Using Evidence-Based Management and HR Analytics in Bangladesh: How These Affect Organizational Performance?

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Abstract: *A real-time strategic tool for improving organizational and employee effectiveness through effective utilization of human resources is people analytics. Employers have always depended on their staff, but firm executives still base important personnel decisions on this established procedure. Thus, the goal of this study is to find out how HR Analytics (HRA) may improve an organization's performance. It also emphasizes how and when HRA has been used to improve business success. The purpose of this study is to analyze the "Impact of HR Analytics on Organizational Performance". 'Access to HR Technology', 'HR analytics (High Quality data, analytical competency; strategic ability to act)', 'Organizational EBM' and 'Organizational Performance' have been adopted as the variables related to HR Analytics. Primary data has been collected and applied for conducting causal research. A suitable questionnaire was created and used, considering the variables utilized in the earlier study. In order to gain a general understanding of HR analytics techniques, this study has included both manufacturing and service-oriented organizations. A total of 160 questionnaires that were deemed usable following the survey were completed by 41 institutions. This article provided a conceptual model that evaluated the effect of HR analytics on organizational performance using 'Access to HR Technology' and 'Organizational EBM', as one of the variables. Regression analysis is done using PLS-SEM. The results of the study corroborated the hypothesis, indicating that having access to HR technology and HR analytics, along with 'Organizational EBM', is a determining element in improving organizational performance. The process of implementing HR analytics, which was adopted to practice 'Organizational EBM', was significantly influenced by the supervision of an HR manager. It has been discovered that this theoretical component of the model effectively influences organizational performance. The study's conclusions indicated that HR technology, HR analytics, and evidence-based management affect overall organizational performance and offered various recommendations for further research.*

Keywords: HR Analytics (HRA), Organizational EBM, Access to HR Technology, People Analytics (PA), HRIS, organizational performance.

INTRODUCTION

The development of technology has resulted in a transition of human resources from simple, conventional record-keeping to innovative techniques. The development of its workforce, cost-effectiveness and employee growth are now human resources' top priorities. By leveraging technological advances, human resources management has evolved to be more strategic, flexible, economical, and client-focused (Chadwick & Li, 2018). In addition to human resource analytics has recently gained prominence (Huselid, 2018). HR analytics, also known as HRA, could help businesses handle and manage their people resources effectively. Real-time insights from HR analytics can be used to make decisions about employee retention, performance, and career advancement (Minbaeva, 2017). The ability to assess employee performance through HR analytics. HR analytics has made it highly helpful for a variety of organizational divisions to carry out their daily tasks. It also facilitated the appropriate deployment of human resources in addition to improving HR policies and procedures (Varma & Chavan, 2020). Analyzing employee performance output information can increase organizational efficiency while keeping costs down. Through HR analytics, firms can use employee requirements and interests to inform more appealing and successful HR activities. Employee engagement, contentment, and productivity all increase as a result. Businesses that use HR analytics have a substantially better chance of finding, hiring, retaining and promoting exceptional employees, giving them a competitive advantage (Varma & Chavan, 2020). Companies are investing a lot in analytics and HRM modernization initiatives, but few have been able to successfully integrate this (Cascio & Boudreau, 2014). Thus, this research aims to comprehend how HR analytics are becoming increasingly integrated into an organization's HR system and how it affects the organizational performance. Finding the associated variables with HR analytics and relate them with organizational performance is the main goal of this study.

Rationale of the Study

The literature on HR analytics that is now available covers a broad range of subjects, from historical background to current issues in the HR field (Minbaeva, 2017). A thorough summary of the current state of HR analytics research has also been produced by several papers (Margherita, 2022). It's still uncertain whether HR analytics improves a company's efficiency and effectiveness, despite a wealth of study on the subject (Fernandez & Gallardo-Gallardo, 2020). Studies analyzing the impact of HRA on an organization's production are scarce (Huselid, 2018). This study examines the relationship between "HR analytics" and "organizational performance" in Bangladesh's workplace. This study aimed to investigate the potential benefits of HR analytics (HRA) which is also known as people analytics (PA), for improving the performance of Bangladeshi enterprises.

Alam et al. (2022) discovered a connection between competitive strategies (CSs) and human resource information systems (HRIS) after reviewing several studies conducted in the setting of Bangladesh. According to Kiran et al. (2022), because firms are in intense competition with one another, Human Capital Management assisted in achieving organizational performance through metadata analysis. Because human capital management, in the words of Pease and Fitz-enz (2012), constitutes a personnel knowledge base that promotes innovation. Another research investigated the relationship between several variables and organizational EHRM (Electronic Human Resource Management) was discovered by Hosain et al. (2015). In 2020, Rahman and colleagues investigated how information and communication technology (ICT) could boost human resource management effectiveness even in the absence of in-person interactions during the

COVID-19 pandemic. In an exceptional circumstance, such as a pandemic, such research can help practitioners utilize ICT to facilitate the decisions to make the necessary adjustments for optimal efficiency by leveraging limited resources (including HR). A further study in Bangladesh was found suggesting a South Asian framework has adopted AI technology in the recruitment process by using the UTAUT model (Islam et al., 2022).

The HRA variables, including "access to HR technology," "HR analytics (high quality data, analytical competency, and strategic ability to act)," "organizational EBM," and "organizational performance," have not been included in any of the aforementioned studies. Furthermore, unless workers are well overseen, using simply HR analytics variables to assess real-time HR practices may not result in overall organizational performance. Along with other HRA variables, close employee supervision—represented by the variable "Stewardship"—must be considered. According to this study, technological innovation may make the analytical outcome of human resource management easier, but it also necessitates close monitoring and human contact while utilizing HR analytics. Such "HR analytics" and "organizational performance" studies can assist businesses in making the most efficient use of their human resources to improve productivity, profitability, and effectiveness. Therefore, it was essential to evaluate the impact of HR analytics in Bangladeshi firms and determine whether it ultimately correlates with organizational success. As a result, every firm in Bangladesh can realize the importance HR analytics in order to increase productivity. Implementing HR analytics in this way can help firms maintain their long-term financial sustenance.
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LITERATURE REVIEW

