Types of HR Analytics Used for the Prediction of Employee Turnover in Different Strategic Firms with the use of Enterprise Social Media

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Abstract

In the era of data science and big data analytics, HR analytics can help organizations and their human resources (HR) managers to predict reason behind the employee exits and reduce attrition rate and employee turnover at an early stage. Organization invests lot of time and money in hiring and training their workforce. Thus, when they leave the job, the reduction of cost of capital is borne by the company. In this context, employee turnover presents a serious problem and a big peril for organizations as it affects not only their productivity but also their planning continuity. To overcome this, HR Analytics is the most important tool for organization to gain insights out of big data, collected from different sources (e.g. public social media, enterprise social media, Internet of Things etc.) to reduce employee turnover. From static to descriptive, descriptive to diagnostic, diagnostic to predictive, predictive to prescriptive type of HR analytics has come a long way.

This research attempts to explore that organization apply different types of HR Analytics in different business strategy firms, with/ without the use of social media / enterprise social media (ESM) for the prediction of employee turnover. (Porter 1980) competitive business strategy includes cost leadership (CL) strategy, differentiator (DIFF) strategy and focus. By using statistical test chi-square, we conclude that there is significant difference between various strategy types and types of HR Analytics used in the organization for prediction of employee turnover with the use of ESM.

Keywords

Business Strategy, Data Analytics, Enterprise Social Media, Employee Turnover, Type of HR Analytics.

Introduction

The phenomenon of employees leaving the company is referred to as employee turnover, employee attrition, and churn rate. When employee leaves the organization, type of attrition depends on how they are leaving involuntary or voluntary or after retirement (McQuerrey 2019).Voluntary attrition is caused by the employees' who owns their decision to leave a company. While in involuntary attrition, a company might have to reduce workforce or replace the employee.

Employee turnover is a major worry for businesses, especially in today's competitive climate, when people are the most valuable asset. Depending on how difficult it is to fill the employees' role (Sesil 2013), the cost of voluntary employee churn can range from 1.5 to 5 times the employee's annual salary. However, because the loss of one person may have an impact on ongoing projects or services, this is only a small part of the entire cost to a business. It could, for example, cause customer and other stakeholder unhappy (Saradhi and Palshikar 2011). It could result in the loss of a company's network or other critical information, especially if an experienced long-term employee leaves. It may also have an impact on other employees, who must cover the task of the individual who has left the company.

Furthermore, it takes time for a new employee to achieve the same level of competence and productivity as the preceding person.

Data is collected through various social and enterprise social networks, about employee, allowing analytics to emerge as a viable alternative to fight employee attrition. HR can also benefit with the arrival of analytics, if implemented in correct manner (Rasmussen and Ulrich 2015). HR specialist are familiar with conventional HR indicators like turnover and retention rates, but a more complex analysis may offer more insights. Together, descriptive methods and qualitative analysis are effective methods for managing human resources in a small and/or medium business. However, for large and multi-national companies, this approach can be unmanageable. This gap created need for rise of analytics in human resource area.

Consultants define HR Analytics (HRA) as the use of statistical techniques to analyze HR practices and managerial performance (Lawler III et al. 2004), a valuable tool in decision-making for HR (Bassi 2011) with direct impact of employee data on business (Mondore et al. 2011) and monitoring of individual performance (Aral et al. 2012). Human Resource Analytics (HRAs) are viewed by academics (and business practitioners) as a fad when adopted without analyzing its necessity or the availability of appropriate data (Rasmussen and Ulrich 2015); (Angrave et al. 2016). As suggested by the authors, a business problem should be established and resources allocated based on need, while HRA and HR work separately and toward a common goal, thus allowing HR to focus on the human side, while HR specialists are trained to have an analytical mindset (Rasmussen and Ulrich 2015).

Due to digitization, torrents of data is collected from different sources (e.g. Mobile phones, social networks, enterprise networks, IOT, wearables etc). Organizations have accumulated more data as a result of the installation of Human Resource Information Systems (HRIS), which has yet to be fully utilised. Staff Churn Analytics is a method of assessing employee turnover rates in order to anticipate future churn and reduce it. Certain tools, such as the Employee Satisfaction Index, Employee Engagement Level, and Staff Advocacy Score, can help with this. Exit interviews and surveys are also useful tools. Thus, in recent years, there has been an increase in interest in conducting research on employing predictive / prescriptive analytics for employee turnover, where data about employees may be obtained in an unrestricted manner from Social / Enterprise Social Media.

The decision makers are now making better decisions by utilizing Human Resource Information Systems (HRIS) in organizations. The HRIS data has primarily been used to report simple descriptive statistics and correlations. The use of advanced data analytics, i.e., predictive and prescriptive, has been proven in other areas such as sales, marketing and finance for better results, However, advanced data analytics are largely underutilized in Human Resources. For example, to reach a broader base of customers or reduce the risk of investments. Russell and Bennett (2015) also suggested that this is mainly because many of the relevant variables in the Human Resources area, for example, personality, is difficult to measure. Secondly, due to lack of skilled HR professionals, employers struggle to develop useful reports from HR's social media data, despite the fact that monitoring social media has become standard. Sinha et al. (2012) explain from a behavioural standpoint, the way organisations can use social media analytics as a useful assessment tool.

