ADOPTION OF HR ANALYTICS AMONG HR PROFESSIONALS' IN INDIA

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By

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I, Susmita Ekka, hereby declare that the thesis entitled, **"Adoption of HR Analytics among HR Professionals' in India"** submitted by me under the supervision of Dr. **Punam Singh,** School of Management Studies, University of Hyderabad, is a bonafide research work which is also free from plagiarism. I also declare that it has not been submitted previously in part or in full to this University or any other University or Institution for the awardof any degree or diploma. I hereby agree that my thesis can be deposited in Shodhganga/INFLIBNET.

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LIST OF ABBREVIATIONS

Acronym	Full Form
ATT--------------------------------------	Attitude Towards HR Analytics
QSE--------------------------------------	Quantitative self-efficacy
PEOU------------------------------------	Perceived Ease of Use
PU--	Perceived Usefulness
SI---	Superior Influence
PI---	Peer Influence
DA---------------------------------------	Data Availability
TT--	Tool Trialability
RT--	Readiness Towards HR Analytics
ADOP------------------------------------	Adoption of HR Analytics
OC--	Organization Culture
HRM-------------------------------------	Human Resource Management
HR--	Human Resource
ROI---------------------------------------	Return on Investment
TPB--------------------------------------	Theory of Planned Behaviour
TAM-------------------------------------	Technology Acceptance Model
TRA--------------------------------------	Theory of Reasoned Action
DOI--------------------------------------	Diffusion of Innovation
IT---	Institutional Theory
IDT---------------------------------------	Innovation Diffusion Theory
TOE--------------------------------------	Technology Organization Environment Framework
UTAUT----------------------------------	Unified theory of Acceptance and Use of Technology
SPSS-------------------------------------	Statistical Package for Social Sciences
KPMG-----------------------------------	Klynveld Peat Marwick Goerdeler

SHRM---------------------------------- Society for Human Resource Management

HRMS---------------------------------- Human Resource Mnagemnet System

eHRM----------------------------------- Electronic Human Resource Management

AI-- Artificial Intelligence

SEM------------------------------------- Structural Equation Modelling

PLS-------------------------------------- Partial Least Square

IV-- Independent Variable

DV-------------------------------------- Dependent Variable

KMO------------------------------------ Kaiser-Meyer-Olkin

CR--------------------------------------- Composite Reliability

CA--------------------------------------- Cronbach's Alpha

CV--------------------------------------- Convergent Validity

AVE------------------------------------- Average Variance Extracted

HTMT---------------------------------- Heterotrait Monotrait

SRMR---------------------------------- Standardized Root Mean Square Residual

ABSTRACT

Analytics is becoming increasingly important across functional areas of management, as it provides valuable insights that enable organizations to make data-driven decisions and achieve their strategic goals. Analytics is used in various functional areas of management, including finance, marketing, operations, and supply chain and HR is no exception. Some organizations that have adopted the use of analytics in their HR departments have been extremely successful. If this is the case, why are not more HR professionals adopting the use of HR analytics?

Why HR professionals have a slow adoption of HR analytics even though it is considered necessary and essential for the sustenance of the HR function in organizations? Could there be facilitators and barriers that function as roadblocks to HR professionals' adoption of HR analytics?

Therefore, the goal of the present study is to identify the facilitators and barriers that influence adoption of HR analytics among HR professionals, further examining the role of organization culture as a moderator. An integrated model of TPB, TAM and DOI has used to understand the factors influencing HR professionals' readiness to adopt HR analytics and the impact of readiness on adoption beahaviour. Partial least squares structural equation modeling (PLS-SEM) was employed to validate the model based on data collected via a survey from 305 HR professionals in India.

Our result points a positive significant relationship between attitude, quantitative self-efficacy, peer influence, superior influence, perceived ease of use, perceived usefulness and tool trialability on readiness towards HR analytics. In contrast data availability was found insignificant. The study also tested the influence of individual, social and technological factors on readiness of HR professionals towards adoption of HR analytics. The present study followed a cross-sectional approach to examine the hypothesised relationships, and it reveals that individual and social factors have a considerable positive affect on readiness towards HR analytics. In contrast, the study finds that influence of

technological factors insignificantly affects the readiness of HR professionals to adopt HR analytics. The current study is the first study in Indian context to test the moderating impact of organization culture on HR professionals' readiness and adoption of HR analytics. There is a considerable positive link between readiness and adoption of HR analytics. However, the moderating role of organisational culture has a negative significant impact on HR analytics readiness and adoption behaviour. Organizations have failed to adopt their culture in order to become more innovative and analytical. Organizations must immediately rethink their culture to keep up with changing times and provide fertile ground for technology to take root, grow, and thrive.

These findings are important because they provide practical guidance for organizations to successfully implement HR analytics. This study also contributes to the literature on adoption of HR analytics. Implications for theory and practice are discussed, as well as further research. Managers, business leaders, and policymakers can use this finding to assist HR analytics adoption in their organizations.

Keywords: HR analytics, Readiness, Adoption, TPB, TAM, DOI, Organization culture.

CHAPTER - 1

INTRODUCTION

1.1 Introduction

In today's world, businesses are facing a rapidly changing and highly competitive environment. This has led to a paradigm shift towards using analytics to create value and transform the organization. Analytics has become increasingly important in globalized world because it provides organizations with the ability to gain insights, make strategic decisions, and stay competitive in a rapidly changing business environment.

Organizations must be able to quickly adapt to changes in the market and stay ahead of the competition. Analytics is becoming increasingly important across functional areas of management, as it provides valuable insights that enable organizations to make data-driven decisions and achieve their strategic goals. By leveraging the power of analytics across functional areas, organizations can gain a competitive edge and position themselves for long-term success. Analytics is used in various functional areas of management, including finance, marketing, operations, and supply chain and HR is no exception (Fernandez & Gallarado, 2020). In finance, analytics can provide insights into financial performance and risk management, helping organizations make informed decisions about investments and financial stability. In marketing, analytics can provide insights into customer behavior and preferences, leading to more effective customer targeting and increased sales. In operations, analytics can help organizations optimize processes, reduce costs, and improve efficiency. In supply chain, analytics can help organizations optimize inventory management, reduce lead times, and improve delivery performance. Similarly in HR, analytics can help organizations optimize their talent management strategies and improve employee performance.

Analytics helps in making strategic decisions across all functionalities of the business and leads to a definite return on investment (ROI). However, the adoption of HR analytics is still relatively slow compared to other functional areas (BenGal, 2019; Marler & Bourdeau,2017) due to lack of skills and resources, complex and fragmented data, resistance to change etc. According to a study conducted by Deloitte in 2018, only 9% of surveyed companies reported that they have a strong HR analytics team, and 30% reported having no HR analytics capabilities at all. To overcome these challenges, HR departments need to invest in the necessary technology and training to build effective analytics capabilities, and develop a data-driven culture that values the insights and recommendations provided by analytics. Organizations need to ensure profitable change and HR professionals' trust to execute this change effectively. It is important for HR professionals to reposition themselves and adopt a strategic working approach in order to add value to every step of the organization

HR departments lack the necessary skills and resources to effectively implement analytics. Unlike other functional areas, HR professionals may not have a background in data analysis, statistics or programming, which makes it difficult for them to use analytics tools effectively. A survey conducted by LinkedIn found that only 10% of HR professionals reported feeling very confident in their ability to use data to make decisions (LinkedIn, 2018). This may be due to the fact that traditional HR functions have historically focused on administrative tasks rather than strategic role.

Additionally, HR departments may not have the necessary budget or resources to invest in the technology and training needed to build effective analytics capabilities. HR data is often complex and fragmented, making it difficult to analyze. HR data may come from a variety of sources, including performance evaluations, employee surveys, and hiring data, which can make it difficult to integrate and analyze effectively. According to a survey by McKinsey, only 29% of HR professionals reported being able to use HR data to predict workforce performance (McKinsey, 2018).

There may be resistance to change within HR departments. HR professionals may be comfortable with traditional HR practices and may not see the value in adopting analytics. This resistance can also be due to concerns around privacy and data security. In addition, HR data is often highly sensitive and may contain personal information about employees. This can make HR professionals hesitant to share data and collaborate with other departments, which can hinder the adoption of analytics. A survey by HR.com found that 42% of HR professionals cited data privacy concerns as a barrier to HR analytics adoption (HR.com, 2018).

Despite the potential benefits of analytics in HR i.e., the adoption of HR analytics remains sluggish (Wandhe, 2020; Vargas, 2018; Marler & Bourdeau, 2017). While other functional areas such as finance and marketing have been quicker to adopt analytics (Fallarado & Gallarado, 2020; Vargas et al., 2018).

HR analytics has proved to be the game changer, enabling organization to enhance employee skills, improve retention and gain competitive edge (Vander togt & Ramussen, 2017). It has been noticed that understanding adoption behaviour is necessary for the adoption of HR analytics (Wang et al., 2020; Vargas et al., 2018). At the individual level, there are lots of differences in opinion and interest while embracing HR analytics (Ejaz et al.,2020; Vargas et al.,2018).Organization culture is identified as critical factors in success and failure of adoption (Masoumeh et al.,2018; Wang & Chang, 2016).Without employees' behavioural changes, the organizational adoption goal is likely to be unsuccessful (Ejaz et al., 2020) and adoption is of no value if it is not adopted by an individual (Vargas et al., 2018; Frambach &Schillewaert, 2002).Scholars and practitioners have emphasized the need for a better understanding of the possible factors influencing user acceptance in the workplace (Ejaz et al., 2020; Vargas et al.,2018; Sherif et al., 2006; Venkatesh et al., 2000).

1.2 HR ANALYTICS

1.2.1 Evolution

The practise of HR analytics began in 1984 with the publication of "How to Assess Human Resource Management" by Jac Fitz who offered a variety of measures that might be used to analyse human resources effectively and efficiently in order to help readers understand the history of HR analytics. Since then, HR analytics has expanded over time and a number of tools and strategies have been created to increase employee satisfaction and sustain organisational retention levels. HR analytics aids in the collection and analysis of all HR-related data using sophisticated mathematical and statistical methods, which produces a wealth of insightful data that HR directors utilise to make their strategic decisions for the advancement of their enterprises.

Human resource management gradually shifts from a focus on accounting for HR operations to one that encompasses a broader view of human capital, with an emphasis on using statistical methods to make predictions. Another reason for the shift to HR Analytics is the growth of HR Function into an evidence-based HR. According to Bassi (2011), systematic reporting of a variety of HR metrics implies the principles of the evidence-based approach and what if scenarios based on predictive models are the key components of sophisticated HR analytics systems. Bassi (2011) notes that there is a growing interest in HR analytics among both researchers and practitioners. This suggests that HR analytics is becoming increasingly popular and relevant over time, as more people recognize its potential to inform and improve HR practices. Marler and Boudreau (2017), conducted the first comprehensive integrative review on HR analytics and noted that there has been a significant increase in publications on the topic, especially since 2010. This suggests that HR analytics is gaining momentum as a unique area of study.

1.2.2 Conceptualisation of HR analytics

HR analytics has yet to be defined with a broad definition and standardized framework, which is holding back its adoption, according to various scholars and practitioners (Reddy & Lakshmikeerthi, 2017; Fink, 2017; Narula, 2015). The term encompasses a wide range of activities, including metrics, data, technology-based HR, and HR measurement, due to the absence of standard HR analytics frameworks (Levenson & Fink, 2017). As HR analytics is a relatively new area of study, the connections between these concepts are frequently unexplored, and a consistent conceptualization is needed before further exploration of these linkages can occur.

While researchers have offered various definitions of HR analytics, few provide specific details on the statistical analysis, techniques, or models required (Sharma & Sharma, 2017). Some define it as a set of statistical tools and techniques used to analyze data for actionable business intelligence (Momin & Mishra, 2014), while others emphasize the importance of showing connections, correlations, and causality between HR metrics and other business measures (Vargas et al., 2018). Additionally, some researchers view HR analytics as a decision-making process and method (Vanden Hevvel & Bondarouk, 2016; Khan & Tang, 2016). Despite these differing definitions, a clear paradigm for HR analytics has yet to be established.

Another issue with the definitions of HR analytics arises from a lack of clarity surrounding the definitions. However, there is confusion about the terms used to describe this field, such as HR analytics, workforce analytics, and people analytics, which are often used interchangeably. Heuvel and Bondarouk (2017) argue that despite these different terms, they all refer to a logical and systematic approach for discovering and measuring the impact of people-related factors on business outcomes, thus enabling improved decision-making. On the other hand, some scholars such as Angrave et al. (2016) and Rasmussen & Ulrich (2015), argue that HR analytics may just be a passing trend or a fad, and that it might not have any lasting impact as a management technique. They believe that the data-driven approach to HR decision-making may not always be rational, and that it may not be as effective as traditional management techniques. Despite this controversy, many organizations continue to invest in HR analytics as a strategic tool for competitive advantage.

Certain similarities exist in the various definitions of HR analytics. According to Heuvel and Bondarouk (2017), although there may be some overlap between HR metrics and HR analytics, they are not the same thing. While HR metrics provide useful information from different perspectives, HR analytics involves linking HR data with other data and business outcomes. It is important to recognize that HR analytics is not simply a matter of collecting HR metrics, but rather involves analyzing and interpreting this data in a meaningful way.

Some perspectives on what is HR analytics are presented, since different definitions are found in the literature. HR analytics can either be seen as: -

“HR Analytics as a statistical measure that can show connections, correlations and even causality between HR metrics and other business measures” (Vargas et al. 2018, p 3055).

“HR Analytics is a HRM practice that is designed to provide managers with information that connects HRM processes to employee attitudes and behaviors and ultimately to organizational outcomes” (Marler & Bourdeau, 2017, p 15).

“An approach, or set of approaches to improve decisions in HR, which aims to link HR investments to financial returns with evidence” (Bassi, 2011; Harris et al., 2011).

“HR Analytics is a process that represents statistical techniques and experimental approaches that can be used to show the impact of HR activities” (Cheng, 2017, p2).

A method (Fitz-Enz, 2009) “which utilises data from the business for reasoning through logical analyses”.

“HR analytics is the application of a methodology and integrated process for improving the quality of people-related decisions for the purpose of improving individual and/or organizational performance” (Mishra et al., 2016 p.33)

Therefore, by summing all the definitions the study defines HR analytics as:

HR analytics is a set of principles and methods that addresses strategic business concern that encompasses collecting, analyzing, and integrating data to improve people-related decisions.

1.2.3 HR analytics is a strategic decision-making tool

HR analytics is a rapidly evolving field that has been identified as a strategic decision-making tool for organizations (Mohammed & Quddus, 2019; Momin &Mishra, 2015). According to Marler & Boudreau (2017), HR analytics is a decision science that applies analytical methods to human resource management. They argue that by using HR analytics, organizations can improve their decision-making processes by using data to inform and validate their decisions. Similarly, Mohammed & Quddus, (2019) state that HR analytics can be used to make better decisions about how to invest in talent and how to manage people more effectively. This can include analyzing data on employee engagement, turnover, productivity, and other HR metrics to identify trends and patterns for insightful decision-making.

One key benefit of HR analytics is that it enables organizations to make data-driven decisions that are based on objective evidence rather than intuition. According to Sambharya and Musteen (2018), HR analytics can help organizations to identify high-performing employees, predict future performance, and develop effective retention strategies. By using data to identify and develop high-performing employees, organizations can improve their overall performance and competitiveness.

Another benefit of HR analytics is that it allows organizations to measure the impact of HR practices on business outcomes. According to Lawler and Boudreau (2018), HR analytics can be used to measure the impact of training and development programs on employee performance, as well as to identify the drivers of employee engagement. By analyzing HR data in relation to business outcomes, organizations can identify which HR practices are most effective in driving performance and make informed decisions about how to allocate resources.

However, implementing HR analytics can be challenging for organizations, as it requires expertise in data analysis and statistical methods. According to Vargas et al. (2018), HR analytics requires a shift in mindset from traditional HR approaches, as well as investment in technology and training. Organizations that are able to overcome these challenges and effectively implement HR analytics can gain a competitive advantage by making more informed and evidence-based decisions.

1.2.4 HR analytics as an Innovation

Companies now rank HR analytics as one of the most important innovations in the field of technology (Vargas et al., 2018; Marler & Boudreau, 2017). One of the key characteristics of an innovation is that it involves the application of new or existing technologies to solve problems in a novel way (Damanpour, 2014).

Overall, there is strong support in the literature for the idea that HR analytics is an innovation in the field of human resources (Qamar & Samad, 2022; Tomar &Gaur, 2020). Its use of data and analytics to improve decision-making about the workforce is a novel approach that is increasingly being adopted by organizations.

HR analytics is an innovative approach to managing and understanding an organization's most valuable asset, its people. As Sheehan (2019) points out, HR analytics is an innovation that leverages data and analytics to uncover insights that can help organizations make better decisions about their workforce. This approach is a significant departure from traditional HR practices that relied on intuition and experience. The use of analytics in HR has been growing in recent years due to the increasing availability of data and advanced technology that can process and analyze this data. Marler and Boudreau (2017) suggest that the demand for HR analytics is driven by several factors, including the need for organizations to become more efficient and effective, the increasing complexity of the business environment, and the need to manage a diverse workforce. The authors also argue that HR analytics can help organizations make better decisions about their human resources by providing insights into areas such as talent acquisition, employee engagement, and performance management.

Vargas et al. (2018) found that companies are increasingly investing in HR analytics to gain a competitive advantage. They argue that HR analytics can help organizations identify trends and patterns in their workforce, which can be used to develop targeted recruitment strategies, improve retention rates, and enhance employee performance. The authors also suggest that HR analytics can help organizations make better decisions about compensation and benefits, as well as identify areas where training and development are needed.

1.2.5 HR analytics is a Complex Technology

HR analytics is a complex technology that involves the analysis of data to help organizations make better decisions related to their human resources (Marler & Bourdeau, 2017). It requires an understanding of the data available and the methods for collecting, analyzing, and interpreting the data (Vargas et al. 2018). HR analytics is a complex technology because it is a combination of data-driven tools and people-oriented skills to be successful. HR analytics requires an understanding of both the data and the human element in order to be effective. This requires a combination of technical knowledge, such as mathematics and statistics, as well as the ability to assess, analyze, and interpret data in order to make meaningful decisions (Konrad, 2017). Additionally, HR analytics requires an understanding of the legal, ethical, and regulatory implications of using data to make decisions (Dawson, 2017). Furthermore, HR analytics is a constantly evolving field, requiring users to stay up to date on new approaches and technologies (Dawson, 2017).

HR analytics involves the use of advanced analytics tools, such as predictive analytics, machine learning, and artificial intelligence, to identify trends and patterns in HR activities and processes. HR analytics is also used to forecast future needs, understand employee engagement and identify areas for improvement. It can also be used to identify the most effective interventions to increase employee motivation, reduce turnover, and optimize performance (Ahmed et al. 2018). This requires sophisticated algorithms and data mining techniques, as well as the use of predictive analytics to anticipate future outcomes (Boudreau & Ramstad, 2017). HR analytics requires the analysis of large datasets to identify patterns and trends in employee data, such as performance, engagement, and attrition. It is also used to understand how different HR practices, such as recruitment, retention, and training, affect employee performance and engagement. As such, HR analytics requires advanced analytics skills to interpret the data and develop insights that can be used to make informed decisions about HR strategies. Additionally, it can help organizations to understand how their HR practices are impacting the business and its people. Therefore, HR analytics is a complex technology as it requires skilled data analysts, sophisticated algorithms, and careful attention to data security and privacy.

HR analytics requires the integration of multiple data sources, the application of advanced analytics techniques, and the analysis of large amounts of data (Kumar & Sharma, 2019). HR analytics involves collecting, analyzing, and synthesizing data from a variety of sources such as HR records, surveys, employee feedback, and performance reviews. This data is then used to identify trends and patterns that can help organizations improve their HR processes and strategies. Furthermore, HR analytics is a complex technology because it requires the use of sophisticated software and analytics tools to interpret the data and generate meaningful insights. As such, organizations must have the right skills and resources to leverage the full potential of HR analytics (Kumar & Sharma, 2019). Additionally, the complexity of HR analytics is further compounded by the need to integrate data from different sources, such as HR systems, payroll systems, and internal databases (Mazurek & Monteiro, 2020). HR analytics also requires a deep understanding of the organization's culture, values, goals, and objectives in order to effectively interpret the data and make meaningful decisions. (Heitman, 2020, Khammash, 2017).

HR analytics is a multidisciplinary field that combines traditional HR management with data science, analytics, and technology i.e., requires an understanding of the various HR technologies available and how to best utilize them to support organizational goals (Warshak and Rospierski, 2018). HR analytics facilitates into the performance of an organization's human capital (Liu, 2018), that requires a sophisticated combination of data management, statistical analysis, and predictive modeling to assess the effectiveness of human resources strategies, gain insights into workforce trends, and predict future outcomes.

1.2.6 Issues and challenges in adoption of HR analytics

The adoption of HR analytics brings with it a number of issues and challenges. One of the biggest challenges in adopting HR analytics is the lack of data, both in terms of availability and quality. HR data can be scattered across multiple systems and span multiple departments, and it can be difficult to access and integrate data from multiple sources (Zhang, 2017). Analyzing large amounts of data requires statistical skills that may be outside the expertise of the existing HR team. This can lead to difficulty in understanding the data and making informed decisions. Organization may have limited knowledge of the data collected or the potential insights that could be gained from it. Without a clear vision of how the data can be used to improve HR processes, the organization may not realize the full potential of HR analytics.

Another challenge is the lack of skill and expertise in using HR analytics. Although HR professionals may be familiar with data and analytics, they often lack the training and expertise necessary to use HR analytics effectively (Vargas et al, 2018). There is also a lack of awareness of the potential of HR analytics, which can lead to a lack of interest and motivation of user to use the technology. Additionally lack of understanding of the technology as HR analytics is a complex technology and many organisations struggle to understand how to use it and the benefits that it can bring. This can be a barrier to adoption (Vargas et al., 2018). As, HR professionals may hesitant to embrace a technology due to its complexity (Kumar et al., 2017).

The attitude and mindset of HR professionals can be a challenge when it comes to adopting HR analytics. This is because HR has traditionally been seen as a function that focuses on people and qualitative aspects of management. However, with the increasing importance of data in HR, professionals may feel unsure about their ability to use data effectively and may be hesitant to embrace analytics. Some HR professionals may also worry that analytics will make HR less human and more technical, leading to an unwillingness to learn about data and its application in their work

Many organizations may lack the necessary resources or the right culture to embrace analytics and use the meaningful insights gained in their decision-making process (Halper, 2014). Without the necessary resources, organizations may not be able to realize the potential of HR analytics. Therefore, while HR analytics can be a powerful tool for organization, it is important to be aware of the issues and challenges that may arise when attempting to adopt it. Organization should ensure that they have the necessary tools, resources, and training in order to ensure successful adoption and implementation of HR analytics.

1.2.7 Why Adoption of analytics is slow in HR?

Human Resources (HR) is an integral part of any organization, yet it has been surprisingly slow to adopt analytics as compared to other areas such as finance, marketing, sales, operations, and logistics. Some prominent reasons that have emerged from literature are: First, HR departments tend to lack the technical expertise to effectively use analytics. While big data and analytics have become commonplace in other areas, HR departments often lack the personnel and resources with the requisite skills and knowledge to properly utilize analytics. Furthermore, HR departments have traditionally relied on manual processes and lack the infrastructure to integrate analytics into their systems (Shet et al., 2021; Diwedi et al., 2021; Van & Boundrouk, 2017)

The adoption of HR analytics has been slower in the HR area largely due to the complexity of the data surrounding. Human resources data is often scattered across multiple systems, making it difficult to capture and analyze (Federado & Gallarado, 2020; Marler & Bourdeau, 2017). This complexity can make it difficult for HR departments to identify the data points that are important and how to most effectively use them to make decisions. Additionally, HR departments may lack the technical expertise necessary to implement a data-driven approach to decision-making (Ekka & Singh, 2022; Dalbhom et al., 2020, Marler & Bourdeau, 2017)

Furthermore, HR departments may be resistant to change and reluctant to invest in new technologies and processes. Many HR departments are focused on the traditional aspects of HR, such as recruiting, employee relations, and compensation, and may not perceive the value of investing in analytics (Shet et al., 2021; Diwedi et al., 2021; Dalbhom et al., 2020). HR departments may also be concerned that data-driven decision-making could be seen to replace the judgment of experienced HR professionals. Many companies may be hesitant to invest in something that is still in its infancy. This can make companies reluctant to adopt HR analytics, as they are uncertain of what the return on investment will be.

Another reason for the slow adoption of HR analytics is the lack of resources available to HR professionals. HR analytics requires specialized skills, such as data analysis, which are not typically part of the HR toolkit. Furthermore, in many organizations, HR professionals are already stretched thin and lack the time or resources to devote to the development and implementation of HR analytics.

Companies often prioritize investments in areas like finance, sales, and operations, while neglecting to invest in HR analytics. This lack of investment limits the ability of HR departments to leverage data and analytics to make effective decisions. HR analytics requires significant upfront investments in terms of resources, technology, and data collection from the HR department. HR analytics is often seen as a “nice to have” rather than a “must have”, leading to slow adoption rates.

Finally, there is a lack of awareness among HR professionals of the potential benefits of HR analytics. Many HR professionals are not aware of the potential insights that can be gained from HR data. As a result, they are not motivated to invest the time and resources necessary to develop and implement HR analytics.

Overall, adoption of HR analytics is slow in the HR area due to a lack of technical expertise, cost, difficulty in implementation and uncertainty of the return on investment.

1.2.8 HR analytics in Indian and International scenario

HR analytics have become an important tool for making strategic decisions and optimizing the performance of HR functions in both Indian and International scenarios. It has become increasingly important for organizations to focus on improving their HR processes and practices in order to remain competitive in the global market. HR analytics has become increasingly popular in both Indian and international scenarios. The adoption of HR analytics differs between India and international scenarios. While organizations in India are yet to recognize the value of HR analytics, organizations in the international scenario are leveraging data-driven insights to make more informed and evidence-based decisions.

In India, HR analytics adoption is still in its nascent stage. Though the technology is being adopted by some progressive organisations, most organisations still rely on traditional methods for managing their HR functions. According to a study conducted by KPMG in 2020, only 26 percent of Indian organisations have adopted HR analytics. The lack of adoption is largely attributed to the traditional culture that many organisations have, which is resistant to change and new technologies. Additionally, organisations in India lack the necessary data infrastructure and analytics capabilities to truly leverage the potential of HR analytics. Moreover, there is a shortage of analytics skills, which further hinders the adoption of HR analytics.

In contrast, in the international scenario, HR analytics has gained traction and is seen as an increasingly important tool in the HR function. In 2020, the Deloitte Human Capital Trends report found that 64 percent of organisations globally had adopted data-driven HR analytics. This is due to the increased focus on data-driven decision making, as well as the availability of sophisticated analytics tools and the proliferation of digital technologies in the workplace. Additionally, organisations in other countries have also been investing in analytics talent and infrastructure, which has enabled them to better leverage the potential of HR analytics. Organizational culture is an important factor in the adoption of HR analytics. In India, many organisations still have traditional cultures which are slow to embrace change and new technologies. This has hindered the adoption of HR analytics in India, as organisations lack the necessary data infrastructure and analytics capabilities. In contrast, organisations in other countries have been willing to invest in data infrastructure, analytics talent and analytics tools, which has enabled them to better leverage the potential of HR analytics.

1.2.9 HR in comparison with other functional area

There is a significant gap between HR and other functional areas like finance, marketing, and supply chain in terms of the adoption of analytics. According to a 2020 study by McKinsey, only 15% of HR leaders reported that their function is using advanced analytics to inform strategic workforce planning, compared to 43% of finance leaders and 40% of supply chain leaders.

HR data is often not structured and standardized compared to other functional areas. This can make it challenging to collect and analyze HR data accurately, leading to difficulties in extracting meaningful insights (Fernandez & Gallarado, 2020; Vargas et al., 2018). According to a survey conducted by the Society for Human Resource Management (SHRM, 2020), only 13% of HR professionals rated their organization's data analysis capability as strong. HR has historically been viewed as a support function rather than a strategic one. Therefore, there may be less investment in HR analytics and resources. According to a survey conducted by Deloitte, while 71% of companies planned to increase their investment in HR analytics in 2017, only 8% of the budget for HR was allocated to analytics. There may be a lack of understanding among HR professionals of how analytics can add value to their function. A 2021 report by Accenture found that only 30% of HR professionals feel confident in their ability to use analytics. HR has traditionally focused on qualitative aspects of people management, which can be more challenging to measure and analyze than quantitative aspects like financial performance or supply chain efficiency.

1.2.10 Sector wise leading and lagging adoption of HR analytics

In India, there has been a growing acceptance of HR analytics and its use in the workplace. According to a 2021 survey by Oracle, 20% of organizations in India are using HR analytics in some form.

The leading sectors adopting HR analytics in India are IT/Software, Banking/Financial Services, and Retail/E-commerce and Pharma and healthcare. These sectors account for over 60% of the adoption of HR analytics in India. The IT/Software sector has the highest adoption rate of HR analytics in India, at 22%. This is followed by the Banking/Financial Services sector at 18%, Retail/E-commerce at 15%, pharma and health care at 8%.

On, the other hand the lagging sectors are Manufacturing, Education, Media & Entertainment, and Government & Public Sector. Manufacturing sector at just 5% followed by Education at 4%, Media & Entertainment at 3%, and Government & Public Sector at 2%.

1.3 Problem Statement

The purpose of this study is to gain insight and understand why HR professionals have a slow adoption of HR analytics even though it is considered necessary and essential for the sustenance of the HR function in organizations. Could there be facilitators and barriers that function as roadblocks to HR professionals' adoption of HR analytics?

Practitioner research shows that HR professionals must become proficient in using data-driven insights to improve decision-making, processes, and the competitiveness of their organizations (Marler & Bourdeau, 2017). This requires HR professionals to embrace analytics and employ a data-driven mindset to accurately interpret and effectively apply data insights in their day-to-day work (Fedarado & Gallarado 2020). Additionally, the lack of understanding of HR analytics among HR professionals can lead to a lack of confidence in their ability to interpret and use data effectively. As a result, HR professionals may be hesitant to adopt HR analytics and use the data to make strategic decisions.

The adoption of HR analytics has become increasingly popular in recent years, with many organizations recognizing the potential benefits of using data-driven insights to inform their HR decisions. Despite expressing interest in using HR analytics, many HR professionals may not follow through on their intentions and fail to adopt and use HR analytics. Therefore, understanding the factors that influence the intention to use HR analytics and the actual behaviour of adoption among HR professionals is crucial to ensure the successful implementation and use of HR analytics in organizations.