Evolution of HR Analytics (HRA)

The use of data analytics in workforce management has been increasing (Singh & Del Giudice, 2019). Since HR operations (including evaluation, upskilling, and quality management) are integrated in organizational behavior, HR analytics studies have expanded over the past few decades by concentrating on industrial and institutional psychology, HR procedures, and general organizational behavior (McCartney & Fu, 2022). Scholars have been attempting to determine how to transform unprocessed data into actionable insights that could improve worker productivity (Singh & Del Giudice, 2019). As a result, this passion has extended to other management domains, like the HRM division. In order to improve employee performance and to make better decisions and plans, a rising number of HR teams are implementing HR analytics (Marler & Boudreau, 2016). The way that contemporary firms handle HR analytics has undergone a notable transformation. Examining particular staff traits is necessary to understand the impact of personnel on the execution of the business strategy (e.g., how a task leader might extend the product lifecycle period) (Huselid, 2018). In a nutshell, HR analytics is the application of analytical techniques to employee data to direct strategic decision-making and enhance operational effectiveness and efficiency within a business.

HR Analytics and HR Tools

HR analytics, people analytics, or HR intelligence, whatever we choose to name it, has been universally accepted as strategically important in the business sector since it helps companies make better "data-driven" decisions (Huselid, 2018). More quantitative approaches to employee-related queries have been considered as a technical necessity as the number of complex employees has grown. The growing difficulties of labour force limits have enhanced the importance of organizational performance (Boudreau & Lawler, 2015). People analytics combines corporate and public talent data to anticipate "who and which candidate should the company pursue, recruit, grow, elevate, or keep" to predict employee behaviors and actions within the organization. This also made it easier to monitor the results (Bennett & Collins, 2015). HR departments may now gather, arrange, and track large volumes of worker data (Bondarouk & Brewster, 2016). Scholars contend that "people analytics" refers to the use of a "data-driven" technique to inform HR initiatives, policies, and procedures. The "data-driven" methodology can be made practical with the use of cutting-edge HR solutions that enable HR/People analytics. Human resource information systems (HRISs), cloud-based services, and applications are examples of HR solutions that are widely available (Bondarouk & Brewster, 2016). The adoption of HR/people analytics has increased as a result of these changes, which has helped critical HR analysis. As an example, the HRIS division of "Google" has developed an "evidence-based" approach to improve its own hiring and selection system. Through the collection and interpretation of applicant and worker data, HR insights can be used to forecast a participant's success by identifying many components of higher performance (Harris et al., 2011). Similarly, HR professionals give businesses the ability to manage several other HR issues, such as employee engagement, diversity and inclusivity, retention, etc., in contrast to recruiting and selection (Andersen, 2017). To measure and analyze diversity metrics, such as representation and inclusion etc. organizations can use HR analytics (Okatta, et. al., 2024, Adisa, et. al., 2024, Chisom, Unachukwu & Osawaru, 2023)

HR Analytics (HRA): A Measuring Variable

HR analytics progresses through three increasingly sophisticated stages of development. The first stage is descriptive analytics, where the primary goal is to leverage HR technologies to gather insights and monitor trends, answering questions about past events and outcomes. The second stage, predictive analytics, uses advanced algorithms, statistical methods, and technology to forecast likely future events and identify their potential causes. Finally, the prescriptive stage aims to recommend the optimal course of action based on the insights derived from the analysis (Margherita, 2022). HR analytics, as defined by Marler and Boudreau (2017), serves as the foundation for this study. An HR practice enabled by information technology that establishes business impact and enables data-driven decision-making through descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks," is how it is defined. This research has followed the human capital analytics approach suggested by Minbaeva (2018) by taking this concept into account. HR analytics combines the three elements that are used in this research: high-quality data, analytical proficiency, organizational performance, and strategic ability to act.

The framework proposed by Minbaeva (2018) was adopted by McCartney and Fu (2022), who emphasized that high-quality data—essential for HR analytics—must be timely, accurate, consistent, and comprehensive. For analytics to generate valuable insights, the data must meet these criteria: it must be precise, reliable, current, and all-encompassing. This set of characteristics was defined as a metric for "high-quality data" within the HR analytics framework. If the data is erroneous, preventing the generation of actionable insights, the analytics become ineffective (Minbaeva, 2017). Analytical proficiency is also critical in HR analytics, as teams must be able to transform employee data into meaningful insights using statistical methods and other approaches. To develop a robust statistical model, these teams must pose cause-and-effect questions (McCartney et al., 2020). The resulting analysis can then be translated into actionable interpretations that provide context and understanding of the situation (Andersen, 2017; Minbaeva, 2018; McCartney et al., 2020). The ability to leverage HR data, information, and insights to make informed decisions and implement them reflects managerial support for strategic actions.

McCartney et al. (2021) adopted five key items from Pipino et al. (2002) to assess the quality of HR data: completeness (ensuring no essential data is missing), accuracy (ensuring the data is correct and reliable), timeliness (ensuring the data is up to date), consistency (ensuring the data is presented in a uniform format), and data process (ensuring regular data collection). They also incorporated five questions from Kryscynski et al. (2018) to evaluate the analytical competency of HR departments, which focus on translating data into insights, identifying problems that can be solved with data, effectively using HR analytics to create value, influencing organizational decision-making, and identifying key questions about the organization that data can answer. To assess strategic competence, McCartney et al. (2021) referred to Minbaeva (2018) and selected five questions based on three areas: inspiring relevant stakeholders to act on findings, justifying HR analytics projects through success stories, and ensuring that organizational stakeholders use the insights provided by the HR department.