Here, role of big data and predictive analytics come into play. It's an emerging set of technologies capable of storing and processing massive amounts of data in real time and at lower costs than ever before (Baer and Campbell 2012); (Bag 2017); (Sedkaoui 2018b); (Bag et al. 2021a). Predictive analytics has long been used in marketing, for example, to anticipate customer attrition and in finance, for determining portfolio investors' financial risk tolerance, but its usage in human resources is relatively restricted.

Predictive analytics in the form of data mining has been used in a variety of Human Resources operations, including predicting employee attrition, employee turnover, severance pay, compensation acceptance, and employee performance (Strohmeier and Piazza 2013). Buck and Morrow (2018), discuss the significance of objectively determining who the top performer within the firm is and who has the ability to lead, as well as prioritising their retention by anticipating turnover early (Harris et al. 2011).
Employee attrition likelihood can be predicted by employing supervised analytical approaches. Analyzing the past and existing employee information is exploited while designing the predictive model. To address the problem of aforementioned prediction, classification techniques are implemented that maps input variable to target classes by considering training data. The input variables are the interfering factors that include salary structure, work life balance,

job satisfaction, comfort in working environment, relationship with supervisor and many more. All these data turn out to be good predictors while identifying employees having probable erosion. This prediction will in turn help the employees by alarming attrition in advance, thus allowing them take informed decisions and act accordingly. Prediction results will even assist the organization also for identifying employees having higher attrition rates and concentrating on them for survival. From 1920 to 2020, many articles on employee turnover were published, making it one of the most important topics in Human Resource Management (Lee et al. 2017).
In this study we are exploring the different types of HR analytics (Descriptive, Diagnostic, Predictive, Prescriptive) used in different strategic firms like Cost leadership (CL) and (Differentiator) DIFF with the use of ESM.
This study stresses on how critical it is to understand the link between analytics and organizational strategy, organizational structure, and the level of uncertainty present in a certain business. We have considered (Porter 1980) "business strategy" in this study, consists of Cost leadership strategy, Differentiator strategy and focus. Cost leadership (CL) and differentiator (DIFF) firms were identified on the basis of organization strategy and organization structure. In this study, five primary variables of the structure of an organization are considered to determine the type of organization (Pugh et al. 1969); (Kerlinger 1966).These variables are specialization, standardization, formalization, centralization, and complexity of work flow.
If an organization scores high on formalization, centralization, specialization and standardization, then it's a cost leader firm involved in monotonous tasks and not innovative (Bucic and Gudergan 2004); (Amason et. al. 1995); (Souitairs 2001). *If an organization scores high on complexity of workflow then it's a differentiator firm.* (Hodge et al. 1988). The purpose of this research is:

1. To contribute to the literature of HR analytics, its use for the prediction of employee turnover in different strategic firms (CL and DIFF).
2. To analyze types of HR analytics used in the prediction of employee turnover.
3. To analyze different type of HR Analytics used in different business strategy firms i.e., (CL) and (DIFF) with the use of ESM. It is expected from this research to contribute to the better use of HR analytics in HR management decisions related to the employee turnover.

2. Literature Review

2.1 Organization Strategy / Business Strategy:

Strategy helps to coordinate different aspects of management's (Chandeler 1962). The strategy is the sequence of actions taken to achieve a person's intended outcome. The strategy in an organisational environment is the plan of action to achieve the organization's vision and mission. Different sorts of organisational strategies exist in an organisation depending on its structure: operating strategy, functional strategy, business strategy, and corporate strategy. An organization's strategy might be either short-term or long-term. An organization's plans should always address market needs and strive to meet stakeholders' expectations (Johnson et al. 2008).

2.2 Organization Strategy Typology

Hofer and Schendel (1978), Miles et al. (1978),.Porter (1980), Mintzberg 5 P's (1987), Miller and Roth (1994), Steensen (2014) and others have all studied strategic typologies, or theories of various strategy styles, which have become a common subject of study in strategic management. We have considered (Porter 1980) "business strategy" in this study. Porter (1980) classifies business strategy in three different ways. These strategies are differentiation, cost leadership, and focus.

In the **differentiation strategy**, a company is more concentred on new product development for their existing customer segments. A company will follow differentiation strategy when customers are not price sensitive and the market is competitive and saturated. If organizations are compatible with resource allocation and R&D activity, then they can go for differentiation strategy. While, in **cost leadership strategy**, organizations are more focused on price. They always try to reduce the cost of the products with the help of their operational excellence. They have less number of products in their product portfolio. On the other hand, in **Focus strategy** of an organization is the combination of differentiation and cost leadership strategy. In focus strategy, organizations are more focused on a niche segment. To target a niche segment, an organization may adopt a cost leadership approach or product differentiation approach.

2.3 Organization Structure

One of the most important elements for defining and fulfilling an organization's goals is its structure. An organization's organisational structure aids in job classification, organisation, and coordination (Mintzberg 1983). People in an organisation are divided into groups or departments based on their jobs and objectives (Nelson and Quick 2012); (Greenberg 2011); (Ajagbe et al. 2016). The general layout of the administrative hierarchy is the first aspect of an organization's structure, while the monitoring, coordination, and control of each level of the administrative hierarchy is the second (Lenz 1980). Chandler (1962), propose “structure follows strategy”. Implementation of strategy depends on the structure of an organization. The structure of an organisation is usually defined by top-level management in accordance with the firm's strategy (Kavale 2012). In the other instance, an organization's good or strict structure plays an important part in implementing any new corporate strategy (Pullan and Bhadeshia 2000). The structure may be found in any organization.