Therefore, the goal of this research is to identify the facilitators and barriers that influence HR professionals' intention to adopt HR analytics and to suggest strategies to improve HR analytics adoption.

1.4 Research Questions:

To address these issues, the goal of this research is to empirically investigate the phenomena of HR analytics, with the goal of adding clarity to factors that hinder as well as factors that facilitate HR analytics adoption among HR professionals' by employing four research questions.

1. What are the factors that lead to slow adoption of HR analytics?
2. How do the individual, social, and technological factors impact the individual adoption of HR analytics?
3. Does Readiness towards HR analytics influence the individual adoption of HR analytics?
4. Does organizational culture moderate the relationship between Readiness towards HR analytics and the individual adoption of HR analytics?

1.5 Research Objectives:

On the basis of the background and research problem, the objective of this research is to deepen the understanding of HR analytics and its implementation. The main objective of this research **is to propose and test an integrated model influencing intention and adoption of HR analytics.**

In order to study the above main objective few sub objectives are formulated.

Specific Objectives:

- To study the factors influencing the HR professionals' readiness towards HR analytics.
- To study the influence of readiness towards HR analytics on individual adoption among HR professionals' in India.
- To study the moderating role of organizational culture towards adoption of HR analytics.
- To understand the influence of individual, social and technological factors on individual adoption of HR analytics.

1.6 Scope of the study

This study develops an adoption model from the perspective of the factors that influence readiness and the adoption based on the Theory of Planned Behavior, the Technology Acceptance Model and the Diffusion Of Innovation integrating the three and introducing organizational culture as a moderator.

The model for this study maintains the basic structure of the Theory of Planned Behaviour and incorporates the elements of the Technology Acceptance Model and Diffusion of Innovation. It will explore major factors which lead to the slow adoption of HR Analytics among HR Professionals'.

The study focuses on determining the relative importance of individual, social and technological factors that affect individual adoption. Moreover, the scope of this study is limited to HR professionals' of India. This study is also to gain insight and understand the factors that influence HR professionals' adoption of HR analytics and to suggest strategies to improve HR analytics adoption and utilization.

1.7 Significance of the study

Research on HR analytics has mainly concentrated on examining how an individual's intention affects the adoption of HR analytics in organizations. This study is first to focuses on both intention and usage behaviour to adopt HR analytics by integrating TPB, TAM and DOI theory in India. It also incorporates organization culture as a moderator to study HR professionals' adoption intention and behaviour in adopting HR analytics. Thus, integrating organizational culture as a moderator in the proposed theory for HR analytics adoption is construed to be a special theoretical contribution. This new perspective will enhance the body of literature on the subject. The proposed theoretical model is expected to be helpful in advancing a calibrated roadmap for future research on HR analytics as well as technology adoption.

The first-ever study on the adoption of HR analytics at an individual level was conducted by Vargas et al. (2018). The present study is unique as it examines HR analytics adoption by using individual, social and technological factors all together. By integrating model of TPB, TAM, and DOI, this study investigates potential factors to assist readiness and utilization to adopt HR analytics. Additionally, this study explores how organizational culture moderates the relationship between the readiness and adoption of HR analytics.

The study not only contributes to the current literature on HR analytics but also takes forward the literature on adoption of technology. The study, as a whole, advances the HR literature by investigating the factors that hinder the intention and utilization of HR analytics. This may enable HR professionals to remove barriers to HR analytics adoption by having a researched backed understanding of the drivers and barriers to analytics adoption. Managers, business leaders, and policymakers can use this finding to assist HR analytics adoption in their organizations. The study assists organization and managers in understanding the facilitators and barriers of HR analytics adoption. HR practitioner will find the recommendations made by researchers to be helpful in implementing HR analytics practise and shifting paradigms in order to look at data in a new way.

1.8 Thesis Outline

This thesis consists of five chapters. This section briefly summarises the contents of each chapter.

Chapter 1: Introduction

This chapter provides background information on HR analytics, including its concept and evolution, the reason it is referred to as an innovative and complex technology, the issues and challenges associated with its adoption, the fact that HR adopts it more slowly than other functional areas, sector wise adoption, and Indian and international scenario. The problem statement, research questions, research purpose, scope of the study, and significance of the study are all further explained in this chapter.

Chapter 2: Literature Review

This chapter provides details regarding the study's theoretical background. This chapter also provides a detailed literature review on the adoption of HR analytics, Organizational culture, identification of the potential factors that hinder its acceptance, and a detailed literature review on the individual, social, and technological factors. It addresses the theoretical foundation, research gaps, and formulation of hypotheses.

Chapter 3: Research Methodology

The research methodology used for the study is covered in this chapter. It includes the research design, sampling, data collection process, questionnaire design, data processing, statistical data analysis, and the results of the pilot study. After the pilot study, it also includes the final data collection information followed by data editing, and coding of data.

Chapter 4: Data Analysis

This chapter provides a detailed description of the study's findings, including the demographic profile, descriptive statistics, data adequacy test, common method bias, and homogeneity test. It evaluates the structural model and verifies the study hypotheses. It represents the testing and validation of the study hypothesis through measurement and structural model evaluation. Additionally, it describes the model fit, moderation analysis and slope analysis.

Chapter 5: Discussion and Conclusion

In the discussion chapter of the thesis, the findings of each study are thoroughly examined in the context of existing literature. An objective wise explanation of the results is provided, and the practical and theoretical contributions of the study are discussed. Additionally, this chapter includes recommendations for future research and an overview of the limitations. Finally, the chapter concludes with a conclusion.

CHAPTER - 2

LITERATURE REVIEW

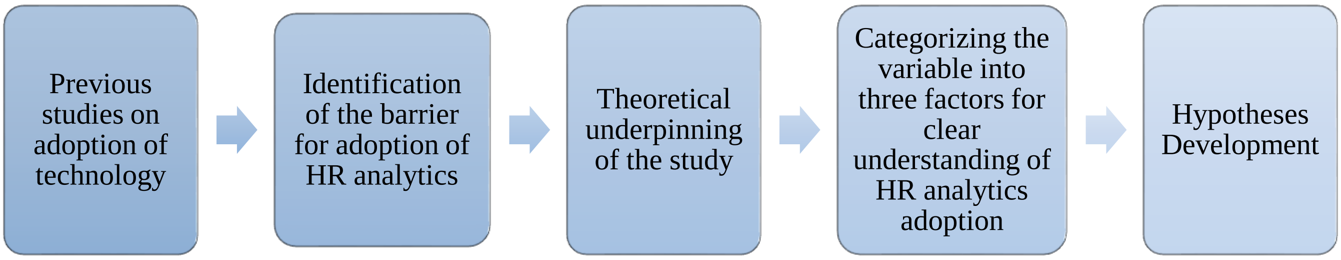
2.1 Overview

The goal of this chapter is to examine prior studies on HR analytics. However, Marler & Bourdeau (2017) noted that there is very little research on the adoption of HR analytics. For this study, we will therefore look into the literature on adoption and diffusion as well as research linked to analytics, big data, artificial intelligence and any technological adoption. This study aims to develop a model that fills in gaps from previous research. This chapter thus, talks about how the model was made possible by identifying the work of Ajzen (2001), Davis et al. (1989), and Rogers (1983). The literature review included academic journal papers, practitioner articles, surveys, and books. This study looked into factors that act as a barrier for HR professionals from using HR analytics. For more comprehensive grasp of HR analytics adoption, this study additionally classified the factors under individual, social, and technological categories.

To that purpose, the literature review chapter is structured into four sections (Figure 2.1) that are related to the aspects mentioned above. The literature on the adoption of HR analytics is gathered in the first section. The identification of potential barriers to HR analytics adoption is covered in the second section. In the third section, the three categorized variables for HR analytics adoption are shown. The fourth segment gathers research on development of theoretical models.

Figure 2.1

Outline of Literature Review



2.2 Human Resource Analytics

2.2.1 Human Resource Analytics Adoption

Companies worldwide are experiencing the digital transformation of all their business functions, and HRM or human resources impact is no exception. Digitalization of HRM, amongst others, includes the adoption of HR analytics i.e., refers to the process of obtaining up-to-date insights that assist in making strategic decisions related to human resources. The adoption of HR analytics has proved to be a game-changer, enabling organizations to enhance employee skills, improve retention and gain a competitive edge (Van der Togt & Rasmussen, 2017). HR analytics is today a huge instrument for making progress; it exploits present information to expect future ROI and is viewed as a wellspring of vital benefit (Ekka et al., 2022; BenGal, 2019; Bindu, 2016). Several studies have testified its role in improving decision-making and managing, among other functions (Wandhe, 2020; Mohammed & Quddus 2019). Despite the perceived benefits, the adoption of HR analytics among HR professionals remains sluggish (Vargas et al., 2018; Marler & Boudreau, 2017), primarily due to the adoption barriers of HR analytics. Understanding the adoption behaviour is necessary for the adoption of HR analytics. Various adoption model is used to study the intention to use technology and its acceptance, i.e., actual adoption (behaviour/actual usage) of technology (Wang et al., 2020). Studies explain how technology adoption impacts behavioural intention (Senaratne et al., 2019; Kabra, 2017). Ajzen (1991) states that "behavioural intention is an individual's subjective possibility of performing a specified behaviour, which is the major contributing factor to actual adoption behaviour." Although research has been extensively conducted and many theories proposed to explain it in different contexts of adoption, some critical issues remain to be addressed. Adoption of HR analytics is a huge challenge (Marler & Bodreau, 2017; Fernadez& Gallardo, 2020), due to its lack of clarity on the factors that hinder its adoption (Fernadez& Gallardo, 2020). Extant literature (eg. Fernandez & Gallardo-Galardo, 2020; Kabra et al., 2017) on HR analytics adoption is more focused to find out the factors that act as a barrier on adoption through literature review or case study. However, it ignores to explain factors towards HR analytics adoption, most specifically the individual as well as organizational factor towards adoption of HR analytics in India.

HR analytics or human resource analytics is used to analyze data to improve employee performance and retention (Vargas et al., 2018; Marler & Bourder, 2017). Successful adoption of HR analytics depends on both the organization and the individual behaviour of employees (Grayson et al., 2018). The adoption model has been used to study user behaviour and Intention to accept or resist HR analytics implementation, thereby predicting its success or failure. According to David (1989), user behaviour is determined by their intention to perform the behaviour. Various researchers have adopted adoption model (TPB, TAM etc.) to analyze the adoption of new technology (Altalhi, 2021; Ammenwerth, 2019). The adoption behaviour of the employee depends to a large extent on the organizational culture, amongst other factors. Existing literature shows that organizational culture can be a barrier to successful HR analytics implementation apart from end-users. TPB has been abundantly used in literature to predict user intention and behaviour towards technology adoption and is considered as amongst the best to study technology adoption in various contexts (Altalhi, 2021; Ammenwerth, 2019).

2.2.2 HR Analytics Adoption and Organization Culture

Accordingly, while thinking about technology acknowledgment and adoption, it is imperative to remember that culture impacts a person’s intention and behaviour. According to studies by Srite (2006) and Hofstede (2001), culture can significantly affect how individuals interact with technology because it influences their behavior, thoughts, and perceptions. Previous literature throws light on how organizational culture impacts individual intention to adopt technology (Akhtar et al., 2019) and impacts their behavioural intention and adoption behvaiour (Gu et al., 2014).

HR analytics is a complex technology (Vargas et al., 2018; Marler & Bourder, 2017). According to Jac Fitz-Enz (2010), “Analytics is a mental framework, first a logical progression and second a set of statistical tools.” The relationship between organizational culture and information technology is complex and confrontational. According to Gu et al. (2014), the relationship between technology adoption and organizational culture are complex and interrelated. The adoption of technology can have a significant impact on an organization's culture. When new technology is adopted, it can disrupt existing work processes and introduce new norms and values. This, in turn, can lead to a redefining of the existing culture to incorporate these new norms. On the other hand, organizational culture can also impact technology adoption. The values, beliefs, and attitudes of the organization's members can influence their acceptance of new technology. For instance, an organization with a culture that values innovation and experimentation may be more open to adopting new technology than an organization with a culture that is resistant to change (Akhtar et al., 2019).

Ribiere and Sitar (2003) showed that organizational culture (OC) represents the character of an organization, which directs its employees’ day-to-day working relationships and guides them on how to behave and communicate. Organizational culture can encourage the use of technology, in fact. However, depending on the OC elements, it may also delay the adoption of new technologies. Although it has been acknowledged that organizational culture and technology adoption are related, there haven't been many actual studies to support this claim. In light of this, it seeks to pinpoint the OC elements and traits that influence HR analytics adoption. Additionally, nothing is known about how organizational culture affects how individuals embrace HR analytics. We discuss and evaluate the effect of organizational culture on HR analytics adoption in order to close this gap.

2.3 Identification of potential factors that hinder the adoption of HR analytics.

A comprehensive examination of existing research was conducted to uncover the potential barriers that might hinder the effective adoption of HR analytics among HR professionals. The factors that hinder the implementation of HR analytics are outlined below.

As a result of the growing usage of analytics, understanding the factors driving HR analytics adoption and its effects on corporate performance has become an important study topic (Aydiner et al., 2019). Even if more companies are investing in the HR analytics sector, the overall percentage still appears to be low. Due to its limited utilisation, researchers find it difficult to assess the importance of HR analytics in an organization's success. As a result, there isn't yet a reliable scholarly model to describe how business adoption of HR analytics works. Despite the widespread usage of HRMS and eHRM in enterprises, these topics are shockingly understudied in terms of theory and research (Stone & Dulebohn, 2013). Angrave et al. (2016) claim that there is little to no evidence in the current HR analytics research about how HR analytics may be used to enhance operational business processes.

Table 2.1

Highlighting the Needs for a Study on HR Analytics Adoption

Description	Authors
There is dearth of scientific evidence aiding to decision-making concerning adoption of HR analytics.	Fernandez & Gallardo-Gallardo (2020); Marler & Boudreau (2017)
HR analytics has positive effects, yet adoption is slow.	Fernandez & Gallardo-Gallardo (2020); Vargas et al. (2018); Marler & Boudreau (2017)
Lack of clarity on factors that hinder the adoption of HR analytics.	Fernandez & Gallardo-Gallardo (2020); Marler & Boudreau (2017)
HR has lagged behind other functional areas in the adoption of analytics among top performing companies.	Ejaz et al. (2020); La Velle et al. (2011)
Companies now rank HR analytics as one of the most important innovations in the field of technology.	Vargas et al. (2018); Marler and Boudreau (2017); Rafter (2013)
HR professionals' attitudes predict the behavioural intention to adopt HR analytics.	Ejaz et al. (2020); Vargas et al. (2018)
Readiness level of HR professionals to adopt HR analytics is their willingness to adopt this new way of measuring HR.	Ejaz et al. (2020)); Gorge & Kamalanbhan (2016); Bazurli et al. (2014)
Individual's perceptions regarding the adoption intention of technology significantly affect the adoption behaviour.	Bankole& Bankole (2017); Moore & Benbasat (1991);
Need for a better understanding of the possible factors influencing user acceptance of innovation in the workplace.	Ejaz et al. (2020); Vargas et al. (2018); Talukder et al. (2008)
Organizational culture is identified as a critical factor in the success or failure of technology adoption in an organization.	Sunny et al. (2019); Mohtaramzadeh et al. (2018); Wang & Chang (2016); Dwivedi, et al. (2016)
Technological innovation has continued to grow at a very high rate, while the adaptation and usage of such technologies have been comparatively slow.	Ejaz et al. (2020); Zhao& Zhao (2018); Rogers (2003)

Before implementing HR analytics into their procedures, organizations must overcome a number of obstacles. They must examine the use of analytics in capturing, arranging, and maximizing HR data to create value. To do this, HR analytics must transform from the current descriptive models to the predictive ones in order to comprehend the strategic impact of human capital (Boudreau & Casico, 2017; Boudreau & Lawler, 2015). The present HR platforms and applications are primarily built to facilitate data reporting; they infrequently help users comprehend how human capital plays a role in “an organization's success (Angrave et al., 2016). The HRM is unable to give top managers and CEOs the support they need in the absence of a strategic perspective on HR analytics, despite the fact that they are universally recognized as significant resources that give them a competitive edge. As a result, organizations should concentrate on developing a “data-driven culture” for an established HR analytics practice.

Efficiency and efficacy in data collection and analysis are other issues that prevent the implementation of HR analytics (Pape, 2016; Rasmussen & Ulrich, 2015). Without dependable data, it is impossible to implement HR analytics; as a result, the data must be synced and made available to the HR analytics platform (Scullen et al., 2000). One of the main problems preventing the deployment of HR analytics is a lack of appropriate and high-quality data (Andersen, 2017). Many companies attempt to compensate for their lack of HR competencies by outsourcing the HR functions to outside suppliers, but this may result in data privacy concerns. In order to close this knowledge gap, businesses must therefore create their own solutions (Minbaeva, 2017). Another issue is the absence of organizational support for HR analytics and the complexity of utilizing AI-powered technologies (Strohmeier & Piazza, 2013). Given the abundance of AI-powered technologies on the market, HR analytics professionals must continuously experiment to identify the tools and methods that will best address the issues facing their business.

Additionally, several research have questioned whether the HR analytics domain ought to even be included in the HR function (Rasmussen & Ulrich, 2015). It has been stated that it is preferable to have a centralised analytics cell within an organisation because HR analytics needs data from several departments, like marketing, in order to handle more significant business concerns (Bersin, 2015). Be aware that data analysis alone will not be useful unless they are used to extract insights and then used to create an engaging narrative to guide decision-making (Andersen, 2017; Green, 2017). Angrave et al. (2016) questioned if HR professionals are even capable of successfully sifting through big data and analytics to produce organisational benefits. Even if HR experts could perform the necessary analysis, gathering data from all sources would still be challenging (Fitz-enz & Mattox, 2014). Part of the reason for their subpar performance in this area is due to the HR departments' non-central posture within organisational structures and a lack of appropriate capabilities (Angrave et al., 2016). The requirement that HR personnel possess mathematical and statistical skills is another factor in the low adoption of HR analytics. Another reason for the low level of HR analytics adoption is that it requires the HR professionals to be able to perform mathematical and statistical analyses (Vargas et al., 2018), which they may not be familiar with.

Although there is a lack of informative literature on how to use such data, HR practitioners must make a compelling case for using data insights to attract investments. Because it is frequently challenging to comprehend the core behaviour and decision-making processes, fixing this problem is trickier in the case of HR analytics (Fitz-End, Phillips, & Ray, 2012). Businesses throughout the world are still battling to take the proper measures in making this a reality, despite the fact that many HR strategists predict a bright future for HR analytics (Angrave et al., 2016). While conceding that HR analytics is under active development at their companies, many consulting firms assert that analytics still represents one of the biggest skill gaps in HR practice (Deliotte, 2015). Despite its low acceptance rates, the idea of HR analytics is becoming more and more popular in academic circles as seen by the numerous programmes and courses that are being provided on the subject, which can increase the adoption rate for HR analytics (Greasley & Thomas, 2020). As a result, further methodological research is needed to understand the uptake of HR analytics (Marler & Boudreau, 2017). However, the organizational dynamics as they currently stand are not yet developed enough to allow for HR analytics both within the HRM and the business. As a result, HR analytics must be implemented by enterprises with a strategic goal of long-term value development (Corte-Real et al., 2019).

Table 2.2

Overview of the Potential Factors that Hinder the Adoption of HR Analytics

Barriers in adoption of HR analytics	Author
Lack of data integration and sharing.	Davenport et al. (2010), OrgVue (2019), McIver et al. (2018), Douthitt and Mondore (2014)
Insufficient data and metrics.	Angrave et al. (2016), Pape (2016), Lawler et al. (2004); HBR (2017).
Low quality of HR data.	Harris et al. (2011), Russell and Bennett (2015), Werkhoven (2017), Minbaeva (2018
Incompatibilities between systems to merge data from different units.	OrgVue (2019), Houghton and Green (2018)
HR professionals have lack of skill to understand the quantitative data and not being able to deal with it.	FitzEnz, (2010); Vargas et al. (2018); Fernadez& Gallardo, (2020).
Lack of knowledge, skills and competences related to analytics.	Angrave et al., 2016), CIPD (2013), HBR (2014), KPMG (2019), Marler and Boudreau (2017), OrgVue (2019), Andersen (2017)
Underestimate the impact of culture.	Vargas et al. (2018), KPMG (2019), Houghton and Green (2018); Fernadez& Gallardo, (2020).
People should have an analytical mindset.	(Rasmussen and Ulrich, 2015; Marler and Boudreau, 2017; Mirski et al., 2017)
Shortage of analytically skilled HR professionals.	Angrave et al., 2016; Marler and Boudreau, 2017; Fernadez& Gallardo, (2020).
Keeping HR analytics only within the HR department.	Rasmussen and Ulrich (2015), McIver et al. (2018), CIPD, 2013)
Lack of strategic business view.	Rasmussen and Ulrich (2015), Bassi (2011), Levenson (2011), Andersen (2017)

2.4 Theoretical Underpinning of the study

2.4.1 Logical framework for theoretical underpinning for HR Analytics Adoption

Researchers have used various innovation appropriation models to analyse user expectations and user adoption of the technology, including the innovation diffusion theory (IDT), the technology-organization-environment framework (TOE), the institutional theory (IT), the theory of planned behaviour (TPB), the technology acceptance model (TAM), and the unified theory of acceptance and use of technology (UTAUT). According to Hosseini et al. (2016) and Cao et al. (2017), these models have been utilised to explain technology adoption practices in the management research industry.

Adopting a technology means that a person plans to use that technology. So, we used TPB to study how people intention change to their adoption behaviour. TPB has been used to study many different kinds of behaviour in many different fields. It has also been used in the past to study technology adoption (Vargas et al., 2018; Weigel et al., 2014). We also used a few components of the TAM model, which is thought to be the most reliable way to adapt to new technologies. Another model used to understand the adoption of HR analytics is the DOI model. By integrating these three models a frame work has been develop to understand the adoption of HR analytics among HR professionals.

A detailed overview of all three models, namely TPB, TAM, and DOI, has been presented below. This analysis includes an explanation of why each model was used in the study as well as the modifications that were implemented into the study.

2.4.2 Theory of Planned Behaviour (TPB)

Ajzen (1991) developed the theory of planned behaviour (TPB) as an extension of the TRA model, attempting to explain distinctive individual behaviour. The theory says that a person's intention and one feeling of control over their behaviour will help predict their behaviour more accurately than other models (Ajzen, 1991). The incorporation of the perceived behavioural control variable impacting intention to use distinguishes it from the TRA model. The purpose that leads to behaviour is the primary focus of this model, however Ajzen (1991) added a variable called perceived behavioural control. He contends that “behavioural purpose can only be expressed in behaviour if the behaviour in question is under volitional control” (Ajzen, 1991, p. 181). By volitional control, he means that an individual can choose whether or not to engage in this behaviour. The decision is influenced by requirements such as whether an individual has the resources to engage in this behaviour. In this context, resources are defined as “time, money, talents, and the participation of others” (Ajzen, 1991, p. 182). These fundamentals are related to the perceived risk of engaging in behaviour. Ajzen (1991) offers an example to support the relationship between perceived behavioural control and behavioural intention. If two individuals try to master the art of skiing, and both individuals having the intention of doing so, the individual with most belief in that he will control the skill of skiing, will be the one who is more plausible to master this activity.

Ajzen's “Theory of Planned Behavior” from 1991 categorized into three parts: attitude toward the behaviour, perceived behavioural control, and subjective norms. Individual attitudes refer to how they feel about something, and how it influences their behavior. Perceived behavioral control refers to individuals' beliefs of their ability to accomplish a certain behaviour and its ease of performance. Subjective norms are about what they believe important people (family, friends, or even the society as a whole) in their life think about the behavior, which can influence their decision to actually do it or not. Understanding these factors can help us predict and explain why people behave in certain ways.

Implementation of TPB model for HR analytics adoption

An organisation that has implemented analytics anticipates that this information will promote a favourable attitude toward analytics among its individuals. Ajzen (1991) claim that attitudes predict behaviour, such that positive attitudes predispose an individual to positive behaviour and negative attitudes predisposition an individual to avoid or reject the item and act accordingly. This relationship has been investigated in numerous technology adoption studies (Vargas et al., 2018). In this study, we're interested in the HR professional's readiness to adopt this new method of measuring HR (Bazurli et al., 2014).

Technology adoption is a multidimensional process since it involves the actions of people whose behaviour can be influenced by others in either accepting or rejecting it (Vargas et al., 2018; Talukder & Quazi, 2011). Subjective norms defined as, the degree to which a decision maker feels it necessary to behave in a manner consistent with the social environment (i.e., Friends, colleagues, or superiors). Subjective norm, also known as social influence, is an important factor in the adoption of technology (Talukder & Quazi,2011, Vargas et al., 2018). Individuals may choose to adopt technology based on their perception of peer and superior influence rather than its use (Talukder, 2012). So, for a better understanding of social influence in an organisation, both peer and superior influences are considered in this study. The study also reveals that peer and superior influence has a direct effect on the inclination to adopt technology (Talukder & Quazi). As a result, this study will explore the impact of peer and superior influence on HR analytics adoption among HR professionals

The adoption of HR analytics in general must be accepted to give businesses a competitive advantage in the current global era (Wandhe et al., 2020; Vargas et al., 2018; Marler & Bourdeau, 2017). Perceived behavioural control refers to an individual's perception of his or her capacity to conduct a particular behavior. Ajzen relates perceived behavioural control to

Bandura's self-efficacy idea (Bandura,1977). In the context of this study, perceived behavioural control and quantitative self-efficacy are interchangeable. Quantitative self-efficacy is dependent on an individual's belief in his potential, i.e., mathematical literacy, to succeed and achieve a specified level of performance (Ozgen 2013, Vargas et al., 2018). Therefore, the adoption and utilization of HR analytics by HR professionals is dependent on their view of their skills.

An individual behavioural intention can be interpreted as individual willingness towards any aspect, reflecting their behaviour. Therefore, it is the predictor of behaviour (Ajzen, 1991), i.e., “a person’s readiness to perform a given behaviour.” Furthermore, behavioural intention also explains why people behave in a certain way in certain situations (Osbourne and Clarke 2006). Research gives evidence that individual willingness, i.e., intention to perform a behaviour predicts the actual behaviour (Wang et al., 2020; Taherdoost, 2020). For this study behavior intention will be interchangeable with readiness towards HR analytics. This study suggests that individuals with intention to use HR analytics will be more amenable to adopting HRA.

2.4.3 Technology acceptance model (TAM)

Fred D. Davis develop a model known as technology acceptance model (TAM) based on the TRA model in 1986. It was created with the goal of explaining and predicting people's acceptance of new technical innovations. Davis (1986) revised the model to make it more technologically applicable.

He found that the social influences of TRA, as well as the previously described subjective norms, do not fit into a technical context of acceptance and adoption. This distinguishes this model from the TRA model. Davis (1986) uses the concept of external variables instead of the subjective norm and divides it into two concepts. These two concepts are perceived usefulness and perceived ease of use, and they are designed to describe the adoption of a new technology. According to Davis, perceived usefulness is "the degree to which an individual believes that utilising a specific system would improve his or her job performance" (Davis, 1986, p. 26). Were as perceived ease of use “the degree to which a person believes that using a particular system would be free from effort” (Davis, 1986, p. 26). Furthermore, he believed that making a system easy to use can boost overall job performance. This is a statement that supports the premise that perceived ease of use influences perceived utility. Previous research (Davis, 1989, p. 333) has demonstrated that perceived utility is the most important factor in determining intention to use when comparing both determinants. By studying the model, both of these categories are related to attitudes toward usage, but perceived usefulness has a direct association to intention to use.

Implementation of TAM model for HR analytics adoption

Adoption of a technology is defined as an intent behavior to use that technology. Thus, we applied TAM to study any technological adoption. TAM has previously been studied in many fields for adoption of technology (Davis 1989). In this study adoption behavior of HR professionals’ towards HR analytics incorporates two elements from TAM model i.e., perceived ease of use and perceived usefulness. Previous study has found a significant relationship between perceived ease of use and perceived usefulness towards adoption of technology (Ferri et al., 2020; Venkatesh and Davis, 2000; Davis, 1989). Both the elements have been used in this study to understand HR professionals’ behavior towards HR analytics, to determine whether the use of HR analytics can improve their job performance and productivity. Also, the study aims to understand the ease and effortlessness of HR professionals’ towards using HR analytics in their work.

2.4.4 Diffusion of Innovation

Rogers first proposed the Diffusion of Innovation theory in 1962. Although it goes by the abbreviation DOI, innovation diffusion theory is another name for it (IDT). The study of DOI examines how, why, and how quickly new concepts, ideas, products, and technologies spread within communities.

Diffusion is a communication technique that involves disseminating novel ideas while retaining some degree of uncertainty, according to Rogers (1983). There seems to be a common set of ideas and generalizations despite the fact that diffusion research has been undertaken across a wide range of fields (Rogers, 1995). According to Rogers (1995), the diffusion process consists of four basic components: invention, communication through channels, communication within a time period, and communication through participants in social systems. An idea, behaviour, or thing that is viewed as novel by a person or other adoption unit is referred to as innovative (Rogers, 1995, p. 11). Rogers (1983) noted that the majority of inventions that have been studied with regards to diffusion are related to technology, which is designed to reduce uncertainty in cause-and-effect relationships to achieve desired outcomes. This study focuses on the use of HR analytics to improve HR decision-making and gain a competitive advantage.

According to Rogers (1983), social system members' evaluations of the innovation's relative advantage, compatibility, complexity, trialability, and observability impact whether and how quickly it is adopted. These are also referred to as the five pillars of innovation (Rogers 1983, 1995). According to Tornatzky and Klein (1982), relative advantage and complexity have a more consistent and meaningful link with adopting innovation. This study examines complexity, trialability, and observability as they relate to individual-level adoption factors.

According to Rogers (2003), diffusion occurs through time and is influenced by innovativeness, which divides society's participants into (a) innovators, (b) early adopters, (c) early majority, (d) late majority, and (e) laggards. A 5-step process that includes (a) knowledge, (b) persuasion, (c) decision, (d) implementation, and (e) confirmation that an innovation's rate of adoption is the speed at which the innovation is adopted makes up the innovation-decision process, which results in the adoption or rejection of an innovation (Rogers, 1983). These characteristics match those of individual innovator adopters, which is the study's main topic.

