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Human Resources Analytics' Acceptance and Adoption in Large Palestinian Enterprises

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انا الموقع ادناه مقدم الرسالة التي تحمل العنوان:

Human Resources Analytics' Acceptance and Adoption in Large Palestinian Enterprises

أقر بأن ما اشتملت عليه هذه الرسالة إنما هو نتاج جهدي الخاص، باستثناء ما تمت الاشارة اليه حيثما ورد، وأن هذه الرسالة ككل أو جزء منها لم يقدم من قبل لنيل أي درجة أو بحث علمي أو بحثي لدى أي مؤسسة تعليمية او بحثية أخرى.

<u>Declaration</u>

The work provided in this thesis, unless otherwise referenced, is the researcher's own work, and has not been submitted elsewhere for any other degree of qualification.

Student's name: **اسم الطالب:**

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Abstract

Recently, as the interest of data science is flourished, many successful firms are turning towards using data analytics to identify new opportunities for promoting their products and services. Besides, to guarantee the benefits of data analytics and its desired effect on business performance; it should be applied throughout the organization. Undoubtedly, this application should include the most important asset of the organizations (people) and which is covered through Human Resources Management (HRM) in the organization. Data Analytics coincides with HRM in a new concept which is Human Resources (HR) Analytics. This innovation will help the HR to become a strategic partner with other departments throughout the organization, help the business in identifying talent needs, find and retain the right people, develop employee skills and capabilities, and plan for the future.

Despite the approved importance of HR Analytics and its significant impact on business outcomes, there is still a lack of adoption of this new technology among organizations. This research aims to investigate this contradiction by investigating the factors that affect the acceptance and adoption of HR Analytics among HR professionals in large Palestinian enterprises.

To achieve the main research objective, a mixed research approach (qualitative and quantitative) is used to conduct the exploratory study. Using the questionnaire as a research tool, required data are collected from a stratified randomly-selected sample consists of 151 HR professionals who are working at large Palestinian enterprises in both service and manufacturing sectors. Statistical analysis of the collected data using Minitab software and linear regression analysis revealed that the factors of data availability, performance expectancy, self-efficacy and quantitative self-efficacy are the most significant factors that affect the individual acceptance and adoption of HR Analytics positively in large Palestinian enterprises. While, the factors of social influence, resource availability, fear appeals and effort expectancy have no significant effect on the acceptance and adoption of HR Analytics. Moreover, the correlation analysis indicates a strong relationship between the individual and organizational level of acceptance and adoption of HR Analytics, and the regression model represents this significant relationship.

Based on the research results, a conceptual framework is developed to describe the proper acceptance and adoption of HR Analytics at the individual level in large Palestinian enterprises.

Chapter One

Introduction

1.1 Chapter Overview

This chapter provides a general overview of this research. It includes a brief introduction, research problem, significance of the research, objectives of the research, research questions, and finally research structure.

1.2 Introduction

With market rivalry pressures, many successful firms are turning towards using data analytics to identify new opportunities for promoting their products and services. Besides, 77% of important organizations consider data analytics as a needed part of business execution (Arora, 2017). Furthermore, data analytics should be applied throughout the organization to guarantee the desired effect on business performance (Mayhew et al., 2016). Undoubtedly, this should include a Human Resources (HR) function as it is a part of every organization and it involves managing its greatest asset which is ‘people’ (Armstrong, 2006; Hamel, 2008). Nowadays, managing people requires keeping up with continuous revolution and innovation to be able to identify new market doors for businesses. This will require a strategic concentrate toward people management since innovations come from people, and any firm cannot boost innovations except if it is being qualified for recruiting and retaining innovators. Transforming to an innovative organization needs recreating traditional HR function in addition to promoting the processes that boost innovation in the organization (Sullivan, 2013a).

Many years ago, HR in its traditional form was called the personnel department, and their primary function was merely for hiring and firing employees. As the name has changed, the role of HR has also changed. These days, HR is a strategic partner, helping the business identify talent needs, find and retain the right people, develop employee skills and capabilities, and plan for the future. Also, there is a good possibility that as part of the overall changes that are taking place in the HR function, there will be considerably more analytics and metrics to be done. Such analytics will help HR being a true strategic partner in organizations and enhance its ability to measure how human capital decisions affect the business outcomes and how business decisions affect human capital (Lawler et al., 2004).

It is not new for HR to play the effective role of being a strategic partner in the organization since there are many studies in the literature that have investigated the potential for HR practices to be strategically important. For example, Becker and Huselid (1998) found a relationship between HR practices and firm performance, as have others. Lawler and Mohrman (2003) have shown how different characteristics of the HR function are related to HR as being a strategic partner in the business. So, it is the time for the HR to join the party and ‘‘get a seat at the analytics table," and not just sit at its own HR analytics table (Rasmussen and Ulrich, 2015). As a result, this will need linking HR data with other systems in the firm such as operational and financial ones, in order to enable managers understanding the demand on human capitals, track workforce costs, align the goals of employees with the organization's business strategy, and measure employee performance (Aral et al., 2012).

As the literature reveals, internationally HR Analytics are still in their infancy, and there are still much rooms for the researchers to investigate in this field; such as the need for quantitative empirical study and frameworks for testable hypotheses and rigorously-constructed research questions (Marler and Boudreau, 2017).

Within the Palestinian context, there is a paucity of research on the effectiveness of Human Resources Management (HRM) practices in general (Al-Jabari, 2011) and to the best of our knowledge, no research has been done in HR Analytics field. This research aims to identify the factors affecting the acceptance and adoption of HR Analytics practices from an individual perspective: that of HR professionals themselves and propose a conceptual framework describing innovation acceptance and adoption of HR Analytics as the basis to understand the current and future of HR Analytics implementation in large Palestinian enterprises. The large Palestinian enterprises are chosen to be the research’s target since they have more efficiency and growth indicators in the Palestinian economy than the small/medium firms. Furthermore, these large enterprises can be expected to be more competitive, have superior technology and create more job opportunities (Amundsen et al., 2004). Such a labor-intensive domain with a massive amount of human capital issues; definitely needs effective techniques in HRM. HR Analytics will play this role through being a strategic partner and affect the organizational outcomes. This research will guide the large Palestinian enterprises achieving this goal through providing a framework for proper adoption of this innovative topic among HR professionals.

1.3 Research Problem

In 2014, Deloitte confirmed the importance of HR Analytics implementation by reporting that 78 % of large companies worldwide rated HR Analytics as a significant trend and placing it among the top three most urgent trends (Deloitte, 2014). In the Palestinian context, large companies have a significant growth indicator in the Palestinian economy, and they can be expected to be more competitive, have superior technology and create more job opportunities than the small/medium firms (Amundsen et al., 2004). So, these labor-intensive enterprises with a massive amount of human capital issues; definitely need effective techniques in their HRM. Fortunately, different analytical approaches can help HR playing an effective role in these enterprises through utilizing their available technological advances and linking their HR investments to the business bottom line (Harris et al., 2011).

On the other hand, despite all the facts about the significant effect of implementing HR Analytics, there are only 16% of organizations reporting the adoption of HR Analytics in their businesses (CedarCrestone, 2015). Furthermore, Marler and Boudreau (2017) figure out similar contradictions in their review paper which are: the limited scientific research on HR Analytics topic despite its popularity, and the limited adoption of HR Analytics even when there are researchers pointed out its positive effect on business outcomes. So, why more HR professionals are not using HR Analytics to improve organizational performance, and to gain and maintain a competitive advantage?