In this study, we have considered the five key dimensions of the organizational structure. These are standardization, specialization, centralization, formalization, and complexity of work flow (Miller and Droge 1986); (Pugh et al. 1968/69), which are described below:

Standardization- The organization, is less involved in new product design and research & development because it follows "standardised product method" (Buzzell 1968); (Cavusgil et al. 1993); (Samiee and Roth 1992).

Centralization - A top-down method is used in a centralised organisation (Pugh et al. 1968). Higher authority make judgments in the majority of circumstances, and those decisions should be followed by other employees in that organisation.

Specialization Hinings et al. (1967) is concerned with the categorization of labors and tasks within an organization. It breaks down tasks into similar small tasks (Niederhoffer 2012). It helps to focus on one specific task.

Formalization is defined as the amount of written documentation of an organization's rules, procedures, instructions, and communications (Pugh et al. 1968); (Fredrickson 1986); (Michaels et al. 1988). Bureaucratic types of a firm are more formalized in nature.

Complexity of workflow is also determined by the organization's complexity. The degree of differentiation that exists within an organisation determines its complexity (Daft 1986); (Fredrickson 1986); (Robbins 1990); (Pratiknyo 2005).

2.4 Relationship between Organizational Structure and Strategy

The relationship between organisational strategy and structure must be thoroughly examined. This helped us figure out whether an organisation is formal, semi-formal, or informal, and how to approach them effectively. A structural feature that affects the choice of organizational structure is centralization, specialization, and complexity of workflow (Mondal et. al 2016). Because all employees work together in CL companies, centralization is common here. While DIFF are less rule-bound and prioritise interdepartmental subcommittees, so workflows are more complex. Specialization is a weak differentiator in comparison to cost leaders because they primarily focus on innovation.

2.5 Analytics in Human Resource Management

Human resource management analytics is recognised as one of the organisational capabilities with enormous potential to improve decision-making ability on human and organisational capital (Rasmussen and Ulrich 2015); (Renaud et al. 2015). Analytics encompasses a wide range of approaches, technologies, and tools for generating fresh knowledge and insights in order to address complicated challenges. In its most basic form, analytics is a comprehensive and multi-disciplined approach to comprehending and dealing with complex circumstances. Analytics uses data and mathematical models to make sense of the ever-increasingly complex world we live in. Despite the fact that analytics encompasses the act of analysis at various phases of the discovery process, it also encompasses synthesis and subsequent implementation. Data analytics is basically the key to sound decision-making since it gives important insight into whether or not a firm is moving in the right direction (Angrave et al. 2016); (Gallardo-Gallardo et al. 2015). Researchers and practitioners defined HR analytics as given below in Table 1 (Margherita 2022):

Table 1. Definitions of HR Analytics

	Adapted definition	Source
1.	Extensive use of data, statistical and quantitative analysis, *explanatory and predictive models*, and fact-based management to drive decisions and actions involving personnel	(Davenport and Harris 2007)
2.	A set of *six kinds of analytics* in terms of human-capital facts, analytical HR, human-capital investment analysis, workforce forecasts, talent value model, and talent supply chain	(Davenport et al. 2010)
3.	*Logical analysis* that uses objective business data as a basis for reasoning, discussion, or calculation	(Fitz-enz. 2010)
4.	*Evidence-based* approach to managing people and people processes within organizations	(Bassi et al. 2010)
5.	Evidence-based HR driving *strategic impact* based on logic-driven analytics, segmentation, risk leverage, synergy and integration and optimization	(Boudreau and Jesuthasan 2011)
6.	Approaches for uncovering unique *insights* about people that enable faster and more accurate *decision-making* to executives	(Guenole et al. 2015)
7.	Rigorously *tracking HR investments and outcomes*	(Ulrich and Dulebohn 2015)
8.	*Multidisciplinary approach* to integrate methodologies for improving the quality of people-related decisions	(Mishra et al. 2016)
9.	Bringing *together HR and business data* for analyzing people-related risks, performance characteristics, engagement and culture, and identifying career paths	(Bersin et al. 2016)
10.	A HR practice enabled by information technology that uses *descriptive, visual, and statistical analyses* of data related to HR capital and organizational performance to establish business impact and enable data-driven decision-making	(Marler and Boudreau, 2017)
11.	HR analytics is the *systematic identification and quantification* of the people drivers of business outcomes	(Van den Heuvel and Bondarouk 2017)
12.	*Data, metrics, statistics and scientific methods*, with the help of technology, to gauge the impact of human capital management practices on business goals	(Kryscynski et al. 2018)

From the beginning of an employee's career in an organisation to enhancing their productive path through the organisation to tracking the benefits of such an investment in the employee, there is a lot to consider. HR Analytics is a well-defined process for capturing new ideas and applying them to increased productivity (Minbaeva 2018).

2.6 Big Data Analytics

Because social media data is overwhelming the modern workplace, social media integration systems that can successfully capture and combine this data are in high demand. Big Data is a revolutionary technology that uses a holistic approach to extract actionable insights from massive amounts of data with a wide variety of sources, high velocity, high veracity, and great value. The concept's popularity encourages businesses to take use of daily flows of real-world data to improve operational visibility and raise performance standards. The organizations who are vouching on Big Data expressed a move towards analytics to refine decision making in various functions, one of them being HR (Staiger 1997).