Last but not least, the social system comprises of individuals who work together to identify solutions to issues in order to advance a common objective (Rogers, 1995). Opinion leaders and change agents are individuals who are part of the social system and who have the power to influence adoption of innovations, slow down their spread, or prevent them from being adopted at all (Rogers, 1995). For the purposes of this research, the term social system refers to the degree to which members of a social group influence one another's conduct in adoption (Talukder & Quazi, 2011, p. 115).

Implementation of DOI for adoption of HR analytics

At the individual or organizational level, the decision to adopt HR analytics can be influenced by a variety of factors, such as how well it works, how available it is, how easy it is to use, how much time and money it saves, and how convenient it is. For this research purposes, trialability is referred to as tool trialability. The trialability of a technology is required for its acceptance (Vargas et al., 2018). Rogers, 2003 defined trialability as “the degree to which an innovation may be experimented with on a limited basis.” Previous research found a significant impact of trialability on adoption of technology (Vargas et al., 2018; Hameed &

Counsell, 2014). The purpose of this study is to assess the HR analytics trialability among HR practitioners.

Availability of resources is an important construct to explain HR analytics adoption. Shareef et al. (2009) contributed a new concept to DOI regarding the availability of resources to understand the adoption of ICT among developing countries. As availability of data is consider a potential obstacle for implementation of HR analytics. We incorporated the construct in order to clearly understand the data availability among HR professional in an organization. Study found a significant relationship of data availability on technology adoption (Vargast et al., 2018).

Removed construct from theory/Abstraction of construct from theory

As complexity has the same meaning as perceived ease of use, which was adopted from TAM. Relative advantage is a matter of perceived relative benefits, capturing the TAM emphasis on perceived usefulness. Therefore, we do not employ these two concepts in our research from DOI theory as it is already captured from TAM.

2.5 Factors influencing HR analytics adoption

We conducted a thorough literature analysis to determine the potential factors that affect the effective adoption of HR analytics, including individual, social, and technological issues (Refer table 2.3).

2.5.1 Individual Factors

Individual factors are one of the key determinants of HR analytics adoption (Lewis et al., 2003; Talukder, 2012; and Haneem et al., 2019). The individual factors refer to individual cognitive beliefs about themselves and adoption (Talukder 2012). Individual elements in this study include users' perceptions of HR analytics adoption and how it impacts their jobs. It can be used to describe, for example, how eager a participant is to adopt HR analytics or how strongly they feel that using HR analytics in their own job will benefit them. According to a number of research, individual factors like attitude toward HR analytics, quantitative self-efficacy, perceived ease of use, and perceived usefulness have a significant impact on HR analytics (i.e., technology) adoption (Maroukfani, 2020; Talukder, 2012; Haneem et al.2019).

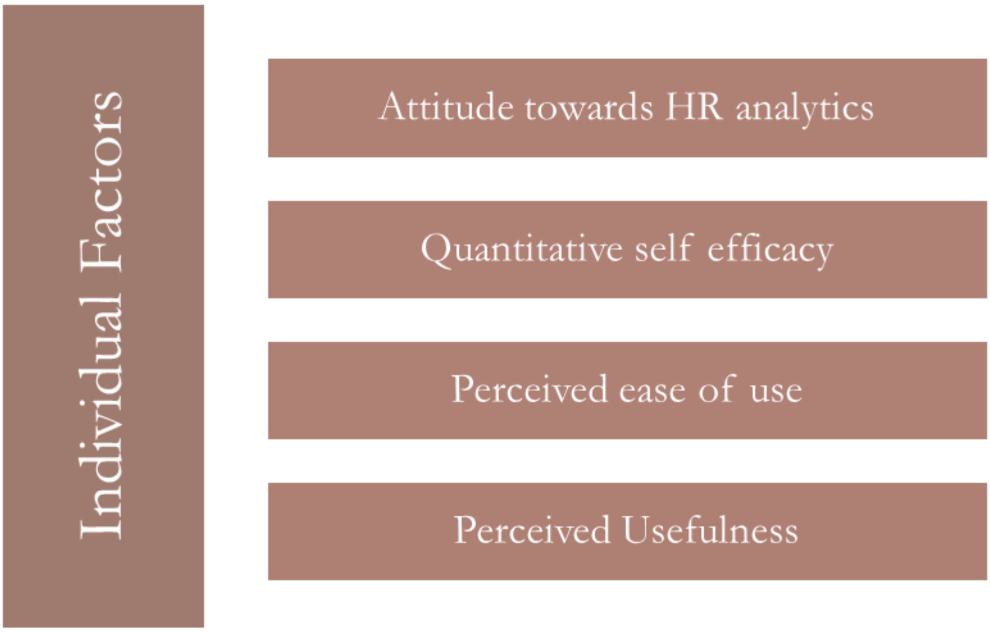
Organizations try to influence their employees' attitude towards HR analytics adoption. As attitude is a significant factor influencing the adoption of technology i.e., HR analytics (Ejaz et al., 2020). A positive attitude makes you more likely to encourage adoption and acceptance, while negative attitudes encourage rejection (Ajzen & Fishbein, 2000). The influence of attitude in explaining the adoption of various technologies has been extensively researched (Dwivedi et al., 2019). As a result, study by Vargas et al., 2018 has found a positive attitude of HR professionals towards adoption of HR analytics.

A quality known as quantitative self-efficacy encourages individuals to obtain the most extensive knowledge necessary to succeed in a specific circumstance (Ajzen & Fishbein, 2000). Self-efficacy refers to one's belief in one's ability to plan and carry out the actions necessary to achieve specific goals (Bandura, 1982). Individual intentions to use HR analytics among HR professionals are highly influenced by their assessment of their own abilities to grasp and use it. Previous research has found that very few HR employees have the necessary knowledge and abilities to derive meaningful insights from the data at their disposal (Vargas et al., 2018; Brown et al., 2015)

Perceived ease of use influences the perception regarding adoption of HR analytics (Akhtar et al., 2019; Jennings et al., 2015). A person is more likely to accept HR analytics, if they perceive that it is easy to use. Prior research (Akhtar et al., 2019; Jennings et al., 2015) discovered a direct link between adoption and perceived ease of use. Adoption is more likely to be accepted if a person believes that using the new system would increase efficiency and effectiveness and it's free of effort or provide them more control over their employment (Lee, 2004). One of the best predictors and a constant factor among all points of evaluation is perceived usefulness (Venkatesh et al., 2003). The success or failure of analytics adoption generally determines the benefits within an organization (Davenport, 2013). As a result, a person may believe that utilising HR analytics will enhance his or her profile and level of performance at work (Venkatesh and Davis, 2000). Individual factors, according to the study, have a major impact on individual behavioural intention to accept HR analytics (Haneem et al., 2019; Talukder, 2012; Lewis et al., 2003).

Figure 2.2

Individual Factors that Influence the Adoption of HR Analytics



2.5.2 Social Factors

Adoption uptake by individuals is influenced by their social environment. The adoption of HR analytics is likely to be significantly influenced by how others individuals in social surroundings use it. Social factors describe how much a social group's members can affect one another's behaviour when it comes to adoption (Konana and Balasubramanian, 2005; Venkatesh and Brown, 2001). Peers are believed to be under influence to adopt HR analytics, and this influence is applied through messages and signals that shape how people value a technology or activity (Fulk and Boyd, 1991) and also by their superior. Such influence is referred to as normative beliefs about the appropriateness of adopting innovation by Ajzen and Fishbein (1980). This viewpoint holds that employees may adopt HR analytics due to perceived social influence rather than because of its utility. Such influence may be interpreted as coming from people whose beliefs and opinions are significant, such as peers and superior (Igbaria et al., 1996).

Superior serve as role models, they can raise the motivation and dedication of their employees in jobs. Superior viewpoint and capability influence the adoption of HR analytics in a comparable manner (expert system). Potential adopters mostly persuade one another internally, according to Abrahamson and Rosenkopf (1997), which is how adoption decisions are made. According to several researches, social factors influence people's decision to adopt HR analytics in an organisation more than economic considerations (Peansupap and Walker 2005; Westphal et al., 1997). Studies have found technology i.e., HR analytics adoption is influenced by social factors (Haneem et al., 2019; Alwaris et al., 2016; Talukder, 2012).

Figure 2.3

Social Factors that Influence the Adoption of HR Analytics

2.5.3 Technological Factors

When a new technology is adopted, it's critical to determine whether it will have a positive or negative impact on how decisions are made (Maduku et al., 2016; Tornatzky & Fleischer, 1990). The choice to implement HR analytics technologies is based on "what" is available and "how" these technologies will integrate with the company's current technology (DePietro et al., 1990; Jeyaraj et al., 2006). The study examines how the technological factors is applied to examine various technological elements that affect the adoption of HR analytics utilizing the framework. The decision to employ an HR analytics technology typically hinges on the innovation's technical and organizational compatibility, as well as how difficult it is to learn and use (Kapoor et al., 2014a; 2014b; Rogers, 2003). Typically, an organization's overall analytical strategy includes the technology infrastructure necessary for the deployment of HR analytics (which includes IT and HRM). The way businesses receive, store, use, and disseminate information about their employees and candidates is affected by technology, in particular (Stone et al., 2015). The adoption of many systemic, complicated technologies, like

HR analytics, has been proposed to raise the return on their adoption, meaning that the initial increase in adoption results in a better technological experience. As a result, technical advancements and utilisation are occurring at an increasing rate, which encourages the acceptance of new technologies (Makinen, Kannianen, & Dedehayir, 2013). In this study, we demonstrate how technological aspects are essential for HR analytics acceptance in a organization.

Tool trialability is the degree to which an innovation can be examined on a regular basis (Rogers, 2003). According to Hameed and Counsell (2014), trialability is a strong element that has a significant impact on adoption. The faster a technology is accessible, the easier and faster it can be adopted. Trialability is a key factor that influences adoption. Vargas et al. (2018) discovered that trialability influences HR analytics adoption. Data availability is essential for making efficient and progressive decisions (Vargas 2015). The HR department uses this information to promote initiatives, address problems, and create a positive workplace culture. Previous study has looked at how data availability affects HR analytics (Vargas et al., 2018; Vargas, 2015). The trialability of HR analytics tools in an organization, as well as the availability of relevant data for HR analytics, are among factors that impact the technological perspective for its adoption. Previous studies show technological factors influence technology adoption significantly (Marukohani et al., 2020; Dmour et al., 2020).

Figure 2.4

Technological Factors that Influence the Adoption of HR Analytics

Table 2.3

Outlining the Challenges of HR Analytics Adoption and the Factors that Influence its Adoption

Author	Challenges	Individual	Social	Technological
Fernadez& Gallardo (2020), DiClaudio (2019), Marler & Boudreau (2017), Angrave et al. (2016)	Shortage of analytically skilled HR professionals.	✓		✓
DiClaudio (2019), Vargas et al. (2018)	Technology is subjected to extensive testing.			✓
Fernadez& Gallardo (2020), DiClaudio (2019), Vargas et al. (2018), FitzEnz (2010)	Inadequate analytical ability.	✓		
OrgVue (2019), Strohmeier (2018), Huselid (2018),Marler &Boudreau (2017), Angrave et al. (2017)	Lack of knowledge, skills and competences related to analytics.	✓		✓

OrgVue (2019), Houghton and Green (2018)	Incompatibilities between systems to merge data from different units.			✓
McIver et al. (2018), Rasmussen and Ulrich (2015)	Keeping HR analytics only within the HR department.		✓	
Fernadez& Gallardo (2020), Strohmeier (2018), Huselid (2018), Marler & Boudreau (2017)	Inadequate comprehension of tools for specific individual's issues.			✓
DiClaudio (2019),OrgVue (2019), McIver et al. (2018), Douthitt and Mondore (2014)	Data accessibility, Data accountability.	✓		✓
Bondarouk et al. (2017)	Include top management backing.		✓	
Bondarouk et al. (2017), Pape (2016)	Effectiveness and efficiency.	✓		
DiClaudio (2019), Marler & Boudreau (2017), Mineva (2017), Deliotte (2015)	Unsynchronized data HRMS integration with management data.			✓
Marler & Bourdeau (2018), Bondarouk et al. (2017), Pape (2016)	Acceptance by the user.	✓	✓	✓
Bondarouk et al. (2017), Mineva (2017)	Communication and cooperation among units.		✓	
Vargas et al. (2018), Bondarouk et al. (2017)	Employee attitudes.	✓		
DiClaudio (2019), Marler & Boudreau (2017), Mineva (2017), Deliotte (2015)	Inadequate employee readiness.	✓	✓	✓

2.6 Hypotheses Development

2.6.1 Individual Factors

Individual characteristics play a crucial role in determining the acceptance and adoption of technology (Haneem et al., 2019; Talukder, 2012; Lewis et al., 2003). These individual factors refer to a person's beliefs and attitudes towards HR analytics and how it affects their work (Talukder, 2012). For example, a person's willingness to embrace HR analytics and their belief that it will be beneficial for their job are considered individual factors. According to a number of research, individual factors like attitude, quantitative self-efficacy, perceived ease of use, and perceived usefulness have a significant impact on adoption (Maroukfani, 2020; Haneem et al., 2019). Individual factors, according to the study, have a major impact on individual behavioural intention to adopt technology (Haneem et al., 2019; Talukder, 2012; Lewis et al., 2003).

2.6.6.1 Attitude towards HR analytics

Ajzen, (2001) defined attitudes as a crucial factor that impact a person's intention to engage in a behavior, as they represent the emotions and evaluations that individuals hold towards that particular behavior. The decision process involves the formation of attitudes towards adoption of HR analytics in an organization. The literature suggests that the attitude of HR professionals towards HR analytics is an important factor that influences its adoption (Fallarado & Gallarado,2020; Marler & Bourdeau,2017).

Ajzen (2001) claim that attitudes predict behaviour such that good attitudes lead one towards positive behaviour while negative attitudes lead one to avoid or reject the item and behave appropriately. In addition, they suggest that using general measures of attitudes to predict behaviour in a particular context can produce contradictory results. It can be stated that HR professionals who have positive attitudes towards HR analytics are more likely to adopt and use it effectively. Conversely, HR professionals who have negative attitudes towards HR analytics are less likely to adopt and use it effectively. Therefore, attitudes play a significant role in shaping behavior. However, the readiness of HR professionals to embrace HR analytics depends on their willingness to learn, commitment to adopt a new way of measuring HR, and intention to use analytics (Bazurli et al., 2014).

HR professionals who have a high level of data literacy are more likely to have a positive attitude towards HR analytics (Dahlbom et al., 2020; Legnick et al., 2018). Data literacy refers to the ability to read, understand, and analyze data. As, HR professionals and leaders only focus on soft skills within the organization may lack confidence in dealing with analytics, especially when it involves people-related issues (Marler &Bourdeau, 2017; Bazuril et al., 2014). They need to be trained to understand analytics better, including where the data comes from, what the data means, and how it aligns with the organization's strategic plan, rather than solely relying on internal metrics. This can help them develop a more positive attitude towards analytics, as highlighted by Prokopeak (2014).

Moreover, previous studies have also shown a clear relationship between an individual's attitude and their intention to adopt HR analytics (Dwivedi et al., 2019; Vargas et al., 2018, Mineva,2017). Thus, the following hypothesis is developed:

Hypothesis 1: Attitude towards HR analytics positively influence readiness of HR professionals to adopt HR analytics.

2.6.1.2 Quantitative self-efficacy

Quantitative self-efficacy is an individual's belief in their ability to perform quantitative task effectively that can inspire them to acquire the necessary knowledge and skills to excel in a specific domain (Ajzen & Fishbein,2000). Incorporating the concept of quantitative self-efficacy into the TPB model, Ajzen in (2000) suggests that an individual's intention to adopt technology is affected by their level of quantitative self-efficacy in performing quantitative tasks sine such complex technologies demand a broad range of knowledge and diverse abilities. Self-efficacy, according to Bandura (1977), is found on a person's belief in his or her ability to succeed and be able to perform at a certain level. According to Hendel (1980), who investigated math anxiety, and Ozgen (2013), who studied mathematical literacy, all found that there is an attitude link between math knowledge and math anxiety and, as a result, an effect on mathematical self-efficacy. The terms mathematical self-efficacy and quantitative self-efficacy are synonymous for the purposes of this study. As a result, HR professionals' acceptance and use of HR analytics would depend on how successful they believe they will be at achieving acceptable performance levels with the help of HR Analytics.

Research conducted by Brown et al. (2015) has revealed that a majority of HR professionals lack the necessary knowledge and skills to analyze data effectively, even when using relatively simple metrics and scorecards. This indicates that an individual's quantitative self-efficacy, which is their belief in their ability to understand and utilize numerical data, can have a significant impact on the acceptance and adoption of HR Analytics. When individuals have low self-efficacy in quantitative skills, they are less likely to use or recommend HR Analytics to others, resulting in lower acceptance.

Moreover, previous studies have also shown a clear relationship between an individual's quantitative self-efficacy and their readiness to adopt HR analytics (Dahlbom et al., 2019; Brown et al., 2015). When HR professionals' feel confident in their ability to understand and utilize quantitative data, they are more likely to embrace HR Analytics. Therefore, organizations should prioritize providing adequate training and resources to enhance the quantitative self-efficacy of their HR professionals, as it can significantly impact the success and adoption of HR Analytics in the workplace. Thus, the following hypothesis is developed:

Hypothesis 2: Quantitative Self-Efficacy positively influences readiness of HR professionals to adopt HR analytics.

2.6.1.3 Perceived ease of use

Perceived ease of use is the degree to which a person believes that using a particular system would be free from effort (Davis 1989). In the context of HR Analytics, it suggests that HR professionals are more likely to adopt and utilize HR analytics if they perceive it to be easy to use. Previous studies have found a positive correlation between perceived ease of use and behavioral intention to adopt HR Analytics (Akhtar et al., 2017; Jennings et al., 2015).

Research has shown that an individual's intention to use HR analytics is influenced by several factors, including the complexity of the system, the ease of utilizing the technology, and the system's compatibility with the individual's experience and expertise (Kabra et al., 2017; Akhtar et al., 2012). When HR professionals perceive HR analytics to be simple to use, they assume that it is effortless to operate, which leads to a greater likelihood of adopting it. Studies have demonstrated a direct relationship between perceived ease of use and users' readiness to HR Analytics (Kabra et al., 2017; Davis, 1989). On the basis of prior study, we hypothesize the following;

Hypothesis 3: Perceived Ease of Use positively influence readiness of HR professionals to adopt HR analytics

2.6.1.4 Perceived Usefulness

Perceived usefulness (PU) is the degree to which a person believes that using a particular system would enhance his/her job performance (Davis, 1989). It reflects the individual opinion of users about how employing new technology will enhance their productivity. In this study, PU relates the belief that an individual, an HR professional, would easily improve their work performance by utilising HR analytics, which influences the readiness to adopt HR analytics. Perceived usefulness has been shown in studies to be a strong predictor of behavioural intention for embracing HR analytics (Ferri et al., 2020; Kabra et al., 2017). According to studies, utilising new technology improves a person's ability to perform their job duties and HR analytics usage raises an individual's performance. HR analytics has shown to be a game-changer for improving decision-making, managing other tasks, and enhancing staff abilities (Wandhe, 2020; Mohammed & Quddus, 2019; Van der Togt & Rasmussen, 2017). According to earlier studies, behavior-changing intentions to adopt new technology are influenced by perceived usefulness (Ferri et al., 2020; Davis, 1989). Based on previous research, we hypothesize the following:

Hypothesis 4: Perceived Usefulness positively influence readiness of HR professionals to adopt HR analytics.

To sum up, each of the aforementioned factors is considered individual factors that affect the adoption of HR analytics. Based on these studies, it can be concluded that individual factors greatly impact a person's intention to adopt HR analytics. That's why we hypothize:

Hypothesis 5: Individual factors significantly affect the adoption intention of HR professionals for HR analytics adoption.

2.6.2 Social Factors

Social factors describe how much a social group's members can affect one another's behaviour when it comes to adoption (Konana and Balasubramanian, 2005; Venkatesh and Brown, 2001). Individuals' adoption of technology is influenced by their social environment around them. This means that how others in their social circle use technology can greatly affect their own adoption behavior. Social factors play a key role in the adoption and determine how much the members of a social group can affect each other's behavior. Employees may adopt new technology due to perceived social influence from peers and superiors, rather than the technology's utility. Adoption decisions are often made through persuasive influence within the potential adopters themselves (Abrahamson and Rosenkopf, 1997). Research has shown that social factors have a greater impact on an individual's decision to adopt HR analytics in an organization compared to economic considerations

(Peansupap and Walker 2005; Westphal et al., 1997). Studies have found that adoption is influenced by social factors (Haneem et al., 2019; Alwaris et al., 2016; Talukder, 2012).

2.6.2.1 Peer Influence

In organizations peers play a significant role (Talukder & Quazi, 2010). They can offer valuable assistance by discussing mutual connections and offering insightful advice about each individual's performance (Schillewaert et al., 2005). Peer-delivered signals and messages have the power to influence how people perceive the value of technology (Talukder et al., 2008). The motivation and inspiration of their coworkers and the moral support of peers have a big impact on employees within organizations. In essence, people inside of companies need communication and connection with others since they are social beings.

When they encounter issues at work, they particularly prefer to consult their peers for help (Lewis et al., 2003; Yuan et al., 2005). The significance and advantages of adopting technological innovations within organisations are reflected in peers' behaviour as they participate enthusiastically in the process. Because of this, the majority of workers in organisations are motivated to observe the actions of their coworkers do and then try to imitate it (Frambach and Schillewaert, 2002).

Furthermore, effective communication inside organizations create strong synergies can help with the adoption of HR analytics (Sykes et al., 2009). When coworkers experience issues at work, key individuals within organisations play a crucial influence in influencing the others (Lewis et al., 2003; Yuan et al., 2005). The value of their coworkers' achievement as measured by their influence over other organisation members (Sarker et al., 2011). Additionally, peer influence can be classified and taken into account as a type of social effect on people's decisions to use technology advancements (Sykes et al., 2009).

According to several past research, the effectiveness of communication and interaction between employees and their peers within firms is crucial to the success of HR analytics (Talukder ,2012; Talukder & Quazi, 2011; Sykes et al., 2009). As a result, the following hypothesis created.

Hypothesis 6: Peer influence has a positive impact on readiness of HR professionals' to adopt HR analytics.

2.6.2.2 Superior Influence

Superiors are individuals of an organisation who have been given the duty by the organisation to be in charge of influencing the systems and people inside it in order to accomplish organisational goals (Talukder, 2012). Taylor and Todd (1995) have shown that employees tend to observe and imitate the behavior and actions of their superiors. This means that if superiors demonstrate a positive behaviour towards HR analytics, employees are more likely to adopt that behavior as well. In addition, Talukder (2012) argues that superiors can serve as role models for their subordinates. When superiors display dedication and motivation towards adoption of HR analytics, this can inspire employees to do the same. As superiors have the potential to increase the motivation and dedication of their employees simply by modeling these qualities themselves (Shet et al., 2019; Javadian et al., 2014). Furthermore, research has consistently shown that motivation and encouragement from superiors can significantly influence employee behavior (Graf et al., 2018; Talukder, 2012; Yuan et al., 2005). This means that when superiors demonstrate a positive attitude towards a particular tool or behavior, employees are more likely to follow it.

In the context of HR analytics adoption, it is reasonable to assume that the influence of superiors can play a critical role. If HR professionals perceive that their superiors value and encourage the use of HR analytics, they may be more willing to adopt it. This suggests that

HR professionals' perception of their superiors' attitudes and behaviors towards HR analytics can influence their own adoption behavior. Therefore, the study hypothesis that:

Hypothesis 7: Superior influence has a positive impact on readiness of HR professionals' to adopt HR analytics.

To sum up, each of the aforementioned factors is considered social factors that affect the adoption of HR analytics. Based on these studies, it can be concluded that social factors greatly impact a person's intention to adopt HR analytics. That's why we hypothize:

Hypothesis 8: Social factors significantly affect the adoption intention of HR professionals for HR analytics adoption.

2.6.3 Technological Factors

When a new technology is adopted, it's critical to determine whether it will have a positive or negative impact on how decisions are made (Maduku et al., 2016; Tornatzky & Fleischer, 1990). The adoption of HR analytics depends on its compatibility with the company's current technology and infrastructure, as well as how difficult it is to learn and use (Kapoor et al., 2014a; 2014b; Rogers, 2003). Thus, before adopting a new technology, companies need to consider the compatibility of the technology with their current infrastructure and assess the resources required for its successful deployment.

Technology infrastructure, which includes both IT and HRM, plays a crucial role in the deployment of HR analytics. Stone et al. (2015) emphasize that adopting new technology can have significant implications for how businesses handle information about their employees. Technology can impact the methods by which companies receive, store, process, and distribute data about their employees. For example, the adoption of HR analytics can enable businesses to collect and analyze data to inform their decision-making processes, leading to more effective human resource management practices. However, it can also create new challenges, such as data privacy concerns and ensuring the accuracy and security of the information collected. Therefore, it is essential for organizations to carefully consider the potential effects of new technology on their HRM practices and ensure they have the necessary infrastructure and processes in place to manage and utilize employee data effectively. This highlights the importance of considering the impact of technology on HRM practices and how it can affect the overall functioning of the organization. The role of technology in HR analytics adoption has found to be significant in previous research (Vargas et al., 2018). Factors such as trialability and data availability significantly impact the adoption of HR analytics (Vargas et al., 2018; Hameed & Counsell, 2014). Studies have shown that technological factors significantly affect adoption (Marukohani et al., 2020; Dmour et al., 2020).

2.6.3.1 Tool trialability

Trialability is defined as the "degree to which an invention can be tried with on a daily basis" (Rogers, 2003, p. 258). A person who is in the adoption process may not be able to embrace the innovation and move on to adoption if he is not competent enough to experiment with it. According to Hameed and Counsell (2014), trialability is a powerful factor that influences adoption in a considerable way. Trialability has been demonstrated to have a good link with adoption (Rogers, 2003; Lin & Bautlsta, 2017). The initial indicator for each individual's HRIS adoption decision was trialability (Obeidat, 2012). Carlson and Kavanagh (2011) describe individuals with relevant skill sets like the ability to read, comprehend, and analyze data for forecasting and decision-making purposes are crucial for making effective use of technology for trialability. Reading data involves the ability to extract useful information from various sources, such as spreadsheets or databases. Comprehending data involves understanding the context and meaning of the information, and identifying patterns or relationships within it. Analyzing data involves applying statistical and mathematical techniques to identify trends, patterns, and insights that can inform strategic decision-making.

The importance of trialability in HR analytics adoption is related to its ability to facilitate learning and experimentation. By allowing individuals to experiment with HR analytics, trialability can help them develop and refine their skills and knowledge, and gain a better understanding of its capabilities and limitations. This can increase the likelihood of HR analytics adoption by reducing uncertainty and increasing confidence. As a result, tool trialability supports in leading individuals toward HR analytics adoption. Research found that trialability with technology adoption has positive relationship (Lin & Bautista, 2017; Hayes et al., 2015). Based on previous research, we hypothesize the following:

Hypothesis 9: Tool trialability positively influences readiness of HR professionals to adopt HR analytics.

2.6.3.2 Data availability

According to Johnston (2006), data availability in HR refers to the accumulated information of the HR department and the organization as a whole. To effectively use HR analytics, organizations should prioritize investing in the necessary infrastructure, governance, integration, and literacy to ensure that they can leverage the full potential of their data (Fernandez and Gallardo ,2021). Organizations need access to a wide range of data sources, including employee records, performance data, compensation information, recruitment data, and other relevant information. Organizations need to invest in data management systems and processes to ensure that they have access to the data they need to make informed decisions about their workforce (Mohamed & Quddus, 2019).

To ensure data availability for adoption of HR analytics, organizations need to prioritize the data infrastructure for collecting, storing, and analyzing data (Alsuliman &Elrayah, 2021; Simbeck, 2019). Neither purchasing nor sharing data from a third-party source may be economically viable (Manyika et al., 2011). Manyika et al. (2011) urge that companies integrate information from diverse data sources to support transformative opportunities. According to Gale (2012), many organizations keep their data in many systems, making it difficult for HR professionals to interpret similarities and variations accurately and effectively. Therefore, organizations should integrate data from multiple sources, such as HR systems, payroll systems, and employee surveys, to provide a comprehensive view of the workforce. This will enable them to perform more accurate and insightful analysis of employee data, and identify key trends and patterns that can inform HR strategies and decision-making.

Even if a vast amount of data is being collected, it is necessary to know where the data is coming from to assure accuracy and limit ethical concerns (Boyd & Crawford, 2011). Less than fifty percent of organizations still utilize spreadsheets and other manual data collection and analysis methods (Gale, 2012). Therefore, organizations must establish clear policies and procedures for data management, including data quality, security, and privacy to ensure that data is accurate, reliable, and secure (Marable, 2022).

Cascio and Boudreau (2011) suggested that many HR professionals are unable of comprehending statistical terms. Organizations should invest in developing data literacy skills among HR professionals and managers (Arora et al., 2022). This will enable them to better understand and interpret data, and use it to make more informed decisions. By investing in data literacy, organizations can ensure that their HR professionals and managers are equipped with the skills and knowledge needed to effectively use data to drive business outcomes.

Therefore, understanding what to do with the obtained data would be challenging. Thus, we hypothesize:

Hypothesis 10: Data availability positively influences readiness of HR professionals to adopt HR analytics.

To sum up, each of the aforementioned factors is considered individual factors that affect the adoption of HR analytics. Studies have shown that technological factors significantly affect technology adoption (Marukohani et al., 2020; Maroufkhani et al., 2020; Dmour et al., 2020). Thus, we hypothesized:

Hypothesis 11: Technological factors significantly affect the adoption intention of HR professionals for HR analytics adoption.

2.6.4 Readiness towards HR analytics

Readiness is "an indication of an individual intention to perform a given behaviour". Readiness towards HR analytics here is consider as the intention of HR professionals' towards adoption of HR analytics. Behavioural intention can be interpreted as individual willingness towards any aspect, reflecting their behavior. As a result, it is the behaviour predictor, or "a person's willingness to undertake a specific behaviour" (Ajzen, 1991). There is a connection between intention and behaviour, as shown by earlier studies (Wang et al., 2020; Taherdoost, 2020; Bankole & Bankole, 2017). Research gives evidence that individual willingness, i.e., intention to perform a behaviour predicts the actual behaviour (Wang et al., 2020; Taherdoost, 2018). Previous research has also confirmed a strong relationship between intention and behaviour (Bankole & Bankole, 2017; Attuquayefio & Addo, 2014). Furthermore, behavioural intention also explains why people behave in a certain way in certain situations (Osbourne & Clarke 2006). Previous literature shows that a person's readiness to use a technology depends on their acceptance and intention to use it (Lin & Chang, 2011; Lin & Hsieh, 2007). Literature proves that behavioural intention (BI) directly impacts actual use (Bankole & Bankole, 2017; Attuquayefio & Addo, 2014). Various other studies also show a direct relationship between intention to adopt and the actual use of technology (Wang et al., 2020; Attuquayefio & Addo, 2014; Venkatesh et al., 2003). This study suggests that individuals with intention to use HR analytics will be more amenable to adopting HR analytics. Thus, in the context of this study, intention of HR professionals' to adopt HR analytics is assumed to have a positive effect on HR analytics adoption. Therefore, the study hypothesis that:

Hypothesis 12: Readiness to adopt HR analytics significantly impacts the adoption behaviour of HR professionals.