Indeed, these observations stimulate to perform this research which will enrich the literature, trying to explain the existing contradictions, through identifying factors that may influence the acceptance and adoption of analytics among HR professionals, particularly in large Palestinian enterprises.

1.4 The significance of the Research

The desire for HR departments to be more analytical arises from a strong need to improve relevance and convert the HR function to be more strategic (Ulrich, 1994). Using data and analysis to quantify HR's impact better, improve measurement and scientific management of people issues offers the promise of doing that (Levenson et al., 2017).

Moreover, the flourishing industry of data analytics gives HR managers much more opportunity to link their investments in HR field with the business performance and take place in the C-suite table (Harris et al., 2011). Even though, the limited scientific research in HR Analytics literature put HR executives in skeptical position about whether to accept and adopt this innovation and reveal their need for more scientific evidence research on this topic (Marler and Boudreau, 2017).

The significance of this study is to gain a better understanding of HR Analytics acceptance and adoption process in large Palestinian enterprises through determining the key factors which will affect the acceptance and adoption of HR Analytics, and proposing a conceptual framework for proper acceptance and adoption of HR Analytics at the individual level in large Palestinian enterprises. Besides, the effective implementation of HR Analytics in large Palestinian enterprises will lead to better decision making, more effective resource allocation and offers competitive advantages for these organizations (Levenson et al., 2017).

1.5 Research Questions

This research aims at answering the following questions:

1) What are the main factors that may influence the acceptance and adoption of HR Analytics at the individual level in large Palestinian enterprises?
2) What is the significance of each factor in affecting the acceptance and adoption of HR Analytics at the individual level in large Palestinian enterprises?
3) What is the relationship between the Individual level of acceptance and adoption and organizational level acceptance and adoption of HR Analytics?

1.6 Objectives of the Research

This research aims to achieve the following objectives:

- To investigate the factors affecting the acceptance and adoption of HR Analytics at the individual level in large Palestinian enterprises.
- To determine the significance of each of these factors in acceptance and adoption of HR Analytics at the individual level in large Palestinian enterprises.
- To examine the relationship between the individual and organizational acceptance and adoption of HR Analytics in large Palestinian enterprises.
- To develop a conceptual framework describing the acceptance and adoption of HR Analytics at the individual level in large Palestinian enterprises.

1.7 Thesis Structure

The thesis consists of five chapters; chapter one familiarizes the reader with the research problem, research objectives and questions. Chapter two reviews the literature regarding HR Analytics and formulate the research hypothesis. Chapter three displays the methodology conducted in this research. Chapter four presents the results of data analysis, hypothesis testing results and the discussion of these findings. Chapter five gives conclusions on hypotheses results, recommendations, and future research suggestions.

Chapter Two

Literature Review

This chapter reviews relevant literature considering HR Analytics. It addresses the main topics pertinent to the research objective. It presents a brief explanation of Data and Business Analytics and HR Analytics. Also, different HR Analytics applications and case study examples are provided to show its significance on business outcomes. Besides, it investigates the factors affecting the acceptance and adoption of HR Analytics. Finally, the research hypotheses are formulated.

2.1 Overview

Last century has witnessed a prominence revolution in data science and business analytics worldwide. Many academic and practitioner literature try to keep pace with this fast-paced development through pinpointing the value that organizations would create through using it (Gillon et al., 2012; Mithas et al., 2013).

Different literature reveal that the applications of analytics have tremendously widespread in various fields such as business, healthcare, and others (Davenport, 2013; McNeill, 2013; Evans, 2015). For example, analytics is used in banking sector to predict and prevent fraud, in pharmaceutical industry to ensure the availability of surviving drugs in market more quickly, in manufacturing to enhance production planning, purchasing, and inventory management, in retailing to promote customer satisfaction and measure marketing campaign results, also in sports to optimize game strategies and ticket prices, in addition to many more applications in different areas (Evans, 2015).

Moreover, many academic and practitioner studies investigate the benefits of this data revolution to businesses. For instance, Chen et al. (2012) indicate that business analytics and regarding technologies can assist organizations to ‘better understand its business and market' and ‘leverage opportunities presented by abundant data and domain-specific analytics.' Other academic studies consider data, and business analytics as an opportunity that differentiates a company among their competitors as this analytics are used to direct its decision-making process to be more productive and gaining higher profits (Brown et al., 2011). Also, many practitioners speak about analytics as a significant source of competitive advantages such as McKinsey, a worldwide management consulting firm, (McGuire, 2013) and the International Institute for Analytics (Seddon et al., 2017).

Further, Business Intelligence firms, as well as various Information Technology (IT) vendors, approve that Business Analytics is probable to make significant participation in firms’ performance (IBM, 2015; SAP, 2014). On the other hand, different academic researchers report about the effect of Business Analytics in organizational performance. LaValle et al. (2011) compare between lower-performing and top-performing organizations as the last ones fasten their decision-making process based on intensive data Analytics. In the same vein, many studies approve the significance of data Analytics on organizations' outcomes and demonstrate that such organizations can enhance their performance with better information management capabilities (Mithas et al., 2011; Mithas et al., 2012; Saldanha et al., 2013; Schryen, 2013). Moreover, Sharma et al. (2014) suggest that organizations' performance improvement is a result of essential decision-making processes which are derived from Business Analytics application.

As Business Analytics is grown exponentially, its applications abound in various disciplines such: marketing, service, supply chain management, information systems, finance, crises management, risk management and human resources management (Holsapple et al., 2014). Regarding to human resources domain, it is not surprising to join this new era of data revolution since HRM is considering management of the most significant asset of organization which is ‘people' as obvious in this definition of HRM, “a strategic and coherent approach to the management of an organization's most valuable assets, the people working there who individually and collectively contribute to the achievement of its objectives” (Armstrong, 2006). Also, the costs of this valuable assets approximately equal 60% of organization's variable costs; thus it is deserving to manage such a significant cost item analytically (Sullivan, 2013b).

Furthermore, there are various researches prop the strategic effectiveness of HR on the business performance (Huselid, 1995; Becker and Gerhart, 1996; Huselid et al., 1997; Ferris et al. 1999). Other studies talk about human resources as they are the primary provenance of sustainable competitive advantage for enterprises (Wright and McMahan, 1992; Pfeffer, 1994; Ferris et al. 1999). Therefore, it is not new to HR being an active role and a strategic partner for the organizations.

Moreover, Aral et al. (2012) argue that HR need to link their data with other systems in the organization to improve its function of engaging the goals of employees with the organization’s business strategy, and measuring employee performance. Achieving this can be obtained through analytics as Lawler et al. (2004) suggest that HR Analytics will assist HR being an active strategic partner in organizations and also reinforce its capability to measure how HR decisions affect the business outcomes. Furthermore, Boudreau and Ramstad (2007) discuss the importance of the LAMP model which talks about Logic, Analytics, Measures and Processes as the four pivotal elements of a measurement system needed to uncover evidence-based relationships and to motivate decision-making process based on those analyses. Also, they argue that the LAMP model with its four components facilitates understanding the cause-effect relationship between HRM processes and strategic HRM and business outcomes (Marler and Boudreau, 2017). Dessler (2011) defines HRM as "the process of acquiring, training, appraising, and compensating employees, and of attending to their labor relations, health and safety, and fairness concerns" (p.30). HR Analytics contributes to managing of HR through different ways, as using HR data to collect insights about specific function or department throughout an organization and take some improvement decisions regarding these insights. They can be related to turnover rate among employees, or related to performance measures which may lead to a new training program for the staff in specific areas. Also, HR Analytics and measurement strategies can be useful to address quantity, quality, and costs incurred when there is a change of employment, whether due to layoffs, promotions, or retirements (Cascio and Boudreau, 2011).