Practical Application of HR Analytics

Human resource analytics consists of five primary phases (Jain & Nagar, 2015). These phases include: 1) Determining the Goals of HR Analytics, 2) Data Gathering, 3) Measurement and Analysis of HR Data, 4) Data Examination, and 5) Conclusion-Making. Kirtane (2015) outlines several key functions within HR analytics, which include Reporting, Data Mining, Dashboards, Predictive Analysis, and Operational Experiments. To support sound decision-making, upper management must be regularly updated on HR metrics shaped by the organization's strategy, HR challenges, and potential opportunities (Kirtane, 2015). One critical activity within HR analytics is data mining, which involves applying statistical methods to raw or unstructured data to uncover meaningful patterns. For example, this technique might be used to analyze employee data and assess whether there is a positive correlation between performance and employee satisfaction (Kirtane, 2015). The "dashboard" offers a more lucid image of the current status of significant HR KPIs for decision-making. When creating visual reports and demonstrations based on the results of statistical and other studies of large data sets, human resources managers can make good use of a "dashboard." This enables all managers to understand the ideas presented in the spreadsheets and illustrations immediately. Because of its interactivity, the HR "dashboard" is an effective reporting and display tool (Chib, 2019). HR analytics provides data supported by facts in "Operational Experiments," which helps HR professionals make wise HR decisions. HR analytics must be used to assess previous choices made for Human Resources to ascertain whether the intended outcomes were attained.

Integrating 'HR analytics' to 'Organizational performance'

Stevenson's (2004) research, as cited by Muriithi et al. (2019), suggests that both individual and collective activities within an organization lead to outcomes—whether positive or negative—that are directly linked to the organization's planned goals and objectives. Therefore, achieving superior organizational performance requires motivating employees with favorable outcomes. Khan (2010) emphasized that resolving conflicts and leveraging synergies from a company-customer perspective can enhance both quality and efficiency. This clearly shows that strong internal relationships within an organization contribute to better overall performance. Douthit and Mondore (2014) found a correlation between organizational performance and the contributions of human capital. Performance improvements were linked to the organization's core capabilities, with analytical skills playing a key role in optimizing performance and ensuring that the organization had access to the resources necessary to meet future needs (Boudreau & Jesuthanan, 2011; Cascio & Boudreau, 2014). Providing employees with critical performance insights is essential for maximizing their output. Incorporating Human Resource Analytics (HRA) into the process of evaluating organizational performance makes this possible. The primary goal of HR analytics is to improve organizational performance through data-driven guidance in HR decision-making, which can be achieved by processing comprehensive data (Kirtane, 2015; Reena et al., 2019).

The benefits of HR analytics include enhanced workplace efficiency, higher return on investment (ROI) for the workforce, opportunities for employees to be assessed for their potential and contributions, the creation of staffing plans by forecasting future vacancies and identifying suitable candidates, alignment of HR practices with long-term organizational goals (including corporate strategy and budget), predictions of future HR trends (such as turnover or absenteeism), identification of factors that drive employee satisfaction and productivity, early identification of employees at risk of leaving, analysis of reasons for turnover, and the development of programs to promote learning, growth, and justify investments in employees etc. In a study by McCartney et al. (2021), based on Delaney and Huselid's (1996) research, seven essential items were identified to assess organizational performance. These included: "Location of key personnel," "Ability to retain key personnel," "Service quality," "Customer service," "Management relations with employees," and "Quality of products, services, or programs." These items were considered as six questions in the questionnaire of the study. Hence, the following hypothesiss can be developed based on the literatures:
H_1: HR analytics has a significant effect on organizational performance.

Evidence-based management (EBM)
Evidence-based management (EBM) is grounded in a cycle of obtaining, evaluating, and applying evidence to inform managerial decisions. This research suggests that HR analytics (HRA), by leveraging institutional data and evidence, can drive strategic decisions and enhance the practice of EBM (Baba & HakemZadeh, 2012). However, simply generating data and insights through HR analytics is not sufficient; organizations must integrate and apply this evidence into their operations to realize its full potential (Fu et al., 2015). According to Barends et al. (2014), the EBM process includes six stages: inquiry (formulating a question), acquisition (gathering relevant data), appraisal (evaluating the quality of evidence), aggregation (compiling the evidence), application (using the evidence in decision-making), and assessment (evaluating the effectiveness of the decision). HR analytics can support managers by providing evidence derived from internal company data, leading to better decision-making (Marler & Boudreau, 2016). As noted by Coron (2021), evidence-based HR management uses employee data and analytics to improve HR decisions. This research suggests that by drawing conclusions from employee data, HR analytics contributes to the development of evidence and supports a positive relationship between HR analytics and EBM. The evidence-based approach to decision-making emphasizes using multiple reliable sources of evidence, such as peer-reviewed academic research, organizational data, expert knowledge, and stakeholder perspectives—approaches that originated in healthcare and the application of evidence-based medicine (Baba & HakemZadeh, 2012; Bezzina et al., 2017).

Integrating EBM to 'Organizational performance'
Managers and directors frequently face decisions that influence the direction of their organizations. While many make decisions based on hearsay, outdated information, or personal judgment, others rely on a broader range of evidence (Baba & HakemZadeh, 2012). This has led management scholars to advocate for a shift towards evidence-based management (EBM), encouraging leaders to make decisions rooted in reliable, systematic evidence (Morrell & Learmonth, 2015). The positive impact of EBM on performance has been widely demonstrated in the healthcare sector, with numerous studies showing improvements in patient outcomes and hospital performance (Roshanghalb et al., 2018). For example, Rosenhalb et al. (2018) compiled 20 studies illustrating how EBM enhanced patient health outcomes, while Grundtvig et al. (2011)

showed that combining expert knowledge and patient reports for decisions about chronic heart failure patients led to fewer hospitalizations. These findings underline how evidence-based decision-making leads to improved performance across organizations.

Applying this concept to HR, HR analytics generates accurate organizational data that provides senior management with actionable, evidence-based insights. When combined with other data, HR analytics can drive decisions that boost organizational performance. Many studies have shown how data-driven decision-making in HR leads to improved HR management and organizational outcomes (Minbaeva, 2017). A case in point is the study by Simón & Ferreiro (2017), which explored how the Spanish retail giant Inditex implemented HR analytics to track success metrics and enhance workplace productivity. By collecting and analyzing HR data, Inditex made better decisions regarding employee management, which in turn increased organizational performance.