2.6.5 Organization Culture

Organizational culture influences the value and beliefs of individual behaviour (Eskiler et al., 2016). According to Liu et al., 2010 "organizational culture is a collection of shared assumptions, values, and beliefs reflected in its practices and goals while also enabling the members to understand the organizational functions." Studies show that organizational culture contributes a major role in adopting technology (Khanzanchi et al., 2017; Liu et al., 2010).

Organizational culture plays an important role in advancing technology adoption decisions of employees, thereby impacting their behaviour (Liu et al., 2010; Khazanchi et al., 2007). They likewise feature the significance of thinking about culture while assessing technology acknowledgment (Borkovich et al., 2015; Srite, 2006). Accordingly, while thinking about HR analytics acknowledgment and adoption, it is imperative to remember that culture impacts a person's intention and behaviour. Previous literature throws light on how organizational culture impacts individual readiness to adopt technology (Akhtar et al., 2019) and impacts their intention and behvaiour (Gu et al., 2014).

HR analytics is one of the more complex technologies in the context of HR (Vargas et al., 2018; Marler & Bourder, 2017). According to Jac Fitz-Enz (2010), “Analytics is a mental framework, first a logical progression and second a set of statistical tools.” The relationship between organizational culture and information technology is complex and confrontational. According to Gu et al. (2014), adopting new technology can disrupt an organization's established culture and change the way things are typically done. In other words, incorporating HR analytics can bring challenges and issues to the standard practices of an organization. This, in turn, leads to a redefining of the existing culture to encompass the new norms. Ribiere and Sitar (2003) showed that organizational culture (OC) represents the character of an organization, which directs its employees’ day-to-day working relationships and guides them on how to behave and communicate. They can be promoted by the culture of an organization.

2.6.5.1 Organization culture as a moderator

Culture has been widely studied in different contexts (Srite, 2006); however, limited attention has been given to study its role in the adoption of technology (Teo & Huang, 2018). A few exceptions show that organizational culture plays a significant role in technology adoption (Bankole et al., 2017; Liu et al., 2010). Organizational culture influences individual behaviour in adopting technology (Bankole & Bankole, 2017; Tseng, 2017). It is seen as a critical factor for technology adoption (Mohtaramzadeh et al., 2018; Borkovich et al., 2015) and either strengthens or weakens it. Researcher claim that organizational culture influences HR professionals behaviour in adoption of HR analytics (Ekka & Singh, 2022). Understanding the importance of organizational culture in the adoption of HR analytics is important as it impacts the thinking and behaviour of the employees (Ekka & Singh, 2022; Teo & Huang, 2018) also, acts as a moderator between intention and behaviour of an individual (Mohtaramzadeh et al.,2018; Zhao & Zhou, 2018). So far, only a few moderating variables, like age, gender, educational qualification, have been explored in the context of HR analytics adoption (Vargas et al., 2018). Culture has been extensively cited in the literature, showing an important role to play in this context (Ekka & Singh, 2022; Halper, 2014). Based on previous research, we hypothesize the following.

Hypothesis 13: Organizational culture significantly moderates the relationship between readiness and adoption of HR analytics among HR Professionals'.

2.7 Proposed model

The present study develops and evaluates an integrated model combining TPB, TAM, and DOI to examine the effect of individual, social, technological, and organizational culture on HR professionals' readiness and adoption of HR analytics in India.

To provide a clear representation of the theoretical foundation, Figure 2.5 presents a comprehensive illustration of the various theory factors that have been incorporated. The proposed research model is depicted in Figure 2.6, and it serves as a visual representation of the relationships between the different factors influencing HR professionals' readiness and adoption of HR analytics in India.

Figure 2.5

Illustrating the utilization of theories in the research framework

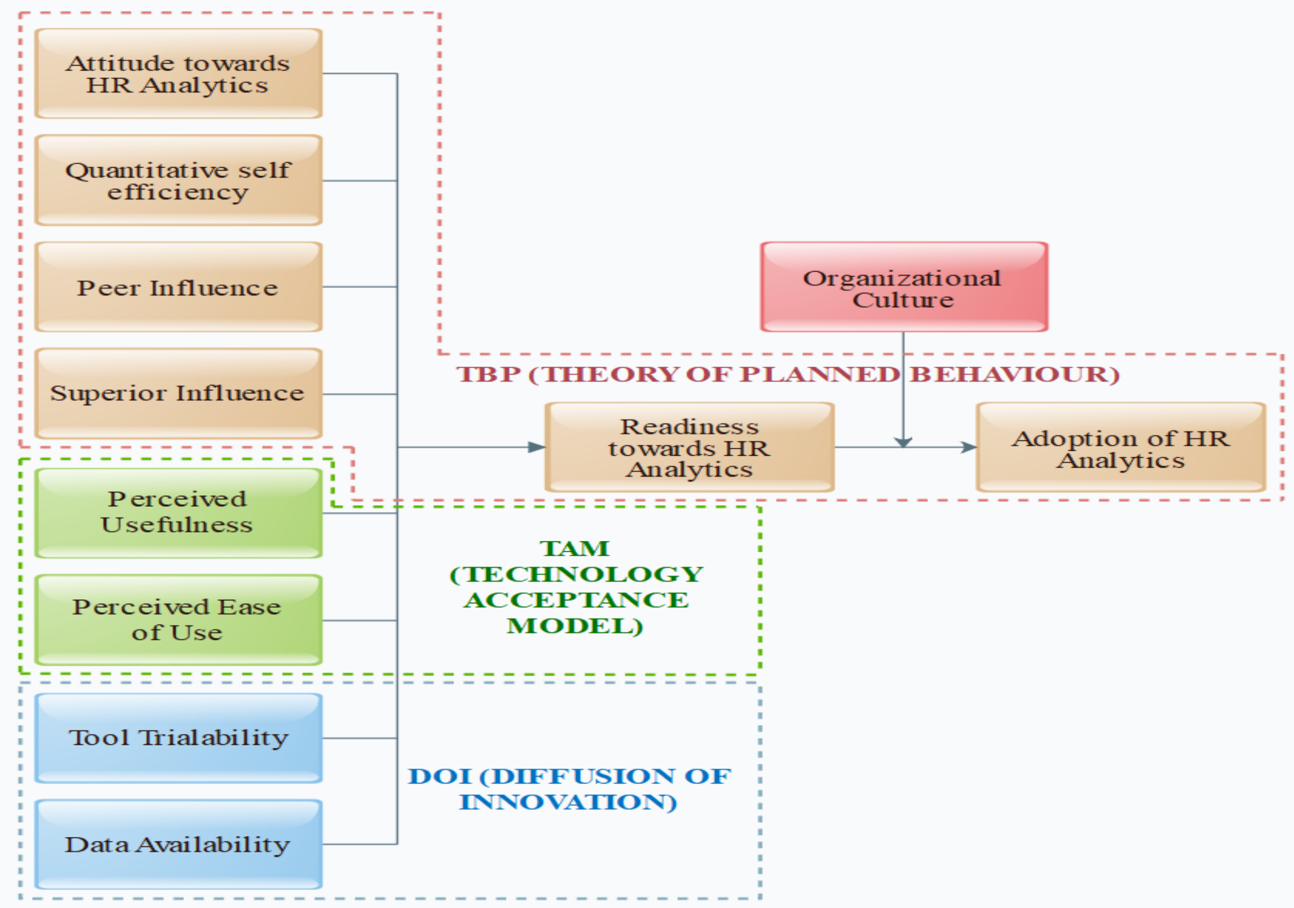
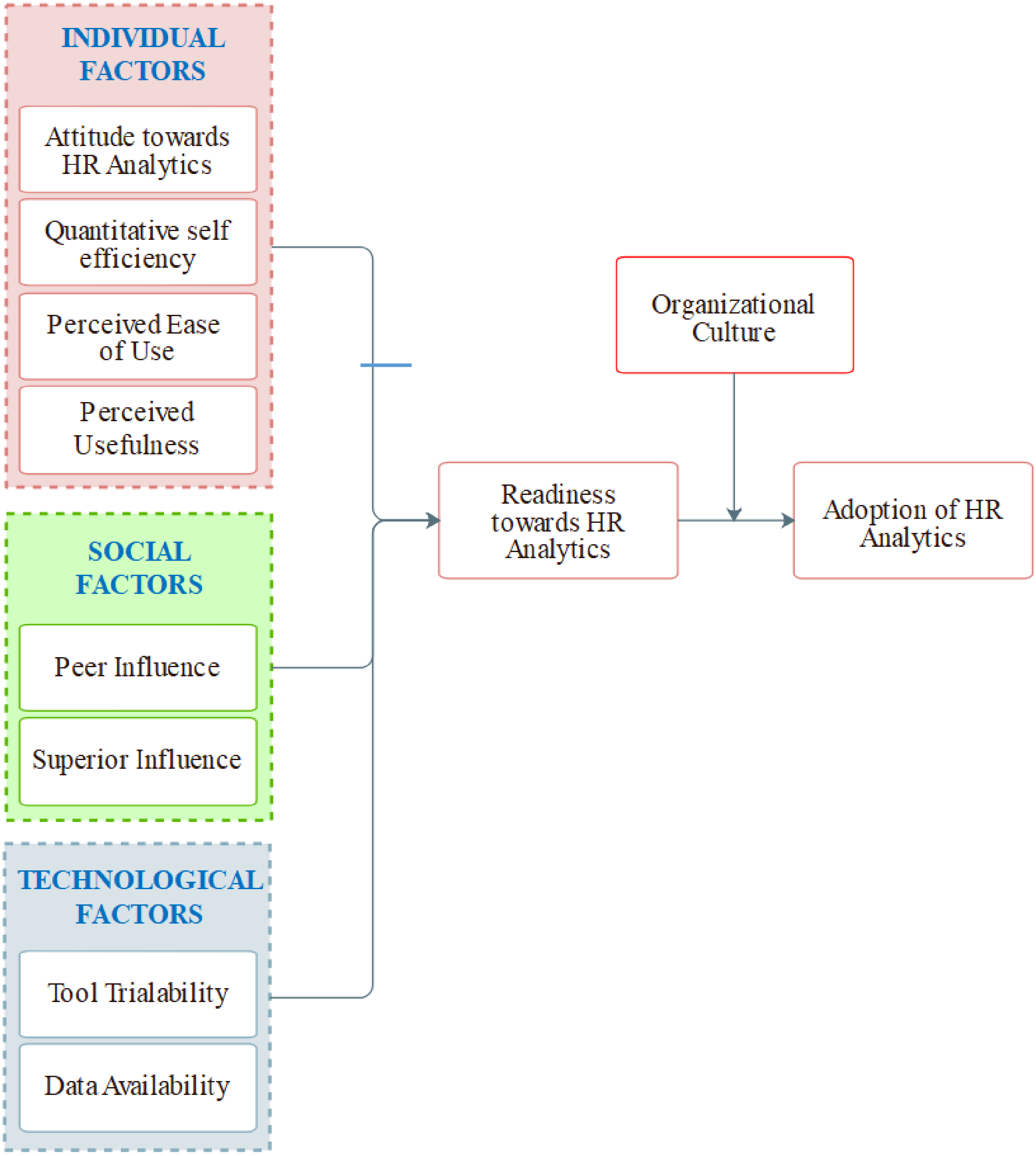


Figure 2.6

Proposed model



2.8 HYPOTHESES OF THE STUDY

Objective 1: ***To understand the influence of individual, social and technological factors on individual adoption of HR analytics*.**

Hypothesis 1: Attitude towards HR analytics positively influences readiness of HR professionals' to adopt HR analytics.

Hypothesis 2: Quantitative self- efficacy HR analytics positively influence readiness of HR professionals' to adopt HR analytics.

Hypothesis 3: Perceived ease of use HR analytics positively influences readiness of HR professionals' to adopt HR analytics.

Hypothesis 4: Perceived usefulness HR analytics positively influences readiness of HR professionals' to adopt HR analytics.

Hypothesis 5: Individual factors influence the readiness of HR professionals' to adopt HR analytics.

Hypothesis 6: Peer influence positively enhance the readiness of HR professionals' to adopt HR analytics.

Hypothesis 7: Superior influence positively enhance the readiness of HR professionals' to adopt HR analytics.

Hypothesis 8: Social factors influence the readiness of HR professionals' to adopt HR analytics.

Hypothesis 9: Tool trialability HR analytics positively influence readiness of HR professionals' to adopt HR analytics.

Hypothesis 10: Data availability HR analytics positively influence readiness of HR professionals' to adopt HR analytics.

Hypothesis 11: Technological factors influence the readiness of HR professionals' to adopt HR analytics.

Objective 3: ***To study the influence of readiness towards HR analytics on individual adoption among HR professionals' in India.***

Hypothesis 12: Readiness to adopt HR analytics significantly influences the adoption behavior of HR professionals.

Objective 4: ***To study the moderating role of organizational culture towards adoption of HR analytics.***

Hypothesis 13: Organizational culture significantly moderates the relationship between readiness and adoption of HR analytics among HR Professionals'.

2.9 Operational Definitions

The current study defines the factors that affect the intention and adoption of HR analytics among human resource professionals.

HR analytics: HR analytics is a set of principles and methods that involve collecting, analyzing, and reporting data to addresses strategic business concerns by utilizing information in a manner that enhances people-related decisions.

Individual factors: The individual factors refer to individual cognitive beliefs about themselves and adoption (Talukder 2012)

Social Factors: A social factors describes how much a social group's members can affect one another's behaviour when it comes to adoption (Konana and Balasubramanian, 2005)

Technological Factors: Technological factors refer to the elements or advancements in technology that can impact or influence an organization or industry (Maduku et al., 2016)

Attitude: Individual response, either positive or negative, that an individual experiences when engaging in a particular behavior. (Ajzen, 1991).

Quantitative Self Efficacy: People's perceptions of their quantitative ability to perform a given behaviour (Vargas et al.,2018).

Peer Influence: Peer influence is the act of peers motivating and encouraging an individual employee to adopt a new technology. (Lewis et al., 2003).

Superior Influence: When an individual's get influence for using a technology that being used by their Superior (Taylor and Todd, 1995).

Perceived Usefulness: Perceived usefulness refers to an individual's belief that utilizing a specific system will improve their job performance (Davis et al., 1989).

Perceived Ease of Use: Perceived ease of use refers to an individual's belief that utilizing a specific system will be effortless (Davis et al., 1989).

Tool Trialability: Tool trialability pertains to the extent to which an innovation can be tried out and experimented with on a regular basis**.** (Rogers, 2003, p. 258).

Data Availability: Data availability refers to the information that is stored within the HR department and across the entire organization (Johnston, 2006).

Readiness towards HR Analytics: An individual willingness i.e., intention towards any aspects reflecting their behaviour (Ajzen, 1991).

Adoption of HR Analytics: Adoption of HR analytics refers the use of analytical tools and methods to analyze HR data and identify patterns to make data-driven decisions. (Mohammed & Quddus, 2019)**.**

Organization Culture: Organizational culture is a collection of shared assumptions, values, and beliefs reflected in its practices and goals while also enabling the members to understand the organizational functions (Liu et al., 2010).

CHAPTER - 3

RESEARCH METHODOLOGY

3.1. Introduction

This chapter is an attempt to provide a complete overview of the research design, questionnaire development, the process of sample selection, and the strategy used for data collection and analysis. This chapter also attempts to check the reliability and validity of the measurement scales used in the research model. This chapter also includes the description of the statistical techniques used to analyze cause and effect relationship between variables i.e., independent variables and dependent variables.

3.2. Research Methodology

Research technique serves as a firm foundation for every study, assisting in the design, implementation, and completion of research activity in any discipline, and thus requires special consideration in this study as well. Research methodology is the systematic process by which valid and reliable results can be obtained based on the research objectives and research problem specified under the study.

Research methodology serves as a road map for the entire research process, which provides the principals, values and theories that supports the research approach. The following sections present the methodological choices for the study, including research design, as well as explain sample selection, sample design, sampling process, and sample justification. It also explains the questionnaire adaption and design process, pre-testing, questionnaire modification based on study needs, and sample features, such as participant demographic information. The purpose of studying research methodology is to give the right directions for research methods and application of the right tools to process to provide a conclusion with solutions.

3.3 Research Design

A descriptive research design is selected for the study's purpose to describe and test an integrated model of TPB, TAM and DOI that influences HR professionals' intentions and adoption of HR analytics. This study follows the purposive sampling techniques to collect cross sectional data. A primary cross sectional data collection method is obtained using structured questionnaire regarding the factors influencing HR analytics adoption among HR professionals. SEM method was used to analyze the integrated model of HR analytics by HR professionals' using Smart PLS.

3.3.1 Questionnaire Design

For obtaining answers for the research questions that identify various factors in adoption of HR analytics, the most appropriate method considered for obtaining data is a structured questionnaire that contains closed-ended questions. The research items/questions for this study were adopted from the previous literature and were modified to fit the context of this study. The present study classified items of the questionnaire on the five-point Likert scale, ranging from "strongly disagree" to "strongly agree." In the study, the researcher developed a basic demographic questionnaire and measurement item for construct adopted from previous research were shown in table below:

Table 3.1

Basic Demographic Profile

Sl.no	Category	Items
Gender	Male Female	
2	**Age**	21-30 31-40 41-50 Above 50
3	**Experience**	6-10 Year 11-15 Year 1-5 Year More than 15 Year
4	**Job Position**	Manager HRIS Generalist Specialist
5	**Industry**	Information Technology Financial Services Retail Health
6	**Education**	Bachelor Master degree MBA Doctorate degree

Table 3. 2

List of Items and Constructs Adopted Sources

Constructs	No Of Items	Adopted From
Attitude towards HR analytics	4	Ajzen, (1991)
Quantitative self -efficacy	6	Bai et al., 2009; Ozgen,2003
Peer Influence	2	Taylor and Todd, (1995)
Superior Influence	3	Taylor and Todd, (1995)
Perceived ease of use	4	Davis, (1989)
Perceived Usefulness	4	Davis, (1989)
Tool trialability	5	Rogers (2003)
Data availability	6	Johntson, (2006); Johnston & Warkentin, (2010)
Readiness towards HR analytics	3	Ajzen, (1991)
Adoption of HR analytics	4	Rogers (2003)
Organization culture	8	Van de Berg & Wilderom, (2004)

3.3.1.1 Scales – 5 point Likert scale

In this study, a 5-point unidimensional Likert scale was employed to gather data on all constructs. This scale was developed by the renowned psychologist Rensis Likert to capture the opinions of respondents. Likert scales of 5-points and 7-points are commonly used in research, and in this study, the 5-point odd Likert scale was used to offer more response options to participants. All items were rated on a scale of 1 to 5, with 1 indicating “strongly disagree” and 5 indicating “strongly agree”. To assess the internal consistency of the research items, a reliability analysis was conducted by summing all items to form a total score. Later, the items were subjected to factor analysis to reduce a large number of variables into a smaller set of easily interpretable underlying factors

3.3.2 Data Collection Procedure

This research work adopts a quantitative approach and follows the logic or philosophy of positivism and primary research. Besides, the present research work reveals strong origins in the existing literature. Therefore, the deductive research approach was selected to suit the context of the study. Saunders et al. (2007) describe the deductive approach requires the collection of quantitative as well as primary data, which ultimately aims at finding a relationship between the variables under study. For the purpose of this study, primary data was collected from HR professionals' working in organization that have adopted HR analytics for at least 2 years. The procedure for data collection consists of identifying the study population, determining eligibility criteria for selection of study population and sample size, and pilot study and pre-testing.

3.3.2.1 The Study Population

For the purpose of this study, HR professionals were chosen as the target population. For the purposes of this study, HR professionals are defined as individuals currently working in the field of HR, regardless of their function, industry, length of time in HR, or job title within the HR department (HR Executives, HR Managers, HR generalist, HR analyst) in India to analyze the HR analytics adoption. Thus, targeting such a population in India is in line with the objective of the current research to identify the factors that can motivate adoption of HR analytics among HR professionals.

3.3.2.2 Inclusion criteria for sample

The inclusion criteria to study the adoption of HR analytics among HR professionals are that the HR professionals should be working in an Indian organization that had adopted HR analytics for at least 2 years. Further, HR professionals should be from the top four industries that have adopted HR analytics in India. A study conducted by AIM & AnalytixLabs in 2020 titled "Analytics and data science Indian industry study 2020" stated that the top four industries to adopt analytics in India are IT, BFSI(Banking financial service and insurance), Retail, Pharma and healthcare. All these sectors account for over 80% of the adoption of HR analytics in India.

3.3.2.3 Sample size justification

The sample size for the present study is determined based on the adopted methodology of analysis that is structural equation modeling (SEM). More often than not, the rules concerning the proper sample size either recommend minimum and acceptable values or suggest a ratio method for assessing the sample size. For instance, past researchers have proposed sample sizes above 100 respondents when conducting the Factor Analysis (Gorsuch, 1983b; Kline, 2004). Hair et al. (2017), suggests that at least 5 to 10 responses for each variable can be a sufficient sample size to conduct SEM.

The conceptual model of the study has 11 constructs and 44 items. Hair et al. (2017), suggests that at least 5 to 10 responses for each variable can be a sufficient sample size. It indicates that the minimum data points required for 44 items is 220, with an average sample size of 220 and a maximum of 440. Other researchers also stated that for conducting any quantitative research at the minimum sample size of around 200 to 500 is consider good sample (Kline, 2004; Crouch, 1994). A total of 305 sample were taken consideration, which indicates adequate sample size based on the above criteria.

3.3.3 Sources of Data

The present research work has collected data from primary source using cross sectional method for the analysis. The primary source of data collection involved direct response through a structured questionnaire from HR professionals' working in an organization that has adopted HR analytics. The data was collected using online as well as an offline mode as per the convenience. A total 500 targeted respondents out of which 312 responses received of which 122 received through offline questionnaire 190 received through online using google survey and the yielded more than 62% response rate and were acceptable for survey.

3. 4. Approaches for Data Analysis

Since the proposed model used a multivariate technique like Structured Equation Modelling (SEM), the assumptions of linearity have to be followed. Therefore, during the initial stages, a series of tests like multivariate normality, linearity, and multicollinearity tests were conducted. "Further, data analysis involved testing of reliability (inter-item consistency) and validity of the scales (convergent validity). In the next stage, the proposal research models were tested by PLS SEM through using Smart PLS. Statistical techniques that are used in this research were classified into two groups. The first set of techniques was used for descriptive purposes, second is Structured Equation Modeling (SEM) was used to estimate interrelated independent relationship (Hair et al., 2006). This technique is very helpful in generating a model of relationships among variables (Hair et al., 2016; Gunzler, & Morris, 2015).

3.4.1. Structural Equation Model (SEM)

Structural Equation Model is "*a set of statistical techniques used to measure and analyse the relationship between observed and latent variables*" (González et al., 2008). It has become increasingly popular among researchers for understanding complex relationships between variables, as it allows for the simultaneous analysis of multiple variables and the exploration of the role of mediating and moderating variables. The strength of the independent variable and dependent variable in the presence and absence of mediating and moderating variables directs the research towards a new level of investigation usually which is not possible with multiple regression. SEM framework allows analysing first-order constructs as well as higher-order constructs. The first phase of SEM analysis, a set of hypothesized relationships between independent and dependent variables is developed based on theories and previous research. The hypothesized relationship predicts the dependent variable based on one or more independent variables. The flexibility and advantages of SEM have made it a popular tool among researchers. By testing hypotheses on complex variable relationships, SEM allows for the testing of new relationships between variables empirically. In this study, SEM was used to analyze the model and test hypotheses, providing a valuable tool for exploring new relationships between variables.

3.4.2. Reasons for using Smart PLS for analysis

Smart PLS was used to analyse the conceptual structural model developed in the study. Smart PLS, which was developed by a Swedish econometrician named Herman O.A Wold. In recent years, there has been an increasing trend among researchers to use Partial Least Squares Structural Equation Modeling (PLS-SEM)(Hair et al., 2012) for analyzing their research data, particularly in social sciences. The main advantage of using PLS-SEM is that it does not require researchers to make any normal distributional assumptions when testing complex models with multiple constructs that have mediating and moderating variables (Hair et al., 2013). This allows researchers to identify hidden path relations among the constructs, which would otherwise be difficult to find using other statistical methods.

Smart PLS is widely used to predict models with statistical robustness (Sarstedt et al., 2017), as it can provide simultaneous results for the measurement model and structural model, without the need to operate on each model separately. Compared to other methods, using Smart PLS for the analysis of structural equation models provides a high degree of statistical power and robustness, as confirmed by studies such as Reinartz et al. (2019). Overall, Smart PLS is a useful tool for researchers working in the social sciences, as it allows them to analyze complex models and identify hidden relations among constructs, even with small sample sizes (Willaby et al., 2015). Our study is an initial attempt to empirically examine the behavioral intention to adopt HR analytics. Consequently, PLS is appropriate to test the inter-relationship we developed based on the literature review.

3.5. Pilot Study and pre- testing

Pilot testing is done to refine the questionnaire by conducting a small-scale study to test a questionnaire, interview checklist or observation schedule to reduce the respondents' tendency of having problem in completing the survey and also enable to gain some assessments of the questions' validity and the reliability of the data (Saunders et al., 2007). According to Malhotra (2003), pilot testing is the test of the questionnaire on a small sample of the respondents similar to the actual population to recognize a potential problem. The aim is to ensure that the questions elicit the required response, identify ambiguous wordings or error before the survey was carried out on a large scale (Malhotra, 1999).

Although the scale used in the research was validated by other researchers previously, the present study considered a pilot study as necessary to validate the items as well as scales. Because the scales are being changed in HR analytics context.

In the present study, the initial pilot survey was conducted on 15 respondents. The questionnaire consists of 50 items. Respondents were requested to comment on the general aspect of questionnaire design besides they were asked to give suggestions if they felt that any of the questions had complicated or ambiguous words. Some overlapping and possible double answer questions were omitted from the list after the review process and further modifications were made based on suggestions given by respondents. Total two questions with similar meaning or ambiguous words are removed from the questionnaire for a clear understanding of it. The two questions removed are from quantitative self-efficacy “Math and/or statistics is one of my favorite subjects” and other one from organizational culture “My organization have a very strong culture.”

The modifies questionnaire with 48 items seemed to be satisfactory from the perspective of respondents so the second round, another pilot study was conducted on 100 respondents to check constructs reliability and validity and some basic data analysis to check the adequacy.

Detail result of the pilot study is described below. From the results of validity and reliability tests, the changes required were modified and instrument was finalized and final data collection procedure was initiated.

3.5.1 Pilot study result

KMO and Bartlett's test was used to check the adequacy of the sample is above threshold to determine the data factorial efficiency. It reveals the data matrix's structure, suitability and identity. It describes the unrelatedness of the data, which renders the data structure unsuitable. A factor analysis determines the usefulness of variables in measuring a particular construct, with values close to one (1.0) indicating high usefulness, and values less than 0.50 indicating low usefulness. In the pilot study, the results suggest that the study is headed in the right direction, as Bartlett's test for data adequacy fell within the acceptance criteria of 0.691, and the degree of freedom was 1128 (Kline, 2011). The KMO and Bartlett's test indicate that the correlation between the underlying constructs is suitable for further analysis (Table 3.3). Cross-loading values in factor analysis explain the variation of each variable in the factors, which is shown in Table 3.4. Cross-loading validates the extracted item value, with values less than 0.5 indicating that the questionnaire may not be accurately measuring what was anticipated. In the pilot study, four items (PEOU3, PU4, OC3, and OC6) had cross-loading values less than 0.5 and were removed from the study.

After validation of the items total variance of factor indicate that all the variables are uni-dimensional with the Eigenvalue of 1 and Cumulative variances of total 11 factors were 73.249 % of variance explained, given in Table 3.5. After removal of the four items from study we checked the internal consistency of 11 constructs reliability Cronbach's alpha values ranged from 0.701 to 0.860. It was more than the threshold value of 0.7 as suggested by Nunally (1978) as shown in Table 3.6.

Table 3.3

KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.691
Bartlett's Test of Sphericity	Approx. Chi-Square	5157.232
	Df	1128
	Sig.	0.000

Table 3.4

Cross loading Table

Items	ADOP	Attitude	DA	OC	PEOU	PI	PU	QSE	RT	SI	TT
ADOP1	**0.794**										
ADOP2	**0.845**										
ADOP3	**0.856**										
ADOP4	**0.860**										
ATT1		**0.808**									
ATT2		**0.694**									
ATT3		**0.650**									
ATT4		**0.738**									
DA1			**0.881**								
DA2			**0.546**								
DA3			**0.858**								
DA4			**0.880**								
DA5			**0.539**								
DA6			**0.855**								
OC1				**0.848**							
OC2				**0.818**							
OC3				**0.297**							
OC4				**0.872**							
OC5				**0.871**							
OC6				**0.825**							
OC7				**0.414**							
OC8				**0.848**							
PEOU1					**0.718**						
PEOU2					**0.908**						
PEOU3					**0.432**						
PEOU4					**0.875**						
PI1						**0.901**					
PI2						**0.929**					
PU1							**0.825**				
PU2							**0.803**				
PU3							**0.768**				
PU4							**0.413**				
QSE1								**0.862**			
QSE2								**0.764**			

QSE3	**0.868**			
QSE4	**0.814**			
QSE5	**0.824**			
RT1		**0.864**		
RT2		**0.846**		
RT3		**0.855**		
SI1			**0.751**	
SI2			**0.956**	
SI3			**0.909**	
TT1				**0.819**
TT2				**0.825**
TT3				**0.848**
TT4				**0.574**
TT5				**0.507**

Table 3.5

Total Variance Explained

Total Variance Explained						
Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	**14.521**	33.002	33.002	14.270	32.432	32.432
2	**4.270**	9.704	42.706	4.017	9.131	41.562
3	**2.975**	6.762	49.468	2.782	6.323	47.885
4	**2.814**	6.396	55.864	2.593	5.893	53.778
5	**2.321**	5.276	61.140	2.019	4.589	58.367
6	**2.044**	4.645	65.784	1.833	4.166	62.533
7	**1.461**	3.320	69.105	1.109	2.519	65.052
8	**1.347**	3.062	72.167	1.057	2.402	67.454
9	**1.241**	2.820	74.986	0.990	2.250	69.704
10	**1.066**	2.422	77.408	0.845	1.922	71.626
11	**1.022**	2.322	79.731	0.714	1.623	73.249
12	0.824	1.874	81.604			
13	0.792	1.800	83.405			
14	0.730	1.660	85.065			
15	0.647	1.471	86.536			
16	0.631	1.434	87.970			
17	0.556	1.264	89.234			
18	0.520	1.182	90.416			
19	0.467	1.062	91.479			
20	0.396	0.900	92.378			
21	0.382	0.869	93.247			
22	0.370	0.842	94.089			
23	0.312	0.709	94.797			
24	0.297	0.675	95.473			
25	0.270	0.613	96.085			
26	0.245	0.557	96.642			
27	0.214	0.487	97.129			
28	0.195	0.443	97.572			
29	0.165	0.374	97.946			
30	0.139	0.316	98.263			
31	0.137	0.312	98.575			
32	0.111	0.251	98.826			
33	0.097	0.221	99.047			
34	0.078	0.178	99.225			
35	0.074	0.168	99.393			
36	0.066	0.150	99.543			
37	0.057	0.129	99.672			
38	0.035	0.079	99.750			
39	0.030	0.069	99.819			
40	0.023	0.053	99.872			
41	0.021	0.049	99.921			
42	0.013	0.030	99.951			
43	0.012	0.028	99.979			
44	0.009	0.021	100.000			

Extraction Method: Principal Axis Factoring.

