypothesis was proposed:

H_1: Length of time using HRIS affects the level of adoption of HCA in the organization.

3. Research Methodology

The positivism philosophy guided the research study, which used a quantitative research strategy. Positivism is an appealing philosophy because it affirms the importance of science while maintaining a clear distinction between true and false (a distinction which many other philosophies muddy up). The study's primary goal was to gather data on the level of human capital analytics adoption and the time span since state universities implemented HRIS, rather than the qualitative aspects of employees' feelings.The identified research strategy and philosophy allowed researchers to maintain an objective perspective while remaining independent of the research (Babbie, 2013).

Previous researchers at the international, regional, and local levels have used the chosen research strategy (Ukandu, Iwu, and Allen-lle, 2014; Makwinja 2015; Samson 2018). The three research studies mentioned above used human resource professionals from private companies and public universities as research subjects. The use of the positivist approach and quantitative research methods is an obvious point of convergence in both studies. Both types of research used data collection tools such as questionnaires and documentary reviews, as well as SPSS data analysis packages. The correlational research design was used by current researchers. The study's design was advantageous because it allowed the researchers to examine the relationship between the level of human capital analytics adoption and the time since state universities began using HRIS. It allows researchers to determine the strength and direction of a relationship, allowing subsequent studies to narrow the findings and, if possible, experimentally determine causation. As a result, the benefit of correlational research is that it allows other scholars to conduct a large amount of additional research. Because correlational research studies take place in real-life situations, the data gathered from this work is typically more applicable to everyday encounters. This advantage enables the discovery of novel relationships between phenomena that do not appear to be linked in any way (Bryman, 2015).

This study's population frame included three thousand, eight hundred and eighty-eight (3 888) respondents. These were human resource professionals, general staff, and senior management personnel from five Zimbabwean state universities. The population was chosen based on the premise that state university human resource professionals typically share a common and binding characteristic in terms of human resource practice. Similarly, general staff members consume human resource services at state universities and are thus key stakeholders in the adoption of human capital analytics. The senior management team was included as policymakers and resource allocators who influence the level of human capital analytics adoption.

Table 3: Sampling Frame

Population	Midlands State University	Zimbabwe Open University	Chinhoyi University of Technology	Lupane State University	Manicaland State University of Applied Social Sciences	**Grand Total**
Senior Management	6	7	6	4	1	**24**
HR Staff	13	13	11	8	6	**51**
Consumers of HR Services	1738	762	863	277	173	**3813**
Total	**1757**	**782**	**880**	**289**	**180**	**3888**

Source: Field Survey, 2021

Sample Size

A sample size of 419 employees identified from the human resources departments of five state institutions was calculated using the Raosoft calculator, with a confidence interval of 95% and a margin of error of +-5%, to collect data for this study.

Table 3: Sample Size Calculation

Stratum	**A**	**B**	**C**	
Population Size	24	51	3813	
Final Sampling Size Results obtained by use of Raosoft Calculator	23	46	350	**419**

Source: Field Survey, 2021

Many researchers (Ross, 2004; Yildrim & Şimşek, 2006; Wilson, 2010) believe that if parametric tests are used, 30-500 research subjects are required to make inferences to the larger population. The Pearson correlation coefficient was used by the researchers. A parametric test was used because it has greater statistical power and allows researchers to identify significant differences when they exist. These numbers (30-500 study subjects) are valid for selecting a sample using random sampling techniques, and the researchers used the stratified random sampling method in this case. Previous researchers on HRIS (Burbach & Dundon 2005; Ikhlas & Al-Shqairat 2010; Delorme & Arcand 2010; Makwinja 2015; Samson 2018) produced acceptable results using similar range sample sizes.

Sampling Method

The researchers used a stratified random sampling procedure to highlight specific subgroups within the population, which in this case were human resource professionals in HR departments, general staff members, and senior management staff. When compared to simple random sampling, this technique provides a researcher with greater statistical precision.

The data for the research study was gathered using a structured questionnaire. The data collection tool was created after a thorough review of previous research (Bersin et al., 2014); Vargas, 2015; Kaur & Fink, 2017; Kremer, 2018; Boakye & Lamptey, 2020), and the questions were modified to fit the current study. The Technology Acceptance Model (TAM) was also useful in developing the study's key research questions. The researchers attempted to mitigate potential response bias and lack of completion by following some of the guidelines listed below when developing the questionnaire.