Another use of HR Analytics may be in the data analysis concerning human-capital investments. For example Sysco, a leading multinational organization dealing with marketing and distributing food products to many facilities besides it consists of nearly 51,000 employees serving about 400,000 customers, increase the retention rate of 20% in six years as a result of concerning more about their employees satisfaction since the analytics show that high achievement lead to higher revenues, lower costs, higher employee retention, excellent customer loyalty and saving approximately $50 million in hiring and training costs (Davenport et al., 2010). In a similar vein, HR Analytics can act as a predictive tool to know more about which employees may leave the organization, which will support the retention process through increasing compensation, responsibilities, or choosing job rotation as a choice (Siegel, 2016). Predictive HR Analytics may be a key for understanding and learning to work with HR analytics at an advanced level, such as the predictive models for diversity analysis, turnover prediction, evaluating interventions, and performance prediction (Edwards and Edwards, 2016). Furthermore, Sullivan (2013b) suggests that executives should take advantage of

Google's business success in HR Analytics and consider this success as a motivation to do the same. Google attributes their success and being at the number three position among the most valuable firms in the world to the use of HR Analytics or to “people analytics” as Google preferred to call. Google uses many different approaches of people analytics such as predictive models and “what if” analysis to enhance their prediction about problems or opportunities related to their candidates for job, using analytics for better workforce planning, improve diversity of employees throughout the organization and develop a prediction algorithm to predict which candidates will perform better after hiring process, in addition to many more applications.

As Marler and Boudreau (2017) reveal after reviewing the most significant literature in the field of HR Analytics, this topic is still in their infancy and there are many related aspects for the researcher to add to it, besides their review research calls for quantitative empirical study and frameworks for testable hypotheses and rigorously-constructed research questions. Echoing this view, this research aims to contribute through investigating factors which affect the acceptance and adoption of HR Analytics, and propose a conceptual framework for proper acceptance and adoption of HR Analytics in large Palestinian enterprises based on testable hypotheses.

2.2 Definition of Data and Business Analytics

Recently, data has considered the ‘hottest commodity’ in the market (Mikkonen, 2014) and treated as ‘the new oil’; it is used for many objectives as discovering new opportunities, and promoting new products and services by leveraging value from this data using analytics (Acito and Khatri, 2014). Analytics is defined as “a process of transforming data into actions through analysis and insights in the context of organizational decision making and problem-solving" (Liberatore and Luo, 2010).

In more details, Evans (2016) introduce analytics as an integration of three primary disciplines; business intelligence (BI)/ information systems (IS), statistics, and operations research (OR). Evans’ definition is “the use of data, information technology, statistical analysis, quantitative methods, and mathematical or computer-based models to help managers gain improved insight about their business operations and make better fact-based decisions." This definition shows the range of various analytical methods that can be used. Moreover, the invention of computers led to a new era of analytics which takes advantage of computers development to facilitate the process of collecting, managing, analyzing and reporting data under the concept of BI. In other words, BI is “referred to as applications and technologies that are used to gather, provide access to, and analyze data and information to support decision-making efforts″ (Baltzan, 2013). On the other hand, statistics plays a significant role in analytics, it has different tools and methods ranging from basics as in descriptive, exporting and deduction techniques to more advanced ones including regression, forecasting, and data mining. Besides, these statistics of different types give a better interpretation of data further of those reports resulting from BI systems (Evans and Lindner, 2012, Evans, 2015). As Evans (2016) definition reveals, another technique of analytics is the use of mathematical or computer-based models as an advanced tool for analyzing more complicated decision problem. Initially, these models are part of OR/ management science (MS) which is used to find the best solution and decision through modeling and optimizing techniques. These techniques convert problems to other forms such as mathematics, spreadsheets, or other computer languages. So, the concept of decision support systems (DSS) appears through integrating BI concepts with OR/MS models to improve decision-making process by producing analytical-based computer systems (Evans, 2015).

As the interest of analytics increases and covers most of the business disciplines; Cadez, and Guilding (2008) argue that ‘data analysis lies at the heart of decision-making in all business applications ‘(Trkman et al., 2010), a new buzzword appears ‘Big Data’ (BD). It refers to a vast amount of data both structured and unstructured. Thus, many researchers suggest the use of BD will help many organizations to improve their competitive advantage by making a better decision-making process (Boyd and Crawford, 2011; McGuire, Manyika, and Chui, 2012).

As well, Business Analytics is usually represented as one of three major perspectives: descriptive, predictive, and prescriptive (Lustig et al., 2010; Evans, 2015):

- Descriptive analytics: a set of techniques that use data to understand and analyze past and current business performance and then make decisions based on those analyses. This type of analytics represents data in meaningful charts and reports to follow trends and pattern in data.

- Predictive analytics: the use of different analytical technologies of historical data to predict the future behaviors and trends. In an advanced form, this type provides predictive models of business performance.
- Prescriptive analytics: the use of advanced analytical techniques as mathematical, statistical and optimization ones with the objective of improving business performance taking into consideration uncertainty in the data. Also, this type includes descriptive and predictive analytics as a pre-stage analysis.

The following section introduces the definition of HR Analytics, as it integrates all the previous concepts, regarding data and business analytics, with HR domain.

2.3 Definition of HR Analytics

The concept of ‘metric’ in Human Resources Management (HRM) has been around since the early 1990s (Kaufman, 2014), and the book of ‘How to Measure Human Resources Management was published in 1984 as the first guide in this field (Fitz-enz, 1995). In advance to HR metrics, the term of HR Analytics comes into view through a published article by Lawler et al. (2004), they distinguish HR analytics, as a new term, from HR metrics which are measures of related HRM outcomes, categorized as efficiency, effectiveness or impact. On the other hand, they illustrate HR Analytics as it involves statistical techniques and experimental approaches which can be used to examine the effect of HR activities.

Bassi (2011) defines HR Analytics as *'an evidence-based approach for making better decisions on the people side of the business; it consists of an array of tools and technologies, ranging from simple reporting of HR metrics all the way up to predictive modeling*.' Through this definition she argues that HR Analytics can be treated both as systematically reporting an array of HR metrics or using more advanced solutions; stand on predictive models and what-if-scenarios. Other researchers intend to link HR analytics to strategic HRM, and they explain the definition as the direct impact of people on significant business outcomes and organizational performance. In this vein, Marler and Boudreau (2017) in their review article paper of the related topic try to sum up the definition of HR Analytics as *'An HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making'*. Also, they link this definition to the innovation theory of Rogers (2003) who defines the innovation as an 'interrelated bundle of new ideas' that prevails over social groups in a perspective and consistent way. Also, explicitly, the HRM innovation as defined regarding whether an HRM program, policy or practice is recognized as new and if it is intended to affect workforce attitudes and behaviors (Kossek, 1987). When the HR Analytics concept introduced to a firm at the first time, it will be realized by those who deal with it as new whether or not the firm has been taking on the concept earlier or being the last to accept this HRM practice. The other requirement for an HRM innovation is that it is recognized to affect workforce attitudes and behaviors.