Table 3.6

Reliability of the Scales – Cronbach's alpha

Construct	No of Indicators	Cronbach's alpha
Attitude towards HR analytics	4	0.701
Quantitative self-efficacy	5	0.847
Peer Influence	2	0.807
Superior Influence	3	0.847
Perceived ease of use	3	0.840
Perceived Usefulness	3	0.758
Tool Trialability	5	0.780
Data Availability	6	0.845
Adoption of HR analytics	5	0.860
Organization Culture	5	0.932
Total	**44**	

3.6 Final data collection

The data were collected through a structured questionnaire that consists of 44 items from HR professionals' working in an organization that has adopted HR analytics. The data was collected using online (i.e., Google form) as well as an offline mode as per the convenience of HR professionals' in India. To avoid duplicate responses in the Google form multiple submission options were disabled. For the survey, the questionnaire was mailed as well as distributed to the HR professionals' by visiting their organizations and the training centers. The potential respondents of this study are HR professionals whose organizations have adopted HR analytics for at least 2 years. No such incentives were provided to the respondents as the research was conducted for the academic purpose. The questionnaire was sent to around 500 HR professionals. A total of 312 responses was received i.e., 122 offline and 190 online from 500 targeted respondents, 305 responses were taken into consideration for analysis and

7 were eliminated due to errors. They yielded more than 61% response rate and were acceptable for the survey (Jennings et al., 2015).

3.6.1 Data Editing and Coding

For the data analysis, Smart PLS and SPSS software was used in this study. After the completion of data collection, the researcher made sure that the data collected are complete, consistent, and reliable. To ensure this, data editing was done by checking and adjusting for errors, omissions, legibility, and consistency in the data. While entering data into Smart PLS and SPSS, data coding and editing was done and abbreviated variable names were given to each item in the questionnaire. A separate sheet was maintained (refer table- 3.7) to show how each variable was coded and the list of the questionnaire with the abbreviated variable names. In order to maintain data accuracy, few tests like frequency analysis were performed for screening and cleaning data before proceeding to the next stage that is data analysis. With the help of frequency analysis, which is a part of descriptive statistics, the frequency of the data of each variable was checked to see if the score was out of range for this category. Besides, the study also performed various other tests to check the minimum, maximum, mean, and standard deviation for each continuous variable to maintain the accuracy and consistency of the data. During analysis, the errors that were detected in the data entry were reconsidered by going back to the questionnaires to confirm the data and when necessary, data correction was undertaken in the data file by correcting the error. Thus, after taking due care, the researcher proceeded to the data analysis stage.

3.6.2 Data Cleaning Procedure

The data cleaning procedure was performed before proceeding with the analysis. According to Tabachnick and Fidell (2014), the occurrence of missing value is the most pervasive problem while using the questionnaire. Therefore, the focus should be given to keep the data set complete by doing missing value analysis. In order to avoid happening of missing value, it is important to frame the questionnaire in a clear and unambiguous manner. The examination of missing value is very important because their presence in the data set affects the result (Kline, 2011).

Table 3.7

Definitions of Items Summary with Indicator Code

Construct	Indicator Code	Measurement items
Attitude towards HR analytics	ATT1	HR analytics makes my job more interesting.
	ATT2	Working with HR analytics is satisfying.
	ATT3	I like working with HR analytics.
	ATT4	I enjoy working with HR analytics.
Quantitative self - efficacy	QSE1	I find using mathematical and/or statistical measurements interesting.
	QSE2	I worry about my ability to solve mathematical and/or statistical problems.
	QSE4	I get nervous when I use mathematics and/or statistics.
	QSE5	I enjoy working with mathematical and/or statistical measures.
Peer Influence	PI1	People who influence my behaviour think that I should use the HR analytics.
	PI2	People who are important to me think that I should use the HR analytics.
Superior Influence	SI1	My senior would think that 1 should use HR analytics.
	SI2	I will have to use the HR analytics because my senior requires it.
	SI3	The senior management of this organization has been helpful in the use of HR analytics.
Perceived ease of use	PEOU1	My role with HR analytics is clear and understandable.
	PEOU2	I would find HR analytics easy to use.
	PEOU3	It is easy for me to become skillful at using HR analytics.
Perceived Usefulness	PU1	I would find the use of HR analytics useful in my job.
	PU2	Using HR analytics enables me to accomplish tasks more quickly.

	PU3	Using HR analytics increases my job performance.
Tool trialability	TT1	I have a full array of HR analytics tools available at work if I choose to use them.
	TT2	I only have very basic HR analytics tools available at work if I choose to use them.
	TT3	My company has invested heavily in HR analytics tools.
	TT4	Before deciding whether to use any HR analytics applications, I am able to properly try them out.
	TT5	I have had a great deal of opportunity to try various HR analytics applications.
Data availability	DA1	My company's database has all the data I need to use HR analytics software.
	DA2	My company's HR system collects data from all HR interactions.
	DA3	We use the same system/platforms for all HR activities.
	DA4	My company has one database for all departments to use.
	DA5	My company's database has an interface that is compatible with other systems.
	DA6	I know where I can get the data for work.
Readiness towards HR analytics	RTT1	I intend to use the HR analytics as often as needed.
	RTT2	Whenever possible, I intend not to use HR analytics.
	RTT3	To the extent possible, I would use the HR analytics frequently.
Adoption of HR analytics	ADOP1	I am beginning to explore using HR analytics.
	ADOP2	I am interested in using HR analytics.
	ADOP3	I use HR analytics for some specific tasks.
	ADOP4	Using HR analytics improve the quality of work I do.
	ADOP5	Using HR analytics gives me greater control over my work.
Organization culture	OC1	Individuals working in different departments have a common view.
	OC2	My organization readily accepts innovations based on research results.
	OC3	Our employees have the chances of introducing their ideas before management makes decisions.
	OC4	My organization gives freedom to the employees to deviate from rule.
	OC5	People from different parts of this organization share a common view.
	OC6	My organization actively seeks innovative ideas but the adoption it voluntarily.

Summary

The chapter broadly discusses the methodology used in the current research. The chapter discusses the research design and sampling design utilized in this study. The chapter covers details regarding sampling techniques, sample size determination, questionnaire design, pre-testing through a pilot study and final data collection process. In the next chapter on data analysis, we have discussed data analysis with interpretation.

CHAPTER – 4

DATA ANALYSIS AND FINDINGS

This chapter presents the findings of analyses carried out with the statistical technique discussed in Chapter 3. This chapter adheres to the commonly established reporting format for PLS analysis, as suggested by prior research (Chin, 2010). First, the sample's demographic information is provided, followed by descriptive statistics and pretest analysis. In addition, the measurement model's validity and reliability are also checked, as well as the structural model is evaluated. This chapter concludes with a summary of the study's findings.

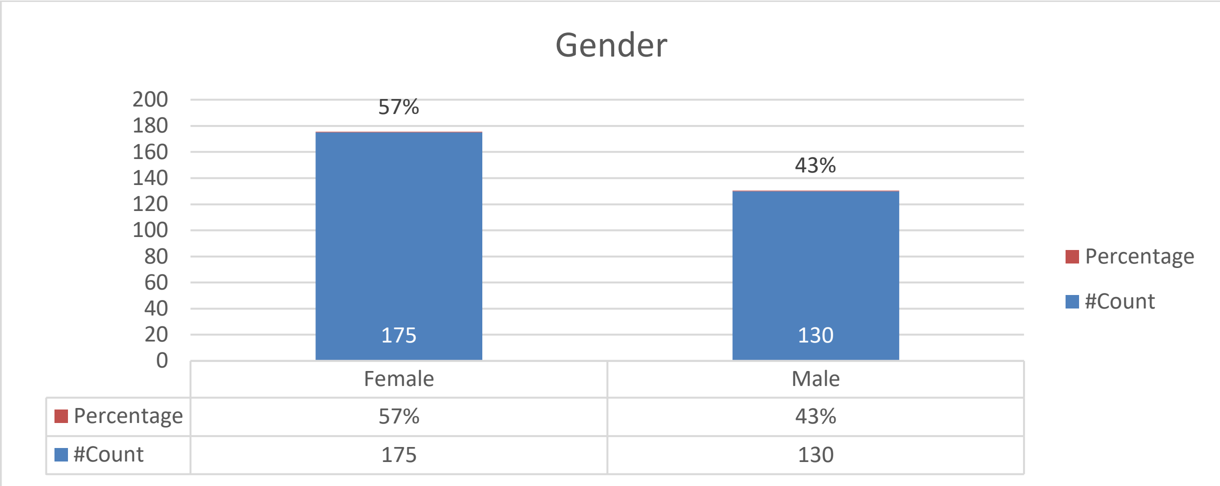
4.1 Demographic Profile of the Respondents

The survey instrument was designed and self-administered through online and offline mode, and the respondents were requested to answer the survey questions under the conditions of informed consent, confidentiality, and anonymity. Section-A of the questionnaire sought demographic details of the survey participants (Appendix-1). This included the respondent's gender, age, qualifications, experience, job position and industry (see table 4.1).

As illustrated by Figure 4.1, 175 of the 305 respondents were female, representing 57%, while 130 of the respondents were male, representing 43%.

Figure 4.1

Gender



The age distribution of the HR professionals who participated in the survey is presented in Figure 4.2. 38% of the population was comprised of those aged 31 to 40 years, followed by 30% of those aged 21 to 30 years, 24% of those aged 41-50 years, and 8% of those aged over 50.

Figure 4.2

Age Group

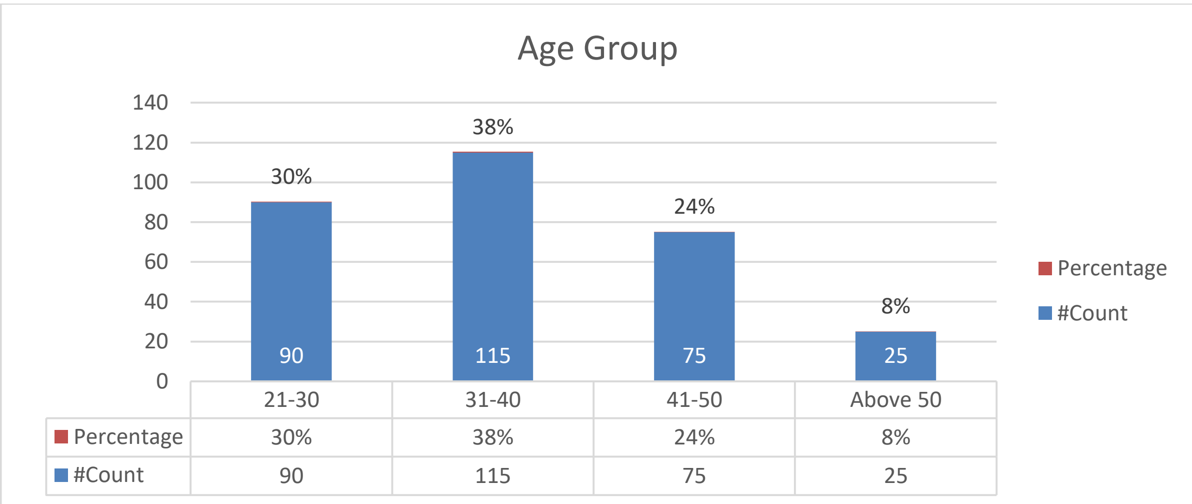


Figure 4.3 illustrates the experience of the study's HR professionals. 44% of 134 individuals have 6 to 10 years of experience, while 26% of 82 individuals have 1 to 5 years of experience. There are 63 individuals with 11 to 15 years of experience, representing 21%, and 26 individuals with more than 15 years of experience, representing 9%.

Figure 4.3

Experience

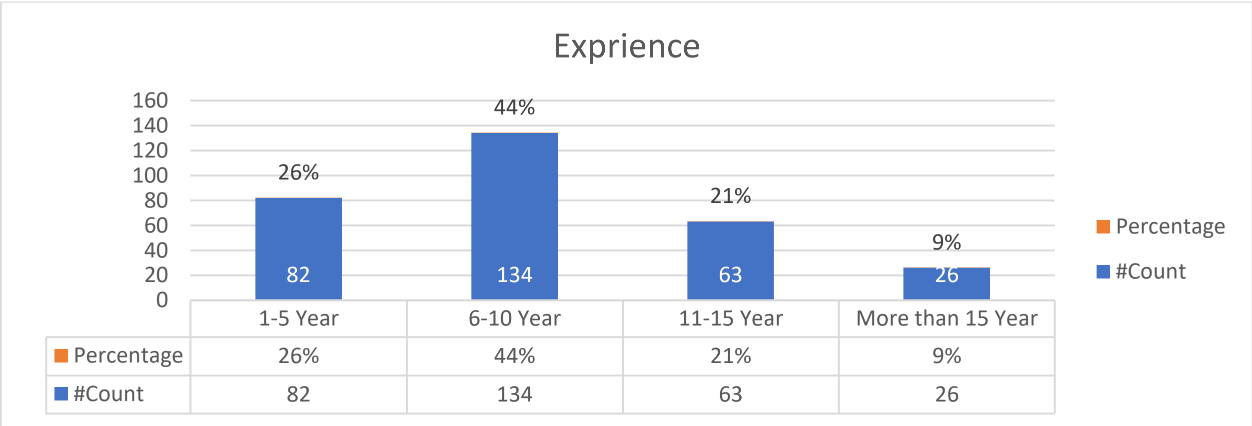
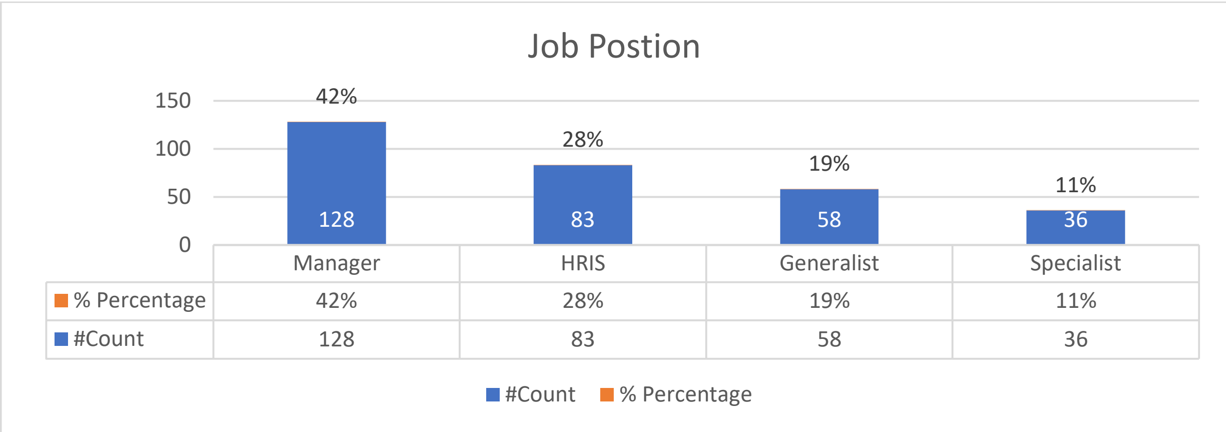


Figure 4.4 displays the job position of HR professionals. 42% of these 128 individuals held managerial positions. 58 people were generalists, comprising 19% of the workforce, while 83 people were HRIS specialists, comprising 28% of the workforce. 11% of HR specialists consist of 36 individuals.

Figure 4.4

Job Position



Among the data collected for the study, the IT industry had 135 people with the highest percentage (44%), followed by financial services, which had 90 people with 30%. The retail industry employs 58 people (19%), while the health industry employs 22 people (7%). See Figure 4.5.

Figure 4.5

Industry

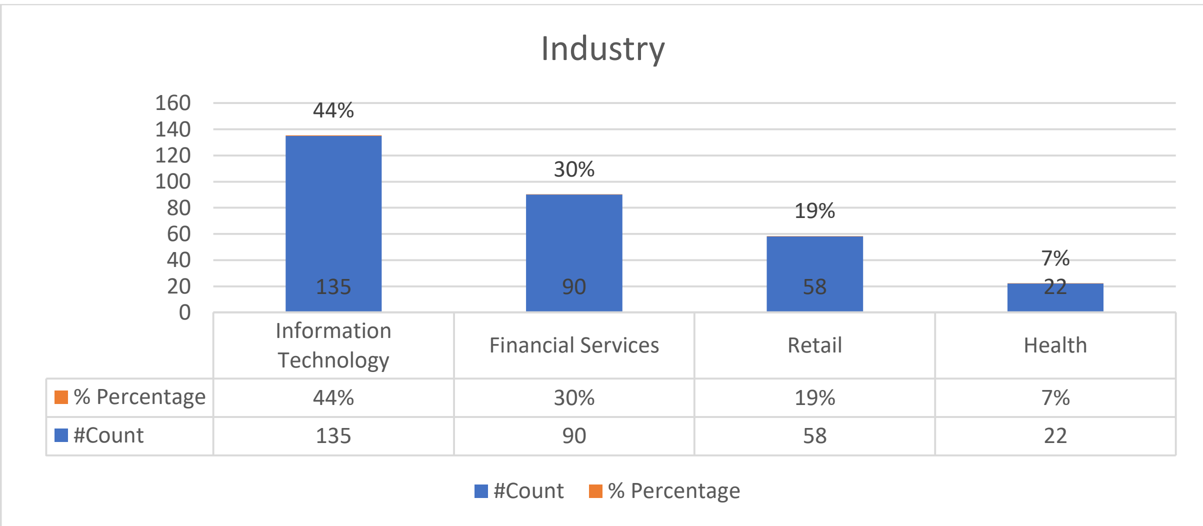


Table 4.1

Demographic Details

Category	Items	Frequency	Percentage
Gender	Female	175	57%
	Male	130	43%
	Grand Total	305	100%
Age	21-30	90	30%
	31-40	115	38%
	41-50	75	24%
	Above 50	25	8%
	Grand Total	305	100%
Experience	6-10 Year	134	44%
	11-15 Year	63	21%
	1-5 Year	82	26%
	More than 15 Year	26	9%
	Grand Total	305	100%
Job Position	Manager	128	42%
	HRIS	83	28%
	Generalist	58	19%
	Specialist	36	11%
	Grand Total	305	100%
Industry	Information Technology	135	44%
	Financial Services	90	30%
	Retail	58	19%
	Health	22	7%
	Grand Total	305	100%

4.2 Descriptive Statistics

The current study describes the descriptive analysis and standardizes the values of its variables, i.e., mean value, standard deviation, maximum, minimum, and standard error (table 4.2). Previous study concluded that the Mean score close to three (3) and the Std. Dev. Close to one (1) is a favorable value (Teo, 2009).

Table 4.2

Descriptive Statistics

Construct	No of items	Min	Max	Mean	Std. Dev
Attitude	4 Items	1	5	3.793	0.999
Quantitative Self-Efficacy	4 Items	1	5	3.741	0.903
Perceived usefulness	3 Items	1	5	3.898	0.942
Ease of use	3 Items	1	5	3.734	0.928
Peer Influence	2 Items	1	5	3.267	0.982
Superior Influence	3 Items	1	5	3.73	0.961
Tool Trialability	5 Items	1	5	3.892	0.919
Data Availability	6 Items	1	5	3.763	0.956
Intention to use	3 Items	1	5	3.658	0.976
Adoption of HR Analytics	5 Items	1	5	3.877	0.954
Organizational Culture	6 Items	1	5	3.724	0.987

The minimum value was 1= “Strongly disagreed” and the maximum value was 5= “Strongly agreed” for all. The mean value and standard deviation of attitude is 3.793 and 0.999; quantitative self-efficacy score has 3.741 mean and 0.903 standard deviation; perceived usefulness has 3.898 mean and 0.942 standard deviation; perceived ease of use has 3.734 mean and 0.928 standard deviation; peer influence has 3.267 mean and 0.982 standard deviation; superior influence has 3.73 mean and 0.961 standard deviation; tool trialability has3.892 mean and 0.919 standard deviation; data availability has 3.763 mean and 0.956 standard deviation; readiness towards HR analytics 3.658 mean and 0.976 standard deviation; adoption of HR analytics has 3.877 mean and 0.954 standard deviation and the last organizational support mean score is 3.724 and 0.987 standard deviation.

4.3 Pre-test Analysis

In this session we verified data using some of the pre-test analysis which indicate the data satisfy all criteria before going to measurement model and structural model. Started with KMO and Bartlett's Test which revealed that the set predicted construct is independent of another construct. Followed by Harmon's single factor and variance inflation factor to check for any statistical bias in the data as the data was collected at one point of the time for both the dependent and independent variable. The homogeneity test was carried out using ANOVA because we collected data from four industries, including information technology, banking, retail, and healthcare.

4.3.1 Data Adequacy

Bartlett‘s test of sphericity and Kaiser-Meyer-Olkin (KMO) Test of sampling adequacy was verified to establish, whether, the research data variables are factorized efficiently. Bartlett‘s test of sphericity evaluates the observed co-relation matrix with the identity matrix. It denotes that the observed correlation matrix is significantly different from the identity matrix (Hair et al., 2010). The correlations among the entire variable become zero in the identity matrix. It is also designated that sphericity test checks degree of redundancy among the variables and the data is reduced to a fewer number of factors.

Sphericity test is found significant with $P<0.001$ at 990 degrees of freedom. The sampling adequacy (KMO) test compares the values of correlations that are partially correlated with each other. The result reveals that KMO is 0.905 (Table 4.3) and it is more than the cut off value of 0.50 (Kaiser, 1974). Thus, the adequacy test suggests that correlations between underlying constructs are sufficient to move for further analysis.

Table 4.3

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.905
Bartlett's Test of Sphericity	Approx. Chi-Square	13440.435
	Df	990.000
	Sig.	0.000

4.3.2 Common method bias

In self-report studies, common method bias has been viewed as a significant source of measurement error and a threat to the model's validity (Podsakoff & Organ 1986). All of the latent (factors) and manifest variables (items) in the proposed model are measured using a single questionnaire at one point in time in this study. As a result, there is a chance that the data may contain common method bias. The current study used three approaches to identify data biases. First, in accordance with Chang et al., (2010) recommendation, the respondents received assurances regarding the privacy and confidentiality of their responses and personal information. In order to accurately record the self-administered responses, the survey was also designed by randomly placing items of independent and dependent variables rather than systematically.

To further assess common method variance, we conducted Harman's one-factor test. As shown in Table 4.4, the Eigenvalue of a single factor variance is 36.330% which is less than 50% of the cutoff value (Podsakoff et al. 2013). This demonstrates that the data do not contain any common method bias. Third, the full collinearity appraisal approach was utilized to distinguish Common method bias (Kock, 2015). The worth of the Variance inflation factor (VIF) was underneath the limit worth of 3.3 (Hair et al. 2017; Kock, 2015); Figure 4.6 the highest VIF was 3.1 for readiness towards HR analytics, which means that this study does not have a common bias problem.

Table 4.4.

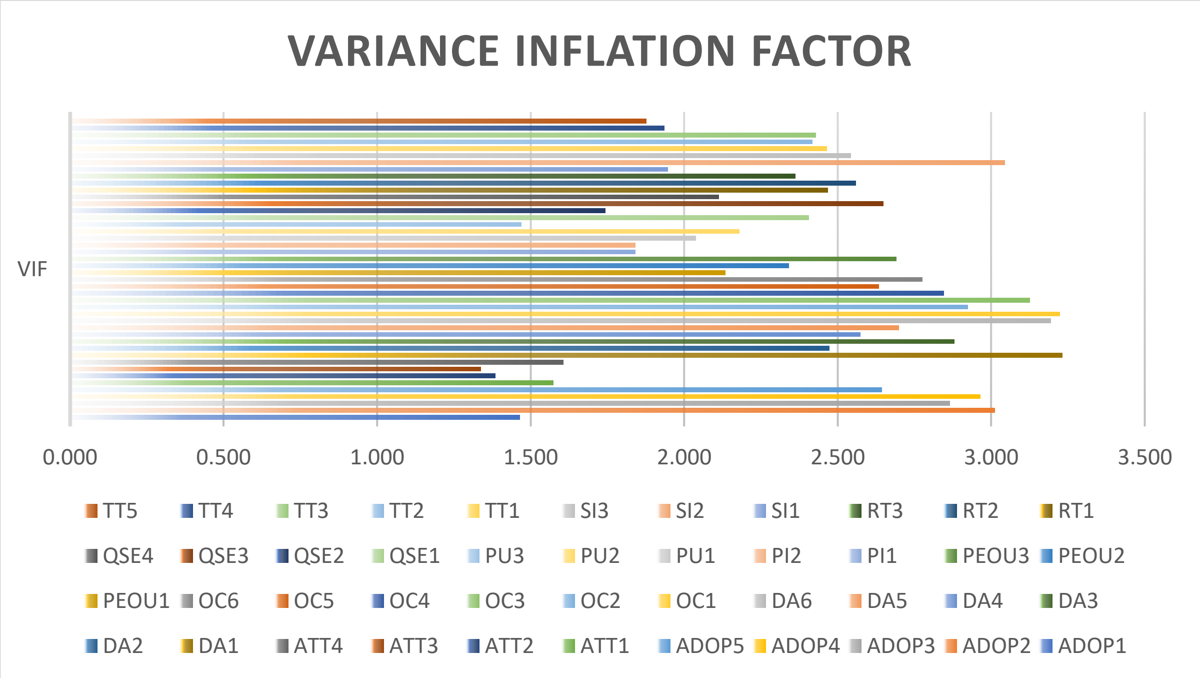
Harman's Single Factor

Total Variance Explained						
Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	16.597	37.720	37.720	15.985	36.330	36.330
2	3.956	8.992	46.712			
3	2.565	5.829	52.541			
4	2.180	4.954	57.496			
5	1.754	3.987	61.483			
6	1.639	3.725	65.208			
7	1.395	3.171	68.379			
8	1.333	3.030	71.409			
9	1.097	2.493	73.902			
10	1.051	2.389	76.292			
11	0.918	2.087	78.378			
12	0.871	1.979	80.358			
13	0.786	1.787	82.145			
14	0.710	1.615	83.759			
15	0.700	1.590	85.349			
16	0.657	1.493	86.842			
17	0.579	1.316	88.158			
18	0.493	1.121	89.279			
19	0.482	1.095	90.375			
20	0.431	0.980	91.355			
21	0.380	0.863	92.218			
22	0.358	0.815	93.032			
23	0.325	0.738	93.770			
24	0.310	0.704	94.474			
25	0.294	0.668	95.142			
26	0.238	0.541	95.683			
27	0.233	0.531	96.213			
28	0.201	0.456	96.670			
29	0.188	0.427	97.097			
30	0.175	0.399	97.495			
31	0.156	0.355	97.850			
32	0.144	0.328	98.178			
33	0.134	0.306	98.483			
34	0.122	0.278	98.762			
35	0.107	0.244	99.006			
36	0.103	0.234	99.240			
37	0.076	0.172	99.412			
38	0.069	0.157	99.569			
39	0.059	0.134	99.703			
40	0.039	0.088	99.791			
41	0.035	0.079	99.870			
42	0.023	0.051	99.922			
43	0.019	0.043	99.965			
44	0.016	0.035	100.000			

Extraction Method: Principal Axis Factoring.

Figure 4.6

Variance inflation factor VIF



4.3.3 Test of homogeneity

The assumption of variance homogeneity implies that the degree of variance for a given variable is constant across the sample. If data is collected in groups, the variance of outcome variables should be the same in each of these groups (i.e., across industry, years, testing groups or predicted values).

The homogeneity assumption is crucial for ANOVA testing and regression models. When homogeneity of variance is compromised in ANOVA, the probability of incorrectly rejecting the null hypothesis increases. Regarding residuals in regression models, the assumption comes into play (errors). In both circumstances, it is beneficial to test for homogeneity. ANNOVA Test reveal that there is no significant difference with respect to gender, age, education, experience, job position and industry.

For this study the data was collected from four industry employees. The behaviour of employee might have differed from one industry to another towards HR analytics. To examine the difference a One-way ANOVA between the groups was performed to compare the mean, whether there is statistically significant difference between industries group with respect to readiness toward HR analytics, adoption behaviour toward HR analytics and organisational culture. See table 4.5.

First the effect of industry group and readiness toward HRA was compared using one-way ANOVA, which revealed a non-significant difference between industry groups ($F (4,301) = 1.073$, $p= 0.361$).Second, when comparing the effect of industry group on HRA adoption, one-way ANOVA results revealed that there was no significant difference across industry groups ($F (4,301) = 1.187$, $p= 0.315$).Third, when comparing the effects of industry group and organizational culture, one-way ANOVA revealed a non-significant difference in industry group ($F (4,301) = 0.875$, $p= 0.455$).The impact of industry group on readiness toward HR analytics, adoption behaviour toward HR analytics, and organizational culture were all determined to be insignificant, as indicated by post-Hoc test and Tukey's HSD tests. It demonstrated that HR professionals have no distinct thoughts and behaviors when it comes to HR analytics adoption across industries.