- ❖ Avoiding double-barreled questions and ambiguity
- ❖ Avoiding making big assumptions
- ❖ Avoiding very lengthy/ difficult questions (Tsouroufli et al., 2021).

The researchers asked the University administration for permission to conduct the research study. This was accomplished by submitting a written application letter containing information about the researchers as well as the topic of the thesis. After the researchers explained the purpose of the study and presented them with the letter of authority, the questionnaires were personally distributed to the selected respondents to ensure that the research was legal. Human resources personnel escorted and assisted in locating offices where students on attachment, part-time employees, and permanent employees were stationed. To give respondents enough time to respond, administered questionnaires were collected two days later (Tichapondwa, 2013). To avoid interfering with the employer's work processes, the delivery and collection processes were completed during tea and lunch breaks.A variety of descriptive and inferential statistics were used to analyze the data. The Statistical Package for the Social Sciences (SPSS) version 28 was used to analyze the primary data collected for this study. The measuring instrument was pre-tested in-house by the researchers to increase data reliability. Pretesting is defined by Casper, Peytcheva, and Cibelli (2011) as "a sequence of activities intended to evaluate the capacity of a survey instrument to collect the desired data, capabilities of the method chosen to collect data, and overall appropriateness of the field procedures." In this study, in-house pretesting was performed to ensure that the questionnaire measured what it claimed to measure. This was accomplished by presenting the draft questionnaire to a panel of research experts during the compulsory research week at Chinhoyi University of Technology. The data collection tool was also submitted to thesis supervisors for evaluation of the questionnaire items' relevance. Minor changes were made with input from the in-house reviewers, main and co-supervisors, to ensure that the items were not too difficult for respondents by providing definitions of key terms such as human capital analytics and human resource information systems, as well as adding appropriate answering instructions to respondents. In-house reviewers also suggested that the questions be divided into scales that represent each construct being measured.

Pilot Testing

The process of investigating the research instrument that will be used in a research study in order to identify ambiguities, misunderstandings, or other deficiencies, particularly from colleagues, groups of experts, or similar populations other than the actual respondents, is known as pilot testing (Zikmund et al., 2016). According to the existing literature (Treece & Treece, 1982; Connelly, 2008), a pilot study sample should be 10% of the larger parent study sample. The questionnaire was pilot-tested using the same protocols as the final administration on a group of forty-two (42) respondents who were purposefully chosen from a similar population different from actual respondents. The main study's projected sample size was 419 people, so 42 people responded. Cost and time constraints influenced the final decision. Respondents provided useful feedback on the missing age range of 18-19 years and suggested that question five be removed from the pretest instrument because it would compromise respondents' identities. Question five on the pretest instrument inquired about respondents' job titles. It was proposed that categories such as senior management, HR service consumers, and HR professionals would work together to replace the job title aspect. The demographic section was one of thirty-nine items on the pretested data collection tool.

4. Findings and Discussions

A total of 419 people were considered for study participation, and data was gathered using a structured questionnaire. 85 of the 419 questionnaires were left blank, and 20 people did not respond. As a result, the overall response rate was 74.9%, with 314 usable questionnaires. Pavin and Kabir (2016) define adequate, satisfactory, and excellent response rates as at least 50%, 60%, and 75%, respectively, so 74.9% was an excellent response rate. Based on this assumption, the findings were better positioned to provide authentic results on the relationship between the level of human capital analytics adoption and the introduction of HRIS in Zimbabwean state universities. The general attitude of respondents toward the study was positive; however, differences could be observed in some departments of three state universities, such as Central Services, Auditing, and Catering, where employees were hesitant to entertain researchers despite the research permission letter. Supervisors discovered at workstations had to refer researchers to their Directors in order to obtain an endorsement in addition to the university-granted research permission letter. Researchers discovered that respondents had not previously participated in human capital analytics studies.It's also worth noting that those who were more willing to participate in the survey recognized and appreciated the importance of research. Data on demographic variables are presented in two parts: descriptive statistics (frequency tables) and variable association.

