A Study on The Role of Hr Analytics in The Decision-Making Process in A Home Appliance Manufacturing Sector in Pune

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Abstract
For a business to thrive in today's cutthroat marketplace, every employee must be able to contribute to the fullest extent of his or her abilities. Human resources remain one of the most crucial differentiating factors a firm may use for competitive growth and value creation in such an environment. Organizations see human capital as a key driver of economic and corporate development as well as a source of competitive advantage. Present organizations are facing competition rival continuously due to changes in technology and the business environment. Today's HR professionals recognize that dealing with data alone is insufficient, but it's also critical to grasp other metrics that might benefit firms. As a result, several HR departments from different firms have already started using analytics, and they are performing rather effectively. This study is aimed at finding the impact of the HRA process on decision-making, the advantages of using HRA and its threats, and the way it is being used in home appliance manufacturing industries. The evaluation of the major influence that the HR analytics process has on the decision-making processes is the primary purpose of this research. The current investigation operationalizes four separate decision-making processes, which are as follows: the descriptive analytics decision-making process; the diagnostic analytics decision-making process; the predictive decision-makingprocess; and the prescriptive decision-making process.

Keywords: Marketplace, Human resource, human capital, HRA, HR analytics, decision making.

1. Introduction

With recent globalization trends, there is a surge in manufacturing locations to take advantageof time and logistics costs across multiple countries. India, being an expanding economy, is seeing a significant expansion in industries. With the changing economic policies, more and more firms are moving to India to set up manufacturing facilities under the Make In India initiative and to benefit from the Indian market. Rising industrialization and urbanization are driving up commodity consumption in India. A few causes, such as infrastructural development, electrification, real estate growth, job creation, and small business availability, are leading to an increase in buyer income.

For a business to thrive in today's cutthroat marketplace, every employee must be able to contribute to the fullest extent of his or her abilities. Human resources remain one ofthe most crucial differentiating factors a firm may use for competitive growth and value creation in such an environment (Bharti, 2017). Organizations see human capital as a key driverof economic and corporate development as well as a source of competitive advantage (Delery & Roumpi, 2017). Present organizations are facing competition rival

continuously due to changes in technology and the business environment (Narendra and Mishra, 2021).
Scholars and professionals have become more interested in the idea of data and analytics and how they are applied in management and trying to comprehend how data may be translated into valuable insights that improve organizational performance (Chierici et al., 2019; Ferraris et al., 2019; Santoro et al., 2019; Singh and Del Giudice, 2019). Human resources management (HRM) has experienced an increase in interest in data and analytics, as indicated by the rise inthe number of HR departments using HR analytics to enhance decision-making. (Marler and Boudreau, 2017; Fernandez and Gallardo-Gallardo, 2020; McCartney et al., 2020).
In addition to focusing on examining and enhancing aspects of human capital, HR analytics also uses analytical methods in conjunction with people data to guide organizational strategy and enhance performance (McCartney and Fu,2022). By collecting and converting high-quality worker data into information and producing crucial organizational insights, HR analytics contributes to the establishment of organizational evidence creation (Marler and Boudreau, 2017; Minbaeva, 2018; Coron, 2021).

The HRM practices that are put in place must be in line with larger expectations and rules for how employees should act and with competitive goals. In addition, using analytics to manage human resources better is a newer HRM trend.
Today's HR professionals recognize that dealing with data alone is insufficient, but it's also critical to grasp other metrics that might benefit firms. As a result, several HR departments from different firms have already started using analytics, and they are performing rather effectively.
This study is aimed at finding the impact of the HRA process on decision-making, the advantages of using HRA and its threats, and the way it is being used in home appliance manufacturing industries.

1.1 Need and Rationale of the study

There is a large amount of data in any organization due to the information age in the modern business environment. Usually, these large amounts of data and the interpretation of these data are considered big tasks as large as the data contained in raw.
HRM methods are evolving in today's data-driven environment as organizations leverage HR metrics and HR analytics to improve decision-making. The firm will become more dependablein its use of data-driven decision-making rather than intuition as a result of this digitization. This can help firms use current strategic and operational data to create a practical solution to HR issues in the future. Utilizing current data to predict future ROI as a source of strategic advantage, HR analytics has grown to be a crucial tool for success (Ekka, 2021).
Organizations view human capital as a critical source of competitive advantages and a necessityfor business success (Andrijević Matovac et al., 2010; Pradana et al., 2020). As a result, it is difficult for firms to manage personnel with broad competencies. However, people are an organization's greatest asset and a powerful means of creating a competitive advantage in the current uncertain market climate. For this reason, generating, examining, and storing massive amounts of data for decision-making is necessary.
Human resource management involves technology that provides managers with insights into various HR operations patterns to sort through the enormous personnel database and identify the top performers. The solution lies in using analytics to handle employee data more logically and sensibly while drawing linkages to corporate outcomes.