HR Analytics signifies different things to different people and organisations; some people and organisations refer to it as data matrices, decision-making platforms, and statistical visualization techniques. (Bloom 2001); (Boudreau and Ramstad 2007). Later studies have identified a synthesised and systematic approach to HR Analytics that goes beyond HR matrices (Levenson and Fink 2017); (Marler and Boudreau 2017), allowing for a more focused approach to draw meaningful insights and play a key role in strategic execution (Levenson and Fink 2017).

HR Analytics became possible for practically all firms as HR data became more accessible through new methods of data gathering and technical developments for analysis. With the study of workforce data, the growth curves accelerated, resulting in improvements to the organization's numerous HR functions (Levenson 2005)—recruitment (Lam and Hawkes 2017), career development (CIPD 2013) , knowledge management (Khan and Vorley 2017), quality of task (Mondore et al. 2011), prediction of employee turnover etc. HR analytics could help identify knowledge stars in the organisation who disproportionately offer expert knowledge, creative ideas, and skills to the organisation (Aguinis and O'Boyle 2014); (Call et al. 2015); (Hamilton and Davison 2018); (Kehoe et al. 2018), as well as the programmes that would be effective for the retention and creation of knowledge stars, including pinpointing the star behaviors new employees should follow (Call et al. 2015); (Hamilton and Sodeman 2020).

2.7 Types / levels of Business Analytics (HR Analytics)

Business analytics, also known as HR analytics, is the broad use of data from many sources, statistical and analytical analysis, predictive and explanatory models, and fact-based management to guide decisions and actions to the key stakeholders (Soltanpoor and Sellis 2016). Business analytics is divided into three stages, each with different degrees of difficulty, value, and intelligence (Akerkar 2013); (Krumeich et al. 2016); (Šikšnys et al. 2016) are:
Descriptive analytics, answering the questions “What has happened?”

Diagnostic analytics “Why did it happen?”, but also “What is happening now?” (exteDescriptive Analytics) (Soltanpoor and Sellis 2016);

Predictive analytics, answering the questions “What will happen?” and “Why will it happen?” in the future;

Prescriptive analytics, answering the questions “What should I do?” and “Why should I do it?”

Descriptive Analytics is the entry level in analytics taxonomy. Because most of the analytics tasks at this level revolve around developing reports to summarise company activity, it's sometimes referred to as business reporting. The range of these reports includes static snapshots of business activities and transactions delivered to knowledge workers (i.e., decision-makers) on a regular basis (e.g., daily, weekly, quarterly); dynamic views of business performance – often in a dashboard-like graphical interface – on a continuous basis; and ad-hoc reporting, in which the decision-maker is given the ability to create his or her own unique report (using an instinctive, drag-and-drop graphical user interface) to address specific issues / decisions based on unique situation (Ram and Delen 2018).
Diagnostic Analytics is a subset of descriptive analytics. It uses tools and techniques such as visualisation, data discovery, drill-down and big data mining methods to conduct exploratory data analysis of existing data in order to identify/discover the fundamental causes of a problem (Delen and Zolbanin 2018). Descriptive and diagnostic analysis can be used to determine turnover rates, cost per hire, and absence rates.

Predictive Analytics is the act of creating intelligent/scientific projections about the future values of particular variables, such as employee behavioural patterns, that can help HR anticipate phenomena such as attrition rates, employee training costs, employee productivity, and employee contribution. It reveals efficiency tendencies in terms of training costs and time, learning and areas for development, and enhancing the quality of hiring, among other things (Hassan 2022); (Bose and Subha 2021). It makes use of diagnostic data gathered over time to forecast outcomes (Fitz-Enz 2010). Forecasting and simulation are examples of predictive capabilities that managers can utilise to make better decisions with the use of Probabilistic Models, Statistical Analysis and Machine Learning/Data Mining. (Lepenioti, et. al 2020).

Prescriptive Analytics gives trustworthy answers for organisational needs and improves decision-making on problem-solving options (Guenole et al. 2017). The results assist to identify inventory that has to be reordered, talent shortages in the organisation due to employee turnover and attrition, and methods to remodel a retail outlet, among other things. Prescriptive analytics considers uncertainty and suggests solutions to limit the risks that can arise as a result: Its capabilities include not just assessing probable outcomes but also to give recommendations to assist managers in making decisions, especially when the data environment is too vast or complex. (Biriowu and Kalio 2020). In comparison to descriptive and predictive, prescriptive analytics is still not mature (Gartner 2017). However, prescriptive analytics has been increasingly gathering interest in research (Larson and Chang 2016). Listed methods for prescriptive analytics used are Evolutionary Computation, Probabilistic Models, Mathematical Programming, Machine Learning/Data Mining, Simulation, optimization techniques, Logic-based Models (Lepenioti et al. 2020); (Angrave et al. 2016); (van den Heuvel and Bondarouk 2017).

The significant majority of business analytics initiatives are currently focused on descriptive and predictive analytics, using common approaches such as data mining, artificial intelligence, machine learning, and simulation (Habeeb et al. 2018); (Larose 2015). Moving from one level to the next entails that the maturity at the previous level has been reached and that the following level is being fully utilised. A company that is committed to cost leadership aims to provide items at the lowest possible cost. Predictive analytics can be used to provide a detailed picture of how trends in the cost of things sold, operating costs, transportation costs, cost of labor, and warehouse charges may change in the future(Ben-Gal 2019).

