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Organizational implementation of HCM Analytics: A Statistical study of factors affecting adoption

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ABSTRACT

Human Capital Management or HCM Analytics (hereafter "HCMA"), also referred to as workplace analytics, people analytics or quite simply HR Analytics, is the collection and analysis of large data sets associated with employee skill, performance and productivity using technology. This includes the application of those data-based insights to unlock improved organizational results. There exists significant research offering evidence that when correctly applied, HCMA technology can help improve all facets of the HCM lifecycle including recruiting, training and onboarding, performance evaluation and retention.

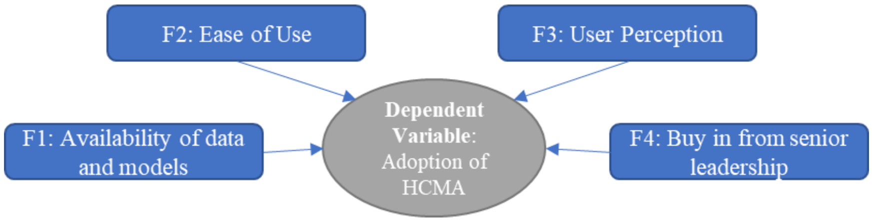
However, as Marler & Boudreau (2016) [1] observed, even though there is clear quantitative evidence of causality between use of data and analytics in HCM and employee as well as company performance, there is poor adoption of such tools and practices and research around this subject is scarce. Therefore, this research paper starts with the assumption that HCMA is beneficial to organizations and attempts to understand adoption of digital HCM practices among HR managers and quantify the relationship between adoption and its drivers. For the purpose of this study we have focused on HR Managers in the state of New York.

KEYWORDS: Human Capital Management, HCM, Analytics, HCM data, Workforce Analytics, Technology

1. INTRODUCTION

HCMA allows HR Managers to make data-backed decisions that are statistically proven to improve the quality of outcomes (Jones 2014 [2]). Momin and Mishra [3] argue for HCMA to be seen as a 'strategic workforce planning' tool that allows organizations to gain a measurable competitive advantage while Tomar and Gaur [4] conduct a literature review of the different organizational areas where HCMA can create a financial impact as measured by key performance metrics and indicators. This paper intends to go one level deeper to understand the reluctance of companies and individuals to rely on HCMA.

In order to do this, we first outline potential factors (Fx) that could impact adoption of HCM analytics into four distinct categories as follows: Availability of data and models (F1), Ease of use (F2), User perception (F3), buy-in from senior leadership (F4). This will also serve as our independent variables while the dependent variable is 'Adoption of HCMA'. We arrived at these factors through an extensive literature review including Zeidan and Itani's [5] work on impact of HCMA on organizational effectiveness, Alsuliman and Elrayah's [6] study of the reasons affecting HCMA implementation and Fernandez and Gallardo-Gallardo's [7] research on barriers to HCMA use.



Below, we define and break down each of these factors.

Availability of Data and models: HCMA uses large amounts of complex employee big data drawing from studies, surveys, employee user patterns, emails, performance evaluations, attrition patters etc. which can lack structure and be hard to derive insights from. This necessitates advanced data processing and analysis software that can break this down in a way that is useful for HR managers. Finally, the data and insights must also be relevant to the business or industry that the organization operates in and not all businesses have this data available in house or the ability to process data at this scale internally.

Ease of use: This factor essentially looks at how easy or difficult it is for an HR Manager to use the HCMA tools available to them. The best HCMA platforms are fully integrated with other organizational databases and enterprise management systems such as performance and payroll. They allow quick processing of large amounts of complex and unstructured data as well as easy interpretation of results instead of simply dumping data on HR managers. They should not require additional skills or training to effectively leverage them and correctly interpret findings. This factor answers questions like: "Is the tool intuitive or does it require incremental analysis to draw the necessary insights?" and "Is it a seamless experience offering one-stop shop solutions or does the user need other platforms to supplement decision making?"

