

## ABSTRACT

Industry is propelled by measurement and the transformative potential of data analysis as a driver of business success. Human Resource (HR) departments have not escaped this impetus, indeed it has gained momentum over the last decade. The promise of analytics is significant: to replace gut and intuition with data-based decision making and evidence-based strategies. HR analytics hails itself as a framework to temper HR intuition with objectivity. It promises rigour and validity to guide and prioritise human capital expenditure. Despite enormous interest, evidence of practical application has been scarce. This research adopts an inductive, interpretivist approach, using multiple case studies of Irish manufacturing firms, underpinned by interviews with HR Managers and industry experts. It contributes to research and practitioner knowledge with insights of industry led practical applications of HR analytics and the levels and application of HR analytics within companies. Furthermore, it reveals the factors impacting application outcomes in firms.

## INTRODUCTION

Analytics has been described as a ‘must have’ capability for the Human Resources (HR) profession, a tool for creating value from people, and a pathway to broadening the strategic influence of the HR function (Chartered Institute of Personnel Development, 2013). An increased desire for more strategic HR, has brought with it an equally rapid rise in demands and expectations for HR measurement (Boudreau, 2006). There is a “desire for strategic HR with measurements that are beyond operational reporting but support key decisions about human capital that drive organisational effectiveness” (Parry & Tyson, 2011:351).

However, there is currently a lack of knowledge pertaining to what HR data is being used for, how it is being applied, and what factors affect the application outcomes. There is also a dearth of research in this field, with academic literature only beginning to emerge (Angrave, Charlwood, Kirkpatrick, Lawrence, & Stuart 2016). The literature which does exist is scant and limited in scope (Rasmussen & Ulrich, 2015). The HR response to the materialisation of literature on HR analytics has been a fervent wish to engage, but with an uncertainty as to how to apply these methods in practice (Angrave et al., 2016). Herein exists an opportunity to investigate the levels and practical application of HR data analytics (DA). Angrave et al. (2016) are disparaging of academic writing in its attention to what should be done, as opposed to an explanation of how it can be achieved, and to what end, and in which situations. Thus, there is a gap to be addressed in investigating HR analytics, and what ought to be done, in what way it should be done, and in what circumstance. In this context, Rasmussen and Ulrich (2015) urge HR to connect business related findings to published research, and to make known what is unearthed during the investigation. Rasmussen and Ulrich (2015:238) state, “so far the published evidence supporting the alleged value of HR analytics is actually quite slim; it is currently based more on belief than evidence”. This exposes an opportunity for research which connects with the practical application of HR analytics and the factors which may impact the application outcomes.

In order to address this gap in research and to bridge the lack of knowledge from both practical and theoretical perspectives, the objective of this research is *‘to investigate the level, application, and outcomes of Human Resources Data Analytics in manufacturing firms in Ireland’*. To undertake the objective, three research questions were developed:

1. What level of Human Resources Data Analytics capabilities exist in manufacturing firms in Ireland?
2. How is Human Resources Data Analytics being applied in manufacturing firms in Ireland?
3. What factors impact application outcomes of Human Resources Data Analytics in manufacturing firms in Ireland?

An extensive review of the literature was conducted and a number of key concepts meriting study emerged. A review of existing research design and a careful consideration of the needs of the study led the researcher to develop a multiple case study research method in order to investigate the phenomenon in contextual settings. The case studies were conducted in three manufacturing companies based in Ireland. The purpose of the case studies was to identify the HR DA capabilities, to ascertain how they are being applied, and to uncover what factors impact application outcomes. This research responds to Angrave et al. (2016), Rasmussen and Ulrich (2015) and Marler and Boudreau (2017) calls for evidence of the application of HR DA in practice. The study provides rich contextual insight into HR DA applications in manufacturing firms in Ireland and supports the current dearth of literature.

## LITERATURE REVIEW

### **Evolution and Definition of Human Resource Data Analytics (HR DA)**

In 1984, Jac Fitz-enz published a book entitled, ‘How to Measure Human Resources Management’; thirty four years later, the field of Human Resource Data Analytics (HR DA) seems to finally be giving life to his work. Data Analytics (DA) has been studied for many years under the guise of mathematics and statistics (Holsapple, Lee-Post, & Pakath, 2014), and as the field of analytics has evolved so too has its application to each of the business functions. However, the HR function

is trailing behind in its embrace of analytical expertise and HR DA remains an emerging field (Marler & Boudreau, 2017; Angrave et al., 2016).