These examples demonstrate how HR analytics facilitates data-driven decision-making and influences corporate outcomes through explanatory, graphical, and quantitative analysis linked to HR functions, organizational performance, and external benchmarks (Boudreau & Martin, 2016). Scholars suggest that the relationship between HR analytics and organizational outcomes is strengthened when moderated by EBM at the institutional level. The measurement items used by McCartney et al. (2021) were derived from the work of Barends et al. (2014) and Rousseau (2006), who defined six key measures based on the EBM concept. These items were included in the study's questionnaire: "We turn a problem or issue into a question that can be answered," "We systematically search for and gather the best available evidence," "We critically assess the reliability and applicability of the information we gather," "We gather and weight the evidence," "We apply the evidence in decision-making," and "We assess the decision's effectiveness". Henceforth, the following hypothesis can be formulated based on the above discussion:
H_2: Evidence-based management (EBM)has a significant effect on organizational performance.

Access to HR Technology
The rapid growth of information technology (IT) has triggered a transformative shift, with organizations increasingly leveraging big data to capitalize on emerging opportunities (Kim et al., 2020). As Marler and Boudreau (2016) note, human resources (HR) as a field is becoming progressively more tech-driven. The rise of HR analytics (HRA) has been significantly supported by the development of HR technologies, such as Human Resource Information Systems (HRIS) and other advanced computerized HR management systems (Kim et al., 2020). HRIS platforms, in particular, are capable of collecting, storing, processing, and disseminating real-time data, while also generating insights on key performance metrics (Stone et al., 2015). These systems have the ability to predict both short- and long-term workforce trends by integrating big data, business intelligence (BI), and advanced analytics tools (Stone et al., 2015). Additionally, HRIS platforms now incorporate artificial intelligence (AI) technologies, such as chatbots, further enhancing their capabilities.

"HR Technology' Enhances Organization Performance
Recent advancements in HR technology have significantly streamlined HR processes (Black & van Esch, 2020). According to this research, HR professionals now leverage HRM software applications to collect, store, and analyze data related to the development of human capital (Aral et al., 2012), a practice commonly referred to as HR technology. The key argument for the adoption of HR analytics (HRA) is that easy access to "HR technology" is critical. This is due to two main factors.

First, HR technology serves as the backbone of HR analytics by providing immediate access to employee data, which can be used to make more informed and strategic decisions (McIver et al., 2018). McIver et al. (2018) emphasize that HR technology facilitates the collection, cleaning, and processing of data from various sources, which is essential for supporting business decision-making. As a result, organizations now have access to high-quality data, a key requirement for effective HR analytics (Minbaeva, 2017).

Second, HR technology enables the quantitative and predictive analysis of employee data, empowering HR professionals, managers, and organizational leaders to make data-driven decisions about HR policies and practices (Aral et al., 2012). Modern HR technology applications also offer a range of advanced features, such as dashboards, performance metrics, and data simulations, which help HR professionals convert raw data into valuable insights (Marler & Boudreau, 2016). According to Ulrich & Dulebohn (2015), HR professionals can use tools like dashboards and scorecards to track and present HR data over time. Similarly, McIver et al. (2018) argue that dashboards provide HR teams with a powerful way to visualize employee trends, helping them identify emerging issues and opportunities. These capabilities align with the final stages of the HR analytics strategy—“strategic ability to act” and “analytical competence” (Minbaeva, 2017). Clearly, access to HR technology is highly beneficial for HR professionals, enabling them to efficiently collect, manage, and present data to higher-level management (McIver et al., 2018). As this paper suggests, the accessibility of HR technology facilitates the transformation of personnel data into actionable insights for the organization.

The feasibility of HR analytics depends largely on access to HR technology, which collects and processes personnel data, as outlined above. The findings of this research confirm that HR analytics, characterized by "high-quality data," "analytical capabilities," and the "strategic ability to act," is a powerful tool that can convert data into meaningful conclusions—similar to corporate factual data—which can then be applied to enhance organizational performance through evidence-based management (EBM) practices. Therefore, the following hypothesis can be adopted based on the above research support.
H_2: Access to HR Technology has a significant effect on organizational performance.

RESEARCH METHODOLOGY

The study conducted a survey between November and December 2022, gathering responses from 190 participants, with 160 completed surveys, yielding an 84.2% response rate. Convenience sampling was used to select the participants. The survey included questions related to HR analytics, organizational behavior, and demographics. A five-point Likert scale was employed, ranging from strongly disagree to strongly agree. This research is deductive and quantitative in nature, focusing on determining the relationship between HR analytics and organizational performance, with a causal study design. Data was collected through surveys and analyzed using statistical techniques, specifically Smart PLS4. The survey was distributed via email to senior executives, business associates, and HR professionals in both the service sector (28 banks) and manufacturing industries (15 companies). Responses were collected through both online forms (Google Forms) and hardcopy surveys.

Measuring Variables:

McCartney and Fu (2022) found that access to HR technology plays a key role in shaping HR analytics. This study also adopted three items from Aral et al. (2012) to assess access to HR technology, including statements like, "My organization invests in the tools needed to conduct HR analytics" and "My organization has the necessary tools to perform HR analytics." To align with the theoretical framework of HR analytics, Minbaeva (2018) developed a set of structured questions and outlined a model that defines HR analytics across three dimensions. The first dimension focuses on high-quality data, for which Pipino et al. (2002) proposed five criteria: completeness ("The HR data we have is complete and contains no missing information"), reliability ("The HR data we have is accurate and dependable"), timeliness ("The HR data we have is sufficiently current"), consistency ("The HR data we have is presented in the same format"), and regularity ("The HR data we have is collected on a regular basis"). McCartney & Fu (2022) also identified these criteria as essential for defining high-quality data. The second dimension, analytical competency, was measured using five questions recommended by Kryscynski et al. (2018), such as "Our HR Department efficiently uses HR analytics to create value for my organization" and "Our HR Department translates data into useful insights."