To summarize, HR Analytics is an HRM practice which is designed to give managers the insights that connect HRM related operations to workforce attitudes and behaviors and ultimately to organizational outcomes. The next part introduces the development of HR Analytics among academics and practitioners.

2.4 HR Analytics Development

As mentioned earlier, the first appearing of HR analytics in published literature was in 2004 in the article of ‘HR Metrics and Analytics: Use and Impact’ by Lawler et al. (2004). In addition to their differentiation between HR metrics and HR analytics in this article, they investigate which kinds of HR metrics are used by organizations, examine the degree to which analytics are used to capture the impact of HR on the business and determine whether those HR organizations that have more metrics and make more excellent use of analytics are more likely to be strategic partners. Through an empirical study consisting of a survey covering 37 large US-based firms that are on the Fortune 500 list, the authors conclude that those HR organizations that can do strategic analysis are the ones that are most likely to be positioned as strategic partners. Moreover, their descriptive statistics study shows that having analytic data about strategy is a powerful way to gain a seat at the strategy table and as a result a strong impact of using HR Analytics.

After that, the interest of HR analytics increased with time revolution, 2011 was a fruitful year that enriches the literature with many useful types of research. More specifically, Coco et al. (2011) document a specific relationship between HR analytics and business impact through an empirical case study. The study shows how a home improvement retail chain used HR analytics to establish a link between HR processes, employee engagement, and store performance. As well, it uses statistical data modeling techniques such as factor analyses, correlations, and structural equation modeling, to confirm these cause-and-effect linkages. The results show that as a result of using HR Analytics, the organization was able to set up that actively engaged employees lead to 4% higher average customer ticket sales per store. In the same context of focusing on the link between analytics and business outcomes, Mondare et al. (2011) define HR Analytics as revealing the direct effect of people on remarkable business outcomes. This definition was derived from conducting a theoretical logic and framework' HR Scorecard' to discuss why HR Analytics work, and how it does affect the business outcomes. The framework was proposed from an empirical case study in the health sector, using SPSS statistical software and structural equations modeling technique to analyze the data. Another research investigates the strategic impact of HR Analytics in an economic illustrative case study; it develops new human capital metrics which link measures of human capital costs to financial measures to calculate HR Return On Investment (DiBernardino, 2011). By referring to the definition of HR Analytics, the needed tools and techniques to analyze data are found to range from simple HR metrics all the way up to predictive statistics. Levenson (2011) provides evidence through a three case-study examples showing that the complexity of statistical skills is not necessarily a barrier to applying HR Analytics. On the other hand, the actual barrier is the time and resources needed, and an understanding of what types of analytics to use, when to apply them and how to do so. Also, this study reviews different proven frameworks that may guide HR professionals in decisions related to identifying which type of analytics is more suitable, and when the time for analytics is limited these framework models will be useful to enhance the accuracy and impact of employees and organizational decision.

Finally, Harris et al. (2011) introduce real cases of technological firms, professional sports teams, banks, food-service companies, and energy companies which are showing how HR can use different analytical tools to take part in business outcomes. For example, they show how Google uses HR Analytics to forecast employee performance by proposing an algorithm which figures a score to predict the likelihood that job seekers will succeed at their firm. This technique increased the percentage of hiring new candidates who are likely to perform well at Google. Besides the conclusion that the organization's previous dependency on GPA as the only screening metric caused them to overlook high performing candidates. Convergys, a company that manages billing, payroll, benefits, and pensions for businesses in 40 countries, it uses predictive analytics to expect employees' priorities and future behaviors and related HR practices to help them keep their valuable talent. Using this analytical approach, Convergys concludes that employees were more likely to stay with the company if they got half of their annual pay raises semi-annually instead of the total amount only once per year. Mullich (2005) reported that this approach saves in recruiting and training costs which are estimated at $57 million, during four years. Valero Energy, a Texas-based oil refiner, uses a real-time optimization as an advanced analytical approach to meet the mix of talent needs. It depends on labor supply chain technique which helped the company determine which suppliers of talent are the best one through analyzing different data related to the quality of talent. Great benefits of using this approach were gained, as one executive reported: ‘‘in 2002, it took 41 pieces of paper to hire someone and more than 120 days to fill an open position. Each hire cost about $12,000. With the labor supply chain in place, little paper is needed to bring someone aboard, the time-to-fill figure is below 40 days, and cost per hire dropped to $2,300 last year" (Frauenheim, 2006). The strategic advantages of a talent Supply chain are: it enables the firm to foresee the demand for talents in the near future, give Valero the opportunity to decide whether to hire new employees, recruit contractors or outsource the work. In addition to illustrative case study examples, Harris et al. (2011) suggests a DELTA model (Data, Enterprise, Leadership, Targets, and Analysts), taken from Accenture and consists of 5 steps technique to ensure the successful use of Analytics. (Davenport et al., 2010).

However, as the interest in HR analytics has grown tremendously, Aral et al. (2012) propose a principal-agent model examining how the three-way complementarities among information technology, performance pay, and HR Analytics practices are working together as an incentive system that produces a more significant productivity premium when the methods are implemented in concert rather than separately. They conducted fixed and random effect regression analyses on 11 years panel data of 189 firms and empirically test hypotheses for a cause-effect relationship between HR Analytics and financial performance. Moreover, Rasmussen and Ulrich (2015) discuss what is contributing to HR Analytics in its current form becoming a management fad, what can help HR analytics deliver value by taking part in management decision-making process through illustrating two cases of HR Analytics being successfully integrated in business analytics and leading to impactful interventions on offshore drilling company's performance optimization and technical talent development.

Another research was conducted by Pape (2016) which addresses the decision problem of data items that a business function should store in its BI system to perform business analytics correctly, propose a prescriptive framework to prioritize data items for business analytics and applies it to human resources field. To achieve this goal, the proposed framework captures core business activities in a comprehensive process map and assesses their relative importance and possible data support with multicriteria decision analysis to ensure the efficiency of related data analysis and its linkage to business outcomes.

Furthermore, Madsen et al. (2017) explore the development of HR Analytics based on management fashion theory. This theory related to "management concepts that relatively speedily gain large shares in the public management discourse." (Jung and Kieser, 2012). Madsen et al. (2017) investigate how different supply-side actors in HRM domain have affected the distribution of HR Analytics as a requisite to recent HR challenges. There are various supply-side actors engaged in HR Analytics such as; consulting and technology firms, conference organizers and professional organizations. Exploratory research has revealed that many supply-side actors have a significant effect on the HR Analytics. Notably, the impact of consulting and technology firms. Also, Madsen et al. (2017) shed light on the importance of social media channels in the popularization of HR Analytics since many different technological innovations spread online nowadays.