Differentiation is a marketing strategy used by companies to create customer value by developing creative, high-quality products that use technology and a unique brand image that sets them apart from their competition. For a specific firm, the most important action is to establish its brand image through division of segments or targeting customers. This can be determined using descriptive analytics techniques, which look at statistics like average dollar spent per customer, site traffic and how much a specific consumer contributed to or deviated from the bottom line. (Marler and Boudreau 2017); (Rasmussen and Ulrich 2015).

2.8 Analytics in Employee Turnover

Saradhi and Palshikar (2011) and Dolatabadi and Keynia (2017) believe that predictive analytics can be applied to employee turnover in the same way that it is applied to consumer churn. Dolatabadi and Keynia (2017) examines multiple strategies for predicting employee and customer churn: Support Vector Machine, Decision Tree, Nave Bayes, and Neural Network. Decision Tree, Nave Bayes, and Neural Network (100 percent) provide better total accuracy than Support Vector Machine for employee churn (99.55 percent). In comparison to the other methods, the Support Vector Machine (99.83 percent) performs the best for customer churn (85.1-92.37 percent). In a study conducted by, the Support Vector Machine also has a very high true positive accuracy when compared to the Random Forest and Nave Bayes (Saradhi and Palshikar 2011).

2.9 Uncertainty in Organization

Uncertainty is seen as lack of information, and knowledge in decision making (Duncan 1972); (Lawrence and Lorsch 1967). Uncertainty is equally viewed as a product of unpredictability (Cyert and March 1963), environmental turbulence (Emery and Trist 1965), and the complexity of influential variables (Galbraith 1973).

2.10 Relationship between Strategy and Environmental uncertainty

Businesses work in a constantly changing environment. They use a range of strategic orientations to modify and adapt to environmental dynamics. As a result, strategy is critical for the survival of business in the long term. Any considerable change in the level of uncertainty necessitates a shift in strategy to keep the organisation in sync with its environment. Environmental uncertainty is important in strategy development because it influences not only the firm's resource availability and the value of its skills and capabilities, but also consumer requirements and needs, as well as the competition.

For Example: Cost leaders (Porter 1980) or defenders (Miles et al. 1978) thrive in stable environments. They isolate and protect relatively stable markets and grow through market penetration (Slater and Narver 1993). Whereas, Prospectors (Miles et al. 1978) or Differentiators (Porter 1980) tend to perceive their environment as highly uncertain (Namiki 1989); or, as Starbuck (1976) suggests, increased levels of innovation create the perception of increased uncertainty among managers (Russell and Russell 1992).

2.11 Enterprise Social Media

Organizations developed the first intranets in the 1990s and 2000s, as networking technology advanced and more ICT was implemented, with the goal of creating a central employee gateway to deliver information (Curry and Stancich 2000). Today's firms are increasingly encouraging employees to work in a more agile and flexible manner (Daft 2012). To facilitate the execution of their work processes, today's enterprises rely on certain IT services, often known as enterprise tools. These enterprise technologies are designed to boost a company's performance and productivity (Kulkarni and Sunkle 2013). Companies and employees are now confronted with totally virtual working environments, remote communication, and online task management, as well as the deployment of new methods for the seamless

execution of tasks and engagement orientations aimed at achieving employees' work-life balance. Many firms present an ESM platform as a new version of the corporate intranet, which is sometimes referred to as the social intranet (Williams and Schubert 2018), with new technology tools and functional principles (Ward 2010).
Enterprise social media, also commonly referred to as Web 2.0 or Enterprise 2.0, consist of software that facilitates group interaction for the sake of forming communities and producing and exchanging information (Von Krogh 2012*)*. Organizations can use social media data in novel ways to examine employee-centric information from an organisational point of view. According to an IBM study, analytics-driven companies have a 33 percent higher revenue growth rate. Consumer experience can be used to more effectively determine a product's or service's performance (IBM Software Group White Paper, 2010). The scholarly literature is establishing global trends in the patterns of online social interaction behaviour on the web.

According to Turban et al. (2011), there are five general approaches of how companies can apply ESM: (1) using publicly available Online Social Networks (OSN), (2) creating enterprise-owned, publicly accessible social networks, (3) introducing internal Enterprise Social Networks (ESNs), (4) enhancing existing communication technologies (e.g., e-mail) with social functionalities, or (5) developing tools that include capabilities to support social networking applications.

In this study, we argue for the conceptualisation of different types of human resource analytics for different business strategy as part of an organisation's strategic management system with a view help clarify strategic human resource analytics and provide empirical evidence in the emergent field of strategic human capital analytics. Next, we discuss the vital role of social media in strategic firms (CL & DIFF) and for HR analytics, as part of a strategic human resource management, in organisation; consider the significant role of ESM; and propose specific hypotheses.

3. Theoretical Framework and Hypothesis formulation

Going through the detailed literature review, various hypotheses have been proposed in this paper. The theoretical framework in this paper has been developed after going through the literature related to HR, analytics, organizational strategy (CL & DIFF), and structure.