Minbaeva (2018) identified three questions to define the third dimension of HR analytics: strategic ability to act. These questions are: "Our HR Department has success stories that justify HR analytics projects," "Our HR Department inspires relevant organizational stakeholders to act based on their findings," and "Our organization's stakeholders use the data-driven insights we provide." Additionally, Rousseau (2006) and Barends et al. (2014) offered six key recommendations for evidence-based decision-making, which include: "We translate an issue or problem into an answerable question," "We rigorously seek and gather the best available evidence," "We assess the reliability and applicability of the information we collect," "We balance and compile the evidence," "We integrate the evidence into the decision-making process," and "We assess the outcome of the decisions." Muriithi & Waithaka (2019) identified staff interactions, leadership philosophies, and staff appraisals as metrics for assessing stewardship, while Delaney and Huselid's (1996) framework for measuring organizational effectiveness includes factors such as the "ability to attract essential employees," "ability to retain essential employees," "quality of services," and "customer service." Drawing on these factors and insights from prior research, the study developed hypotheses to link these variables and proposed a conceptual model.

Proposed Model and Hypothesis:

In this research, “HR technology”, “HR analytics”, “EBM”, “Stewardship” has been taken as measuring variable influencing “organizational performance”. The researcher mainly took two papers to depict the variables. One study possesses “HR technology”, “HR analytics”, and “EBM” which directly and indirectly affecting “organizational performance” (McCartney & Fu, 2022). Another study included “Stewardship” affecting “organizational performance” (Muriithi & Waithaka, 2019). In addition to these two publications, the literature review discussion and the measuring variables section above also included other writers who used variables and questions (items) from theory and literature. In order to provide a clear understanding of the questionnaire's structure, the variables utilized in the survey together with the items taken from the prior study are displayed in a tabular format:

Table1: Variables with references

Constructs	Number of Items	Sources
“Access To HR Technology” (HT)	5	(McCartney & Fu, 2022)
“HR Analytics” (HRA)	15	(McCartney & Fu, 2022)
“Organizational EBM” (EBM)	8	(McCartney & Fu, 2022)
“Organizational Performance” (OP)	6	(McCartney & Fu, 2022)

So as the hypotheses can be constructed as follows:
H1: 'Access to HR technology' has a positively impact on with 'Organizational performance'.
H2: 'HR Analytics (HRA) has a positively impact on 'Organizational performance'
H3: 'Organizational EBM' has a positive impact on the 'Organizational performance'

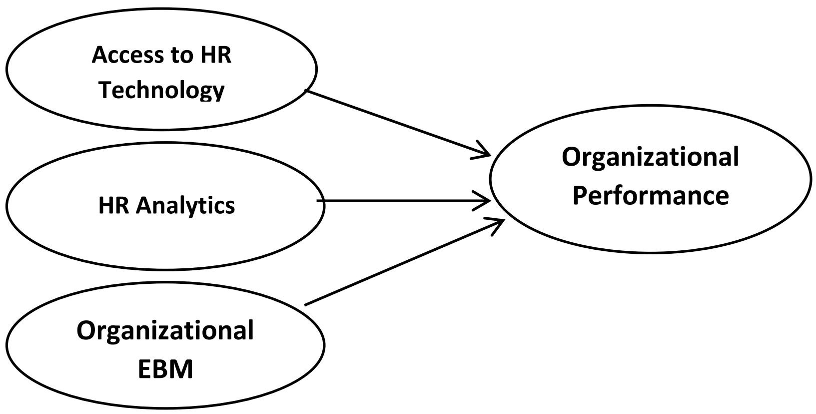

Figure 1: The proposed model of the given study

FINDINGS AND ANALYSIS

Demographic Details

There are 160 persons in the sample. 26.1% of respondents are female and 73.9% of respondents are male. The age range of the bulk of survey participants is between 21 and 30 years old, with a significant percentage falling between 31 and 40 years old. People are more reluctant to complete the poll, even if they should be older. The sample population's educational attainment (41.3% bachelor's degree, 9.4% higher secondary degree, 38.8% graduate or professional degree, 1.3% secondary degree, and others 9.4) indicates that the participants had very high levels of literacy. Of the respondents, 48.1% held a job in line management, 36.3% held a position in senior management, and 15.6% were stakeholders in the company53.1% of people are in the manufacturing sector, while 46.9% are in the service sector. More than 87% of respondents said their company uses an HR information system, while 13% said they don't use one at all.