As the interest of HR Analytics increased, Van den Heuvel and Bondarouk (2017) investigate the future development of HR Analytics. An exploratory study is conducted among HR Analytics practitioners in large Dutch organizations to take their opinions about how HR Analytics will look like in 2025. The results of this study show that the future of HR Analytics will prospectively be developed employing integration. The integration of HR department data with data from other departments inside an organization and also data from outside such as social media streams. Also, the integration of IT data structure is vital in centralizing the data source from different disciplines in a single database to ease related data analysis. Also, the integration of analytics teams from various functions including HR to construct a centralized analytics function with the primary aim which enhances business performance as a whole.

Interestingly, after reviewing the literature in the context of HR Analytics, it is evident that most of the published research in this vein provide short illustrative case studies and predominance of them do not involve quantitative empirical studies. As a result, and regard to the conclusion of (Marler and Boudreau, 2017) in their ‘An-evidence based review of HR Analytics ' article, there is still a need for more scientific researches to add to the literature in this fertile and infancy field. Also, the authors shed light on the need for investigating the factors that will lead HR professionals and other leaders to accept and adopt HR Analytics in their organizations. So, this research will contribute to HR Analytics literature with a quantitative empirical study which will identify the factors affecting the acceptance and adoption of HR Analytics from an HR professional's perspective and propose a framework describing the acceptance and adoption of HR Analytics as the basis to understand HR Analytics implementation.

Therefore, the following section investigates the literature regarding factors affecting the acceptance and adoption of HR Analytics at the individual level.

2.5 Factors Affecting Acceptance and Adoption of HR Analytics

The following literature on the IDT, TAM and the UTAUT theories were reviewed to identify potential factors impacting acceptance and adoption of an HR Analytics as a technological innovation at the individual level, specifically of analytics among HR professionals, these earlier researches will be used as the groundwork for this research.

2.5.1 Innovation Diffusion Theory (IDT)

As the theory statement ‘Innovation Diffusion' contains two terms ‘Diffusion' and ‘Innovation,' Rogers explains both of them as follows. He defines diffusion as a sharing process of new concepts or ideas with some extent of uncertainty. Also, Rogers illustrates the diffusion process has four main elements which are innovation, communication through channels, communication within a time frame, and communication with members of social systems (Rogers, 1983). On the other hand, he defines innovation as ″an idea, practice, or object that is perceived as new by an individual or other units of adoption″ (Rogers, 1995). Also, most of the literature which studied innovations concerning diffusion have been in ‘technology’ which is defined by Rogers (1983) as ″a design for instrumental action that reduces the uncertainty in the cause-effect relationships involved in achieving the desired outcome." Regarding this research, the innovation represents the use of HR Analytics as a new technological technique used for improving HRM decision-making process and becoming a more strategically function through affecting the organization's bottom line and gaining competitive advantage among rivals.

Furthermore, the model of Rogers (1995) indicates that five characteristics of innovation are suggested to affect members', of the social system, behavioral intention to use. These are the relative advantage, compatibility, complexity, trialability, and observability. These characteristics also named as the five traits of innovation (Rogers 1983, 1995). Otherwise, there are different opinions among researchers about which of these traits are have a more consistent and significant relationship to adopting an innovation. For example, some researchers like Agarwal and Prasad (1998), Kolodinsky et al. (2004), Zolait and Sulaiman (2008), Phuangthong and Malisuwan (2008), Tornatzky and Klein (1982) and Giovanis et al. (2012) argue that only relative advantage, compatibility, and complexity are the most effective traits on the innovation adoption process. On the contrary, other studies such as Seyal and Rahman (2003) and Ramdani et al. (2013) demonstrate that the traits of observability and trialability are the most influential on the adoption of new technology.

In this research, to investigate HR professionals' intention toward acceptance and adoption of HR Analytics; complexity, trialability, and observability will be used as related to the factors of acceptance and adoption at the individual level.

Moreover, as stated by Rogers (1995) the social system contains members who are interested in solving problems together in an attempt to achieve the same goal. Group members of the social system are considered either opinion leaders or change agents, some of whom can affect the adoption of the innovation, slow down the diffusion, or reject the acceptance of the innovation altogether (Rogers, 1995). For this research objectives, the social system is referred to as ‘social influence’ and is defined as “the extent to which members of a social group influence one another’s behavior in adoption″ (Talukder and Quazi, 2011).

Finally, Using IDT model as the groundwork, there have been many researches on both the macro (organizational) and the micro (individual) levels of adoption that have driven to other models, such as Fishbein and Ajze (1975) TRA, which in turn led to TAM by Davis (1989) as well as Ajzen (1991) TPB and UTAUT by Venkatesh et al. (2003), as well as others. The following will discuss TAM and UTAUT theories as of the basis for this research.

2.5.2 Technology Acceptance Model (TAM)

Through literature, TAM proved their effectiveness in clarifying the attitude and behavior toward the acceptance of new technology and innovation (Davis et al., 1989; Lymperopoulos and Chaniotakis, 2005). Davis (1989) proposes TAM in an attempt to illustrate the reasons beyond either acceptance or rejection of information technology. He considers ‘perceived usefulness’ and ‘ease of use’ are the most two features that will influence individual’s acceptance of new technology (Davis, 1989). Theory of Reasoned Action (TRA) model is developed by Ajzen and Fishbein’s (1980) with the aim to explain and predict an individual's behavior. TAM is proposed as an extension of TRA considering the behavior as the use of a technological system (Davis, 1989; Alrousan and Jones, 2016). By "perceived usefulness", Davis (1989) means "the degree to which a person believes that using a particular system would enhance his or her job performance", and by "perceived ease of use"; he means "the degree to which a person believes that using a particular system would be free of effort".

Moreover, various studies discuss the significant impact of perceived usefulness and the perceived ease of use on the adoption of new technology and innovation (Leong at al., 2011; Gangwar et al., 2015). Besides, regarding technological innovation systems, many studies have revealed that attitudes toward computers, in general, will affect the perceived usefulness and the perceived ease of use of a computer system, which, and then, can ″affect the behavioral intention of using the system″ (Chau, 2001). Thus, it would be the same situation when using analytical tools. Computer self-efficacy is defined by Compeau and Higgins (1995) as "a judgment of one's capability to use a computer. It is not concerned with what one has done in the past, but rather with judgments of what could be done in the future". Also, Compeau and Higgins (1995) found computer self-efficacy to be a critical component affecting perceived usefulness. Similarly, Chau (2001) states, ″computer self-efficacy is a facilitating factor if the system is useful and easy to use in general."

Hence, perceived usefulness, perceived ease of use and self-efficacy will be used as factors that may affect HR Analytics' acceptance and adoption.

2.5.3 Unified Theory of Acceptance and Use of Technology (UTAUT)

Among the literature, acceptance research in the discipline of information technology and information systems propose many contended models. So, the unified theory of acceptance and use of technology (UTAUT) is proposed and tested by Venkatesh et al. (2003). UTAUT model is validated through different prior models such as; TRA, TAM, and others. Whereas TAM suggests two elements, which are perceived usefulness and ease of use, affecting the behavior of the individual's adoption, UTAUT offers additional factors, such as social influence and facilitating conditions, inclusive of moderating variables (Jeyaraj and Sabherwal, 2008). In the context of this study, UTAUT related elements which are; performance expectancy (related to perceived usefulness in TAM), effort expectancy (ease of use), social influence, and facilitating conditions will be used as the factors that will affect the acceptance and adoption of HR Analytics.