4.1 Descriptive Statistics of Demographic Variables

Gender of Respondents

Primary data shows that male dominance existed, with more males (51.3%) than females (48.7%) in the study sample. According to ZIMSTAT (2012a:9), females outnumber males (51.94%) in Zimbabwe. It is claimed that males are still more likely to be breadwinners in some cases, and thus the sample distribution was thought to be reasonably representative, despite contradicting the ZIMSTAT official report.

Age-Range

Primary data revealed that the age range 20-30 years had 22 respondents (7%), 31- 41 years had 95 respondents representing thirty point three percent (30.3%) of the sample size. The age range 42-52 years had the highest percentage of 36.9% representing 116 respondents. Seventy respondents (22.3%) were in the age range 53-63 years and 64-75 years age range had the least number of 11 respondents (3.5%). Almost twenty-five percent of the respondents were nearing retirement age of 60-65 years (National Social Security Act (NSSA) (Chapter 17:04). This depiction would imply that the management of the studied universities would need to increase their succession planning efforts. This would help to prevent critical staff shortages in key university areas. Nonetheless, seventy-four point two (74.2%) of the study sample's respondents were between the ages of 20 and 52. The workforce at the state universities studied is young, with the majority of respondents in their mid-career.

Level of Education of Respondents

According to the above table, few respondents (1.9%) had an O level certificate of education, two (2) respondents (0.6% had Advanced level education, and 8.0% had a professional certificate. Twenty-nine percent (29%) of those polled held a diploma, while 16.9% held a bachelor's degree. Thirty-three percent (33.1%) had a Masters' degree, 8.6% had a Doctorate, and (1.9%) were Professors. This suggests that the study sample was made up of educated workers. This can be attributed to the general observation, as reported in the response rate, that some respondents were more willing to participate in the survey because they valued research, possibly because they would have done research elsewhere, particularly at the tertiary level. State universities tend to attract a greater number of employees with higher educational qualifications because they provide more diverse employment opportunities. As a result, because the sample included representatives from each educational level, its composition was deemed acceptable.

Respondents' Job Position in the University

Seventy-nine point nine percentage (79.9%) of the sample respondents were consumers of HR services in the state universities. Thirty-four percent (13.4%) of those polled were human resource professionals, and 6.7% were senior management members of state universities. Consumers of human resource services within state universities are the other staff members who do not work as HR officials regardless of their job titles. HR professionals are those that practiced human resource management and were office bearers seized with day-to-day HR duties within state universities. Senior management refers to the principal officers of the universities as defined by various university acts, for example, the Chinhoyi University of Technology Act (Chapter 25:23). The team of senior management was included as policymakers and resource allocators who influence the acceptation level of human capital analytics. Therefore, all important stakeholders were represented in the sample, indicating typical state universities' hierarchical setup.

Length of Service of Respondents

The majority of respondents (36.3%) had been with their current organizations for 11-15 years. There were 66 (21%) respondents who had served for 6-10 years, 17,5% who had served for 1-5 years in their organizations, and 52 (16.6%) who had served for 16-20 years in their organizations. The final category, 21 years or more of service, had twenty-seven (8.6%) respondents. Overall, 193 (61.5%) of respondents had been with their organizations for more than ten years, indicating fewer different types of staff movements outside the organization. As a result of their seniority and the abundance of institutional memory, many respondents were able to answer some of the questions about university HR practices.

4.2 Relationship between Demographic Variables

Organizations use demographics to learn more about the characteristics of a population for a variety of reasons. This includes policy development, learning more about a specific population's generalities in terms of technology appreciation, and strategic planning (that includes better management of resources and identifying people nearing retirement age). The analyses on demographic variable associations were carried out on the following possible combinations of demographic variables: age and length of service, job position, gender, and education. Only the results for pairs of demographic variables that were found to be significantly associated are reported (Field, 2018). The respondents' demographic variables were analyzed using techniques such as Cramer's V (Vc) and Spearman's rank coefficient (rs).Spearman's rank coefficient was used to examine the relationship between age range and length of service in the organization (rs).

Table 6: Correlations

			the age range of respondent	length of service in the organization
Spearman's rho	the age range of respondent	Correlation Coefficient	1.000	.487**
		Sig. (2-tailed)	.	<.001
		N	314	314
	length of service in the organization	Correlation Coefficient	.487**	1.000
		Sig. (2-tailed)	<.001	.
		N	314	314

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

Source: Field Data (2022)

Data show that there is a significant association between age range and length of service in the organization at the 1% level of significance ($\alpha = 0.01$). Age and length of service in the organization have a positive relationship (rs =.487, p <.001). In other words, older age groups have a longer length of service in the organization. This would imply that the longer a person serves in the organization, the more mature he or she becomes, profession wise.