Detailing Measurement Model

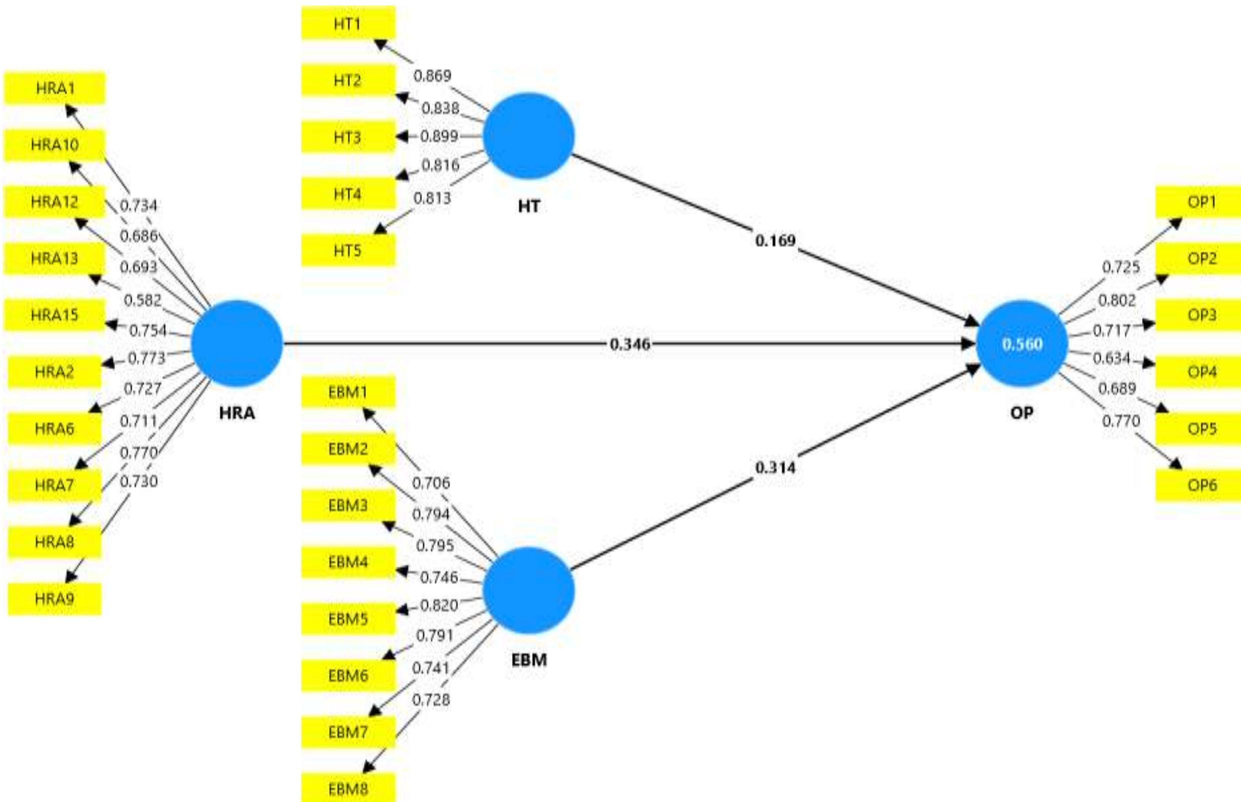

Figure 2: Measurement Model

Hair et al. (2014) recommended that Cronbach alpha acceptable values fall between 0.60 and 0.70, with higher values than 0.70 in more advanced stages. According to Nunnally and Bernstein (1994), a number below 0.60 may be indicative of a lack of reliability.

Table 2: Assessment of Measurement Model

Variables	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
EBM	0.900	0.919	0.587
HRA	0.895	0.914	0.515
HT	0.902	0.927	0.719
OP	0.818	0.869	0.526

Consequently, from the above table, all the values are above 0.7 and constructs has been found reliable. Bagozzi and Yi (1989) said that a composite reliability score of 0.7 or greater is considered satisfactory. All the composite reliability values in Table 2 are greater than 0.7, and satisfied this condition. According to Bagozzi and Yi (1988), Hair et al. (2014), Henseler et al. (2009), and Bagozzi et al. (1988), an average variance extracted (AVE) value of 0.5 or higher is deemed acceptable and it is considered sufficient for convergent validity (Henseler et al., 2015). Here all the constructs are having a higher value of 0.5 and data were found to have convergent validity here.

Cross Loading and Outer Loadings

For the first time, Chin (1998) has suggested that a construct's outer loadings should be greater than the cross-loadings on other constructs. Hair et al. (2011) presented a discriminant validity criterion that is more lenient and it states that any indicators cross loadings with all other constructs should be smaller than its outer loading of a related latent construct. Hair et al. (2014) state that an indicator is loaded on the other constructions if a certain construct has a higher outer loading than the cross loading of another construct.

Table 3: Cross Loading

Variables	EBM	HRA	HT	OP	VIF
EBM1	**0.706**	0.550	0.435	0.360	1.937
EBM2	**0.794**	0.586	0.487	0.492	2.530
EBM3	**0.795**	0.548	0.484	0.486	2.350
EBM4	**0.746**	0.543	0.495	0.532	1.939
EBM5	**0.820**	0.597	0.467	0.600	2.391
EBM6	**0.791**	0.645	0.552	0.623	2.048
EBM7	**0.741**	0.544	0.476	0.498	1.850
EBM8	**0.728**	0.506	0.422	0.475	1.874
HRA1	0.482	**0.734**	0.585	0.539	2.239
HRA10	0.551	**0.686**	0.438	0.499	1.745
HRA12	0.456	**0.693**	0.532	0.514	1.811
HRA13	0.442	**0.582**	0.438	0.382	1.617
HRA15	0.609	**0.754**	0.514	0.553	1.931
HRA2	0.591	**0.773**	0.58	0.519	2.449
HRA6	0.569	**0.727**	0.536	0.474	1.867
HRA7	0.505	**0.711**	0.467	0.437	1.809
HRA8	0.559	**0.770**	0.620	0.556	2.130
HRA9	0.532	**0.730**	0.563	0.536	2.019
HT1	0.494	0.643	**0.869**	0.51	3.035

HT2	0.485	0.563	**0.838**	0.498	2.801
HT3	0.542	0.650	**0.899**	0.546	3.491
HT4	0.534	0.600	**0.816**	0.514	2.277
HT5	0.587	0.665	**0.813**	0.557	2.060
OP1	0.512	0.558	0.395	**0.725**	2.146
OP2	0.558	0.549	0.435	**0.802**	2.576
OP3	0.453	0.466	0.424	**0.717**	1.561
OP4	0.442	0.452	0.465	**0.634**	1.375
OP5	0.371	0.440	0.421	**0.689**	1.606
OP6	0.569	0.569	0.548	**0.770**	1.682

As a result, table 4 shows that all of the latent construct's outer loadings are larger than the loadings of every other construct. Hence the criterion for discriminant validity has been fulfilled by the above values in the table.

Kock (2011) For formative factors, the variance inflation factor (VIF) should be less than 3.3 for a more stringent examination, but 10 at most. For our formative indicators, sufficient construct validity was indicated by all of the indicators' VIFs being below 3.3. Kock (2011) suggested removing any indicators from the model if their scores had been greater than 10. Here no value has been found above the indicated threshold and fulfilled the conditions of Kock (2011).