1.1 Significance of the study

When an organization has a good understanding of the issue, the data and information on the business process can support the organization in making decisions that are beneficial to the organization's growth.
In the human resources (HR) function, which provides the resources for running the business, their trend pattern to behave with the business and seasonality helps the organization plan betterso that it can anticipate crises and turn them into opportunities.

According to Andrijevi Matovac et al. (2010), businesses are vying for the best talent by competing to recruit, select, retain, and inspire them.

Digitalization has an impact on both our daily lives and the economic world. The corporate sector is heavily reliant on technology. During these years, it will be impossible to conduct business without technology (BarNir et al., 2003).

Large amounts of data and analytics technologies enabled firms to foresee and make data-driven decisions in various contexts (Angrave et al., 2016).

Utilizing statistical models, HR Analytics delves deep into a company's employee data to predict attrition rates, training costs, and employee contributions, among other things.

This study would suggest organizations employ the organizational facts generated by HR analytics and incorporate them into their decision-making process.

1.3 Human Resource Analytics Process

Marler and Boudreau (2017) define HR analytics as, "an HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making" (p. 15).

According to Mr. Ferrar (an expert in HR analytics working in IBM Smarter Workforce), "analytics is expanding to new areas, such as conducting a risk analysis of labor relations, compensation optimization, social media analysis, recruitment analytics, and corporate employee engagement" (quoted from SHRM Foundation, 2016).

The application of using workforce data to improve decision-making has been synonymously referred to by scholars as HR analytics (Aral et al., 2012; Rasmussen and Ulrich, 2015; Angrave et al., 2016; Marler and Boudreau, 2017; McCartney et al., 2020), people analytics (Kane, 2015; Green, 2017; Nielsen and McCullough, 2018; Tursunbayeva et al., 2018; Peeters et al., 2020), talent analytics (Harris et al., 2011; Sivathanu and Pillai, 2020), human capital analytics (Andersen, 2017; Boudreau and Cascio, 2017; Levenson and Fink, 2017; Minbaeva, 2018) and workforce analytics (Huselid, 2018; Simon and Ferreiro, 2018).

1.4 Decisions making in Analytics

Margherita (2020) asserted that HR analytics adheres to a linear, three-stage maturity model. At its most basic level, "descriptive" HR analytics concentrates on using HR technology to produce reports and dashboards that respond to inquiries about what has occurred. The "predictive" stage then makes use of statistical methods, cutting-edge algorithms, and machine learning to predict potential future events and their causes. The "prescriptive" step, which comes last, focuses on choosing the best course of action to follow in response to the analysis.

The strategic value of HR analytics is widely acknowledged in academia and practice since it gives organizations the data, information, and insights they need to make data-driven decisions (Huselid, 2018; Minbaeva, 2018).

To improve decision-making, van den Heuvel and Bondarouk (2017) define HR analytics as the methodical identification and quantification of the human drivers of business outcomes.

Descriptive, predictive, and optimization analytics are the three main types of analytics (Watson, Narula, 2015).

1.5 HRA Process and Decision-making

Human resources management (HRM) has experienced an increase in interest in data and analytics, as indicated by the rise in the number of HR departments using HR analytics to enhance decision-making (Marler and Boudreau, 2017; Fernandez and Gallardo-Gallardo, 2020; McCartney et al., 2020).

The use of data-driven decision-making to support human resource management (HRM) decision-making and the accessibility of big data are seen as opportunities for future expansion in the field of HR analytics (Milon, 2019).

Adopting HR analytics will help firms create more robust connections for attracting and retaining top personnel and improve HRM decision-making (Fitz-Enz, 2010).

Rasmussen and Ulrich's (2015) study looks into the idea that HR analytics helps with managerial and HR decision-making by providing data that can be trusted and backed up by statistics. The report argues that if Analytics doesn't want to become simply another "management craze," it should aim to improve the way HR and other relevant departments typically operate to ensure that it produces effective outcomes. Instead of the usual "inside-out" approach to human resources, the study suggests that organizations should adopt an "outside-in" approach that emphasizes tangible activities. This alternate strategy proposal is amenable to this aspect.