Table 7: level of education * respondent job position in the organization

			respondent job position in the organisation			Total
			Consumer of HR Services	HR Professional	Senior Management	
level of education	O level	Count	6	0	0	6
		% within respondent job position in the organisation	2.4%	0.0%	0.0%	1.9%
	A level	Count	2	0	0	2
		% within respondent job position in the organisation	0.8%	0.0%	0.0%	0.6%
	Professional certificate	Count	25	0	0	25
		% within respondent job position in the organisation	10.0%	0.0%	0.0%	8.0%
	Diploma	Count	58	24	0	82
		% within respondent job position in the organisation	23.1%	57.1%	0.0%	26.1%
	Bachelor's degree	Count	47	6	0	53
		% within respondent job position in the organisation	18.7%	14.3%	0.0%	16.9%
	Master's degree	Count	91	11	9	111
		% within respondent job position in the organisation	36.3%	26.2%	42.9%	35.4%
	Doctorate degree	Count	21	1	7	29
		% within respondent job position in the organisation	8.4%	2.4%	33.3%	9.2%
	Professor	Count	1	0	5	6
		% within respondent job position in the organisation	0.4%	0.0%	23.8%	1.9%
Total		Count	251	42	21	314
		% within respondent job position in the organisation	100.0%	100.0%	100.0%	100.0%

Source**:** Field Data (2022)

When there is more than a 2 X 2 contingency, Cramer's V is used to examine the relationship between two categorical variables, and the above table is an 8 X 3 contingency table (Cramer,1946). The Cramer's V formula is used to determine the strength of a relationship between two variables. Variables of interest should be categorical, with two or more unique values per category, in order to use it (Hinton et al., 2014). Cramer's V is a suitable test in this case because level of education and job position in the organization had more than two unique values per category.

Cramer's V Assumptions

There are assumptions in every statistical method. Assumptions are conditions that data must meet in order for statistical method results to be accurate. Cramer's V makes the following assumptions:

- Two variables must be categorical for this test. A categorical variable is one that describes a category but does not naturally relate to a number (Wegner, 2007). As shown in the cross-table above, categorical variables include respondent level of education and job position within the organization. Cramer's V values range from 0 to 1, with 0 representing no relationship and 1 representing perfect association. The p-value represents the likelihood of seeing results if the variables did not have a relationship. A p-value of less than or equal to 0.05 indicates that the outcome is statistically significant and that the difference is not due to chance alone (Hinton et al., 2014). For Cramer's V, the following adjectives are used to describe the strength of a relationship:
- >.5 strong association .3 to.5 moderate association.1 to.3 weak association
- If there is any association, it is between 0 and.1.

Table 8: Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	107.784[a]	14	<.001
Likelihood Ratio	80.595	14	<.001
Linear-by-Linear Association	17.878	1	<.001
N of Valid Cases	314		

a. 14 cells (58.3%) have expected count less than 5. The minimum expected count is .13.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.586	<.001
	Cramer's V	.414	<.001
N of Valid Cases		314	

Cramer's statistic for these data is .414 out of a possible maximum value of 1. This indicates a moderate relationship between the respondent's level of education and job position within the organization. In practice, the level of education attained by various respondents in the host organizations does not squarely correspond with their current job position. This value is highly significant (p <.001), indicating that such a large value of the test statistic is unlikely to have occurred by chance, and thus the strength of the relationship is significant. These findings support what the chi-square test previously indicated.

4.3 Hypothesis Testing Using Pearson Correlation Coefficient

H_0 : Length of time using HRIS does not affect level of adoption of HCA in the organization

H_1 : Length of time using HRIS affects level of adoption of HCA in the organization.

The hypothesis test for the study was carried out and, the study examined data for normality which is the underlying assumption for most parametric tests. For each category of the independent variable, the dependent variable must be approximately normally distributed. Parametric tests are preferred for normally distributed data because they are more accurate. However, if the data fails the normality test, non-parametric analysis can be used, or a bootstrapping procedure can be used. A visual examination of the associated histograms, normal Q-Q plots, and box plots revealed that the length of time spent using HRIS was not normally distributed for the organization's level of HCA adoption. A Kolmogorov-Smirnov Test was conducted and produced the below stated results.