A number of varying definitions have been proposed for HR DA by CIPD (2016), Angrave et al. (2016), Fitz-enz (2010) and Boudreau and Ramstad (2006). However, the definition of HR DA adopted for the purposes of this study by Marler and Boudreau (2017) acknowledges its evolution which now includes larger volumes of data, incorporating the use of visualisation tools to convey results while also emphasising the interpretation and perceptive articulation of data results through HR practitioners. Marler and Boudreau (2017) define HR DA as “*a HR practice enabled by IT that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organisational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making*”.

### **Relevant Research Models and Frameworks**

Three frameworks relevant to this study dominate the literature:

1. Rasmussen and Ulrich (2015) propose a diagnostic framework suggesting the process commences with questions surrounding context, stakeholders, and strategies.
2. Harris, Craig, and Light (2011) propose a ‘Ladder of Analytical HR Applications’, an assortment of analytical methods applied in consecutive order.
3. Boudreau and Ramstad (2006) propose a framework entitled ‘LAMP’ to enable HR professionals to create a meaningful strategic difference when using HR measurements.

Although the LAMP model is one of the earliest proposed, it is a highly regarded academic model created specifically for this discipline, and it still remains enormously relevant in the context of the literature over the past ten years (Marler & Boudreau, 2017).

### **Levels of Application of Human Resource Data Analytics (HR DA)**

Many multinationals who have invested significant resources in embedding HR DA within their organisations and the HR function have testified that progression beyond historical data analysis has been limited (CAHRS, 2014a). The CIPD (2013) suggest that organisations can employ HR DA at three levels: (1) basic analytics; (2) multidimensional data analytics, and (3) predictive analytics to discover concepts and apply modelling systems to their business. However, most of the HR DA examples provided in the literature seldom echo rich bottom line impact but speak of narrow focused endeavours such as turnover predictions (Rasmussen & Ulrich, 2015). Limited levels of predictive analytics exist and there is scant evidence of prescriptive analytics being applied (Pape, 2016). It appears that effort is all too frequently dispensed on descriptive input measurement such as training hours instead of predictive and prescriptive output measurement such as incremental improvements in labour productivity post training event (Harris et al., 2011).

Ulrich (2016) suggest that significant opportunities lie with HR DA when the HR function move from transactional and administrative activities, to strategic outcome driven HR actions. Angrave et al. (2016) make assurances that organisations who embrace and apply strategic HR DA will outperform their competitors and that HR DA will emerge as a critical source of competitive advantage. Rasmussen and Ulrich (2015) suggest that the potential benefits of HR DA deployed strategically are inordinate. Similarly, Maisel and Cokins (2015) contend that while at one time analytics was considered a discretionary undertaking, it is now not only a competitive advantage but a business critical factor. Intuition can also help to evolve DA, by combining DA and intuition more effective decision outputs can be reached, particularly regarding strategic evaluations (Ransbotham, Kiron, & Prentice, 2016).

However, while HR DA should be driven by the challenges faced by the business unfortunately, it tends to start with the data rather than the problem (Rasmussen & Ulrich, 2015). When DA is driven by push and not pull there is a probability that it will yield little financial return but remain as little more than ideals (Rasmussen & Ulrich, 2015). To establish relevancy Rasmussen and Ulrich (2015) advocate the need to expand HR DA and transcend the functional boundaries, to integrate existing end to end organisational systems so as to achieve an ‘outside in’ approach.

### **Application of Human Resource Data Analytics (HR DA) in Practice**

There exists a necessity to glean intelligence, insight and deductions from the wealth of internal and external data accumulated by companies’ technologies (Maisel & Cokins, 2015). A penchant towards DA has developed within the HR function according to Pape (2016), with Human Resource Information Systems (HRIS) such as Work Day, Success Factor, Org Vue and Fusion proliferating the marketplace. Predominantly, organisations deploy interpretive tools for novice users which remove the requirement for statisticians to uncover insights (Maisel & Cokins, 2015). Angrave et al. (2016) propose that these HRIS characteristically offer solutions to a narrower set of demands which are determined by operational reporting.