2. Review Literature

For various people, HR analytics can mean different things. Some people just use the term "HRanalytics" to refer to descriptive HR metrics, while others use the term to refer to complex predictive modeling techniques (Bassi, 2011). More recently, Levenson and Fink (2017) argue that, in the context of HR, the term "analytics" has unfortunately come to mean everything involving numbers, data collection, and measurement.

According to Chaudhary and Srivastava (2021), HR analytics concentrates on making it easier to understand how to manage the staff effectively and grasp corporate objectives. Because there is so much information available, Human Resource departments need to prioritize classifying which data is crucial in addition to determining how to use it for the greatest return on investment. Companies should gather data and use it for practical development and decision-making to significantly influence HR analytics. Many firms recognize the value of data in helping them identify and lease people with genuine potential.

Kluemper, Rosen, and Mossholder (2012) found that an employee's IQ, personality tests, and structured interviews can be used to predict how well they will do their job and how they will act on the job. After considering legal and ethical considerations, these assessments may also be employed in the recruiting process because of their association with the candidate's Facebook profile. Best Buy uses HR analytics to forecast store performance every quarter by looking at employee engagement rates. It found, for instance, that for every one percent increase in employee engagement, there would be a one hundred thousand dollar gain in sales.(Erik van Vulpen n.d).

The technology giant Hewlett-Packard (HP) implemented a solution in 2011 called "Flight Risk Score" to predict how many employees would leave the company. They discovered that pay raises, promotions, and positive reviews all have a detrimental impact on one another. If an employee receives a promotion but no pay increase, they are more inclined to look for a newjob. HP developed a central hub for its HR managers, complete with crucial personnel data matrices shown in an easy-to-read dashboard format. In addition to predicting how employees would behave, predictive HR analysis may also forecast how they will contribute to the company's performance, saving millions of dollars annually. Ballinger, Cross, and Holtom investigated the effects of network structure on voluntary turnover in a 2016 study. The study's primary focus was on how business productivity is affected by employees' social networks.

According to the study, an important factor in figuring out the frequency with which employeesswitch jobs is correlated with their network reputation, which opens doors to influential individuals. The brokerage acts as a moderating factor in terms of growth, innovation, and efficiency, as stated by Ballinger, Cross, and Holtom (2016). The primary finding of this research on employee turnover is that workers who have a larger social network have greater access to brokerage and reputation resources and are consequently more likely to leave their companies.

In 2016, Mishra, Lama, and Pal investigated the application of predictive analytics to the field of human resource analytics. By identifying and suggesting particular metrics that can be utilized for predictive modeling, the study discovered that HR predictive analytics has far-reaching effects on all areas of human resource management. It aids businesses in lowering the price of adopting HR-related changes, boosting productivity, and increasing employee engagement. Low talent retention and high attrition rates are linked, as shown by the study.

Analytics in today's world scenario is no longer about getting fascinating evidence and reproaching it for supervisors, right now data is being processed to apprehend each magnitude of enterprise maneuvering, and analytical techniques are entrenched in for day-to-day efficacious conclusion building (Fineman, Tsuchida, & Collins, 2017).

Alzhrani (2020) investigated the impact of collected data on HRP and the career development of candidates. For this data was collected from secondary sources such as online journals, newspapers, books, etc. it is concluded that HRP plays an important role in making an organization competitive in the current market by keeping healthy and easy to manage. It also points out the skill set of workers by which a company becomes more productive and innovative.

Selvaraj and Rengamani (2018) studied the role of HRIS in Human resource planning and labor force tracking. For this data was collected from 127 respondents from 7 IT companies. It is concluded that there is a positive relation between using HRIS and the increased efficiency and effectiveness of HRP. This study also reveals that the most accepted feature of HRIS is to identify unfilled job positions.

Das and Bhar (2018) investigated the manpower planning of microfinance industries. This data is collected from secondary data. It reveals a dynamics-based model from which the required number of manpower related to staff and managers at different levels can be evaluated.

Kumar and Mishra (2014) researched on the relation between HR functions and HRIS for global competition. For this data was collected from secondary sources. It is revealed that some of the functions show a positive relation with HRIS such as performance management, Knowledge management, and records whereas some functions such as strategic integration, forecasting, and planning show a negative relation with HRIS.