Furthermore, UTAUT has been used as the primary model in many types of research and has been used in different technologies. Also, UTAUT approves its effectiveness of the adoption of technology at the individual level (Venkatesh et al., 2012).

2.5.4 Social Influence

Social factors significantly affect user behavior. There are many studies indicate that social influence is essential in shaping user behavior. Also, IDT suggests that user adoption decisions are influenced by a social system regarding an individual’s decision toward a new technology or innovation. (Hsu et al., 2004)

Social influence is defined as the degree to which members of a social group influence one another’s behavior in an adoption process for a new idea (Konana and Balasubramanian, 2005; Talukder and Quazi, 2011; Vargas, 2015).

Moreover, Talukder (2012) argue that individuals’ decision about whether or not to adopt an innovation may be a result of their peer influence and not primarily depends on the usefulness of that innovation.

Furthermore, different studies pinpoint the existence of a relationship between social influence and the adoption of a product or innovation. Likewise, colleagues and coworkers can have an impact and influence the behavior, ″motivation, and encouragement″ of the adoption of an innovation (Talukder and Quazi, 2011; Vargas, 2015). Besides, Jeyaraj and Sabherwal (2008) examine influencer’s behavior concerning the individual adoption of innovation of information systems, and the results show there is no common response to acceptance. However, as mentioned earlier in this research, since many HR professionals are not excited about the use of analytics despite its approved effectiveness, social influence would be a factor in adopting analytics. So this leads to the first hypothesis about the factors which may affect the individual acceptance and adoption of HR Analytics.

- H1: Social influence affects the individual acceptance and adoption of HR Analytics positively in large Palestinian enterprises.

2.5.5 Resource Availability

Resource availability is defined as having all the resources needed to adopt HR Analytics process properly. These resources include; systems and software required, appropriate skills compatible with these systems, and the ability to deal with data concerns as collecting it from a reliable resource, cleansing the data, analyzing and interpreting it in a proper manner (Vargas, 2015).

Nowadays, technology and web revolution make it easier for organizations to manage their business in a computerized way that facilitating the process of holding more information and data. This new development provides HR functions with different HRIS's that change the direction of managing people (Carlson and Kavanagh, 2011). In addition to the technological tools, individuals with appropriate specific technical skills and knowledge are needed to accomplish the use of HR Analytics (Carlson and Kavanagh, 2011).

Moreover, organizations should ensure there is a coordination between HRIS and other information systems in different departments; to guarantee a better HR Analytics which then result in a better decision making for the entire organization (Manyika et al., 2011).

So, resource availability will be a factor that may influence the acceptance and adoption of HR Analytics as many studies argue that the lack of inappropriate resources is a significant reason for poor organizational performance (SuccessFactors, 2013).

- H2: Resource Availability affects the individual acceptance and adoption of HR Analytics positively in large Palestinian enterprises.

2.5.6 Data Availability

Data availability is defined as the process of securing the availability of data as needed to perform what is required. Also, "it is the extent to which data is readily usable along with the necessary IT and management procedures, tools and technologies required to enable, manage and continue to make data available." (Techopedia, 2017)

Moreover, the term data availability is connected with the degree of accessibility to obtain the required data. Also, this related to the internal IT that combines all different departments within an organization. Manyika et al. (2011) advice organizations to increase their attention pertaining the integration of IT from various department to make the process of data transformation easier. In the same vein, Gale (2012) mentions that many organizations store their data in different and various systems; which making it more difficult for HR professionals to make a proper usage and interpretation of data when they need to connect HR data analysis with different departments.

Furthermore, data also stems from the administrative process conducting within HR department. This process includes recording different administrative data such as time needed to fill an available position, the cost per hire. Also, the administrative process contains both reporting and benchmarking which are the most two activities used in HR metrics and analytics when talking about an efficient administrative process (Carlson and Kavanagh, 2011).

On the other hand, there are different sources of data collection varying between simple spreadsheets that display administrative metrics, and other data comes from the internal information system. So, there is a need to be aware where the data comes from to assure the accuracy and the efficiency of the results based on this data analysis (Boyd and Crawford, 2011)

For this research, data availability is considered as a factor affects the acceptance and adoption of HR Analytics since the data collection and availability is the first step for any analysis process.

- H3: Data Availability affects the individual acceptance and adoption of HR Analytics positively in large Palestinian enterprises.

2.5.7 Fear Appeals

De Hoog et al. (2005) describe fear appeal as a convincing method that depends on arouse fear with the aim to change behavior by the impendence of risk or threat. Fear appeal is used too much in the health sector and advertising as a strategy to persuade an audience to change an attitude, make a specific action or buying a particular product through urge fear.

Fear appeal has been found to be effective in changing behavior toward specific action (Rogers, 1983; Shelton and Rogers, 1981). In this study, it is considered one of the factors that are affecting the individual behavior for the acceptance and adoption of HR Analytics.

In general, data analysis needs specific mathematical, statistical and problem-solving skills, and there is a shortage of these skills among HR professionals. Also, at the same time organizations have to fill the positions that require such skills with qualified employees (Bersin, 2013). On the other hand, HR professionals may have some fear of losing their jobs by replacing them with more qualified employees having the required skills (Vargas, 2015). This resulting fear may affect the acceptance and adoption of HR Analytics among HR professionals negatively or positively; the following hypothesis examines the positive effect of fear appeals.

- H4: Fear Appeals affects the individual acceptance and adoption of HR Analytics positively in large Palestinian enterprises.

2.5.8 Effort Expectancy

Venkatesh et al. (2003) define effort expectancy as the extent to which a system is easy to use. Also, Venkatesh et al. (2012) argue that effort expectancy is one of the significant factors that affect behavioral intention towards the acceptance of new technology. So they discuss how employees take into considerations both time and effort when they decide whether to accept and use new technology.

This research investigates if HR professionals are focusing on the degree of ease related to the use of HR Analytics as a new technology, and based on that take their decision of the acceptance and adoption. Hypothesis five tested this factor.

- H5: Effort Expectancy affects the individual acceptance and adoption of HR Analytics positively in large Palestinian enterprises.

2.5.9 Performance Expectancy

Performance expectancy refers to the extent to which users believe that using a specific system will assist or enhance their job performance (Venkatesh et al., 2003). Also, Venkatesh et al. (2012) suggest that performance expectancy is a robust foreteller of behavioral intention to use new technology, and argue that many other studies in the same vein assured this suggestion.

This research investigates to what extent HR professionals are considering performance expectancy as a factor affecting their acceptance and adoption of HR Analytics as a new technology. The following hypothesis tested that.

- H6: Performance Expectancy affects the individual acceptance and adoption of HR Analytics positively in large Palestinian enterprises.

2.5.10 Self-Efficacy

In this research, self-efficacy is investigated as a factor affecting the acceptance and adoption of HR Analytics among HR professionals as dependent on their expectancy about their capabilities. This factor is chosen based on Bandura’s (1977) theory of self-efficacy. This theory based on individuals’ belief in their skills to succeed and obtain the desired performance.

Regarding Bandura's (1977) theory of self-efficacy, there are four reasons to consider individuals' expectancy as a significant part of their efficacy. These factors are 1) performance accomplishments which will affect the efficacy either positively as an outcome of successes, or negatively as continuous fails. 2) Vicarious experience is about the individuals' belief to gain successful results, as are their colleagues when performing tasks and responsibilities. 3) Verbal persuasion is most commonly used, as individuals will propose methods of accomplishing or accepting their ability to implement. And 4) physiological states are related to emotion and fear of success.