Table 4.5

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
RT Mean	Between Groups	1.995	4	0.665	1.073	0.361
	Within Groups	186.648	301	0.620		
	Total	188.643	305			
OC Mean	Between Groups	1.716	4	0.572	1.187	0.315
	Within Groups	144.990	301	0.482		
	Total	146.705	305			
ADOP Mean	Between Groups	1.293	4	0.431	0.875	0.455
	Within Groups	148.391	301	0.493		
	Total	149.685	305			

(RT- Readiness Towards HR Analytics; OC- Organization Culture; ADOP- Adoption of HR Analytics)

4.4 Evaluation of Structural Equation Model with smart PLS

There are three different phases within the analysis. The first step is to examine the Measurement Model, and once all of the criteria have been met, the analysis can proceed to the second step, which is the Structural model. After testing the measurement model, we can then consider the possibility of mediation or moderation between any constructs during the third phase. The assessment based on the Measurement Model varies depend on the reflective construct.

The reflective construct is a latent construct by definition, meaning it exists even in the absence of all of its indicators and irrespective of its measured use (Borsboom et al. 2004). Bollen and Lennox, (1991) create this relationship between the construct and the objects in this direction (1991). It implies that a modification in the components has no impact on the construct (Rossiter, 2002). There is no significant difference detected when one item is added or removed because all the components of this build have the same theme. Jarvis and co. (2003)

4.4.1 Evaluation of Measurement model

Smart PLS 4 is used to assess the measurement and structural model. This statistical software assesses the psychometric properties of the measurement model and estimates the parameters of the structural model. The validity and reliability of the measurement model is evaluated by assessing: (1) indicator reliability (2) internal consistency reliability; (3) convergent validity; and, (4) discriminant validity. The following sections present the description of the methods for all analysis to evaluate the validity and reliability of the lower and higher order measurement model.

4.4.1.1 Evaluation of lower order measurement model

4.4.1.1.1 Indicator Reliability

The indicator reliability of the measurement model is measured by examining the items loadings. When each item's loading estimate is greater than 0.5, a measurement model is deemed to have adequate indicator reliability (Hair et al., 2010). Based on the results of the analysis, every variable in the measurement model had loadings greater than 0.5. The loading for each item is displayed in Table 4.6.

Factor loading of adoption of HR analytics construct has five items ADOP1 to ADOP5 has value greater than 0.698. ADOP4 was found to have the highest loading with a value of 0.864. The four items of attitude towards HR analytics from ATT1 to ATT4 all recorded loadings above 0.691. ATT1 was found to have the highest loading of 0.818. Six data availability items from DA1 to DA6 also recorded loadings above 0.706. The DA3 item was found to have the highest loading of 0.864. Six items OC1 to OC6 in organization culture loaded with value above0.844. OC4 was found to have highest loading of 0.904. The three items for perceived ease of use from PEOU1 to PEOU3 had loading above 0.830 with PEOU2 having the highest loading of 0.941. Both PI1 and PI2 loaded with value of 0.904 and0.926 respectively on the peer influence scale. Three of the Perceived usefulness items PU1 to PU3 loaded with value above 0.838. The item PU2 was found to have highest loading of 0.904. The three loadings of readiness towards HR analytics from RT1 to RT3 loaded above 0.897. RT2 was found to have highest loading of 0.901. The loadings of the four item of quantitative self-efficacy from QSE1 to QSE4 were above 0.780. The highest loading was observed for QSE3 at 0.891. Superior influence has three items SI1 to SI3 recorded loading above 0.834. SI2 was found to have highest loading of 0.947. The five item loadings of tool trialability from TT1 to TT5 were loaded above 0.645. TT3 was found to have highest loading at 0.868. As all items value was greater than 0.6. Therefore, the indicator reliability of all items used in this study is adequate, and none of the indicators have been eliminated.

Table 4.6

Indicator reliability

		Attitude	**DA**	**OC**	**PEOU**	**PI**	**PU**	**QSE**	**RT**	**SI**	**TT**
ADOP1	0.698										
ADOP2	0.829										
ADOP3	0.854										
ADOP4	0.864										
ADOP5	0.856										
AT1		0.818									
AT2		0.691									
AT3		0.700									
AT4		0.806									
DA1			0.813								
DA2			0.708								
DA3			0.864								
DA4			0.804								
DA5			0.706								
DA6			0.849								

OC1	0.881							
OC2	0.862							
OC3	0.871							
OC4	0.904							
OC5	0.844							
OC6	0.883							
PEOU1		0.830						
PEOU2		0.941						
PEOU3		0.907						
PI1			0.904					
PI2			0.926					
PU1				0.840				
PU2				0.861				
PU3				0.838				
QSE1					0.878			
QSE2					0.780			
QSE3					0.891			
QSE4					0.827			
RT1						0.899		
RT2						0.901		
RT3						0.897		
SI1							0.834	
SI2							0.947	
SI3							0.870	
TT1								0.862
TT2								0.867
TT3								0.868
TT4								0.683
TT5								0.645

(ADOP- Adoption of HR analytics, RT- Readiness towards HR analytics, OC- Organization Culture, QSE- Quantitative self-efficacy, PEOU- Perceived Ease of Use, PU-Perceived Usefulness, PI-Peer Influence, SI- Superior Influence, TT- Tool Trialability, DA- Data Availability)

4.4.1.1.2 Internal Consistency Reliability

The internal consistency reliability of a measurement model is deemed satisfactory when the composite reliability (CR) and Cronbach alpha of each construct exceed the threshold value of 0.70. Table 4.7 displays that the CR and Cronbach alpha ranges for each construct.

The Cronbach's alpha values of all constructs ranged from 0.751 to 0.938, which is greater than the recommended minimum value of 0.7. (Nunnally, 1978). Adoption of HR analytics construct has a Cronbach’s alpha (C.A) value of 0. 878, while readiness toward HR analytics construct has a C.A value of 0.881. Cronbach's alpha values for organisational culture, attitude toward HR analytics, and data availability are 0.938, 0.751, and 0.884 respectively. Perceived ease of use and peer influence have Cronbach’s alpha value 0.874 and 0.806 respectively. Perceived usefulness has an alpha value of 0.805. Quantitative self-efficacy has an alpha value of 0.866, superior influence has an alpha value of 0.861, and tool trialability has an alpha value of 0.853.

The Composite reliability values of all constructs ranged from 0.842 to 0.951, which is greater than the recommended minimum value of 0.7. (Ringle et al, 2015). Adoption of HR analytics construct has a C.R value of 0.912, while readiness toward HR analytics construct has a C.R value of 0.927. Composite reliability values for organisational culture, attitude toward HR analytics, and data availability are 0.951, 0.842, and 0.9104 respectively. Perceived ease of use and peer influence have C.R value 0.922 and 0.911 respectively. Perceived usefulness has a C.R value of 0.883. Quantitative self-efficacy has a C.R value of 0.909, superior influence has a C.R value of 0.915, and tool trialability has a C.R value of 0.892. The C.R and Cronbach’s alpha value of all the constructs are above the cut off value of 0.7. Thus, all constructs demonstrate adequate reliability. These results indicate that the items used to represent the constructs have adequate internal consistency reliability.

Table 4.7 Construct reliability

Construct	Cronbach's alpha(α)	Composite Reliability (CR)
Adoption Of HR	0.878	0.912
Readiness Toward HRA	0.881	0.927
Organisational Culture	0.938	0.951
Attitude	0.751	0.842
Data Availability	0.884	0.91
Perceived Easy to Use	0.874	0.922
Peer Influence	0.806	0.911
Perceive Usefulness	0.805	0.883
Quantitative Self Efficacy	0.866	0.909
Superior Influence'	0.861	0.915
Tool Trialability	0.853	0.892

4.4.1.1.2 Validity

The validity of a test indicates the extent to which it measures what it is intended to measure, and instrument validation is crucial for implementation and interpretation. The validity was determined in two stages. The first step was to evaluate the convergent validity, and the second was to evaluate the discriminant validity, as illustrated below.

4.4.1.1.2.1 Convergent Validity

Convergent validity (C.V) is defined as the correlation between two measures of the same concept (Hair et al., 2010). In this study, the convergent validity of the measurement model is determined by analysing its average variance extracted (AVE) value. Constructs are deemed to have adequate convergent validity when their average variance extracted (AVE) value is close to or greater than 0.5.

All of the constructs in the current investigation satisfy the required criteria. The AVE for construct adoption of HR analytics is 0.0677, which is greater than 0.5. The AVE for the construct readiness for HR analytics is 0.808, which is greater than 0.5. The AVE for construct organisation culture is 0.764, which is greater than 0.5. The AVE for construct attitude towards HR analytics is 0.572, which is greater than 0.5. The AVE for construct data availability is 0.629, which is greater than 0.5. Also, the AVE for perceived ease of use construct is 0.79, which is greater than 0.5. In the case of peer influence, the AVE is 0.837, which is greater than 0.5. In addition, the AVE values for other constructs perceived usefulness, quantitative self-efficacy, superior influence, and tool trialability were 0.716, 0.714, 0.783, and 0.626, respectively, which are greater than 0.5. AVE values are displayed in table 4.8.

From the findings, it is noted that the criteria are full filled to ensure convergent validity as the AVE value of all construct are greater than 0.5, convergence validity has been established.

Table 4.8

Construct Validity

Construct	**Average variance extracted (AVE)**
Adoption of HR analytics	0.677
Readiness Toward HR analytics	0.808
Organisational Culture	0.764
Attitude towards HR analytics	0.572
Data Availability	0.629
Perceived Easy to Use	0.799
Peer Influence	0.837
Perceive Usefulness	0.716
Quantitative Self Efficacy	0.714
Superior Influence	0.783
Tool Trailability	0.626

4.4.1.1.2.2 Discriminant Validity

Discriminant validity is the “degree to which two conceptually similar concepts are distinct” (Hair et al., 2010). For the purpose of determining the discriminant validity, three measures were taken into account. (1) Fornell and Larcker’s criterion (2) Cross loading; and (3) Heterotrait Monotrait (HTMT) Ratio.

4.4.1.1.2.2.1 Fornel and Lacker

In order to evaluate the discriminant validity of the constructs, Fronell and Lacker's criterion is used. Fornell and Lacker in (1981), state that the square root of the AVE for a construct must be greater than the correlation between that construct and all other constructs.

The Fronell Larcker criterion for discrimination validity was satisfied because the square of AVE for each construct was greater than the other values in the corresponding rows, as shown in the table 4.9.

Table 4.9

Fornell-Larcker

	1	2	3	4	5	6	7	8	9	10	11
1.ADOP	**0.823**										
2.Attitude	0.535	**0.756**									
3.DA	0.497	0.503	**0.793**								
4.OC	0.666	0.469	0.573	**0.874**							
5.PEOU	0.499	0.548	0.54	0.525	**0.894**						
6.PI	0.321	0.478	0.452	0.348	0.485	**0.915**					
7.PU	0.714	0.567	0.635	0.541	0.531	0.437	**0.846**				
8.QSE	0.526	0.455	0.548	0.495	0.56	0.318	0.586	**0.845**			
9.RT	0.457	0.588	0.611	0.505	0.68	0.531	0.663	0.643	**0.899**		
10.SI	0.34	0.459	0.591	0.371	0.576	0.474	0.523	0.514	0.725	**0.885**	
11.TT	0.547	0.56	0.72	0.577	0.611	0.416	0.652	0.697	0.71	0.603	**0.791**

(ADOP- Adoption of HR analytics, RT- Readiness towards HR analytics, OC- Organization Culture, QSE- Quantitative self-efficacy, PEOU- Perceived Ease of Use, PU-Perceived Usefulness, PI-Peer Influence, SI- Superior Influence, TT- Tool Trialability, DA- Data Availability)

4.4.1.1.2.2.2 Cross loading

Cross loading is used to evaluate the constructs' discriminant validity. Cross-loading primarily conveys the strength of the indicator's loading to the corresponding parent construct. There is a problem with the discriminant validity if any indicator is loading more on the other construct than the parent construct. All of the indicator values in this cross loading assessment process should be higher in their parent construct when compared to the other constructs.

Cross-loading validity was established because all indicators were loaded more heavily in their respective parent constructs than the other constructs in the cross-loadings, shown in table 4.10.

Table 4.10

Cross loading

	ADOP	Attitude	DA	OC	PEOU	PI	PU	QSE	RT	SI	TT
ADOP1	**0.698**	0.477	0.379	0.505	0.328	0.371	0.477	0.356	0.368	0.33	0.37
ADOP2	**0.829**	0.449	0.498	0.641	0.449	0.261	0.575	0.418	0.354	0.279	0.529
ADOP3	**0.854**	0.439	0.371	0.519	0.422	0.242	0.647	0.473	0.4	0.279	0.441
ADOP4	**0.864**	0.41	0.409	0.536	0.414	0.2	0.566	0.446	0.342	0.215	0.441
ADOP5	**0.856**	0.421	0.376	0.523	0.426	0.248	0.661	0.466	0.414	0.295	0.45
ATT1	0.42	**0.818**	0.467	0.372	0.547	0.447	0.472	0.35	0.537	0.453	0.434
ATT2	0.312	**0.691**	0.244	0.288	0.29	0.261	0.251	0.289	0.337	0.258	0.266
ATT3	0.312	**0.7**	0.287	0.267	0.31	0.385	0.421	0.301	0.406	0.253	0.374
ATT4	0.547	**0.806**	0.475	0.472	0.457	0.327	0.529	0.426	0.465	0.384	0.583
DA1	0.331	0.431	**0.813**	0.408	0.422	0.343	0.531	0.407	0.555	0.438	0.573
DA2	0.396	0.296	**0.708**	0.417	0.36	0.333	0.433	0.399	0.337	0.509	0.581
DA3	0.518	0.482	**0.864**	0.58	0.506	0.424	0.581	0.534	0.549	0.514	0.611
DA4	0.3	0.399	**0.804**	0.386	0.419	0.346	0.499	0.391	0.542	0.44	0.56
DA5	0.359	0.283	**0.706**	0.388	0.324	0.316	0.406	0.361	0.316	0.482	0.56
DA6	0.479	0.443	**0.849**	0.538	0.5	0.386	0.538	0.504	0.514	0.481	0.579
OC1	0.589	0.378	0.458	**0.881**	0.475	0.276	0.407	0.406	0.396	0.314	0.518
OC2	0.586	0.419	0.511	**0.862**	0.47	0.33	0.475	0.427	0.44	0.315	0.486
OC3	0.557	0.425	0.498	**0.871**	0.412	0.279	0.409	0.401	0.353	0.235	0.442
OC4	0.594	0.38	0.514	**0.904**	0.45	0.318	0.467	0.413	0.429	0.31	0.503
OC5	0.492	0.393	0.502	**0.844**	0.494	0.292	0.479	0.445	0.482	0.397	0.497
OC6	0.655	0.46	0.521	**0.883**	0.459	0.329	0.588	0.5	0.544	0.377	0.57

PEOU1	0.514	0.509	0.459	0.517	**0.83**	0.336	0.438	0.48	0.498	0.478	0.558
PEOU2	0.487	0.496	0.474	0.513	**0.941**	0.491	0.501	0.514	0.599	0.5	0.54
PEOU3	0.365	0.476	0.511	0.402	**0.907**	0.458	0.481	0.508	0.699	0.558	0.548
PI1	0.273	0.393	0.384	0.256	0.46	**0.904**	0.39	0.249	0.455	0.437	0.345
PI2	0.312	0.477	0.441	0.375	0.43	**0.926**	0.409	0.328	0.513	0.431	0.412
PU1	0.736	0.483	0.497	0.562	0.526	0.345	**0.84**	0.508	0.503	0.398	0.601
PU2	0.652	0.421	0.459	0.451	0.392	0.293	**0.861**	0.504	0.498	0.356	0.494
PU3	0.464	0.521	0.628	0.381	0.431	0.446	**0.838**	0.48	0.652	0.541	0.557
QSE1	0.345	0.387	0.543	0.394	0.502	0.348	0.449	**0.878**	0.582	0.485	0.621
QSE2	0.556	0.414	0.442	0.514	0.488	0.255	0.493	**0.78**	0.477	0.419	0.531
QSE3	0.492	0.405	0.48	0.42	0.49	0.257	0.571	**0.891**	0.605	0.476	0.661
QSE4	0.403	0.333	0.377	0.361	0.411	0.205	0.467	**0.827**	0.496	0.347	0.527
RT1	0.292	0.483	0.581	0.397	0.64	0.462	0.552	0.581	**0.899**	0.752	0.624
RT2	0.469	0.56	0.498	0.461	0.607	0.419	0.586	0.573	**0.901**	0.601	0.615
RT3	0.472	0.543	0.567	0.503	0.587	0.547	0.647	0.58	**0.897**	0.604	0.675
SI1	0.383	0.374	0.579	0.342	0.519	0.327	0.477	0.508	0.572	**0.834**	0.598
SI2	0.32	0.463	0.563	0.353	0.557	0.504	0.514	0.491	0.758	**0.947**	0.568
SI3	0.2	0.37	0.423	0.287	0.447	0.406	0.388	0.363	0.57	**0.87**	0.434
TT1	0.434	0.488	0.669	0.446	0.58	0.389	0.56	0.628	0.671	0.566	**0.862**
TT2	0.389	0.495	0.618	0.413	0.552	0.39	0.511	0.6	0.687	0.599	**0.867**
TT3	0.48	0.478	0.625	0.491	0.494	0.366	0.624	0.578	0.606	0.508	**0.867**
TT4	0.518	0.398	0.495	0.57	0.405	0.249	0.498	0.517	0.389	0.343	**0.683**
TT5	0.427	0.325	0.372	0.47	0.319	0.171	0.371	0.4	0.318	0.241	**0.645**

(ADOP- Adoption of HR Analytics, RTT- Readiness towards HR Analytics, OC- Organization Culture, QSE- Quantitative self-efficacy, PEOU- Perceived Ease of Use, PU-Perceived Usefulness, PI-Peer Influence, SI- Superior Influence, TT- Tool Trialability, DA- Data Availability)

4.4.1.1.2.2.3 Heterotrait Monotrait (HTMT) Ratio

The Heterotrait Monotrait (HTMT) ratio method is a new technique, and numerous researchers are evaluating the discriminant validity of the constructs using it. Despite the fact that there is no consensus on the validity of HTMT ratio values, many authors agree to the conservative threshold value of 0.90 is appropriate (Teo et al, 2008). In this study, Heterotrait Monotrait Ratio (HTMT) ratio less than 0.85 are considered to be valid (Kline, 2015). When reliability, convergent validity, and discriminant validity are met, the measurement model is validated.

All values that were less than 0.85 as shown in the table 4.11 for the Heterotrait Monotrait (HTMT) Ratio were valid. Hence After completing the three aforementioned criteria, discriminant validity was determined.

Table 4.11

Hetrotrait-Metrotrait (HTMT) Ratio

	1	2	3	4	5	6	7	8	9	10	11
1.ADOP											
2.Attitude	0.649										
3.DA	0.564	0.580									
4.OC	0.727	0.549	0.624								
5.PEOU	0.580	0.659	0.602	0.591							
6.PI	0.381	0.599	0.531	0.395	0.572						
7.PU	0.865	0.703	0.729	0.628	0.632	0.528					
8.QSE	0.610	0.560	0.617	0.554	0.644	0.374	0.703				
9.RT	0.520	0.709	0.666	0.554	0.763	0.626	0.771	0.732			
10.SI	0.392	0.549	0.688	0.413	0.658	0.561	0.609	0.591	0.822		
11.TT	0.651	0.673	0.817	0.672	0.690	0.473	0.779	0.794	0.775	0.664	

(ADOP- HR Analytics Adoption, OC- Organization Culture, QSE- Quantitative self-efficacy, PEOU- Perceived Ease of Use, PU-Perceived Usefulness, PI-Peer Influence, SI- Superior Influence, TT- Tool Trialability, DA- Data Availability)

As reliability, convergent validity, and discriminant validity are met, the measurement model is validated.

4.4.1.2 Higher Order Construct

The higher order construct was tested for discriminant validity with other lower order construct as recommended by Sarstedt et. al., (2019). The construct reliability and validity indicate that higher order construct are reliable, later checked discriminant validity of higher order construct with lower order construct.

4.4.1.2.1 Higher order construct reliability and validity

According to the uniqueness, complexity and the needs of the study, a Higher Order test has been carried out in which the first order factors act as indicators of the second order factors.

In the present study, the Higher Order test involves three main constructs; Individual factors, social factors and technological factors. The main construct Individual factors includes four sub-constructs i.e., Attitude towards HR analytics, Quantitative self-efficacy, Perceived ease of use, and perceived usefulness; Social factors includes two sub-constructs i.e., Peer Influence, and Superior Influence; and technological factors include two sub- constructs i.e., Tool Trialability and Data Availability.

The validity and reliability of higher order construct of the measurement model is evaluated by assessing: (1) reliability (2) convergent validity and, (3) discriminant validity. The following sections present the description of the methods for all analysis to evaluate the validity and reliability of the measurement model.

4.4.1.2.2.1 Reliability

The internal consistency reliability of a measurement model is deemed satisfactory when the composite reliability (CR) and Cronbach alpha of each construct exceed the threshold value of 0.70. Table 4.12 displays that the CR and Cronbach alpha ranges for each construct.

The Cronbach's alpha values of all constructs ranged from 0.643 to 0.837, which is greater than the recommended minimum value of 0.6. (Hair et at.,2006). Individual factors construct has a Cronbach’s alpha (C.A) value of 0.825, while social factors construct has a C.A value of 0.643. cronbach’s alpha value for technological factors construct is 0.837.

The Composite reliability values of all constructs ranged from 0.845 to 0.924, which is greater than the recommended minimum value of 0.7. (Ringle et al, 2015). Individual factors construct has a C.R value of 0.884, social factors construct has a C.R value of 0.947. Composite reliability values for technological factors are 0.924.

All the constructs Cronbach's alpha value are above the cut off value of 0.5 and C.R value are above the cut off value of 0.7. Thus, all constructs demonstrate adequate reliability. These results indicate that the items used to represent the constructs have adequate reliability.

Table 4.12

Higher Order Construct Reliability

Higher Order Constrict	Cronbach alpha(α)	Composite Reliability (CR)
Individual	0.825	0.884
Social	0.643	0.845
Technological	0.837	0.924

4.4.1.2.2.2 Validity

The validity for higher order construct was determined in two stages. The first step was to evaluate the convergent validity, and the second was to evaluate the discriminant validity, as illustrated below.

4.4.1.2.2.2.1 Convergent Validity

The convergent validity of the measurement model is determined by analysing its average variance extracted (AVE) value. Constructs are deemed to have adequate convergent validity when their average variance extracted (AVE) value is close to or greater than 0.5. The AVE for construct Individual factors is 0.656, which is greater than 0.5. The AVE for the construct social factors is 0.733, which is greater than 0.5. The AVE for construct technological factors is 0.859, which is greater than 0.5. From the findings (refer table 4.13), it is noted that the criteria are full filled to ensure convergent validity as the AVE value of all construct are greater than 0.5, convergence validity has been established.

Table 4.13

Higher Order Construct Validity

Higher Order Construct	Average variance extracted (AVE)
Individual	0.656
Social	0.733
Technological	0.859

4.4.1.2.2.2 Discriminant Validity

For the purpose of determining the discriminant validity of higher order construct, two measures were taken into account. (1) Fornell and Larcker's criterion and (2) Heterotrait Monotrait (HTMT) Ratio

4.4.1.2.2.2.1 Fornel and Lacker

Fornell and Lacker, (1981) state that "the square root of the AVE for a construct must be greater than the correlation between that construct and all other constructs".

The Fronell Larcker criterion for discrimination validity was satisfied because the square of AVE for each construct was greater than the other values in the corresponding rows, as shown in the table 4.14

Table 4.14

Fornel and Lacker

Fornel-Larceker	1	2	3	4	5	6
1. Adoption	**0.823**					
2. Individual	0.702	**0.81**				
3. Organizational Culture	0.666	0.628	**0.874**			
4. Readiness	0.458	0.796	0.506	**0.899**		
5. Social	0.385	0.689	0.419	0.746	**0.856**	
6. Technological	0.565	0.795	0.62	0.716	0.66	**0.927**

4.4.1.2.2.2.2 Heterotrait Monotrait(HTMT) Ratio

In this study, Heterotrait Monotrait Ratio (HTMT) ratio less than 0.90 are considered to be valid (Teo et al., 2008). All values were valid as they were less than 0.90 as shown in the table 4.15 for the Heterotrait Monotrait (HTMT) Ratio. Hence After completing the two aforementioned criteria, discriminant validity was determined.

Table 4.15

HTMT table

HTMT	**1**	**2**	**3**	**4**	**5**	**6**
1. Adoption						
2. Individual	0.824					
3. Organizational Culture	0.727	0.711				
4. Readiness	0.52	0.832	0.554			
5. Social	0.514	0.835	0.539	0.871		
6. Technological	0.654	0.851	0.698	0.829	0.883	

As reliability, convergent validity, and discriminant validity are met, the measurement model is for higher order construct is validated. Overall, the measurement model's reliability and validity tests are satisfactory, indicating that the items used to measure the constructs in this study are reliable and suitable for use in estimating the parameters of the structural model.

4.4.2 Structural model

The second step is to evaluate the structural model following the evaluation of the measurement model. When evaluating the structural model, the researcher should look at the overall fit of the estimated model, the path coefficient estimates, their significance, the effect sizes (f2), the coefficient of determination (R2) and the predictive relevance (Q2). Table 4.16 summarises the steps involved in evaluating the structural model. In this study, the structural model was evaluated by following bootstrapping with 5000 subsamples. The same process was followed for all models i.e., lower order model and higher order model, and the outcomes were displayed at the conclusion of each model.

Twelve latent variables are present in the research model used in this study, so it is important to analyse them with a method that can estimate their scores. As a result, the model was first run through a PLS algorithm to determine the loadings (as shown in Table 4.17). and weights of the indicators (path coefficients). The structural model's robustness was then assessed using a bootstrapping method with 5000 re-samples (Chin 1998). The following subsections discuss the findings.

4.4.2.1 Bootstrapping

Since the Smart PLS analyses the data without making the assumption that it has been normalised, it is not possible to test the outer weights, outer loadings, and path coefficient using parametric tests when performing regression analysis. Instead of using a randomly selected sample from the data set to create subsamples as part of the bootstrapping procedure. It guarantees the data set's stability (Hair et al. 2017). 5000 randomly chosen bootstrapping subsamples are used in place of the original data set in this procedure, and on these 5000 subsamples, outer weights, outer loadings, and path coefficient are estimated using parametric estimation. With the help of t-values obtained through bootstrapping, the significance can be estimated.

Table 4.16

Steps to Follow In Evaluation of Structural Equation Model

Steps	Description	Criterion	Suggested threshold	Interpretation
Overall fit of estimated model	Evaluating the model fit of the estimated model by examining the empirical indicator variance–covariance matrix to its model-implemented counterpart.	SRMR	SRMR < 0.080 SRMR < HI95 dULS < HI95 dG dG < HI95	Empirical support for the postulated model is provided by values of the discrepancy measure that are below the 95% quantile of the corresponding reference distribution. To put it another way, it's possible that the empirical data come from a world that behaves as the model predicts.
Consider path coefficient estimates and their significance levels	Standardized regression coefficients are interpreted as changes in the dependent variable's standard deviations if one independent variable goes up by one standard deviation while all the other independent variables remain constant.	Path coefficient estimates and their significance level	Significant at 5% significance level, i.e., p-value < 5%	Effect of independent variables on dependent variables is statistically significant.
Consider effect sizes (f2)	Measure of the magnitude of an effect that is independent of sample size. Give an indication about the practical relevance of an effect	f2	f2 < 0.020: no substantial effect 0.020 ≤ f2 < 0.150: weak effect size 0.150 ≤ f2 < 0.350: medium effect size f2 ≥ 0.350: large effect size	Degree of strength of an effect.
Evaluate R2	Explained variance of an dependent construct	R2	When the phenomena are already quite well understood, one would expect a high R^2. When the phenomena are not yet well understood, a lower R^2 is acceptable	Degree of variance explained for phenomenon under investigation.
Q2	Explained the predictive relevance of the model	Q2	Q2>0	whether a model has predictive relevance or not.