Google's HR analytics team has developed an evidence-based strategy to improve its recruitment and selection process by identifying several components of high performance that could foretell a candidate's likelihood of success through the use of cutting-edge HR technology to collect and analyze candidate and employee data (Harris et al., 2011; Shrivastava et al., 2018).

Ore and Sposato (2022) investigated the implementation of HR analytics in the recruitment and selection process in multicultural MNCs. For this data was collected from interviews of 10 professional recruiters. It is reported that HR analytics with the help of artificial intelligence improves recruitment strategies whereas automation increases the fear of losing a job eventhough recruiters will always be humans.

Kambur and Akar (2022) studied the implementation of artificial intelligence in the HR department. For this data was collected from 821 HR managers and employees from Turkey'sorganization. It is concluded that AI releases monotony and stress to find an eligible candidatewith the required qualification.

McCartney, Murphy, and McCarthy (2021) investigated the competencies required in HR Analysts for the recruitment and selection process, HR development, and HR system alignment. Forthis data was collected from 110 HR analyst job profiles from 5 different countries. It is concluded that an HR analyst must possess technical knowledge, Consultancy quality, Data analysis and interpretation knowledge, business judgment, research, communication, anddiscovery nature for different HRM processes.

Johnson, Stone, and Lukaszewski (2021) researched the challenges faced by the tourism industry related to recruiting and selecting eligible candidates, retaining employees, and reducing the time needed for hiring a replacement. For this data is collected from different industries of tourism. It is suggested that using eHRM and AI can reduce the time needed to recruit eligible candidates. It also helps to get better employee and organizational outcomes.

2.1 Gap Analysis

Managers and senior executives must make important decisions every day to ensure the success of their enterprises. Many people make decisions based on intuition, out-of-date knowledge,
personal experience, or a combination of the three, rather than using a variety of facts to support them (Rousseau and Barends, 2011; Baba and HakemZadeh, 2012).
Organizations have started to use HR analytics as a result of the rising interest in the field. HR analytics teams have been created that are focused on leveraging workforce data to make strategic workforce choices (Rasmussen and Ulrich, 2015; Andersen, 2017; McIver et al., 2018).
Despite the high level of interest in using HR analytics in practice, McIver et al. (2018) claim that there is still a lack of understanding of how businesses may benefit from and apply HR analytics to improve organizational performance.
However, very little empirical evidence supports the impact HR analytics has on organizational decision-making in the Indian context, particularly in the home appliance industry.

3. Research Methodology

In the era of information technology, most work is being simplified, accurate, and on time in almost every sphere of personal and professional life. Human resources practices are no exception in this case, and the buzzword is human resource analytics. Therefore, it is imperative to understand the practices under HR analytics and its impact on other HR functions. This study aims to find the impact of the HR Analytics (HRA) process on different levels of decision-making in the home appliances manufacturing industry in Pune. The research problem of this study is to get insight into analytics-based interventions used for predictive decision-making about various parameters that are pivotal to organizational operations with real and case-basedpractices adopted in the home appliances manufacturing industry in Pune. It also attempts to understand the possible threats and opportunities of implementing and using human resource analytics.

3.1 Research Questions

- What are the impacts of the HR Analytics (HRA) process on different levels of decision-making in the home appliances manufacturing industry in Pune?
- What are the possible threats and opportunities of implementing and using human resource analytics?

3.2 Research Objectives

- To find the impact of the HR Analytics (HRA) process on different levels of decision-making in the home appliances manufacturing industry in Pune.
- To find out the threats and opportunities of implementing and using human resource analytics.

3.3 Proposed alternative hypotheses

In this study, the Process of HRA consists of five steps - Analytics mindset, Preparedness with analytical capacity, availability of the database, Using HR Analytics, and Results and Interpretations; whereas the four levels of decision-making are – descriptive, diagnostic, predictive, and prescriptive.
Based on the dimensions of both variables, the following alternate hypotheses are proposed –

- H1 - There is a significant impact of the HRA process on descriptive decision-making in the home appliances manufacturing industry in Pune.
- H2 - There is a significant impact of the HRA process on diagnostic decision-making in the manufacturing of home appliances in Pune.

3.4 Research Design

Descriptive research was used in this study to test the hypotheses listed above. Descriptive research is more formal and structured than exploratory research. This research's findings are considered conclusive in nature (Malhotra & Dash, 2012). A descriptive survey designmethodology was adopted. Both primary and secondary data were used as a source of data for the research. A Single Cross-Sectional research design was used to collect data from target customers at one point in time, and the data would be analyzed to test the stated hypotheses.