While articles in practitioner outlets and consultancy reports with respect to HR DA are becoming more prevalent, the content can be repetitive and it often lacks rigorous scientific investigative evidence of practical applications (Schoenherr & Speier-Pero, 2015). Furthermore, managers who embrace HR DA often perceive the benefits to be greater than the

tangible outcomes (Troilo, Bouchet, Urban, & Sutton, 2016). Further evidence of this arose in a study by Pape (2016), who found evidence of HR departments collecting little data aside from what was already at their disposal in traditional Human Resource Information Systems (HRIS) despite their belief that they had performed analytics. A disconnect also exists concerning the evidence of positive business outcomes and the choices made to embrace and apply HR DA (Marler & Boudreau, 2017).

### **Factors Impacting Application Outcomes of Human Resource Data Analytics (HR DA)**

The advancement HR DA compels a ‘decision science’ that informs and enhances results (Boudreau, 2006). The answer for HR must commence with the question of how HR DA can be used to generate, manipulate and safeguard value (Angrave et al., 2016). The root of HR DA must be in the understanding and the context of the source to determine its meaning, as it is what necessitates ‘logic-driven’ analytics (Boudreau & Jesuthasan, 2011).

Marler and Boudreau (2017) conducted a comprehensive review of fourteen recent peer reviewed articles and identified three significant factors which effect HR DA application outcomes. These include (1) practitioner analytical skills (Angrave et al., 2016; Bassi, 2011; Giurida, 2014; Levenson, 2011; Mondare, Douthitt, and Carson 2011; Rasmussen and Ulrich, 2015), (2) achievement of management buy-in (Coco, 2011; Giurida, 2014; Levenson, 2011; Rasmussen and Ulrich, 2015), and (3) IT capabilities (Angrave et al., 2016; Aral, Brynjolfsson, & Wu 2012; Douthitt & Mondore, 2014), (Marler & Boudreau, 2017). These factors are considered key to impacting on HR DA outcomes and were adopted for this study.

### **RESEARCH GAP**

The HR response to the materialisation of literature on HR DA has been a desire to engage but an ambivalence as to how to apply these methods in practice (Angrave et al., 2016). Falletta (2014) also identifies a gap in evidential knowledge of industry. Herein exists an opportunity to investigate the levels and practical application of HR DA. Angrave et al. (2016) are disparaging of academic writing in their attention to what should be done, as opposed to an explanation of how it can be achieved, to what end and in which situations. The prevalence of articles and consultant reports has grown but the content remains repetitive and lacking both comprehensive and thorough investigation (Schoenherr & Speier-Pero, 2015). Thus, there appears to be a gap to be addressed in investigating HR DA and what ought to be done, in what way it should be done and in what circumstance. According to Rasmussen and Ulrich (2015:238), “*so far the published evidence supporting the alleged value of HR analytics is actually quite slim—it is currently based more on belief than evidence*”. A critical gap in the literature evidenced in Rasmussen and Ulrich’s (2015) statement is the lack of evidence supporting the application outcomes of HR DA. This research contributes to addressing this gap.

### **RESEARCH METHOD**

The case sample followed a structured theoretical sampling plan. The three firms selected were determined by prior investigation through document analysis, exploratory and an interview with a HR DA industry expert. This formed the selection criteria for the participant companies. Additional information was garnered from exploratory telephone interviews with five field specialists, coupled with an in-depth personal interview with an industry expert in the field of HR analytics. The HR DA industry expert is a CEO of an Irish DA firm working in the field of HR revealed use of HR DA to a predictive level exclusively. These interviews offered a scaffold of insights and information for the case study data collection which followed. Semi structured personal interviews were conducted with Human Resources Managers on site for each case study. The research was carried out over a five month period in 2017. The case study sites included Pharmaceutical, Food, and Nutritional manufacturing firms located in Ireland.

### **RESEARCH FINDINGS**

At the Food manufacturing company substantial evidence of descriptive level analytics was unearthed, coupled with examples of multidimensional analytics combining accident, performance and recruitment data investigating relationships among the differing elements. Predictive levels determining causality were not evident. The application of HR DA was apparent for length of service, headcount, accidents analysis, performance review scores, time to hire analysis as well as absence reporting. Data insights were perceived as a positive addition to the HR function, supporting credibility of HR intuitive decision making at the firm. A gap in HR analytic skills was considered to be a detrimental factor for positive analytic outcomes at the site. The HRIS was felt to be restrictive and excel was relied upon for data manipulation. The firm noted a requirement for awareness and multifunctional strategic engagement to enable HR DA to be effective.