4.4.2.2 Structural model (lower order model)

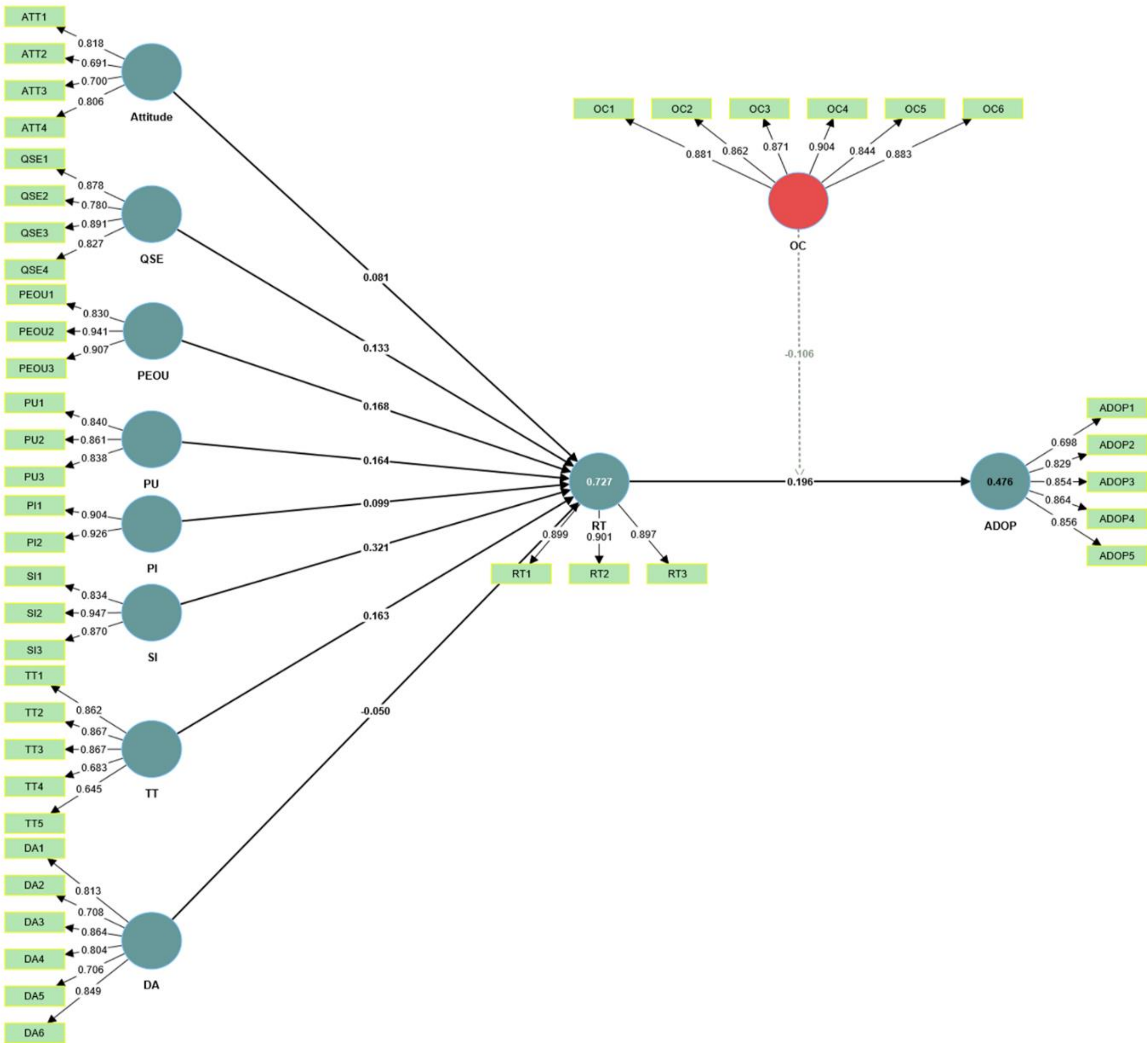
Figure 4.7 illustrates the outcomes of a bootstrapping technique with 5000 resamples. Attitude, Quantitative self -efficacy, Superior Influence, Peer Influence, Perceived ease of use, Perceived Usefulness, and Tool trialability were found to be significant predictors of Readiness towards HR analytics, while Data availability was found insignificant. Readiness towards HR analytics was reported to have a significant effect on Adoption of HR analytics. The role of Readiness towards HR analytics and Adoption of HR analytics was observed to be negatively moderated by Organization culture. The following sections present the description of the methods for all analysis to evaluate the lower order structural model. The path coefficients, t-statistics, and significance level for each hypothesised relationship are shown in Table 4.17. Each proposed hypothesis is either accepted or rejected based on the outcomes of the path assessment

4.4.2.2.1 Path Coefficient

Each path connects two latent variables that correspond to a hypothesis within the structural model. Path coefficients help the researcher to assess the strength of the relationships between the dependent and independent variables and allow them to confirm or disprove for each hypothesis. Path coefficients, which are computed in ordinary least squares regression, can be thought of as standardised beta coefficients. Along with t-statistics, the bootstrapping technique is used to determine whether the path coefficients are significant. The path coefficients, t-statistics, and significance level for each hypothesised relationship are shown in Table 4.17. Each proposed hypothesis is either accepted or rejected based on the outcomes of the path assessment. The following section discusses these findings.

Figure 4.7

Lower order structural model



4.4.2.2.2 Testing Hypotheses

After running the bootstrapping with 5000 subsamples, path coefficients between latent variables are evaluated to test the suggested hypotheses and the structural model. To take into account a specific impact within the model, a path coefficient value must be at least 0.1. (Hair et al. 2011; Wetzels et al. 2009). The Beta value measures the impact of the dependent variable on the independent variable. On the basis of the t-value and p-value, the significance of the relationship between the constructs is determined.

Including standard coefficients, path coefficients, and their significance in hypothesis testing. We can find supported hypotheses in the study based on the significance of the standardised coefficients, also known as (β) values. The significance of the unstandardized estimates and item loadings for each construct is assessed. Additionally, it confirmed that construct item loadings are highly significant at the level of 0.001 (0.1%), and their P values. Table 4.13 shows the proposed interconstruct structural relationships and path coefficients (β).

Nine of the proposed hypotheses in this lower order model's path coefficients (see Table 4.17) are supported. Supported hypotheses have signs in the expected directions, are significant at the level of 0.05, and have a path coefficient value (β) ranging from 0.17 to 0.50.

All hypothesis path values of β, t-values, and p-values are presented below:

Hypothesis 1: Attitude towards HR analytics positively influence readiness of HR professionals to adopt HR analytics.

The study found that Attitude towards HR analytics has a significant effect on readiness of HR professionals to adopt HR analytics ($\beta=0.083$, $t = 2.212$, $p<0.027$), indicating that the hypothesis is supported (H1).

Hypothesis 2: Quantitative Self-Efficacy positively influence readiness of HR professionals to adopt HR analytics.

The study found that Quantitative Self-Efficacy has a significant effect on readiness of HR professionals to adopt HR analytics ($\beta=0.133$, $t = 2.330$, $p< 0.020$), indicating that the hypothesis is supported (H2).

Hypothesis 3: Perceived Ease of Use positively influence readiness of HR professionals to adopt HR analytics

The study found that Perceived ease of use has a significant effect on readiness of HR professionals to adopt HR analytics (β =0.167, t = 3.432, p< 0.001), indicating that the hypothesis is supported (H3).

Hypothesis 4: Perceived Usefulness positively influence readiness of HR professionals to adopt HR analytics.

The study found that Perceived usefulness has a significant effect on readiness of HR professionals to adopt HR analytics (β =0.165, t = 3.688, p< 0.000), indicating that the hypothesis is supported (H4).

Hypothesis 6: Peer influence positively influence readiness of HR professionals to adopt HR analytics.

The study found that Peer influence has a significant effect on readiness of HR professionals to adopt HR analytics (β =0.099, t = 2.586, p< 0.010), indicating that the hypothesis is supported (H6).

Hypothesis 7: Superior influence positively influence readiness of HR professionals to adopt HR analytics.

The study found that Superior influence has a significant effect on readiness of HR professionals to adopt HR analytics (β=0.318, t = 6.006, p< 0.000), indicating that the hypothesis is supported (H7).

Hypothesis 9: Tool Trialability positively influence readiness of HR professionals to adopt HR analytics

The study found that Tool Trialability has a significant effect on readiness of HR professionals to adopt HR analytics (β =0.165, t = 2.936, p< 0.003), indicating that the hypothesis is supported (H9).

Hypothesis 10: Data Availability positively influence readiness of HR professionals to adopt HR analytics.

The study found that Data availability has insignificant effect on readiness of HR professionals to adopt HR analytics (β=0.051 t = 0.911, p< 0.362), indicating that the hypothesis is not supported (H10).

Hypothesis 12: The readiness of HR professionals to adopt HR analytics significantly influences their adoption behaviour.

The study found that readiness of HR professionals to adopt HR analytics has a significant effect on the adoption behaviour of HR analytics (β=0.197, t = 3.064, p< 0.002), indicating that the hypothesis is supported (H12).

Table 4.17

Hypothesis Testing of Lower Order Model

Path	Beta Coefficient	T Value	P Value	Status
Attitude -> Readiness towards HR analytics	0.083	2.212	0.027	Accepted
Data availability -> Readiness towards HR analytics	-0.051	0.911	0.362	**Rejected**
Perceived ease of use -> Readiness towards HR analytics	0.167	3.432	0.001	Accepted
Peer Influence -> Readiness towards HR analytics	0.099	2.586	0.010	Accepted
Perceived Usefulness -> Readiness towards HR analytics	0.165	3.688	0.000	Accepted
Quantitative self -efficacy -> Readiness towards HR analytics	0.133	2.330	0.020	Accepted
Readiness towards HR analytics -> Adoption of HR analytics	0.197	3.064	0.002	Accepted
Superior Influence -> Readiness towards HR analytics	0.318	6.006	0.000	Accepted
Tool trialability -> Readiness towards HR analytics	0.165	2.936	0.003	Accepted

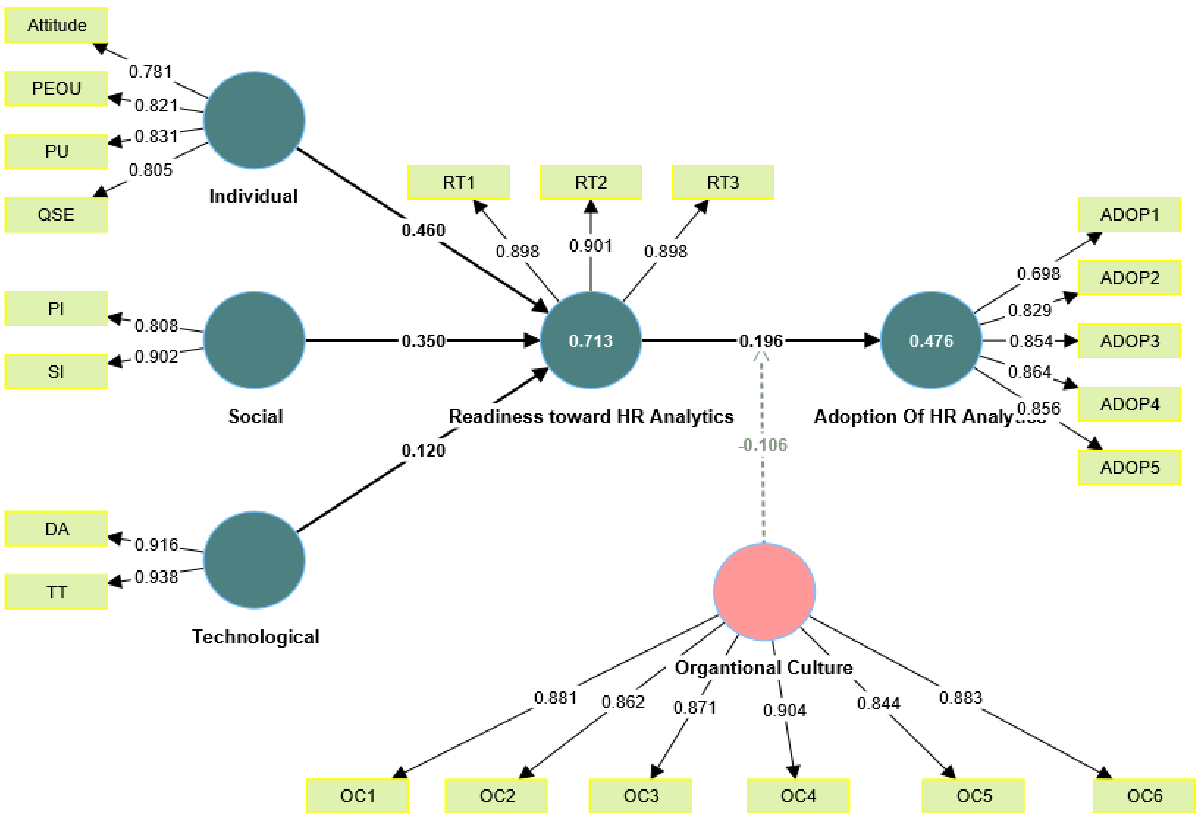
4.4.2.3 Higher order structural model

Structural model evaluation was done after validating higher-order constructs. According to the uniqueness, complexity and the needs of the study, a higher order has been carried out in which the first order factors act as indicators of the second order factors. In the present study, the higher order test involves three main constructs: individual factors, social factors and technological factors.

Figure 4.8 depicts the results obtained using a bootstrapping method with 5000 re-samples. Individual and social was found to have significant relationship with readiness towards HR analytics whereas technological was found to have insignificant relationship. The following sections present the description of the methods for all analysis to evaluate the higher order structural model. The path coefficients, t-statistics, and significance level for each hypothesised relationship are shown in Table 4.18. Each proposed hypothesis is either accepted or rejected based on the outcomes of the path assessment.

Figure 4.8

Higher Order Structural Model



4.4.2.3.1 Hypothesis testing of higher order model

Based on the theory research gaps were identified. To address the gaps empirically, hypotheses were framed. The following were the hypotheses of study to understand ***the influence of individual, social, and technological factors on adoption of HR analytics***

H5: Individual factors influence HR professionals' readiness to adopt HR analytics.

H8: Social factors influence HR professionals' readiness to adopt HR analytics.

H11: Technological factors affect HR professionals' readiness to adopt HR analytics.

The following section discusses values (β, t-value and P-values) were drawn from the data and presented in table 4.18.

Hypothesis 5: Individual factors influence HR professionals' readiness to adopt HR analytics.

The study found that individual factors has a significant effect on readiness to adopt HR analytics (β=0.460, t = 7.405, p< 0.000), indicating that the hypothesis is supported (H5).

Hypothesis 8: Social factors influence HR professionals' readiness to adopt HR analytics.

The study found that social factors has a significant effect on readiness to adopt HR analytics (β=0.350, t = 6.847, p< 0.000), indicating that the hypothesis is supported (H8).

Hypothesis 11: Technological factors influence HR professionals' readiness to adopt HR analytics.

The study found that technological factors has no significant effect on readiness to adopt HR analytics (β=0.082, t = 1.742, p> 0.05), indicating that the hypothesis is not supported (H11).

Table 4.18

Hypothesis Table for Higher Order

Path	Beta Coefficient	T Value	P values	Status
Individual -> Readiness	0.460	7.405	0.000	Accepted
Readiness -> Adoption	0.196	3.192	0.001	Accepted
Social -> Readiness	0.350	6.847	0.000	Accepted
Technological -> Readiness	0.088	1.742	0.082	**Rejected**

4.4.2.4 Model Fit / Evaluation of the estimated model's overall fit

To get empirical support for the proposed theory, we should first assess the estimated model's overall fit using the bootstrap-based test of overall model fit and the SRMR as a measure of approximate fit. Research analysis would be incomplete without considering the overall model, as doing so would mean ignoring empirical evidence supporting and refuting the proposed model and the postulated theory (Henseler et al., 2014).

The estimated model in our study was not rejected at a 5% significance level because all values of the discrepancy measures were below the 95% quantile of their corresponding reference distribution (HI95) (see Table 4.19).

4.4.2.4.1 Standardized Root Mean Square Residual (SRMR)

The "SRMR is the difference between the correlation that was seen and the correlation that was assumed by the model". So, it lets you use the average size of the differences between observed and expected correlations as a measure of how well a model fits. Henseler et al. (2014) come up with the SRMR as a measure of how well PLS-SEM fits the data that can be used to avoid misspecification of the model. A good fit is when the value is less than 0.08 (Hair et al. 2017; Hu & Bentler, 1999).

Additionally, the SRMR was 0.06 for both the proposed model which was below the initially proposed threshold of 0.080, demonstrating a good model fit (Table 4.19). This finding suggests that the proposed model is well suited for validating and explaining how adoption behaviour and readiness towards HR analytics among HR professionals 'have evolved among organization.

4.4.2.4.2 F-Square /Assessment of effect sizes

Examining the effect sizes/f square of the relationships between the constructs is necessary for determining "the practical relevance of significant effects". Effect size is a measurement of an effect's magnitude that is independent of sample size.

The f2 values between 0.020 and 0.150, 0.150 and 0.350, or greater than or equal to 0.350 indicate a small, moderate, or large effect size, respectively (Cohen, 1988). In our lower order model, the hypothesised relationship f2 values range from 0.008 to 0.369, representing small to large effect size. Whereas in higher model, the hypothesised relationship f2 values range from 0.017 to 0.236, representing small to moderate effect size.

Table 4.19 Model fit

Variable	Outcomes	R square	Q Square	F square	SRMR
Readiness Toward HRA	Adoption Toward HRA	0.476	0.490	0.057	0.062
Organisational Culture				0.369	
OC*RT (Moderating)				0.029	
Attitude	Readiness Toward HRA	0.727	0.711	0.016	
QSE				0.035	
PEOU				0.055	
PU				0.046	
PI				0.026	
SI				0.202	
TT				0.035	
DA				0.008	
Individual	Readiness Toward HRA	0.713	0.705	0.236	
Social				0.209	
Technological				0.017	

(HRA- HR analytics, OC- Organization Culture, QSE- Quantitative self-efficacy, PEOU-Perceived Ease of Use, PU-Perceived Usefulness, PI-Peer Influence, SI- Superior Influence, TT- Tool Trialability, DA- Data Availability)

4.4.2.4.3 Explanatory power of the model (R square)

R square explain the endogenous variable's variance is explained by the exogenous variables. It indicates that one or more independent variables account for a portion of the change in the dependent variable. As a result, it sheds light on a model's ability to predict outcomes within a sample (Becker et al., 2013). The interpretation of R square is subject to a variety of interpretations. R square value should, according to Falk and Miller (1992), be greater than 0.10. According to Cohen (1988), an R square value of 0.26 indicates a model's explanatory power is substantial, 0.13 is moderate, and 0.02 is weak. Additionally, Chin (1998) claimed that an R square value of 0.67 indicates a model's explanatory power to be substantial, 0.33 indicates a moderate level, and 0.19 indicates a low level. Using the SmartPLS software, the R square values for both models were calculated. According to Falk and Miller (1992) and Cohen (1998), all of the values were significant and moderate.

The phenomenon being studied determines the expected value of R square. One would anticipate a relatively high R square given that some phenomena are already fairly well understood. A lower R square is acceptable for phenomena that are less well understood. It is important to compare the R square values to studies that focus on the same dependent variable. In our study, the Rsquare values for adoption behaviour towards HR analytics were 0.476, indicating a moderate level of model explanation, whereas the R square value for readiness towards HR analytics was 0.727, indicating a higher level of model explanation. As well as the higher order model R square value for readiness towards HR analytics were 0.713, indicating a higher level of model explanation.

In our study, the lower order model eight understudied exogenous variable explain 72.7% of variance in the development of readiness towards HR analytics. Further the readiness towards HR analytics and organization culture accounts 47.6% of variation in adoption behaviour of HR analytics. The higher order model three exogenous variable explain 71.3% of variance in the development of readiness towards HR analytics.

4.4.2.4.4 Power of prediction of the model (Q square)

Q square is utilised to evaluate the predictive relevance of the model. In addition, Q square establishes the predictive value of endogenous constructs. Any model with a Q square value greater than zero is considered to have a high predictive relevance (Hair et al., 2017; Henseler, 2014). In Smart PLS, the Q square value is determined using the Blindfolding procedure. All values of the constructs were greater than 0 and have predictive value.

4.4.3 Moderation analysis

When two constructs have a relationship that is not constant but rather depends on the values of a third variable, which is known as a moderator variable, the situation is said to be in moderation. A relationship between two constructs in the model may change in the model's moderator variable's strength or even in its direction. A moderating variable is one that affects how the independent and dependent variables are related, i.e., it has a significant contingent impact on the relationship between IV and DV. However, Moderating variable has an impact on the strength and direction of the relationship between IV and DV even though it is unaffected by IV.

The researcher made the assumption that organization culture, because of its benefits, would act as a buffer between the association between HR professionals' readiness towards HR analytics and adoption behaviour of HR analytics. **(OC* RT →ADOP).** A simple and direct slope plot (Figure 4.9) provides additional insight into the moderation effect.

Hypothesis 13: Organizational Culture moderates the relationship between Readiness towards HR analytics and adoption of HR analytics.

In testing the interaction effect between HR professionals' readiness towards HR analytics and adoption behaviour towards HR analytics, the result indicates that organizational cultures have a negative significant moderating effect ($\beta = -0.107$, $t = 2.531$, $p < 0.011$), thus supporting

H10 provided table 11. The direct link between readiness towards HR analytics and adoption behaviour of HR analytics is provided in Table 4.20 and shows that it is positive and significant. However, the interaction link between HR professionals' readiness towards HR analytics and organizational culture toward the HR analytics adoption behaviour (OC*RT → ADOP) is negative (-0.116) and significant. The negative moderating effect between organizational cultures means that if the value of organizational culture increases, the direct link between readiness to adopt HR analytics and HR analytics adoption behaviour decreases. Therefore, hypothesis H 13 is supported.

Table 4.20

Moderating Table

Path	Beta Coefficient	T Value	P values	Status
Organizational Culture x Readiness -> Adoption	-0.106	2.46	0.014	Accepted

4.4.3.1 Simple slope analysis

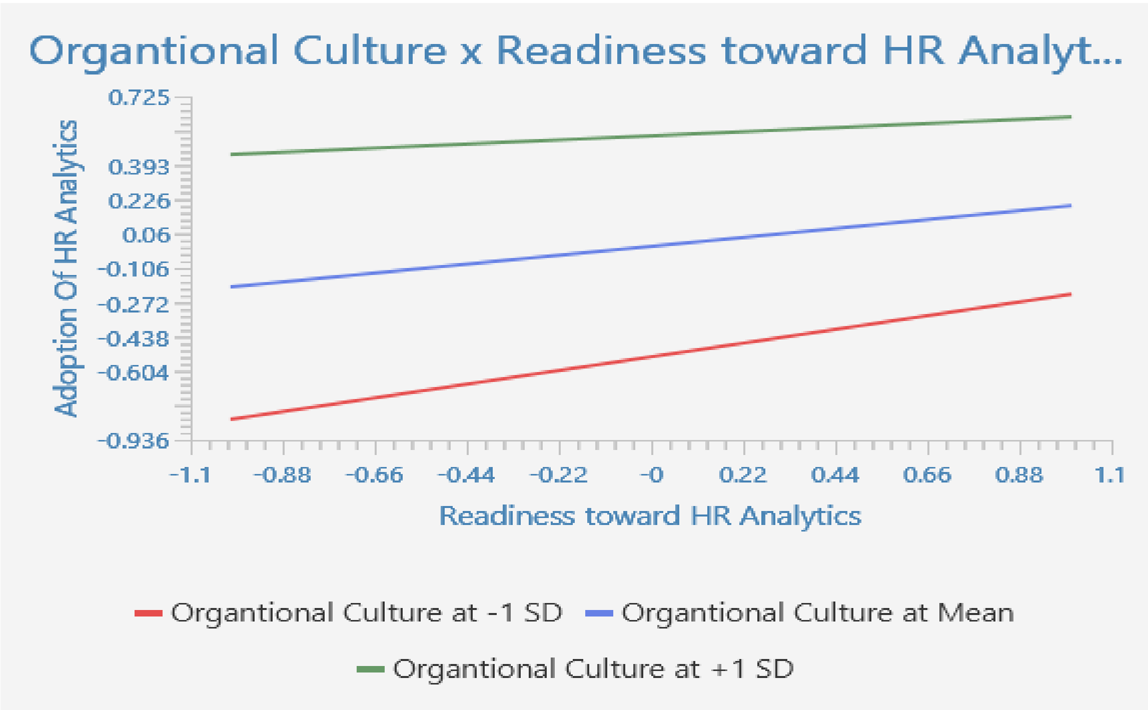
Simple slope plots are commonly used to represent the results of moderator analyses. In the results report, SmartPLS offers straightforward slope plots. The relationship between HR professionals' readiness and adoption of HR analytics, which is tempered by organizational culture in the model, is depicted in the following figure no 4.9 as a simple and direct slope plot.

Slope demonstrates that the relationship between RTT and ADOP is weaker (i.e., flatter line) for high organization culture (i.e., +1 standard deviation above the mean; green line) than for low organization culture (i.e., -1 standard deviation below the mean; red line), where the slope is higher. It demonstrates that the readiness and adoption behaviour to adopt HR analytics has a greater impact on HR professionals who perceive a low organisational culture than on those who perceive a high organisational culture

Figure 4.9 demonstrates the moderating interaction pattern using Aiken (1991), which is the process of finding slopes above and below the mean within one standard deviation of organizational culture. The findings suggests that organisations with low organisational culture show a stronger effect between HR analytics readiness and adoption behaviour than high organisational culture, as indicated in figure 3. The relationship between HR analytics readiness and adoption behaviour is linear, even in the case of high organisational culture, demonstrating the importance of both high and low organisational culture in predicting HR analytics adoption behaviour. However, high organizational culture is less predictive than low organizational culture.

Figure 4.9

Slope Analysis



In summary, the chapter presented the results and findings of several methods of analysis used in the current study. The chapter provided a summary of the demographic characteristics of the participants in this investigation. The chapter also included descriptive data for each item on the measuring scale, as well as pre-test analysis such as data adequacy test, common method bias and homogeneity test. Finally, the chapter concluded by providing the results of the measurement model, the structural model, and the moderation analysis, together with applicable reporting of each essential statistic.

CHAPTER - 5

DISCUSSION AND CONCLUSION

5.1 Overview

The goal of this study is (i) to explore the potential factors influencing the HR professionals' readiness towards HR analytics, (ii) to study the influence of readiness towards HR analytics on adoption among HR professionals in India, (iii) to study the moderating role of organizational culture between readiness and adoption of HR analytics among HR professionals' and (iv) to understand the influence of individual, social, and technological factors on individual adoption of HR analytics.

This chapter discusses the results from the previous chapter to explain the connections between the existing literature and current research. By doing so, the chapter highlights the importance and contribution to the relevance of the results. The current research investigate the factors influencing HR professionals' readiness and adoption of HR analytics by integrating TPB, TAM, and DOI theories. Additionally, it examines the role of organizational culture as a moderator between HR professionals' readiness and adoption of HR analytics.

It also explains the theoretical and practical use of potential factors for readiness towards HR analytics, and the role of organisational culture in HR analytics adoption among HR professionals. Managers, business leaders, and policymakers can use this finding to assist HR analytics adoption in their organizations. The significance of the research for the field of HR analytics is emphasized by explaining both the theoretical and practical implications of the results. The limitations of the study are acknowledged and suggestions for future research are provided.

5.2 Discussion

A detailed discussion of the findings, organized according to research objectives and hypotheses, is provided below. The findings are analyzed and explained in relation to the original research questions and hypotheses, providing a comprehensive understanding of the results obtained. This section aims to present a clear and thorough examination of the findings, highlighting their significance and implications.

5.2.1 Relationship between HR Professionals' attitude towards HR analytics on readiness to adopt HR analytics. (H1)

The findings from the study indicate that there is a significant positive relationship between HR professionals' attitude towards HR analytics and their readiness to adopt it, supporting Hypothesis 1 (H1). This means that HR professionals who have positive attitude towards HR analytics tend to be more willing and prepared to use it. This result aligns with previous research conducted by Ejaz et al. (2020) and Vargas et al. (2018), who also found that attitude play a role in shaping HR professionals' readiness towards HR analytics.

HR professionals having a positive attitude towards HR analytics can lead to an increased willingness to use it, which can result in a faster and more successful implementation. Positive attitude of HR professionals towards HR analytics are more likely to actively seek out training and assistance in using it. This leads to a greater understanding of the benefits and capabilities of HR analytics, which can result in more effective and efficient use.HR professionals with positive attitude towards HR analytics are more likely to be engaged in using it and to be more proactive in seeking out new ways to apply it to improve HR practices. This leads to increased innovation and the development of new HR analytics solutions. Also, having a positive attitude towards HR analytics can also impact the attitudes of others within the organization. HR professionals who are positive about HR analytics can act as ambassadors and help to build support and interest in its adoption among other HR professionals and stakeholders.

5.2.2 Relationship between HR professionals' quantitative self-efficacy and readiness to adopt HR analytics (H2).

The study also finds a significant impact of quantitative self-efficacy on HR professionals' readiness to adopt HR analytics (H2). This result is in line with the findings of Vargas et al., 2018; Ejaz et al., 2020; Brown et al., 2015. As a result, if HR professionals feel confident in their quantitative skills and believe they can perform well, they are more likely to adopt HR analytics.

HR professionals' acceptance and adoption of HR analytics is a critical factor in the successful implementation of HR analytics initiatives within organizations. HR analytics involves the use of data and statistical methods to inform and support human resource decision-making. However, not all HR professionals have the skills and confidence to use this technology effectively (Marler & Bourdeau, 2017; Bindu, 2016).

Quantitative self-efficacy refers to an individual's belief in their ability to perform a task successfully, in this case, the use of data and analytics for informed HR decisions. HR professionals with high levels of quantitative self-efficacy see HR analytics as a valuable tool that can enhance their decision-making processes and improve their performance. They believe in their ability to understand and use the data and insights provided by HR analytics, and they view the technology as a useful resource that can help them to make more informed decisions.

In contrast, HR professionals with low levels of quantitative self-efficacy may view HR analytics as too complex or challenging to use effectively. They may lack confidence in their ability to understand and interpret the data, and they may be less likely to trust the insights provided by the technology. This lack of confidence can lead to a lack of adoption of HR analytics and a reluctance to integrate it into their daily work.

Based on the findings of the study, if HR professionals believe they are not capable of working at their best with HR analytics, they will be opposed to its implementation. This can be attributed to their lack of faith in their abilities to apply analytics (Vargas et al. 2018; Boyd & Crawford, 2011).Therefore, HR professionals' quantitative self-efficacy directly affects their perceived usefulness and ease of use of HR analytics (Fernanadez & Gallarado, 2021; Kabra et al., 2017). HR professionals with high levels of quantitative self-efficacy are more likely to embrace HR analytics and integrate it into their work, while those with low levels of quantitative self-efficacy may be less likely to do so. It is important for organizations to support HR professionals in building their quantitative self-efficacy so that they can effectively use HR analytics to support their decision-making processes.

5.2.3 Relationship between HR professionals' perceived ease of use and readiness to adopt HR analytics (H3).

This study found that HR professionals' perception of HR analytics usability have a significant effect on their intention to adopt it (H3). When HR professionals perceive HR analytics to be easy to use, they are more likely to use it. Previous study indicates that HR professionals are constrained by their own judgments that they lack the aptitude to learn important skills such as data analysis (Bandura, 1982; Talukder & Quazi, 2011). According to studies by Kabra et al., (2017) and Jennings et al., (2015), individuals consider a system is easy to use because of the ease or effort to use it. As a result, HR professionals generally try to avoid data analysis unless the technologies are simple to use and training is offered (Ejaz et al., 2020; Vargas et al., 2018).

The perception of HR professionals on the usability of HR analytics plays a crucial role in their readiness to adopt it. HR professionals are more likely to utilize HR analytics if they believe it is user-friendly and can be easily integrated into their work processes. On the other hand, if they perceive the technology to be complex and challenging to use, they may be less likely to adopt it.

The ease of use of HR analytics is a critical factor for HR professionals because many of them may lack the technical skills or training in data analysis (Fernando & Gallarado, 2021; Bindu , 2016, Sharma & Sharma, 2017) . Therefore, if they perceive the technology to be easy to use, they are more likely to overcome any perceived limitations and embrace its use. This perception can be shaped by factors such as the user interface, the availability of training, and the support offered by the technology vendor.

Therefore, the willingness of HR professionals to adopt HR analytics is closely tied to their perception of its ease of use. Therefore, it is important for technology vendors and HR organizations to ensure that HR analytics solutions are designed to be user-friendly and provide adequate training and support to help HR professionals effectively utilize the technology.