This study used deductive approaches. A deductive approach has been used in this research because the data is collected through the studies that have already been done and the theories that have already existed. The questions and objectives of the research are also formulated through the existing theories.

4. Data Analysis & Interpretations

4.1 Brief description of the measurement model techniques

This measurement model consists of IV (independent variables) and DV (Dependent variables). In each variable, we describe the scales developed to measure the indicators of IV and DV. In addition, it will comprise the description of items and their major themes. We measured all scales and subscales on a 5-point Likert scale (1-5); (1=strongly disagree, 2= disagree, 3= agree to some extent, 4= agree, 5= strongly agree).

We describe the factor loading process and the status of which item of the respective scale was retained or dropped. Next, we presented the descriptive statistics of each item of all scales. And finally, we provided the psychometric properties of measurement scales.

We calculated central tendency (Mean and Mode) and dispersion (range and standard deviation) as part of each scale's descriptive properties. We considered the normality of data if Mean≥2SD.

Furthermore, we calculated the skewness and Kurtosis of each item of all scales to estimate normality.

Table 4.2

Psychometric property and status of retaining and removal of scale items of Preparedness with analytical capacity (PAC)

Preparedness with analytical capacity (PAC)									
Item name	**Scale item description**	***M***	**SD**	**Mo**	**Min-Max**	**SK**	**K**	**λ**	**Retained/ dropped**
PAC1	My organization conducted groundwork on their inputs in the analytics journey	4.27	.95	5	1-5	-1.73	3.40	0.82	Retained
PAC2	My HR team has enough technological capacity	4.21	.98	5	1-5	-1.54	2.46	0.86	Retained
PAC3	My organization has skillful human resourcesfor using HR analytics	4.15	.97	5	1-5	-1.34	1.83	0.84	Retained
PAC4	We can align the goals of HR Analytics withbusiness-level strategy.	4.38	.87	5	1-5	-2.05	5.23	0.83	Retained
PAC5	A full array of HR analytical tools is available atmy work	4.14	.98	5	1-5	-1.49	2.52	0.89	Retained
PAC6	Our organization invested quite heavily in HRAnalytical tools.	4.01	1.07	5	1-5	-1.16	1.06	0.82	Retained
PAC7	The organization provides a lot of opportunities to use HR Analytical tools	4.18	.98	5	1-5	-1.53	2.63	0.88	Retained

PAC8	Top management initiated some policy changes toadopt HR Analytics	4.23	.94	5	1-5	-1.50	2.56	0.84	Retained

Note. M: Mean; SD: Standard deviation; Mo: Mode Min: Minimum, Max: Maximum, SK: Skewness; K: Kurtosis; λ: Factor loading

4.3 Testing of hypothesis-1

H1: There will be a significant impact of HRAP (HR analytics process) on descriptive decision-making (DECA) in the home appliance manufacturing industry in Pune.

Equation-1: Y1(DECA) = β0X0+ β1X1 (HRAP) + C1

H1: The first method: Simple regression equation

Using simple linear regression, we tested only a single outcome variable against only an explanatory variable (HRAP). In table 1, we elaborated on the results of simple linear regression. Parallelly, we adopted the ANOVA method for further confirmation of the proposed hypotheses. The results of ANOVA are described in Table 3.2.

In the first hypothesis, the first outcome variable was DECA (descriptive analytics decision). The value of (= .114) suggests that descriptive decision was increasing even when the HR analytics process was not started, which means when the value of HRAP was zero. The positive correlation between HRAP and DECA (r =.93) suggests a strong correlation between HRAP and DECA. Since correlation is a two-way relation, we haveto confirm a one-way association using a regression equation. One unit change in HRAP brings 0.168 changes in DECA, which is shown in (β1 = .168). The standardized beta in this equation (Standardized β= 0.937), which is also an indicator of an effect size of this relation, shows a high effect size. The 'T' value (t= 33.24) is 17 times higher than a minimum critical value of 't' at an infinite degree of freedom (1.96). The higher 't' valueis also indicative of a highly significant relation. This equation is highly statistically significant (p=0.0000) at a 99.99999% confidence interval.