Table 4: Outer Loadings

Variables	EBM	HRA	HT	OP
EBM1	0.706			
EBM2	0.794			
EBM3	0.795			
EBM4	0.746			
EBM5	0.820			
EBM6	0.791			
EBM7	0.741			
EBM8	0.728			
HRA1		0.734		
HRA10		0.686		
HRA12		0.693		
HRA13		0.582		
HRA15		0.754		

HRA2		0.773		
HRA6		0.727		
HRA7		0.711		
HRA8		0.770		
HRA9		0.730		
HT1			0.869	
HT2			0.838	
HT3			0.899	
HT4			0.816	
HT5			0.813	
OP1				0.725
OP2				0.802
OP3				0.717
OP4				0.634
OP5				0.689
OP6				0.770

Individual factor loadings were retained which are greater than 0.6, with mostly greater than 0.7 (Birkinshaw et al., 1995). Factor loadings should be 0.5, or ideally 0.7, according to Hair et al. (2009). Table 2 shows that no item has a loading below o.6 and that the maximum loading has more than 0.7. Thus, all the construct have been fulfilled the conditions.

The Heterotrait-Monotrait (HTMT) Ratio and Fornell-Lacker Criterion

The Heterotrait-Monotrait (HTMT) ratios of correlation, the Fornell & Larcker criterion are also used to assess the discriminant validity (Hamid et al. 2017). The Heterotrait-Monotrait (HTMT) ratio of correlation is the metric used to assess discriminant validity. By using a Monte Carlo simulation analysis, (Henseler et al.2015) demonstrated the method's superior performance and discovered that HTMT can obtain greater rates of specificity and sensitivity with a value between 0.97 to 0.99.

Table 5: Heterotrait-Monotrait (HTMT) Ratio

Variables	EBM	HRA	HT	OP
EBM				
HRA	0.822			
HT	0.690	0.818		
OP	0.766	0.813	0.72	

Every value ought to fall below (Kline's, 2011) recommended cutoff point of 0.85. Furthermore, it was suggested that the appropriate threshold ought to be 0.90 (Hamid et al. 2017). On the above table no value has been found more than 0.85, discriminant validity has been achieved.

Table 6: Fornell-Larker Criterion

Variables	EBM	HRA	HT	OP	Composite reliability	Average variance extracted (AVE)
EBM	**0.766**				**0.919**	**0.587**
HRA	0.739	**0.718**			**0.914**	**0.515**
HT	0.625	0.738	**0.848**		**0.927**	**0.719**
OP	0.675	0.703	0.621	**0.725**	**0.869**	**0.526**

Using the Fornell-Lacker criterion to evaluate discriminant validity is the second requirement. This technique contrasts the correlation of latent constructs with the square root of the average variance extracted (AVE) Amora 2021). Rather than the variance of other latent constructs, a latent construct should be better able to explain the variance of its own indicator. Consequently, each construct's square root of AVE should be larger than its correlations with other latent constructs.

Following Hamid et al., (2017). since composite reliability for all constructs are above 0.70 and the AVE values are above 0.5. There is little dispute between HRA-HT construct the difference is small (0.02) and can be ignored (Hamid et al., 2017; Rahim et al., 1995). Overall, as other conditions have been fulfilled the discriminant validity of this measurement model can be accepted.

Assessment of Structural Model

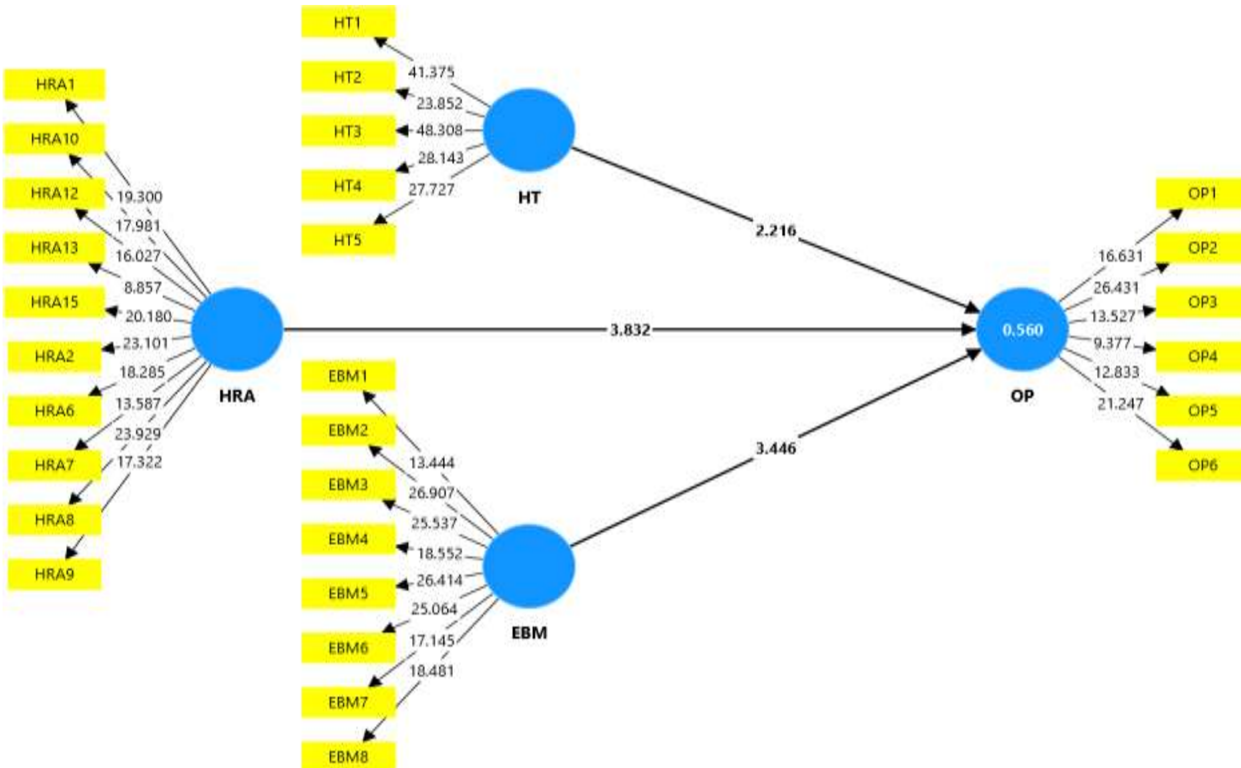

Figure 3: Structural Model

Table 7: Path coefficients, R-square, Q²predict and f-square

H. Path	f-square	Path coefficients	Standard deviation	T -values	P-values	Decision
EBM -> OP	0.098	0.31	0.09	3.45	0.00	Supported
HRA -> OP	0.089	0.35	0.09	3.83	0.00	Supported
HT -> OP	0.029	0.17	0.08	2.22	0.03	Supported
R-square	0.56					
Q^2 predict	0.528					