Table 9: One-Sample Kolmogorov-Smirnov Test

			Time period since the introduction of HRIS	HR Analytics Maturity Level
N			314	314
Normal Parameters[a,b]	Mean		2.44	1.45
	Std. Deviation		.705	.499
Most Extreme Differences	Absolute		.351	.366
	Positive		.213	.366
	Negative		-.351	-.316
Test Statistic			.351	.366
Asymp. Sig. (2-tailed)[c]			<.001	<.001
Monte Carlo Sig. (2-tailed)[d]	Sig.		.000	.000
	99% Confidence Interval	Lower Bound	.000	.000
		Upper Bound	.000	.000

a. Test distribution is Normal.

b. Calculated from data.

c. Lilliefors Significance Correction.

d. Lilliefors' method based on 10000 Monte Carlo samples with starting seed 2000000.

The decision-making process in the Kolmogorov-Smirnov normality test.

1. If the Asymp.Sig. value is greater than 0.05, the data is normally distributed.
2. If Asymp.Sig.< 0.05, the research data is not normally distributed (Field,2018). Based on the output of One-Sample Kolmogorov-Smirnov Test, the value of the variable Asymp.Sig Time period since the introduction of HRIS value is <.001 and HR Analytics Maturity Level variables is <.001. In accordance with the basic decision-making in normality test, the value Asymp.Sig in all study variables are < 0.05, it can be concluded that the data Time period since the introduction of HRIS and HR Analytics Maturity Level are not normally distributed.

Bootstrap Specifications

Sampling Method	Simple
Number of Samples	1000
Confidence Interval Level	95.0%
Confidence Interval Type	Bias-corrected and accelerated (BCa)

Correlations

				HR Analytics Maturity Level	Time period since the introduction of HRIS
HR Analytics Maturity Level	Pearson Correlation			1	-.186**
	Sig. (1-tailed)				<.001
	N			314	314
	Bootstrap[c]	Bias		0	.003
		Std. Error		0	.055
		BCa 95% Confidence Interval	Lower	.	-.295
			Upper	.	-.074
Time period since the introduction of HRIS	Pearson Correlation			-.186**	1
	Sig. (1-tailed)			<.001	
	N			314	314
	Bootstrap[c]	Bias		.003	0
		Std. Error		.055	0
		BCa 95% Confidence Interval	Lower	-.295	.
			Upper	-.074	.

**. Correlation is significant at the 0.01 level (1-tailed).

c. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

All of the significance values are less than .05, indicating a statistically significant relationship. Given the lack of normality in these variables, the researchers were more concerned with the bootstrapped confidence intervals rather than the significance value itself. This is because the bootstrap confidence intervals will be unaffected by the distribution of scores, whereas the significance value may be. These confidence intervals are labeled BCa 95% Confidence Interval and are presented as two values: the upper and lower boundaries. For the relationship between HR Analytics maturity level and the time period since the introduction of HRIS the interval is -.295 to -.074. HR Analytics maturity level was significantly correlated with time period since the introduction of HRIS, $\boldsymbol{r}$ = -.186 [-.295, -.074], (p = <.001) and that it is scant negative. For the Bootstrapped correlation to be significant the CIs must be on the same side, as either both negative or both positive. The CIs [-.295 and -.074] are both negative, which corroborates Pearson's correlation coefficient test's p and r values. Therefore, the alternate hypothesis of length of time using HRIS affects level of adoption of HCA in the organization can be rejected.

The findings are consistent with those of Angrave et al. (2016), as reported by Lydgate (2018), who discovered that organizational HR information systems may be functionally restricted and only report historical data, resulting in descriptive analytics. Traditional analytics, while useful for reporting, is incapable of predicting critical employee and organizational outcomes. Instead of investing more resources in HR analytics, a company's focus may be on the day-to-day operations of running a business and achieving stability. Furthermore, current HR analysts' and managers' knowledge, skills, and abilities, particularly their quantitative skills, influence the extent to which HR analytics will result in prescriptive action in support of strategic business initiatives (Bassi, 2011). Previously, researchers discovered a negative relationship between the two variables "time period since the introduction of HRIS and HR analytics maturity level." The researchers wanted to look into this relationship further by seeing if the time period since the introduction of HRIS reliably predicts the HR analytics maturity level. The linear regression statistical technique was used to accomplish this. The first table below summarizes the prediction of HR Analytics Maturity Level (the dependent variable) over time since the implementation of HRIS (the independent variable).