The R square value (R^2= 0.87) indicates that the independent variable HR analytics process explains the outcome variable DECA (Descriptive analytics decision) 87%. Rest, 13% are other variables that are influencing the DECA. Thus, considering all beta, standardized beta, effect size, t-value, p-value, and value of R square suggests that this hypothesis is accepted (Table 4.2).

For further confirmation of the acceptance of
H_1 : (HRAP→ DECA; **Y1(DECA) = β0X0+ β1X1 (HRAP) + C1** we adopted the method of ANOVA (Analysis of Variance)

The between-group sum of squares (SS=4494.16, df=1) and the within-group sum of squares(SS= 621.98, df=153). The mean sum of squares between groups and within groups were 4494.6 and 4.06, respectively. Therefore, the ratio of the mean sum of squares between groups and within groups was (F=1105.49, df=1, 153), which is highly significant at
(p=0.000***). Therefore, even after using the ANOVA method, the H_1 : (HRAP→ DECA;
Y1(DECA) = β0X0+ β1X1 (HRAP) + C1) is accepted. The ANOVA method further confirms the acceptance of H1 (Table 4.2).

Table: 4.3
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PAC8	Top management initiated some policy changes toadopt HR Analytics	4.23	.94	5	1-5	-1.50	2.56	0.84	Retained

Note. M: Mean; SD: Standard deviation; Mo: Mode Min: Minimum, Max: Maximum, SK: Skewness; K: Kurtosis; λ: Factor loading

4.3 H2: Testing of Hypothesis-2

The second hypothesis is about testing the influence of HRAP on diagnostic decision-making (DIGA). H2 : (HRAP→ DIGA; $Y_1(DIGA) = \beta_0 X_0 + \beta_1 X_1 (HRAP) + C_1$)

H2: The first method: Simple regression equation

This equation (β_0= 11.58) shows that there were 11.58 changes in DIGA when HRAP was not functional. With each one unit change in HRAP, there were 0.067-unit changes noted, as is evident from (β_1= 0.067). The value of standardized beta (Standardized β= 0.734) was higher than 0.50, which means a high effect size. The standardized beta is also a test of effect size in the regression model. The T value (t=13.37) is seven times higher than the minimum acceptable value of T (1.96), indicative of high statistical significance. The correlation between HRAP and DIGA is 0.73 showing high positive two-way relations.

This correlation is also equal to standardized beta. The one regression relation of HRAPas the explanatory variable and DIGA and outcome variable is statistically significant at alpha value (α= 0.0001, p = 0.0000***) at a 99.9999% confidence interval.

The impact of HRAP on DIGA is 53% which is shown in the value of R square (R^2=0.53). It also means rest 47% of other factors are impacting DIGA apart from HRAP.Therefore, the standardized beta values, T value, effect size, Pearson correlation coefficient, R square, and P value suggest the high acceptance of hypothesis 2.

HRAP greatly influences the diagnostic analytics decision process (DIGA) (Table 4.3).

H2: The second method: Uses of the ANOVA test

The result of the ANOVA test is as follows. The sum of squares between groups with (df=1) is 717.58, and the sum of squares within groups (df=153) is 613.83. Thus, the calculated mean sum of the square between the group is 717.58 and within the group (613.83/153= 4.01). After dividing the mean sum of the square between the group and themean sum of the square within the group, we get the F test value (F= 178.86, df=1, 153). This F test is also a regression coefficient and residuals ratio, which is highly significant at (p=0.0000***).

The ANOVA test also confirms the positive effect of HRAP on DIGA in one way. Thus, the second hypothesis is accepted (H_2 : (HRAP→ DIGA; $Y_{1(DIGA)} = \beta_0 X_0 + \beta_1 X_{1\ (HRAP)} + C1$) with ANOVA test as well.

5. Conclusion and Recommendations

The evaluation of the major influence that the HR analytics process has on the decision-making processes is the primary purpose of this research. The current investigation operationalizes four separate decision-making processes, which are as follows: the descriptive analytics decision-making process; the diagnostic analytics decision-making process; the predictive decision-making process; and the prescriptive decision-making process.

After establishing the reliability and validity of prepared tools. We moved further on hypothesis testing.

We further separated the main goal into two hypotheses to better understand it. The first thing that we did was integrate two distinct outcome factors into a single predictor variable. This was the first step in our analysis. Then, after completing an exhaustive examination of the existing research pertinent to our investigation, we formulated two more hypotheses.