Investigation of the level of analytics employed at the Nutritional manufacturing firm exhibited routine use of descriptive analytics. There was an emergence of multidimensional analytics for absence investigation, but no predictive levels were manifest. Application of HR DA included turnover reporting, budgetary monitoring, training analysis, illness and performance review as well as diversity analysis. Practitioner skill was noted to be crucial in interpreting and extracting

outcomes from data. The HRIS was found to be both useful and effective. The case study analysis revealed constraints on HR time, people resources and financial investment to be negatively affecting application outcomes.

Descriptive analytics were used in the Pharmaceutical manufacturing firm on a routine basis. Multidimensional analytics were recurrently used for succession planning, employee satisfaction analysis, success of hires, and to explore other relationships at the site. The exploratory interview revealed that technology to apply analytics at a predictive level is being developed at group level. Applications of analytics included, turnover reporting, post course assessments, compliance metrics, training misses, success of hires, candidate satisfaction, time to fill vacancies, performance and leadership ratings and headcount. Strategic analytics was predominant in the firm, as was multifunctional engagement with HR DA. This was evidenced on several occasions during the study. This strategic multifunctional engagement was cited as a positive resource enabling the application of HR DA outcomes.

A predominance of basic analytics was evident in each firm. Application of HR DA manifested in each case study as descriptive data primarily reporting historical statistics. However, multidimensional data was used regularly in the Pharmaceutical and Food firms and was beginning to emerge in the Nutritional firm. The findings relating to factors impacting application outcomes were consistent across each manufacturing site.

Interviews with the HR DA industry expert noted the restrictive nature of excel capabilities for HR DA, which significantly contrasted with the reported experiences of each HR Manager. Similarly, only the industry expert was engaged with predictive HR DA. The HR DA industry expert constructs algorithms and automate processes to generate data output and insights. They use correlations and causality to produce data generating organizational awareness. The expert cited automation as enabling HR to gain data insights freeing up their time to use their soft skills to remain connected to their employees. HRIS and excel were deemed to be inhibiting factors of positive application due to their restrictive functionality.

## DISCUSSION

Exploration of the levels of HR DA in practice reflect a predisposition towards inward looking descriptive analytics. Only the industry HR DA expert DA demonstrated exclusive predictive level analytics This reflects the literature assertion that there is a bias towards the application of descriptive level of analysis by practitioners (Pape, 2016) and supports findings by Kapoor and Sherif (2012), Angrave et al. (2016) and Bassi and McMurren (2016) who suggest that HR departments are trailing other functions in DA implementation.

Minbaeva, (2017) submits that HR have struggled to move from operational statistics, to analysis of causality and generation of actionable insights. The study findings concur with that assessment and are displayed in Figure 1.0. The evidence exposes a predominance for operational, inward-looking data. The HR DA industry expert however, revealed analytic applications which focused on solutions for explicit business challenges. Hueslid (2018) endorses concentration on a few key analytic variables which aid decision making, rather than collection of a range of ineffectual generic statistics.

**FIGURE 1**  
**Evidence of Human Resource Data Analytics (HR DA) in Practice**

| HR DA Industry Expert   | Food Manufacturing Firm  | Nutritional Manufacturing Firm   | Pharmaceutical Manufacturing Firm   |
|---|--|--|---|
| <ul style="list-style-type: none"> <li>•Predicting Turnover</li> <li>•Predicting Training Needs</li> <li>•Understanding Aspirations/Interests</li> <li>•Prescreening automation</li> <li>•Analysis of passive applicants</li> </ul> | <ul style="list-style-type: none"> <li>•Reporting Headcount</li> <li>•Logging Starters/Leavers</li> <li>•Analysing Accidents</li> <li>•Comparing Performance Reviews Scores</li> <li>•Reporting Length of Service</li> <li>•Analysing Time to Hire</li> <li>•Analysing Quality of Hires</li> <li>•Reporting Absence</li> </ul> | <ul style="list-style-type: none"> <li>•Payment of wages</li> <li>•Reporting Turnover</li> <li>•Reporting Absences</li> <li>•Monitoring Budget</li> <li>•Training Analysis</li> <li>•Analysing Sickness</li> <li>•Performance Reviews</li> <li>•Logging industrial relations indicators</li> <li>•Analysing Diversity</li> </ul> | <ul style="list-style-type: none"> <li>•Reporting Turnover</li> <li>•Post course assessments</li> <li>•Compliance Metrics</li> <li>•Training Misses</li> <li>•Success of Hires</li> <li>•Candidate Satisfaction</li> <li>•Time to fill</li> <li>•Performance and Leadership ratings</li> <li>•Headcount</li> <li>•Absenteeism</li> <li>•Predictive succession Planning</li> </ul> |