Jobs are less enriched in CL as compared to DIFF. Companies spend a fortune on employee training; and it hurts when they leave the company. Hence, HR Analytics for employee is a major issue; as one may like to know why employees are leaving. Exit interviews are conducted to find this out. By using people analytics in talent development, companies can find out the main reason behind employee exits, and find out how to reduce the attrition rate. Most leaders have no real idea about how to interpret an employee turnover rate, because they know generally that lower turnover is not always beneficial and vice versa, but they do not know how to tell which situation they are facing.
Using the right information, we can pinpoint the fundamental reason of staff turnover in cost leadership or differentiation-based organizations. Employee turnover costs businesses tens of millions of dollars every year, but it may be avoided. We can better predict the future over time by using analytics (Kremer 2018). People analytics could be utilised in a revolutionary way to encourage people to show off their skills and talents at work. Data analytics can help identify the aspects of a company's infrastructure, leadership, structure, and culture that attract people. Later the company can concentrate on enhancing these factors to persuade employees to return and boost employee engagement, productivity, and retention.

Descriptive Analytics is primarily concerned with what has occurred. i.e., historical business documents. The goal of the organisation in terms of attrition is to determine turnover rate, revenue per employee, ROI, and employee absent rate etc., in order to scale HR functions in terms of attrition level, recruitment time, work schedule, employee turnover, and subsequent talent identifications. Concrete and suitable measurements are essential for demonstrating how strategic HR initiatives can influence organisational outcomes (Mishra et al. 2016). The 9-box grid, overtime expense, absent rate, Employee productivity index, Employee satisfaction index, voluntary turnover rate, turnover rate, and feedback from employees leaving the firm are the measures used to predict employee turnover.

To start, make sure that resignation rates are calculated consistently across all divisions and locations (if you have multiple offices). Keep an eye on resigned employees: when going through the data presented by this metric. Is it a star performer in its industry? Who are the most senior executives in this organisation? To investigate and address this problem, we could employ brainstorming, study-based methodologies, or simply check for a fundamental pattern and data distribution. Whether the goal is to attain cost leadership or to serve as a competitive differentiator, analytics is heavily contingent on the organization's goals. As a result of our observations, the following hypothesis is offered (Hussain and Lee 2015); (Kaur and Phutela 2018) ; (Williams 2011).

Diagnostic Analytics- Monthly income is a common predictor variable of employee turnover in this analytics (Fallucchi et al. 2020). Promotion, time spent at work, over time, travel distance, performance reviews and relationship with management are all popular predictive variables (DiClaudio 2019). Because employees rarely leave the organization until retirement, all of this information is readily available in CL firms. As a result, predictive HR analytics interventions help to retain workers based on modelling outputs (linear analysis, simulation analysis) in Cost Leader organisations.

Predictive Analytics- Starting with the resignation rate, conduct an analysis using a clustering method to identify what factors influence resignations, i.e., use performance indicators (major attributes) to determine the likely reason of unusual behaviour. Based on this data, you may successfully target and decide your retention strategy (and not gut feeling or anecdote). Rather than reporting particular metrics like salary ratio, wage rises, advancement wait time, results, tenure and training opportunities, dig into how these factors influence resignations. If you find such correlations, it will be easy to provide employees with the knowledge or compensation they seek before they leave the organisation. (DiClaudio 2019); (Margherita 2022); (Oladipupo and Olubusayo 2020). As you may be aware, analytics is mainly dependent on the approach used by a firm, whether it is to implement a cost-cutting strategy or gain a competitive edge (DiClaudio 2019); (Margherita 2022); (Oladipupo and Olubusayo 2020).

Prescriptive Analytics- The technology identifies and ranks all of the factors that contribute to resignations in real time, enabling measures to be implemented to reduce the rate of resignations while also retaining high-performing or critical employees. When all relevant employee attributes are taken into account, the solution accurately predicts the possibility that employees will retire. Comparing resignation rates across positions, locations, tenure, age groups, diversity, and other groups will help you figure out where to focus your programme investments to get maximum impact. Before rushing to incorporate a new set of characteristics into your already complex workplace environment, think about taking a more scientific approach to planning and implementing these solutions (Lepenioti et al. 2020); (Pape 2016). Only this way you will receive comprehensive support for what your organisation truly requires: an efficient retention problem solution. According to what we all know about prescriptive analytics, it is a more advanced kind of analytics, and applying it to a little issue would be inefficient in terms of money (Berk et al. 2019); (King 2016); (Margherita 2022); (Pessach et al. 2020).

We argue that prediction is easy when complexity is low in CL (firms with cost leadership strategy); and is difficult when complexity is high in DIFF (firms with differentiation strategy). But with the use of ESM (enterprise social media) predicting of turnover/attrition becomes easier; so analytics will predictive / prescriptive. Constructing a predictive model of an organization, here, we concentrated on identifying the most appropriate analytics (Descriptive/Diagnostic/Predictive/Perspective) for a given organization.

Hypothesis H1 & H2: Defender or Cost leader strategy (Segev 1989), have a "buy" orientation. These organisations will focus upon numerical and functional agility with short-term relationships, limited training and development, and external pay comparability in order to improve or maximize efficiency. Internal recruitment may be preferred in cost leaders / defenders, as it is less expensive and contributes to the improvement of the quality of the internal labour market (Heraty and Morley 1998). Hence, lot of data is easily available about an employee.