We put the hypotheses to the test using four different approaches, and we discovered that the outcomes of each approach were consistent with one another. This provides more evidence that the integrity of the data obtained utilizing numerous methods has been confirmed. We used procedures that involved two steps: (1) Carrying out a single linear regression with the use of SPSS, (2) Applying the ANOVA methodology within SPSS,

The conclusions are described briefly, answering each hypothesis.

1. H1: HRAP (HR analytics process) will significantly impact descriptive decision-making (DECA) in the home appliance manufacturing industry in Pune.

Conclusion-1: The HR analytics process (HRAP) significantly predicts descriptive decision-making (DECA). Therefore hypothesis 1 is accepted.

2. H2: HRAP (HR analytics process) will significantly impact diagnostic decision-making (DIGA) in the home appliance manufacturing industry in Pune.

Conclusion-2: The HR analytics process (HRAP) significantly determines diagnostic decision-making. Therefore, hypothesis 2 is accepted.

References

1. Sommer, F., Anderson, J. M., Bharti, R., Raes, J., & Rosenstiel, P. (2017). The resilience of the intestinal microbiota influences health and disease. *Nature Reviews Microbiology*, *15*(10), 630-638.
2. Delery, J. E., & Roumpi, D. (2017). Strategic human resource management, human capital, and competitive advantage: is the field going in circles? *Human Resource Management Journal*, *27*(1), 1-21.
3. Mishra, N. K., Singh, P., & Joshi, S. D. (2021). Automated detection of COVID-19 from CT scan using convolutional neural network. *Biocybernetics and biomedical engineering*, *41*(2), 572-588.
4. Tortora, D., Chierici, R., Briamonte, M. F., & Tiscini, R. (2021). 'I digitize so I exist'. Searching for critical capabilities affecting firms' digital innovation. *Journal of Business Research*, *129*, 193-204.
5. McCartney, S., & Fu, N. (2022). Bridging the gap: why, how and when HR analytics can impact organizational performance. *Management Decision*, *60*(13), 25-47.
6. Wang, L., Zhou, Y., Sanders, K., Marler, J. H., & Zou, Y. (2024). Determinants of effective HR analytics Implementation: An In-Depth review and a dynamic framework for future research. *Journal of Business Research*, *170*, 114312.
7. Ekka, B., Dhar, G., Sahu, S., Mishra, M., Dash, P., & Patel, R. K. (2021). Removal of Cr (VI) by

silica-titania core-shell nanocomposites: In vivo toxicity assessment of the adsorbent by Drosophila melanogaster. *Ceramics International*, *47*(13), 19079-19089.

8. Alsuliman, B. R. A., & Elrayah, M. (2021). The Reasons that affect the implementation of HR analytics among HR professionals. *Can. J. Bus. Inf. Stud*, *3*(2), 29-37.
9. BarNir, A., Gallaugher, J. M., & Auger, P. (2003). Business process digitization, strategy, and the impact of firm age and size: the case of the magazine publishing industry. *Journal of Business Venturing*, *18*(6), 789-814.
10. Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: why HR is set to fail the big data challenge. *Human resource management journal*, *26*(1), 1-11.
11. Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR Analytics. *The International Journal of Human Resource Management*, *28*(1), 3-26
12. Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: why HR is set to fail the big data challenge. *Human resource management journal*, *26*(1), 1-11.
13. O'Kane, H., Ferguson, E., Kaler, J., & Green, L. (2017). Associations between sheep farmer attitudes, beliefs, emotions and personality, and their barriers to uptake of best practice: The example of footrot. *Preventive veterinary medicine*, *139*, 123-133.
14. McCartney, S., & Fu, N. (2022). Bridging the gap: why, how and when HR analytics can impact organizational performance. *Management Decision*, *60*(13), 25-47
15. Pillai, R., & Sivathanu, B. (2020). Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations. *Benchmarking: An International Journal*, *27*(9), 2599-2629.
16. Levenson, A., & Fink, A. (2017). Human capital analytics: too much data and analysis, not enough models and business insights. *Journal of Organizational Effectiveness: People and Performance*, *4*(2), 145-156.
17. Simón, C., & Ferreiro, E. (2018). Workforce analytics: A case study of scholar–practitioner collaboration. *Human Resource Management*, *57*(3), 781-793.
18. Elia, G., Margherita, A., & Passiante, G. (2020). Digital entrepreneurship ecosystem: How digital technologies and collective intelligence are reshaping the entrepreneurial process. *Technological forecasting and social change*, *150*, 119791.
19. Van den Heuvel, S., & Bondarouk, T. (2017). The rise (and fall?) of HR analytics: A study into the future application, value, structure, and system support. *Journal of Organizational Effectiveness: People and Performance*, *4*(2), 157-178.
20. Bolger, N., Zee, K. S., Rossignac-Milon, M., & Hassin, R. R. (2019). Causal processes in psychology are heterogeneous. *Journal of Experimental Psychology: General*, *148*(4), 601.
21. Fitz-Enz, J. (2010). *The new HR analytics*. American Management Association.
22. Rasmussen, T., & Ulrich, D. (2015). Learning from practice: how HR analytics avoids being a management fad. *Organizational Dynamics*, *44*(3), 236-242.
23. Bassi, L. (2011). Raging debates in HR analytics. *People and Strategy*, *34*(2), 14.
24. Levenson, A., & Fink, A. (2017). Human capital analytics: too much data and analysis, not enough models and business insights. *Journal of Organizational Effectiveness: People and Performance*, *4*(2), 145-156.
25. Flythe, J. E., Assimon, M. M., Tugman, M. J., Chang, E. H., Gupta, S., Shah, J., ... & Zonies, D. (2021). Characteristics and outcomes of individuals with pre-existing kidney disease and COVID-19 admitted to intensive care units in the United States. *American Journal of Kidney Diseases*, *77*(2), 190-203.
26. Kluemper, D. H., Rosen, P. A., & Mossholder, K. W. (2012). Social networking websites, personality ratings, and the organizational context: More than meets the eye? 1. *Journal of Applied Social Psychology*, *42*(5), 1143-1172.
27. Ballinger, G. A., Cross, R., & Holtom, B. C. (2016). The right friends in the right places: Understanding network structure as a predictor of voluntary turnover. *Journal of Applied*