Hair et al. (2018) suggested that if P value less than 0.05, it indicate the relationship between the variables are statistically significant. From the above table 6, we see all the P-values are less than the recommended threshold. Hence relationships between EBM, HRA and HT variables and organizational performance are statistically significant. Hair et al. (2018) concluded based on Henseler et al., (2009) and Hair et al., (2011) prescribed moderate R^2 values whereas Hair et al., (2012) considered R^2 value as satisfactory when it is at least 10%. From the above table 6 we can see 56% variation in organizational performance (OP) is defined by all the independent variables (EBM, HRA and HT). This means HR Analytics (HA), Evidence Based management (EBM) and Access to HR technology (HT) affecting Organizational Performance (OP) more than 56%.

The values which are higher than 0, are considered as the predictive accuracy (Hair et al., 2018) and the prescribed the PLS path model affect the dependent constructs. Hence in this model Q2 predict is 0.528 which is more than zero and proves the predictive accuracy of the prescribed path model. Cohen (1988) suggested f^2 value between 0.02 to 0.14 is having small effect size, value and value 0.35 or above is considered as having significant effect size. Since the value of the above table 6, the variable HT has small effect size and EBM, and HRA has a significant effect size. Following Hair et al. (2014) when the critical value such as 1.96 at 5% level of significance for two tail test is smaller than the calculated t-value, the coefficient is significant. Therefore all the hypotheses, H1, H2 and H3, are statistically significant. Therefore by doing bootstrapping of the path model and considering all the score of T-value and P-value, R-square, f-square and Q square predict, it has been found that all the variables are showing satisfactory score and establish significant relationships between the constructs.

FINDINGS & ANALYSIS

HR analytics can be applied in a dynamic manner to quantify the investigation of a crucial issue by determining the degree to which it enhances business performance and by identifying the relationship between the relevant factors. Some hypotheses are used to analyze the paper.. The responses of a representative sample of the population were used to produce the survey data. The investigator is receiving helpful information from a large number of potential employees. The data gathered from a range of surveys shows the study's findings. Using the appropriate techniques, data analysis was carried out to answer all research questions, establish the degree to which each variable influenced its other variables, verify the relative importance of each factor in explaining the observed increase in organizational performance during HRA implementation, and create a "multiple-regression model" for connecting the variables. The first topic covered is demographics, then variable frequency distribution, Anova, multiple regression, coefficient, and correlation and finally reliability testing. The summery of tested hypothesis is presented in Table 8.

Table 8: Summary of the Tested Hypothesis

Hypothesis	Variables	Accepted/Rejected
H1	‘Access to HR technology’	Accepted
H2	‘HR Analytics’	Accepted
H3	‘Organizational EBM’	Accepted

In summary, the test results are consistent with those reported in the academic literature. Overall, the sample population's opinions are consistent with the optimistic forecast for HRA. Since HRA provides a complete view of organizational performance and may be used in conjunction with other digital systems to further improve performance, it should be adopted and implemented to drive progress in organizational performances.

KEY FINDINGS AND CONCLUSION

The findings indicate that all variables—HR Analytics, Organizational Evidence-Based Management (EBM), and Access to HR Technology—significantly impact organizational performance. Specifically, HR analytics encompasses three key dimensions: high-quality data, analytical competency, and strategic action. High-quality data is defined as timely, accurate, consistent, and complete, which is crucial for effective analysis (McCartney and Fu, 2022). The analysis confirms a significant relationship between HR analytics and organizational performance, aligning with previous studies (Lochab et al., 2018; McCartney and Fu, 2022). This demonstrates that organizations can now utilize comprehensive, reliable, and timely HR data. By achieving analytical competency, organizations can convert data into valuable insights, address challenges, and generate value. Stakeholders, line managers, and senior management can act on these insights effectively. Furthermore, the evidence-based management practices revealed several actively influential factors, such as the organization’s ability to solve problems, seek out and evaluate the best available evidence, and critically assess its relevance and trustworthiness. This fulfills the necessary stages of the EBM process: asking, acquiring, appraising, aggregating, applying, and assessing. Access to HR technology has also been shown to significantly influence outcomes. Hence if organization have necessary and appropriate tools for doing HR analytics, if organization invest more to arrange necessary tools to do HR analytics, it will help boost the organizational performances as well. If organization has the HR system which enables the HR professionals to manage employees in a cost-effective way, this would become a great advantage

Recommendation

In summary, the test results align with existing academic literature, indicating a generally positive perception of HR Analytics among the sample population. HR Analytics (HRA) should be embraced and utilized to enhance organizational activities, as it provides a comprehensive view of performance and can be integrated with other digital systems to further improve results.

Organisations can leverage HR analytics to identify essential skills for employees at various levels. It serves as a valuable tool for HR professionals assessing the effectiveness of HR initiatives. To fully harness the benefits of HRA, companies must invest significantly in staff training and development. Maximizing analytics requires integrating its use with various organizational processes. Leaders must cultivate a culture that prioritizes data and facts over intuition in decision-making. Isolated data points are often ineffective; analytics is about synthesizing information to create a cohesive understanding. Strong internal engagement is crucial, as it encourages collaboration and individual contributions, ensuring that everyone is aligned with the organization's objectives.

While interest in HR analytics is growing, the field remains relatively immature. Researchers and industry experts are preparing to explore the impact of HR digitization and the increase in employee data on decision-making and organizational outcomes. This research aims to enhance the understanding of HR analytics' effects on organizational performance, with hopes of inspiring further studies to clarify how HRA can benefit organizations.

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