Bandura (1982) argues that individuals may have prior expectations about whether or not they will gain successful results in whatever tasks they may be performing. In the same thinking, HR professionals may not accept or adopt HR Analytics based on their beliefs and expectations of their work and results are that they may not have an impact or may be viewed negatively by others within their environment or social networks (Bandura, 1982).

So, self-efficacy has a prospective effect on whether HR professionals will accept and adopt HR analytics and to what extent. Hypothesis seven is formulated.

- H7: Self-Efficacy affects the individual acceptance and adoption of HR Analytics positively in large Palestinian enterprises.

2.5.11 Quantitative Self-Efficacy

There are many prior studies regarding mathematical literacy (Ozgen, 2013; Ozgen and Bindak, 2008) and math anxiety (Hendel, 1980) which indicate there is an attitudinal relationship and, therefore, an impact on mathematical self-efficacy. In this research, mathematical self-efficacy is named quantitative self-efficacy.

Quantitative self-efficacy is considered as an upgrade level of general self-efficacy. Ozgen (2013) argues that there are many studies such as Bandura (1982), Schunk (2012), and Zimmerman (2000) that realize individuals who have a higher level of self-efficacy, also have a proclivity to work better on activities where they obtained knowledge and understanding, which in turn facilitate the learning process. In the same vein, Baki et al. (2009) and Ozgen (2013) indicate that individuals who integrate mathematics in their real-life problems; enhance their performance in math and simultaneously can benefit from their mathematics skill at work and make life easier with this integration (Ozgen, 2013).

On the other hand, (Ozgen, 2013) recognizes that the lack of integration between mathematics and the real life would affect the work performance negatively. And this lack of integration is a result of deficient or lack of adequate training.

As mentioned earlier in this chapter, the definition of HR Analytics contains the use of metrics and statistical tools to conduct the required analysis. So, quantitative self-efficacy is considered as a factor affecting the individual acceptance and adoption of HR Analytics.

- H8: Quantitative Self-Efficacy affects the individual acceptance and adoption of HR Analytics positively in large Palestinian enterprises.

2.6 Research Framework and Hypotheses

Based on the prior literature, theories and models, the most significant factors that affect the acceptance and adoption of HR Analytics at the individual levels are managed. Figure (2.1) shows the framework that represents these factors and the research hypotheses related to each factor.

2.7 Large Enterprises in Palestine

Up to the best of the researcher’s investigation, it has noticed that there are almost nonexistent clear publications regarding large Palestinian enterprises. Also, the statistics available in Palestinian Central Bureau of Statistics (PCBS) does not mention a classification of large enterprises in a clear way.

The PCBS (2013) publication based on the volume of employment, mentions the following classes for statistical purposes: very small enterprises are those contains (1-4) employees, small enterprises are having (5-9) workers, medium enterprises including (10-19). From this classification, it is concluded that large enterprises are becoming in the next class of medium ones with more than 19 employees.

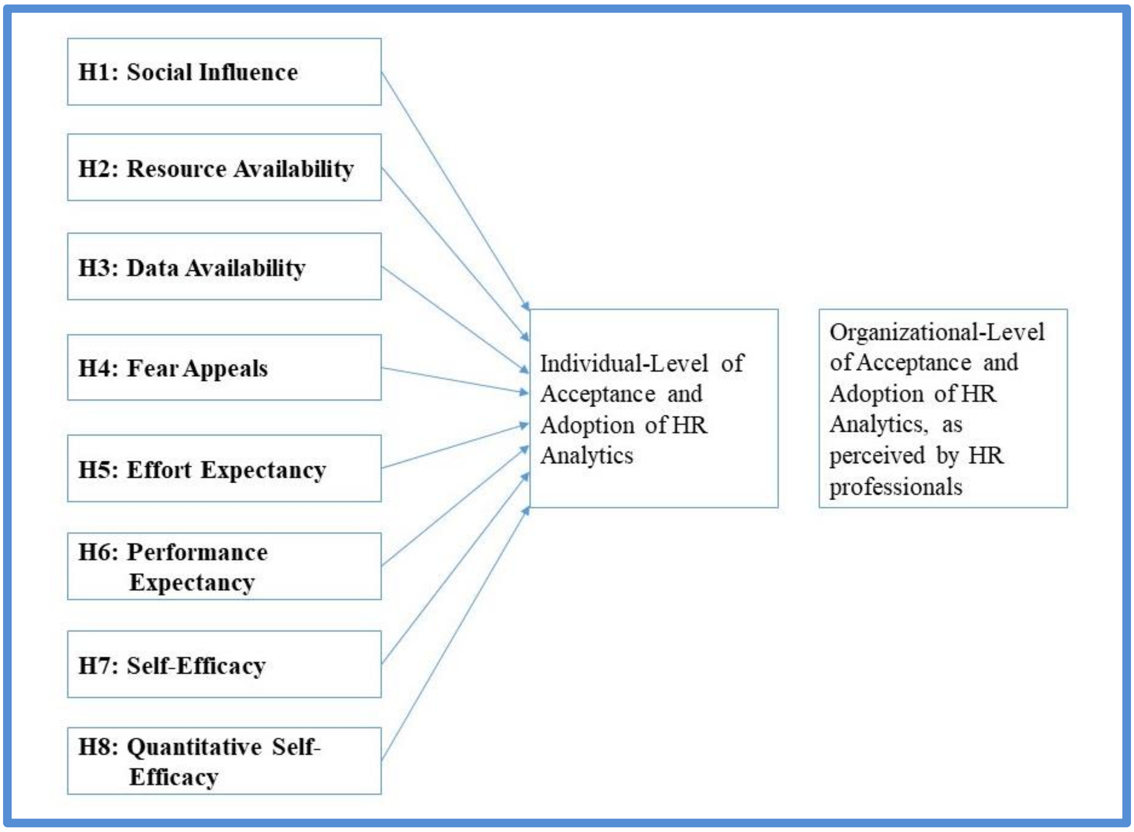

Figure (2.1): The Research Conceptual Framework

After many communications with the PCBS; to inform more about this classification and to know if there are any non-published statistics regarding large enterprises, a decision of the Palestinian Council of Ministers in 2011 is founded with a clear statement about the classification of large enterprises. Table (2.1) summarizes this decision:

Table (2.1): Classification of Palestinian Enterprises (Palestinian Council of Ministers, 2011)

Class size	Employment	Annual business volume $	The registered capital $
Very small enterprises	1-4	Up to 20,000 $	Up to 5,000 $
Small enterprises	5-9	20,001 to 200,000 $	5,001 to 50,000 $
Medium enterprises	10-19	200,001 to 500,000 $	50,001 to 100,000 $
Large enterprises	20 and more	500,001 $ and more	100,001 $ and more

Moreover, Amundsen et al. (2004) argue that large Palestinian enterprises have more efficiency and growth indicators in the Palestinian economy than the small/medium enterprises have. Furthermore, they indicate that these large enterprises can be expected to be more competitive, have superior technology and create more job opportunities. Hence, this labor-intensive domain with a massive amount of human capital issues; needs effective techniques in HR management. Also, findings show that larger firms apply more formalized HR practices than smaller ones (Al-Jabari and Hafiz; 2013).