User Perception: This answers the question of how likely is an HR Manager to use the HCMA tools available to them. A great HCMA system will be perceived by users as effective and better at decision making than human intuition. Credibility of results and how much HR managers trust them is essential. This factor answers questions like: "If insights from HCMA clash with HR Managers' understanding of how things should operate or what they have learned in their years of experience would they ignore the data or blindly trust it?" and "Do users perceive available tools as archaic or an inadequate reflection of the needs of modern personnel management?"

Buy in from leadership: Adopting big data in HCM practices requires a stark change in organizational culture that can often be met with resistance unless it comes from senior decision makers. McAfee & Brynjolfsson (2012) [8] introduced the concept of 'HIPPO' or 'highest paid person's opinion' and went on to argue that change can only be carried out when it is pushed top down in the org structure. This factor analyzes the role played by senior leadership in creating an organizational culture that values data-based decision making and attempts to eliminate human biases, stereotypes and intuitive decision-making. HCM as a function tends to hold a peripheral organizational position as a cost center rather than a revenue generating center essential to business. Therefore, in order to move towards adopting data driven HCM practices, significant amount of financial and human resources must be invested which makes 'buy-in from leadership' a crucial factor.

2. METHODOLOGY

In order to determine the relationship between the factors outlined above and HCMA implementation in an organization we decided to leverage hypothesis testing. In order to do this, we first quantify both our independent and dependent variables. We will measure our dependent variable i.e. 'organizational implementation of HCMA' as a binary outcome of 1 or 0 based on whether or not they employ HCMA tools and practices within their organization. Separately, we formulated our questionnaire so that each HR Manager surveyed can be assigned a score out of 10 for how each factor (Fx) impacts this outcome within their organization. This was done so we could easily compare correlation between factor scores and the dependent variable and quantify this relationship. Further, we define our hypothesis and null hypothesis respectively as:

H1: There exists a relationship between Fx and organizational implementation of HCM analytics

H0: There exists no relationship between Fx and organizational implementation of HCM analytics
Finally, we outline our approach to data collection. In order to determine the right sample size to survey, we follow SM Smith's [9] approach as follows:

$$n = \frac{n_0 N}{n_0 + (N - 1)} \quad \text{where} \quad n_0 = \frac{Z^2 \sigma^2}{e^2}$$

Here, N refers to our total population size, σ is the standard deviation which reflects the expected variance in our survey responses, z is the z-score associated with our assumed confidence level and e is the margin of error or confidence interval. For the purpose of this research we selected a 90% confidence level which gives us a z of 1.645, a 7% margin of error and a standard deviation of 50%. Our total population or N is 10,440 which is the total number of HR managers in the state of New York as per the US Bureau of Labor Statistics [10]. Using Smith's formula, we arrive at a required sample size of 138 or larger. The actual sample size of this study was 154 HR managers spread across the state of New York who completed our questionnaire-based survey. The survey was administered using the Qualtrics survey platform shared with them via email, text message and LinkedIn. In some cases, survey responses were also recorded over the phone. Once all responses were received, we used the Qualtrics statistical analytics tools to process results and gain insights.

3. RESULTS

We ensured a diverse sample that would be truly representative of the population. An analysis of the demographic characteristics of the 154 survey respondents is presented below.

Race	**% respondents**
White	68%
African American	15%
Asian	9%
Hispanic	4%
Other	2%
Did not disclose	2%
Gender	**% respondents**
Female	65%
Male	35%
Non-Binary	0%
Age Group (years)	**% respondents**
<30	2%
30-40	41%
41-50	32%
51-60	22%
>60	3%
Education Level	**% respondents**
High School or equivalent	2%
Diploma	5%
Bachelor	54%
Masters	39%
Doctorate	0%
Location	**% respondents**
New York City	74%
Rest of New York State	26%
Years of experience in HCM	**% respondents**
0-5	5%
5-10	35%
10-15	47%
15-20	7%
>20	6%

We were able to sample an experienced set of HR managers, 82% of whom had between 5 to 15 years of experience in the field. Over 93% held an advanced degree (either a bachelors or masters). The demographical composition of our sample broadly reflects that of the residents of New York State which in turn is assumed to be representative of our population (HR Managers in New York State).