Given the fact that cost leaders are more characterized by top-down management, hierarchical channels, centralized control, and the like (Miles et al. 1978), it is not surprising that their career management is also organized more in a top-down fashion in comparison with prospectors or differentiators. These organizations are unlikely to employ coaching, irrespective of who could offer it, or for what type of agenda, but focus quite strongly on the organizational needs with the use of appraisal records, as well as looking at the contributions a person made to the organization in the managerial promotion process. They will also lay off employees if needed. Midlevel managers are likely to stay in the organization until retirement.

They don't have a training and development system, so they're unlikely to use coaching. They also do not prioritise increasing organisational commitment, and if a midlevel manager leaves, they are unlikely to replace him or her. The likelihood of leaving is low, however, because these organisations expect these managers to stay with them until retirement, and the organisations themselves are not inclined to dismiss people. Given that (McDonald et al. 2005) discovered that traditional career paths are still prevalent in the public sector, it appears that tenure may play a role in becoming a manager, as one's appraisal record, managerial skills, or contributions to the organisation are not regarded as important. On the other hand, people joining these organizations have a very low need to achieve or to have a high-flying career.

Since too much data is easily available about an employee, HR analytics used will be predictive. Also, with the help of Enterprise social media / Social media, lot of positive and negative data is available / can be collected about the employee like personality , cognitive maps, genetic predisposition (individuality) and decipher his/her values, attitudes and opinions on key issue without his/her knowledge (in an unobtrusive manner) (Salminen et al. 2020). This data is helpful in analysing the tendency of employee of job hopping's or leaving organization. Hence, we propose:

H1. HR Analytics used for Cost Leaders will be Predictive with the use of ESM for employee turnover
H2. HR Analytics used for Cost Leaders will be Predictive without use of ESM for employee turnover

Hypothesis H3 & H4: Organizations with a differentiator strategy, similar to Miles and Snow's prospector, should have a "make" orientation. This implies, for example, a performance appraisal system that clearly focuses on the long term, with a lot of training and career development. This strategy seeks low employee turnover or high commitment to the organisation from key employees in order to preserve the accumulated skills and knowledge required for innovation (Segers and Inceoglu 2012). They are organic organisations that are highly unpredictable (Miles et al. 1978); (Porter 1980). So, not too much information is available about an employee. So analytics will be descriptive / diagnostic.

But with the use of Enterprise social media, lot of data can be collected about an employee about their personality, values, cognitions etc. Hence HR analytics can be predictive / prescriptive with the use of ESM. So, Analytics used will be predictive / prescriptive in differentiators with the use of ESM. Hence, we propose:

H3. HR Analytics used for Differentiators will be predictive/ prescriptive with the use of ESM for employee turnover
H4. HR Analytics used for Differentiators will be descriptive/ diagnostic without use of ESM for employee turnover.

4. Methodology

The research targeted population is international firms from U.K., U.S. and Europe. Participants are data scientists, senior managers, heads of HR department and C – suites who are using HR analytics and enterprise social media (ESM) in their organization. The purposive random sampling was used for data collection. Chi square test was done to analyse data and software used for it was SPSS version 25.

Questionnaire design and coding was done based on the research model, a questionnaire with close- ended questions was designed using a 5-point Likert scale with 1 and 5 representing strongly disagree and agree respectively, 3 representing neutral while 2 and 4 were respective intermediate values for OS1 , OS2 ,ESM. While the type of HR Analytics is treated as categorical variable i.e. Descriptive was coded as "1", Diagnostic as "2", Predictive as "3" and Prescriptive as "4". "Type of business strategy" i.e., CL and DIFF were coded as cluster 1 and cluster 2 and "Use of ESM" is coded as 1 and "No ESM as 2".

In total 500 questionnaires were distributed and out of these 235 questionnaires were returned. The usable questionnaires were coded and transcribed into the statistical package for social scientists (SPSS) v25. The constructs and their attributes were coded as; Cost leader was coded as (CL); Differentiator as (DIFF); Organizational strategy as (OS1); Organizational structure as (OS2) ; Enterprise social media (ESM); No Enterprise social media as (No ESM); Descriptive Analytics as (Descriptive); Diagnostic Analytics as (Diagnostic); Predictive Analytics as (Predictive); Prescriptive Analytics as (Prescriptive).

5. Results

Correlation was calculated. Chi-square (χ2) analysis refers to a multipurpose statistical test used to observe the significance of relationships between two or more nominal-level variables. The results on the Chi-square shows that all the constructs were accepted. Fisher-exact test was also calculated. K- Means clustering was done to divide CL and DIFF clusters on the basis of "OS1, OS2". Table 2 shows two clusters of two different business strategy (CL and DIFF) on the basis of euclidean distance.

Table 2. K-means clustering – CL and DIFF

Number of Cases in each Cluster		
Cluster	1 CL	88.000
	2 DIFF	147.000
Valid		235.000
Missing		0.000

Table 3. shows two clusters of two different users who use ESM and don't use ESM.

Table 3. K-means clustering- ESM and No ESM

Number of Cases in each Cluster		
Cluster	1 No ESM	84.000
	2 ESM	151.000
Valid		235.000
Missing		0.000

Table 4. This shows count and expected count of respondents.