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Time period since the introduction of HRIS[b]	.	Enter

a. Dependent Variable: HR Analytics Maturity Level
b. All requested variables entered.

The following table is a model summary that includes the correlation coefficient. This table was compared to the results of the Pearson correlation on the same data, which was shown earlier.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.186[a]	.034	.031	.491

a. Predictors: (Constant), Time period since the introduction of HRIS

The R Square value in the Model Summary table represents the amount of variance in the dependent variable that the independent variable can explain. In this case, the independent variable of time since HRIS implementation accounts for 3.4% of the variation in HR analytics maturity level. The R value (.186[a]) indicates that as time period since the introduction of HRIS study time increases the HR analytics maturity level score does not also increase, and this is a negative correlation, with r = -.186. It is known to be statistically significant from the Pearson correlation output.

The ANOVA summary table that shows details of the significance of the regression.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.681	1	2.681	11.137	<.001[b]
	Residual	75.103	312	.241		
	Total	77.783	313			

a. Dependent Variable: HR Analytics Maturity Level

b. Predictors: (Constant), Time period since the introduction of HRIS

Analysis of variance examines the regression model's significance. Does the independent variable, time since the introduction of HRIS, explain a significant portion of the variance in the dependent variable, HR Analytics Maturity Level, in this case? The essential pieces of information required for any ANOVA are the df, the F value, and the probability value. It can be observed from the above table that $F(1,312) = 11.137$, p <.001[b], and therefore can be concluded that the regression is statistically significant. Now there is the Coefficients output table, which gives the regression equation.

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Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.773	.100		17.738	<.001
	Time period since the introduction of HRIS	-.131	.039	-.186	-3.337	<.001

a. Dependent Variable: HR Analytics Maturity Level

The Unstandardized Coefficients B column gives us the value of the intercept (for the Constant row) and the slope of the regression line (from the Time period since the introduction of HRIS row) (Hinton et al., 2014). This gives the following regression equation:

HR Analytics Maturity Level score = 1.773 + -.131 time period since the introduction of HRIS

The Standardized Beta Coefficient column informs us of the contribution that an individual variable makes to the model (Field, 2018). From the above table it can be observed that time period since the introduction of HRIS 'contributes' -.186 to HR Analytics Maturity Level, which is the Pearson's r value. The t value (t = 17.738, p <.001) for Constant tells that the intercept is significantly different from zero. The t value for time period since the introduction of HRIS (t = -3.337, p <.001) shows that the regression is significant.

Conclusion

This article highlighted that HR Analytics maturity level was significantly correlated with time period since the introduction of HRIS, ***r* =** -.186 [-.295, -.074], (p = <.001) and that it is scant negative. For the Bootstrapped correlation to be significant the CIs must be on the same side, as either both negative or both positive. The CIs [-.295 and -.074] are both negative, which corroborates Pearson's correlation coefficient test's p and r values; therefore, the alternate hypothesis of length of time using HRIS affects level of adoption of HCA in the organization can be rejected. The outcomes of this study provide an impetus for improving and future adoption of human capital analytics in state universities. This work makes three contributions. First, it fills a gap in the literature by empirically evaluating human capital analytics adoption in Zimbabwean state universities, which has received little attention. Second, the study provides management and university council members with valuable insights into the key issues influencing human capital analytics adoption in tertiary institutions. Third, the study would provide useful directions for future research by scholars. This study, like any other, has limitations that must be considered when reading the findings. For example, the study is restricted to the length of HRIS and the level of HCA adoption in state universities using a single parametric test. The Pearson product moment correlation coefficient was used to test the relationship between two variables understudy, but it does not test causality. As a result, future research could focus on another sector, such as private sector organizations, and employ more parametric tests. Causal comparative research design or mixed methods strategies would further assist in gathering more information for this topical issue. Despite these limitations, the study's findings have significant theoretical and practical implications for the implementation of human capital analytics in Zimbabwean state universities.

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