Next, we review the findings from a statistical analysis of our survey results. We measured the Pearson Correlation Coefficient as well as used logistical regression to quantify the relationship between our dependent and independent variables.

	Independent Variables			
	Availability of data and models	Ease of Use	User Perception	Buy in from senior leadership
Correlation Coefficient	0.6659	0.7629	0.5397	0.6774
Sample Size	154	154	154	154
Degree of freedom	153	153	153	153
T-stat	8.5561	7.9981	8.2236	9.7715
P-value	0.001	0.001	0.002	0.001

Results from logistical regression:

		coefficients	P-value
	Intercept	0.849	
Fx1	Availability of data and models	1.7269	0.0013
Fx2	Ease of Use	0.8446	0.0164
Fx3	User Perception	0.2655	0.0268
Fx4	Buy in from senior leadership	1.2643	0.0130

We also analyzed the scores that respondents assigned to each factor based on how much it influences HCMA adoption. Below we present the mean scores and standard deviations associated.

Factor influencing HCMA Adoption	Minimum Score	Maximum Score	Mean	Standard Deviation
Availability of data and models	1	10	8.37	1.03
Ease of Use	1	10	6.49	1.98
User Perception	1	10	6.22	1.24
Buy in from senior leadership	1	10	7.51	1.37

We observe that all four of our independent variables or factors (Fx) have a positive relationship with the dependent variable. Correlation coefficients of 0.5 and above signify that there is a strong positive correlation between the two. The small p-values close to 0 tell us that this relationship is statistically significant. Our logistical regression confirms these results with positive and non-zero factor coefficients. This means we can reject our null hypothesis and conclude that our Independent Variables are strong influencers of HCMA adoption in organizations. Two factors stood out as particularly strong influencers of HCMA adoption with their high Pearson correlation coefficients as well as positive regression coefficients – 'availability of data and models' as well as 'buy in from senior leadership'. The main concerns driving these included insufficient real-time employee data and the presence of various HCM databases and interfaces that are poorly integrated and don't talk to each other. Many of these tools are also out of touch and do not reflect new age technologies around predictive analytics and big data processing using AIML making their use redundant. Finally, 84% of respondents called out management support as the biggest driving factor of resource prioritization and whether an organization is willing to invest in HCMA. Next, a qualitative deep dive into survey results revealed key contributing factors as 1) high capital expenditure required for establishing digital HCM tools and processes, 2) a lack of skills, training, knowhow and competencies among HR managers around leveraging and correctly interpreting/using them, 3) the degree to which the company values retention and employee satisfaction, 4) the ability to directly attribute better HCM processes and decision making to organizational results, 5) Institutional resistance to change and associated perceptions around whether or not HCMA even adds value and justifies the capital and training costs, not to mention data and privacy ethics concerns. These concerns and barriers could be alleviated by 1) Using services that provide pooled and anonymizing data across organizations thereby reducing costs and privacy concerns, 2)Establishing a centralized HCM Analytics function that is separate from the rest of the organization and is staffed with highly skilled, trained talent operating under clear guidelines, structure and expectations, 3) Training HR managers about the benefits of data driven decision making and sharing trends and real life impact of them on employee performance and satisfaction.

4. CONCLUSION

This study succeeded in establishing a positive causal relationship between organizational implementation of HCM analytics and its four key influencing factors as identified by us at the start of the study. In addition, we gained insights around challenges faced by companies and HR managers in adopting digital HCM practices and reviewed opportunities to reduce or eliminate these barriers. As a next step, we'd be conducting a deeper analysis of which specific steps or processes are the most effective in lifting each of these individual barriers.

We expect this study to serve as a foundational tool for institutions, senior leaders and HR managers to preempt these barriers and respond to them early and effectively for an integrated data driven approach to people management. We recommend expanding this study to a larger sample size for a deeper understanding of causality between the different aspects of HCM analytics and user behavior. Another way to build on this research would be to introduce additional factors impacting adoption or studying user behavior in different geographies, scale of industry and demographics.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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