Cost Leader	**Descriptive**	**Diagnostic**	**Predictive**	**Prescriptive**
No ESM (C)	9	23	6	5
No ESM(EC)	6.8	19.1	11.7	5.4
ESM(C)	5	16	18	6
ESM(EC)	7.2	19.9	12.3	5.6
Differentiator	**Descriptive**	**Diagnostic**	**Predictive**	**Prescriptive**
No ESM(C)	4	17	13	7
No ESM(EC)	2.5	11.4	16.2	10.9
ESM(C)	5	24	45	32
ESM(EC)	6.5	29.6	41.8	28.1

Here, C is count of respondents and EC is expected count

Table 5. Chi square table results (This table shows significance of chi square test)

Strategy Type	**Use of ESM**	**No. of respondent**	**Type of HR Analytics**				**$\chi 2$ Calc.**	**P value**	**Fisher's Exact Test**	**P value**	**Cramer's V**	**P value**
			Descriptive Analytics	Diagnostic Analytics	Predictive Analytics	Prescriptive Analytics						
CL	ESM	45	5	16	18	6	8.449*	0.03	8.458*	0.03	0.310*	0.038
	No ESM	43	9	23	6	5						
DIFF	ESM	106	5	24	45	32	7.837*	0.04	7.676*	0.04	0.23*	0.049
	No ESM	41	5	17	13	6						

"*" d*enotes significant i.e., p value<=0.05 and df = 3.*

The results of (Table 2) indicate that out of 235 respondents 88 are CL and 147 are DIFF. (Table 3.) indicates that out of 235 respondents 84 are using ESM and 151 are not using. (Table 4) indicates CL (using ESM) are 45 respondents and DIFF (using ESM) are 106 respondents while on other hand CL (without using ESM) are 43 and DIFF (without using ESM) are 41. For E.g. ESM users in CL firm who use prescriptive analytics are 6. (Table 5) shows that Pearson chi-square value / table value is 8.449 in CL which is greater than 7.8 critical / table value at degree of freedom = 3. Additionally, the p value is 0.03 which is less than p=0.05. Hence the relationship between strategy type and analytics type is significant in CL. One of the assumptions when performing the chi-square test is that none of the expected cell counts is less than 5. In those cases, where that assumption is violated, you can rely on the Fisher's Exact Test results (Field 2018). Although we do not have a violation of this assumption in the current analysis, the results of the test also indicates a statistically significant association (p<.001). We calculated Fishers exact value for more precision in results and it is also significant for CL i.e. p= 0.03. Cramer's v tells the strength of the relationship in 2*2 contingency table. But in case of (rows>2 and column >2) contingency table, ω (omega) is used. Cohen (1988) proposed use of the coefficient, omega (ω), as a general measure of effect size and presented mathematical proofs showing how ω, φ (phi), & φ′ (Cramer's V) are related. This index reflects the overall discrepancy between observed and expected joint probabilities associated with the cells in your analysis (Cohen 1988). It turns out that Cramer's V (φ') can be converted into ω using the following formula: $\omega=\varphi'\sqrt{\min(\#r,\#c)-1}$

Hence, ω= $0.310\sqrt{\min(2,4)-1}$ => $0.310\sqrt{2-1}$ = 0.310. So, we can say that for (table 5.) ω=φ' i.e. Cramer's V. And p value is significant at p=0.03. So, good and significant Cramer's V tells strong association between variables in CL firms.

Similarly for DIFF firms, (Table 5) shows that Pearson chi-square value / table value is 7.837, which is greater than 7.8 table value at degree of freedom = 3. Additionally, the p value is 0.00 which is less than p=0.05. Hence the relationship between strategy type and analytics type is significant in DIFF. We calculated Fishers exact value for more precision in results and it is also significant for DIFF i.e. 0.04. Cramer's v value 0.23 and p value 0.04 tells significant association between variables in DIFF firms.

6. Conclusion:

We finds that if an organization is a CL firm, it should employ predictive or prescriptive analytics techniques for employee turnover. To analyse future employee behavior, they use simulation approaches and linear equation to read past data of employees, who have voluntarily left firms and predict future intention of leaving for existing employees. As a result, if we know early about turnover intention of employee, there will be less turnover among the workforce. It will increase the profit of the firm while retaining the key employees. In the view of human resources, the most important duty of a big company is to ensure that its employees have a work-life balance keeping its brand image preserved. We also finds that if an organization is a DIFF firm, it is able to employ descriptive or diagnostic analytics techniques for prediction of employee turnover. These approaches are used to examine a variety of metrics such as revenue per employee, employee's efficiency, how much skill an employee has in his or her field of interest, and how his or her behavior changes the behavior of other people in the business. With the use of diagnostic analytics, we discover the reasons why key workers wish to leave the company. But we also found that with the help of social media, knowledge about employee is gathered in unobstructed manner and it is able to employee predictive or prescriptive analytics in DIFF firms because past data is proved helpful in forecasting future.

Table 6. Hypothesis status

1.	HR Analytics used for Cost Leaders will be predictive with the use of ESM for prediction of employee turnover	Fail to reject
2.	HR Analytics used for Cost leaders will be predictive without use of ESM for prediction of employee turnover.	Rejected
3.	HR Analytics used for Differentiators will be predictive/ prescriptive with the use of ESM for prediction of employee turnover	Fail to reject
4.	HR Analytics used for Differentiators will be descriptive/ diagnostic without use of ESM for prediction of employee turnover.	Fail to reject

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