Overall, the findings largely support Marler and Boudreau's (2017) contention that three significant factors effect HR DA application outcomes, namely, practitioner analytical skills, achievement of management buy-in and IT capabilities. With respect to IT capabilities, Angrave et al. (2016), Rasmussen and Ulrich (2015) and Aral et al. (2012) cite the restrictive and inadequate scope of HRIS dashboards. However, this study reveals mixed results in this context from practice. While one respondent is complementary of a number of HRIS which allow data manipulation within the systems, other respondents describe HRIS as restrictive while others only use it to extract data for analysis/correlation elsewhere such as through MS Excel. However, the HR DA industry expert considered excel too limited a tool to be used effectively in HR DA.

The findings also suggest an extension to the categorization of practitioner analytical skills and achievement of management buy-in.

### **Practitioner Analytical Skills**

The influence of intuition and gut feeling was also found to be a significant impacting factor and was consistent across all respondents. Intuition and gut feeling was reported to have occurred in conjunction with use of practitioner analytical skills. As this evidence was so compelling, the themes of intuition and gut feeling were combined practitioner analytical skill and re-categorized as "practitioner analytical and interpretive skills" in the study findings. There is some evidence to support this contention in the existing literature, as Ransbotham et al. (2016) suggest intuition may help evolve HR DA and result in more effective strategic evaluation outputs.

### **Management Buy-In**

Marler and Boudreau (2017) categorized the achievement of management buy-in as a significant factor affecting the outcome of HR DA. The findings suggest moving beyond simple attainment of management buy-in, to employing a more strategic focus to bolster the impact of HR DA. The extrapolations also emulate the expectations of the study and the opinion of many seminal writers on the subject, that outcomes are not limited to management buy-in but to an organisational wide strategic analytic perspective. This is evidence to suggest support this contention in the literature as Ulrich (2016) and Rasmussen and Ulrich (2015) assert that impactful HR DA has more to do with business strategy than to the component data configurations. Thus, this study extends the parameters of this to a more organisational wide strategic analytic perspective.

Additional factors revealed in the findings as having a significant impact on HR DA included financial, people and time resources.

## **LIMITATIONS**

The field of HR DA is a relatively new and unexplored. While this makes research exciting, few individuals felt they had sufficient knowledge to make substantive contribution to the research and were reluctant to be involved beyond an informal discussion on the topic. Thus, significant difficulty was encountered in securing cases to be studied and expert interviews. Secondly, while this research was conducted with three case studies and an in-depth expert interview, a larger number of respondents in diverse size of organisations would bring greater validity and credibility addressing the impact of IT capabilities on HR DA.

## **RECOMMENDATIONS AND CONCLUSIONS**

Based upon the findings of the research the following practical recommendations can be considered:

1. HR practitioners should gain a greater awareness of the potential applications and benefits of HR DA to enable a progressive interpretative approach to DA.
2. Due consideration should be given to accessing the support of external analytic providers to accelerate learning and implementation to predictive levels where these resources do not already exist within the firm.
3. HR DA should be used strategically to address strategic business problems and be implemented in a multi-functional way, engaging other departments in converting data driven decisions to tangible business outcomes.

As the field of HR DA is relatively new in Ireland it is recommended that studies could be extended to the international arena where more evidence of HR DA exists. Researchers are encouraged to replicate this study and focus on what is being done, to what extent, in what contexts and with what results. Indeed, Minbaeva (2017) suggests organisations should explore what levels and through which mechanisms analytics should be designed as a capability. Future case studies could also focus on firms who are currently analytical innovators, which would reveal greater insight for others and offer evidence of practical application of HR DA. The study findings highlighted the need for further research into the factors which are impacting the application outcomes. These are addressed in a very limited manner in existing literature. Regardless of where an organization is on the HR analytic journey, Van der Togt and Rasmussen (2017:131) assert that "in a world where we have more access to a wider set of data, including data about people and their behaviors, HR analytics offers an opportunity to get better HR for less".

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