Psychology, *101*(4), 535.

28. Moore, P. V. (2019). Watching the watchers: Surveillance at work and notes for trade unionists. *International Journal of Labour Research*, *9*(1/2), 103-122.
29. Alsaab, H. O., Alghamdi, M. S., Alotaibi, A. S., Alzhrani, R., Alwuthaynani, F., Althobaiti, Y. S., ... & Iyer, A. K. (2020). Progress in clinical trials of photodynamic therapy for solid tumors and the role of nanomedicine. *Cancers*, *12*(10), 2793.
30. Selvaraj, A. M., & Rengamani, J. A STUDY ON THE ROLE OF HUMAN RESOURCE INFORMATION SYSTEM IN HUMAN RESOURCE PLANNING IN INDIA.
31. Roy, A., Ray, A., Sadhukhan, P., Naskar, K., Lal, G., Bhar, R., ... & Das, S. (2018). Polyaniline-multiwalled carbon nanotube (PANI-MWCNT): Room temperature resistive carbon monoxide (CO) sensor. *Synthetic Metals*, *245*, 182-189.
32. Xu, W., Cai, J. F., Mishra, K. V., Cho, M., & Kruger, A. (2014, February). Precise semidefinite programming formulation of atomic norm minimization for recovering d-dimensional ($d \geq 2$) off-the-grid frequencies. In *2014 information theory and applications workshop (ITA)* (pp. 1-4). IEEE.
33. Ore, O., & Sposato, M. (2022). Opportunities and risks of artificial intelligence in recruitment and selection. *International Journal of Organizational Analysis*, *30*(6), 1771-1782.
34. Kambur, E., & Akar, C. (2022). Human resource developments with the touch of artificial intelligence: a scale development study. *International Journal of Manpower*, *43*(1), 168-205.
35. McCartney, S., Murphy, C., & Mccarthy, J. (2021). 21st century HR: a competency model for the emerging role of HR Analysts. *Personnel review*, *50*(6), 1495-1513.
36. Johnson, R. D., Stone, D. L., & Lukaszewski, K. M. (2021). The future is now! Promise and pitfalls of artificial intelligence in human resource management. *Manuscript submitted for publication. Department of Management, Information Systems, and Entrepreneurship. Washington State University, Pullman, WA.*
37. McCartney, S., & Fu, N. (2022). Bridging the gap: why, how and when HR analytics can impact organizational performance. *Management Decision*, *60*(13), 25-47.
38. Malhotra, N. K., Mukhopadhyay, S., Liu, X., & Dash, S. (2012). One, few or many?: an integrated framework for identifying the items in measurement scales. *International Journal of Market Research*, *54*(6), 835-862.