5.2.4 Relationship between HR professionals' perceived usefulness and readiness to adopt HR analytics. (H4)

According to the findings, HR professionals who believe that HR analytics will improve their job performance and lead to promotions are more likely to adopt HRA. The intended performance enhancement has been shown to be a strong predictor of behavioural intention (Venkatesh et al., 2012). This finding is consistent with previous research that an individual's belief that using the technology will improve job performance has a significant effect on his or her intention to use the technology and the associated behaviours (Wandhe, 2020; Kabra et al. 2017).

HR professionals who perceive HR analytics as a tool to enhance their job performance and increase their opportunities for advancement are more inclined to adopt and integrate HR analytics into their work processes. By utilizing HR analytics, these professionals aim to gain a deeper understanding of the human capital in their organization, track key HR metrics, and make data-driven decisions that can positively impact the overall performance and success of the company. The use of HR analytics enables these professionals to demonstrate their value and expertise, contributing to their professional growth and career advancement.

5.2.5 Relationship of individual factors on readiness of HR professionals for adoption of HR analytics (H5).

The present study followed a cross-sectional approach to examine the hypothesised relationships, and it reveals that individual factors have a considerable positive affect on HR professionals’ readiness to adopt HR analytics (H5). From revealed results (H5), it seems that individual factors, according to the study, have a major impact on HR professionals’ intention to adopt HR analytics. The findings of this study are also in line with the findings of Haneem et al. (2019), and Talukder, (2012) who indicated individual factors have a significant impact on adoption.

The study suggests that HR professionals' readiness to adopt HR analytics is influenced by their assessment of their own abilities to grasp and use it. Four key individual factors were identified as playing a role in this assessment: attitude, quantitative self-efficacy, perceived ease of use, and perceived usefulness.

Of these individual factors, the study found that ease of use and usefulness were equally and highly important in determining HR professionals' adoption of HR analytics. This suggests that the perceived ease of using HR analytics and the perceived usefulness of HR analytics are key drivers in determining whether HR professionals are willing to adopt it.

In contrast, the study found that HR professionals' attitude had a lesser effect on the adoption of HR analytics. This could be because technology is always evolving, and HR professionals might be hesitant to embrace new changes. In such cases, the ease of using and the usefulness of HR analytics could become more crucial in determining whether they will adopt it, as these factors can help to reduce discomfort associated with change.

Therefore, the study highlights the importance of ease of use and usefulness in determining HR professionals' willingness to adopt HR analytics. This underscores the need for organizations to invest in HR analytics to deliver tangible benefits to HR professionals to make strategic decision. Additionally, organizations may need to provide training and support to HR professionals to help them develop the skills and confidence they need to effectively use HR analytics.

5.2.6 Relationship between peer influence and readiness to adopt HR analytics among HR professionals (H6).

The influence of peers has a positive effect on the adoption of HR analytics among HR professionals (H6). This finding is consistent with findings from other studies indicating that co-workers can impact and influence the behaviour, motivation, and encouragement, of an employee's adoption of a new technology (Graf et al., 2018; Talukder, 2012; Talukder & Quazi, 2011; Persaud & Schillo, 2017). Seeing others coworkers in similar positions successfully using and benefiting from HR analytics can make individuals more confident in their own ability to use it effectively and more likely to try it themselves.

The positive influence of peers on the adoption of HR analytics among HR professionals can be recognized to several factors. Firstly, observing colleagues in similar positions using HR analytics successfully can increase confidence in one's own ability to effectively use it. Secondly, peers can provide validation and support, helping to alleviate any perceived barriers or concerns about adoption. Additionally, peer support can serve as a source of information, best practices, and guidance for individuals who are considering HR analytics adoption. Finally, the positive experiences of peers can serve as a model for others, demonstrating the potential benefits and success that can be achieved through the use of HR analytics. All of these factors combined can significantly contribute to the positive influence of peers on the adoption of HR analytics among HR professionals.

5.2.7 Relationship between superior influence and readiness to adopt HR analytics among HR professionals (H7).

This study indicates that the influence of superiors positively affects the adoption of HR analytics (H7). Several studies, including Graf et al. (2018), Talukder (2012), Talukder & Quazi (2011), and Persaud & Schillo (2017), have reported similar results, indicating that superior have the potential to affect and influence the behavior, motivation, and encouragement of employees when it comes to adoption.

When superior/leaders express support for HR analytics and its benefits, HR professionals are more likely to be receptive to the idea of using it. Additionally, when superior use HR analytics themselves and demonstrate its value through their actions, it inspires others to do the same. Superior can also provide the necessary resources and support to help HR professionals adopt HR analytics, such as training, access to tools, and ongoing support. Furthermore, when superior set expectations for the use of HR analytics, it helps HR professionals understand its importance and motivates them to use it. Overall, superior influence can play a crucial role in increasing the adoption of HR analytics and making it an integral part of HR practices.

5.2.8 Relationship of social factors on readiness towards HR analytics (H8).

The study finds that social factors significantly impact the readiness of HR professionals to adopt HR analytics (H8), which is in line with previous research by Haneem et al. (2019), Alwaris et al. (2016), and Talukder (2012). These findings suggest that individual are influenced by their social group's members i.e. peer and superior who can affect one another's behaviour when it comes to adoption. Accordingly, the findings of the current study identified that HR professionals' readiness to use HR analytics are due to perceived social influence by peer and superior, hence role model, mentors and change champions influence adoption of HR analytics.

Furthermore, the study finds that superior influence has a stronger impact on HR adoption compared to peer influence. This indicates that HR professionals tend to be more oriented towards decisions made by their superiors and are more likely to follow their lead when it comes to adopting HR analytics. This highlights the importance of superior and support for the successful implementation and adoption of HR analytics within an organization. By creating a culture that supports and encourages the adoption of HR analytics, superiors can help increase the likelihood that HR professionals will adopt the technology and use it to drive business outcomes.

5.2.9 Relationship between tool trialability and readiness to adopt HR analytics among HR professionals. (H9)

The trialability of appropriate HR analytics technologies has a significant impact on HR professionals' decision to employ HR analytics. The concept of trialability refers to the ability of an individual to test or try a technology before fully adopting it. In the context of HR analytics, trialability refers to the ability of HR professionals to try and test HR analytics technologies before making a decision to use it on a larger scale.

Research by Ejaz et al., (2020) and Lin & Bautista (2016) supports the idea that trialability has a positive relationship with HR analytics adoption. In other words, the ability to trial and test HR analytics technologies before fully adopting it increases the likelihood of HR professionals adopting it. This is important because it allows HR professionals to understand the capabilities and limitations of HR analytics, and how it can be used to support HR decision-making.

However, it is important to note that the validation of the significance of resource trialability systems and software is not the only tool required for the effective adoption of HR analytics. Other factors, such as the availability of data, the skills of HR professionals, and the support and resources provided by the organization, also play a role in determining the adoption of HR analytics.

For HR professionals to effectively use HR analytics, they need access to appropriate technologies that are user-friendly, easily accessible, and meet their needs. In addition, they need access to training and support, and the necessary resources to effectively implement and use HR analytics. Without these, HR professionals may struggle to effectively use HR analytics, and the potential benefits of using HR analytics may not be fully realized.

5.2.10 Relationship between data availability and readiness to adopt HR analytics among HR professionals. (H10)

The availability of data is a critical factor that affects the adoption of HR analytics by HR professionals. Despite this, the findings of a study show that data availability has no impact on the adoption of HR analytics (H10). This suggests that the presence of data alone may not be enough to drive HR professionals to adopt HR analytics.

There could be various reasons why data availability has no impact on HR analytics adoption. HR professionals may lack the skills or resources to effectively access, analyze, and interpret data. They may also face challenges in differentiating and interpreting data, which is related to their quantitative self-efficacy. In some cases, HR professionals may not understand the value of HR analytics and how it can be used to support HR decision-making.

Additionally, organizations may collect large amounts of data but not make it accessible to HR professionals, which can limit their ability to use HR analytics. Furthermore, HR professionals may not have the necessary support or resources to effectively implement HR analytics, such as training, access to tools, and ongoing support. Without these, the availability of data alone may not drive HR professionals to adopt HR analytics

5.2.11 Relationship of technological factors on readiness towards HR analytics (H11).

The results of the study suggest that the influence of technological factors on the readiness of HR professionals to adopt HR analytics is not significant (H11). This finding is in line with previous research that has shown no significant relationship between technological characteristics and adoption (Parisa et al., 2020; Cheng et al., 2020; Marukohani et al., 2018).

Despite this lack of significant influence, the study also found that within the technological factor, tool trialability has impact on HR adoption. This means that HR professionals are open to trying new and innovative technologies to gain experience and perceive value. However, the lack of data differentiation and data accessibility restricts HR professionals from fully utilizing HR analytics.

HR analytics relies heavily on data availability, and the increasing use of technology and automation has made it easier than ever to collect and analyze HR-related data. However, the lack of data differentiation can be a significant challenge for HR professionals looking to fully utilize HR analytics. This means that HR professionals may not have access to the specific types of data they need to answer their research questions or make informed decisions. For example, HR analytics may require data that is not commonly collected or reported by HR systems, such as information on employee engagement, workplace culture, or employee satisfaction. Without this type of data, HR professionals may struggle to gain a complete understanding of their organization's workforce and make data-driven decisions.

Data quality is an essential factor in the adoption of HR analytics. Without high-quality data, HR professionals cannot effectively analyze and make strategic decisions based on the insights generated from the analytics. Therefore, organizations need to ensure that their data is accurate, complete, relevant, and timely to maximize the value of HR analytics.

Additionally, HR professionals may encounter challenges in data integration, where data from different sources needs to be combined and analyzed. This can be particularly difficult when organizations use multiple HR systems or have data stored in various locations, which can make it challenging to create a complete and accurate picture of the workforce.

These findings have important implications for Indian organizations, which need to provide proper training and facilities to support HR professionals in using HR analytics. Providing training can help HR professionals overcome any barriers to adoption and effectively use the technology to drive business outcomes. In addition, ensuring data differentiation, data quality and data accessibility can help HR professionals fully leverage the capabilities of HR analytics.

5.2.12 The Relationship between readiness towards HR analytics and adoption of HR analytics (H12)

The goal of this study is to find out how HR professionals' readiness influences their behaviour to adopt HR analytics in India. The previous study also said that both intentions and behaviour influence how individuals use technology (Attuquayefio & Addo, 2014; Venkatesh et al., 2003), but less research has been conducted to find out HR professionals adoption behaviour. That is why the present study has made an attempt to study the influence of HR professionals' readiness on adoption behaviour and found to be significant (H12). The result from the study indicates that HR profesionals' readiness predicts the actual behaviour. The hypothesized relationship between readiness and behaviour to adopt HR analytics is consistent with the earlier findings o (Wang et al., 2020; Taherdoost, 2020; Attuquayefio & Addo, 2014; Venkatesh et al., 2003). The authors indicated that the construct readiness is the most influential factor affecting adoption behaviour of HR analytics. Accordingly, the findings of the current study identified that HR professionals' with readiness to use HR analytics will be more amenable to adopt HR analytics.

5.2.13 Moderating role of Organization culture between readiness towards HR analytics and adoption of HR analytics (H13)

Organizational culture influences individual behaviour in adoption (Bankole & Bankole, 2017; Tseng, 2017). Understanding the importance of organizational culture in the adoption of HR analytics is important as it is seen as a critical factor (Mohtaramzadeh et al., 2018; Borkovich et al., 2015) as it either strengthens or weakens the relationship. Researchers claim that organizational culture influences individual behaviour in adoption of technology (Mohtaramzadeh et al., 2018). So, the present study lays down to investigate the moderating role of organizational culture towards adoption of HR analytics (H13*)*. The association between HR analytics readiness and adoption of HR analytics reveals a significant negative impact of organisational culture. In other words, organisational culture "weakens" the relationship between HR analytics adoption readiness and behaviour. These findings are highlighted by the fact that organisations with a "strong culture" are better positioned to adopt HR analytics. This is due to the fact that organisations with a strong culture are more likely to be innovative, able to transmit information, skills, and data along the value chain; accept technology with confidence; emphasise team building; and have more advocates and have more champions when contrasted with organizations with weak culture (Liu et al., 2010;

Khazanchi et al., 2007). Accordingly, organisations with a strong innovative culture are more likely to embrace new technologies when contrasted with those with weak culture. Halper (2014) suggests that organizations that are using analytics, "analytics culture" is important for adoption of it. Vargas et al. (2018) state that organizations must redefine their culture to analytics culture to gain benefits of HR analytics. Different countries have different cultures, i.e., a national culture. Technology adoption varies from country to country and organisation to organisation due to cultural variances. Various studies have shown how national culture impacts adoption (Brown et al., 1998; Suite & Karahanna, 2006; Merchant, 2007). Therefore, the adoption of HR analytics differs from country to country and organization to organization. Wang et al. (2020) conducted a study in the context of China and discovered that organisational culture plays a positive moderating role in information technology adoption (ICT). In contrast, a study conducted by Mohataramzadeh et al. (2018) in Iran found that organisational culture has a negative moderating effect on B2BE adoption. Therefore, the findings of this study convey a very important message for Indian organizations to establish an innovative culture in order to successfully implement HR analytics. The study reveals that currently most organizations culture is not supportive of HR analytics adoption. The culture is not in line with HR analytics adoption strategy.

Indian organizations to rely on traditional methods of decision making, such as intuition and experience, rather than data-driven approaches. In these organizations, there may be a belief that relying on data alone is not sufficient to make informed decisions and that human judgement and experience are more important.

This cultural resistance to data-driven decision making may hinder the adoption of HR analytics in India, as HR professionals in these organizations may not see the value in using data and technology to inform their decision making. Instead, they may prefer to rely on their own experiences and instincts to make decisions about issues such as recruitment, performance management, and employee retention.

In contrast, organizations that embrace data-driven decision making see the benefits of using data and technology to make informed decisions. They understand that HR analytics can provide valuable insights into important HR issues and that these insights can help organizations make informed, data-driven decisions that are more effective and efficient.

To overcome cultural resistance to data-driven decision making, it is important to educate HR professionals on the benefits of HR analytics and to demonstrate how it can support better decision making. Additionally, organizations can work to build a culture of data literacy, where data and technology are valued and used for strategic decision making throughout the organization. By promoting a culture of data literacy and investing in the necessary resources to support HR analytics, organizations can overcome cultural resistance to data-driven decision making and reap the benefits of using HR analytics for strategic decision making.

5.3 Theoretical Implications

The study contributes noteworthy research insights into HR analytics adoption. The study fills the main gap in the literature concerning the empirical evidence for HR analytics adoption. As previous study by Marler & Bourdeau, 2018 & Fedrado & Gallarado, 2020 says there are dearth of theoretical and empirical evidence for HR analytics.

Even though HR analytics has various benefits still its adoption is sluggish, so the study conducted an extensive literature analysis to identify the potential factors influencing HR analytics adoption. HR analytics adoption has always been studied by using individual factors (Vargas et al. 2018). The present study is unique as it examines HR analytics adoption by using individual, social and technological factors holistically.

A major part of existing research has only focused on the intention and have not studied the relationship between intention and behaviour. Our research is first of the few comprehensive study to focus on both intention and usage behaviour to adopt HR analytics by integrating TPB, TAM and DOI theory in India. Secondly, it is probably the first study in HR analytics adoption that incorporate organization culture as a moderator to study HR professionals' adoption intention and behaviour in adopting HR analytics. Thus, integrating organizational culture as a moderator in the proposed theory for HR analytics adoption is construed to be a special theoretical contribution from our study. We claim this is a new perspective that will enhance the body of literature on the subject. Our proposed theoretical model is expected to be helpful in advancing a calibrated roadmap for future research on HR analytics as well as technology adoption.

5.4 Practical Implications

This study has numerous practical contributions. The study assists organization and managers in understanding the facilitators and barriers of HR analytics adoption. The study reveals that Individual and social factors influence the adoption of HR analytics. Thus, organizations have to first encourage in bringing a change in the mindset of HR professionals and a transformation towards data driven decision. Organizations have to develop the qualitative self-efficacy of HR professionals by providing them training, coaching, and organizational support. The study supports the fact that HR professionals may be more likely to use HR analytics if systems are easy to use and training is provided. Through the use of cases and success stories, the organizations can demonstrate the usefulness of HR analytics and how it contributes to better decision making and enhanced performance. This will serve as a facilitator for other individuals to change their attitude towards HR analytics.

Social factors such as peer influence and superior influence act as facilitators of HR adoption. Senior HR professionals should start influencing and working with their junior counterparts, who may have some knowledge of software and quantitative analysis, to build a professional learning environment inside their networks and businesses. Similarly, HR experts who are already utilising HR analytics should encourage their colleagues who aren't utilising analytics so that they can overcome their barrier. Managers can remove barriers to HR analytics adoption through role plays, demonstration, recognizing innovation champions, and building support groups.

The value of HR analytics adoption needs to be promoted to increase the positive behavioural intention towards HR analytics as it directly influences the HR analytics adoption. Open and greater communication can increase the probability of adoption among potential employees. Providing the tools, resources, adequate timely support, and training will result in developing positive intention, which has been shown to positively influence adoption behaviour.

The success of HR analytics adoption relies heavily on the involvement of the HR professionals to understand what data needs to be collected, what data is already being collected, and how to utilise the data to make better strategic decisions. HR professionals must overcome the roadblock they keep encountering by investigating, embracing, and implementing HR analytics.

The study provides insights on the importance of organizational culture in HR analytics adoption. The moderating effect of organizational culture between intention and adoption is found to be negative. Which means that employees may be willing to adopt but are restricted by the organizational culture. Thus, the study emphasises the need for creating an analytics culture which serves as a fertile ground for HR analytics adoption. Thus, organization which aim to be leaders in HR analytics adoption first need to create an analytics culture and also work towards an alignment between HR practices, strategy, and culture.

The study also has important implications for educational Institutions in terms of course and curriculum design. Educational institutions should also redesign and revise their curriculum in line with industry requirements and changing technology. Educational Institutions could also influence the adoption of HR analytics by promoting and communicating the significance of HR analytics in their courses. In contrast, universities and colleges that neglect to provide the necessary training and/or skill sets, such as courses on analytics, as part of their HR programmes miss an opportunity to influence the mindset and enhance self-efficacy of graduating students to use HR analytics. Thus, the study has numerous implications for researchers, academicians, strategists, and practitioners alike.

5.5 Limitations and Scope for future research

This study has certain limitations that can be the subject of future research. First, it is only limited to organizations in India. However, cross - country research can also be conducted to enhance the generalizability of the findings. This is more true as cultural ethos and values vary from one country to another. A study on cross-cultural differences on HR analytics adoption is also needed.

Second, HR analytics adoption data is collected using cross-sectional method i.e., at one point of time. Therefore, a longitudinal survey method research would be preferable for more casual inference between variables.

Third, the study focuses only on organizational culture as a moderating variable between the intention and adoption behaviour. There is a need to understand whether other moderating factors can affect or influence intention to adoption behaviour. Future studies can be conducted to understand other moderating variables that can affect the intensity of behavioural intention to adoption behaviour. Future work can also be focussed on testing the model in different culture which will provide better and deeper insights on the role of culture in promoting HR adoption.

This finding can be replicated on a greater scale in future investigations. Also, Research on non-adopters is advised. As Frambach and Schillewaert (2002) point out, non-adoption is not the inverse of adoption. Although research has been conducted on the adoption, there has been little research on the reasons for non-acceptance.

5.6 Conclusion

The purpose of the present study is to examine the factors influencing adoption of HR analytics among HR professionals, further examining the role of organization culture as a moderator through an integrated model of TPB, TAM, and DOI. The research points a positive significant relationship between attitude, quantitative self-efficacy, peer influence, superior influence, perceived ease of use, perceived usefulness and tool trialability on readiness towards HR analytics. In contrast data availability was found insignificant. The study also tested the influence of individual, social and technological factors on readiness of HR professionals towards adoption of HR analytics. The study reveals that individual and social factors have a considerable positive affect on readiness towards HR analytics. In contrast, the study finds that technological factors insignificantly affect the readiness of HR professionals to adopt HR analytics.

There is a considerable positive link between HR analytics adoption intention and HR analytics adoption behaviour. However, the moderating role of organisational culture has a negative significant impact on HR analytics adoption intention and behaviour. This finding implies that organizational culture should be carefully managed for the successful adoption of HR analytics. Organizations have failed to adapt their culture in order to become more innovative and analytical. Organizations must immediately rethink their culture to keep up with changing times and provide fertile ground for technology to take root, grow, and thrive.

Adoption of HR analytics is a multi-faceted process that requires the collaboration and support of both HR professionals and the organization There are several factors that play a crucial role in the successful implementation and adoption of HR analytics, and these factors are often influenced by both HR professionals and the organization.

For HR professionals, factors such as their level of familiarity and comfort with data analysis and technology, as well as their willingness to embrace data-driven decision making, can play a significant role in the adoption of HR analytics. HR professionals who are trained in data analysis are more likely to adopt and effectively utilize HR analytics.

On the other hand, organizations can play a significant role in the adoption of HR analytics by providing the necessary resources, infrastructure, and support for HR professionals to effectively utilize analytics. This includes investments in technology, data storage, and data analysis tools, as well as providing training and development opportunities for HR professionals to become proficient in HR analytics.

Additionally, the organization's overall culture and attitude towards data-driven decision making can also impact the adoption of HR analytics. The study findings align with previous research and offer new insights into guiding HR professionals in adopting HR analytics. The study suggests that organizations can encourage HR professionals to adopt HR analytics through various approaches to intention and usage behavior. These findings are important because they provide practical guidance for organizations to successfully implement HR analytics. Managers, business leaders, and policymakers can use these findings to assist HR analytics adoption in their organizations.

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APPENDIX

Dear Participant,

I am a PhD research scholar and I am seeking your assistance, in an effort to meet one of the requirements for a doctoral degree at the University of Hyderabad, I am conducting a research study to understand the barrier related to the adoption of HR Analytics. The data collected by this study and the conclusions generated will complete my doctoral thesis.

On the following pages you will find several different kinds of questions about demographics, attitude towards using technology, level of comfort working with numbers and/or statistical information, knowledge of analytics and social support.

This survey is completely anonymous, so please answer each question honestly. Your participation in this study will be particularly important to the accuracy of the results. Google Form is used in order to maintain and ensure anonymity. The data provided by you will be kept confidential as it is academic research. Please take a few minutes to complete the survey.

Please accept my gratitude now for your participation in this study, as I will not be able to thank you at completion due to the anonymity of the survey.

Sincerely,
SusmitaEkka
rosesumita987@gmail.com

Section -A

Demographic Information: Please check the appropriate box for each of the following items.

1. Does your organization use HR analytics
   YES ◯ NO ◯

2. Gender
   Male ◯ Female ◯

3. Age:
   21-30 ◯
   31-40 ◯
   41-50 ◯
   Above 50 ◯

4. Education (highest level):

   Bachelor ◯

   Master Degree ◯

   MBA ◯

   Doctorate Degree ◯

5. Current Position
   Manager ◯
   HRIS ◯
   Generalist ◯
   Specialist ◯

6. Experience
   1-5 ◯
   6-10 ◯
   11-15 ◯
   More than 15 ◯

7. How long you have worked in the field of Human Resources?
   ----

8. Industry/ sector in which you are employed.

   Information technology (IT) ◯
   Financial Services ◯
   Retail ◯
   Health ◯

Section- B

After reading the following statement, choose the most appropriate answer from the drop down menu

1	**2**	**3**	**4**	**5**
Strongly Disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**

Q. No	**Questions**	**1**	**2**	**3**	**4**	**5**
1	HR analytics makes my job more interesting					
2	Working with HR analytics is satisfying.					
3	I like working with HR analytics.					
4	I enjoy working with HR analytics.					
5	I find using mathematical and/or statistical measurements interesting.					
6	I worry about my ability to solve mathematical and/or statistical problems.					
7	I get nervous when I use mathematics and/or statistics					
8	I enjoy working with mathematical and/or statistical measures.					
9	People who influence my behaviour think that I should use the HR analytics.					
10	People who are important to me think that I should use the HR analytics.					
11	My senior would think that 1 should use HR analytics					
12	I will have to use the HR analytics because my senior require it.					
13	The senior management of this organization has been helpful in the use of HR analytics.					
14	My role with HR analytics is clear and understandable.					
15	I would find HR analytics easy to use.					
16	It is easy for me to become skillful at using HR analytics.					
17	I would find the use of HR analytics useful in my job.					
18	Using HR analytics enables me to accomplish tasks more quickly.					
19	Using HR analytics increases my job performance.					
20	I have a full array of HR analytics tools available at work if I choose to use them.					

21	I only have very basic HR analytics tools available at work if I choose to use them.					
22	My company has invested heavily in HR analytics tools					
232	Before deciding whether to use any HR analytics applications, I am able to properly try them out.					
24	I have had a great deal of opportunity to try various HR analytics applications					
25	My company's database has all the data I need to use HR analytics software					
26	My company's HR system collects data from all HR interactions.					
27	We use the same system/platforms for all HR activities.					
28	My company has one database for all departments to use.					
29	My company's database has an interface that is compatible with other systems.					
30	I know where I can get the data for work.					
31	I intend to use the HR analytics as often as needed					
32	Whenever possible, I intend not to use HR analytics.					
33	To the extent possible, I would use the HR analytics frequently					
34	I am beginning to explore using HR analytics.					
35	I am interested in using HR analytics.					
36	I use HR analytics for some specific tasks.					
37	Using HR analytics improve the quality of work I do					
38	Using HR analytics gives me greater control over my work					
39	Individuals working in different departments have a common view					
40	My organization readily accepts innovations based on research results.					
41	My organization gives freedom to the employees to deviate from rule.					
42	Our employees have the chances of introducing their ideas before management makes decisions					
43	People from different parts of this organization share a common view					
44	My organization actively seeks innovative ideas but the adoption it voluntarily.					

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Predicting HR Professionals' Adoption of HR Analytics: An Extension of UTAUT Model

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Background and Purpose: To scale up HR innovation with HR technology, organizations worldwide are putting effort into adopting HR Analytics (HRA) among HR professionals and the actual use of HRA for organizational decision-making. This study aims to explore the behavioral intention to use HRA from the perspective of HR professionals by using UTAUT.
Methodology: Partial least squares structural equation modeling (PLS-SEM) was employed to validate the model based on data collected via a survey from 270 HR professionals in India.
Results: The result revealed a significant positive impact of performance expectancy, effort expectancy, social influence, and facilitating condition on behavioral intention to use HRA. However, organization culture negatively moderates the relationship between HRA adoption intention and adoption behavior. The establishment of organizational culture as a moderator in Indian organizations is unique.
Conclusion: The study extends the explanatory context of UTAUT and provides feasibility for the organizations to guide HR professionals to adopt HRA from multiple paths of intention and usage behavior. Managers, business leaders, and policymakers can use this finding to assist HRA adoption in their organizations.

Keywords: *Human resource analytics, Adoption intention, Adoption behaviour, Organization culture, UTAUT*

1 Introduction

Companies worldwide are experiencing the digital transformation of all their business functions, and HR or human resources has no exception. Digitalization of HR, amongst others, includes the adoption of HR analytics, a software tool to garner real-time and metrics-based insights for improved decision-making. The adoption of HR analytics has proved to be a game-changer, enabling organizations to enhance employee skills, improve retention and gain a competitive edge (Van der Togt & Rasmussen, 2017). HR analytics is today a huge instrument for making progress; it exploits present information to expect future ROI and is viewed as a wellspring of vital benefit (Ben-Gal, 2019; Bindu, 2016). Several studies have testified its role in improving decision-making and managing, among other functions (Wandhe, 2020; Mohammed & Quddus, 2019). Despite the perceived benefits, the adoption of HRA among HR professionals remains sluggish (Vargas et al., 2018; Marler & Boudreau, 2017), primarily due to the adoption barriers of technology.

Understanding the adoption behaviour is necessary for the adoption of technology. Various adoption model is used to study the intention to use technology and its acceptance, i.e., actual adoption (behaviour/actual usage) of technology (Wang et al., 2020). Studies explain how technology adoption impacts behavioural intention (Senaratne et al., 2019; Kabra , 2017). Ajzen (1985) states that "behavioural intention is an individual's subjective possibility of performing a specified behaviour, which is the major contributing factor to actual usage behaviour."

Although research has been extensively conducted and many theories proposed to explain it in different contexts of adoption, some critical issues remain to be addressed.

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HR ANALYTICS: WHY IT MATTERS

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Abstract
In today's data driven world, HRM strategies are changing in terms of HR metrics and HR analytics being used in the organization for better decision making. This digitalization will help the organization to become more reliable towards data driven decision making rather than intuition. Which can assist organizations to take up present strategic and operational data and turn it into an effective approach to the HR problems of tomorrow. HR analytics has become a significant instrument for achieving success; taking advantage of present data to anticipate future ROI as a source of strategic advantage. The current study is an attempt to give an overview of developments in HR analytics at present by briefly focusing to identify the shift in the HR roles in different perspective. This paper also discusses the importance of understanding the implications of HRA. In addition, article also highlighted the future need for HR analytics, befitting for today's world of business industry.
Keywords: HR Analytics, HR Metrics, Human Resource Management, Strategic Management

1. Introduction

Human Resource Management (HRM) has been seen in the past as an administrative function where decisions were generally based on previous knowledge, emotions, or intuition. A survey done by The Economist Intelligence Unit (EIU) in the year 2014 also confirms that decisions related to all functions whether in marketing, finances, sales or human resource in organization are dependent on their personal experience and intuition. Still many organization are lagging behind to adopt human resource analytics (Fernandez, & Gallardo-Gallardo, 2020; Vargas et.al, 2018; Marler& Boudreau, 2017) despite of avaibility access of information. Human resource analytics is data driven (Mohammed, & Quddus ,2019) and when it comes to mind its related only to statistical analysis i.e. is incorrect(Anjani & Nithya, 2018; Vargas et.al , 2018) ;as according to Jac Fitz-Enz, (2010) said "Analytics is a mental framework, first a logical progression and second a set of statistical tools ." Implementing it to

The Impact of HR Analytics Adoption on Firm Return on Investment: A PSM Model Approach

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Abstract

Human resource analytics (HRA), adopted by firms in India and across the globe, is forecasted to increase at a decent pace, as reported by various market research firms. However, few studies have explained that mixed benefits may be due to differences in company HR practices. This research paper studies HR adoption at the firm level in the Indian context. Data from 116 Indian BSE listed companies for the 2018-2019 period is investigated using propensity score matching (PSM) followed by linear regression analysis. The result reveals that HR analytics firms have a higher return on investment. Our findings will prove helpful to firms who wish to adopt HRA practices.

Keywords: HR Analytics, Return of Investment (ROI), Propensity Score Matching

JEL Classification: M15, M21, O33

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by Susmita Ekka

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