This research intends to guide the large Palestinian enterprises achieving all the benefits from HR Analytics through providing a framework for proper acceptance and adoption of this innovative topic among HR professionals.

2.8 Human Resource Management in Palestine

The last few years witnessed an unprecedented interest of HRM in Palestine. Regarding HRM practices, Al-Jabari (2011) explores the nature of these factors at family businesses in Palestine. His results show that family firms are not applying HRM practices at all; except some of them are using it partially and sporadically. This study presents a better understanding of HRM practices at family firms within Palestinian context.

At the same vein regarding HRM practices, Al-Jabari and Hafiz (2013) conduct empirical research with the aim to study the factors that affect HR practices in some Palestinian organizations regarding firm size, sector, and profitability. Through statistical analysis techniques, the research concludes that sector has a significant effect on the level of HRM practices in Palestine since the results indicate the non-government organization sector proved to have a much higher level than both private and government sectors and non-profit sector is practicing HR higher than profit sectors. Also, the findings show that larger firms apply more formalized HR practices than smaller ones.

Also, Abu Teir and Zhang (2016) present a conceptual framework for HRM practices in higher education and investigate the current recognition of this model in higher education institutions in the Palestinian context, concerning the applied practices and the significance level for each practice. As well, the research suggests improvement plans to enhance HRM process in Palestinian higher education. Recently, many Palestinian researchers, in the field of HRM, keep up with innovation and modern technological development. For example, Saleh and Saleh (2016) investigate the factors affecting the adoption of e-HRM technology at service sector within Palestinian context. The results of the statistical analysis suggest the most significant factors affecting the adoption of this technology are: perceived ease of use, attitude, intention, and communication. While the factors of perceived risk, system security, organization's role, and availability of resources are less influential.

Furthermore, Al Shobaki et al. (2017) identify the effect of electronic human resources management on the evolution of electronic educational services in the Palestinian universities located in Gaza Strip. This research conducts a statistical analysis of the data collected by questionnaire as a survey tool. The results reveal that the university system concerning electronic educational services impacts the process of converting to electronic human resources management practices by using specific information technology system. Also, the study suggests that the universities should give the same interest of electronic evolution to human resources management as this for electronic educational services.

Keeping pace with the environmental global development, Masri and Jaaron (2017) present a significant empirical research study to assess green human resources management practices in Palestinian manufacturing firms and to investigate the impact of those practices on environmental performance at organizations. Besides, it proposes a strategic conceptual framework to guide manufacturing organizations in the process of engaging their HR functions with their environmental performance to gain competitive advantage.

Although there is a growing interest to investigate the domain of HRM within Palestinian context in the last ten years; there is much more to add to the related literature of HRM as the aspects of this domain are growing continuously and tremendously. Besides, relevant HR Analytics technology, there are no researches founded. Moreover, no studies are investigating the concept of HRM in the full scene as for both service and manufacturing business sectors at the same time. Thus, this research will add to the literature through investigating the concept of HR Analytics as a new technology in large Palestinian enterprises in both sectors; service and manufacturing.

2.9 Summary

This chapter provides a review of the literature regarding definition and development of HR Analytics. Also, it views the backdrop researches to this study. The factors that affect the acceptance and adoption of HR Analytics at the individual level are also mentioned. Finally, a research framework is developed. The following chapter will outline and explain the methodology used in this study, including the targeted sample, data collection, and tools used to collect and analyze the data.

Chapter Three

Research Methodology

The importance of the research methodology stems from being a combination of activities linked to conducting research, methods, and strategies, in addition to providing criteria that will guarantee the success of research and achieve its goals (Sekaran, 2006). So, this chapter explains the methodology used in this research regarding research type, research approach, research strategy, research methodology framework, research population and sampling techniques. Also, in the end, this chapter defines data analysis approach.

3.1 Research Type

This study conducts an exploratory research type. It intends to explore "what is happening; to seek new insights; to ask questions and to assess the phenomena in a new light" (Robson, 2002). This type of research is essential here mainly as the literature reveals; there is very little information known about the acceptance and adoption of HR Analytics. Therefore, this study aims to investigate the factors affecting the acceptance and adoption of HR Analytics in large Palestinian enterprises and provide a conceptual framework for proper acceptance and adoption of this theme.

3.2 Research approach

The research approach selection depends mainly on the research objective, the nature of research, the research problem, research questions, and research hypotheses that content with the research's requirements to achieve the desired outputs (Creswell, 2017; Alhamdani et al., 2006). Also, the research approaches are varying between qualitative versus quantitative and deductive versus inductive. And it is recommended to use a variety of methods, if and when required by the research (Jackson, 1994).

In this study, a type of mixed-method approach (qualitative and quantitative) is used. The purpose of this mixed approach is typically to use the initial qualitative phase to understand the research topic more clearly and to guide the questionnaire design. In this research, the qualitative phase is conducted through reviewing the related literature to understand the topic of HR Analytics more thoroughly, and to construct the survey statements based on previous studies. Also, a pilot study is conducted with many experts in the field of HR to arbitrate on the questionnaire validity and ensure it is designed as to achieve the primary objectives of the research. Moreover, during this qualitative phase many telephone interviews conducting among large Palestinian enterprises to identify which of them having an HRIS and to determine the total number of HR professionals in these enterprises. Then, the sample size of this research is determined to design the larger-scale, quantitative part of this study. Quantitative approach objective is "to test hypotheses that the researcher generates" (Creswell, 2017). It is based on formulating hypotheses about the elements of a study, collecting data and then statistically analyzing the results to reject or accept the formulating hypotheses (El-Gohary et al., 2008). It answers the questions of what, where and when (Rajaskar et al., 2013). In this research, it is used as it intends to answer the ‘what’ questions related to the research objectives. The research questions are: what are the main factors that may influence the acceptance and adoption of HR Analytics, what is the importance of each factor and what is the relationship between the Individual acceptance and adoption and the organizational acceptance and adoption of HR Analytics in large Palestinian enterprises? Moreover, the deductive approach is used as this approach aims to study known theories to propose hypotheses on their basis, and then test these hypotheses (Marcoulides, 1998). In this research, this appears through the fact that the factors, the models and the theories that affect the acceptance and adoption of HR Analytics at the individual level among HR professionals are chosen from literature and exploratory interviews.

3.3 Research Methodology Framework

Figure (3.1) shows the research methodology framework, which represents sequentially the activities that are conducted to obtain the research objective. At the beginning of this study, the topic of HR Analytics is selected as a new trend in HR management domain, identify the research scope and primary objective to be investigating the main factors that affect the acceptance and adoption of this new trend. After that, a review of literature is done to dig into this selected topic and formulate the research questions and hypotheses. As the next step in data collection process, the study population is determined to be HR professionals in large Palestinian enterprises, then the interviews are conducted, the questionnaire is developed, a pilot study test is done, and the survey is distributed to a representative sample as a final step in this phase. Then, data is processed and analyzed, and hypotheses are tested. After that, a conceptual framework is proposed based on the data analysis; this framework will introduce a proper acceptance and adoption of HR Analytics in the large Palestinian enterprises at the individual level. Finally, discussion of the results and recommendations are provided.

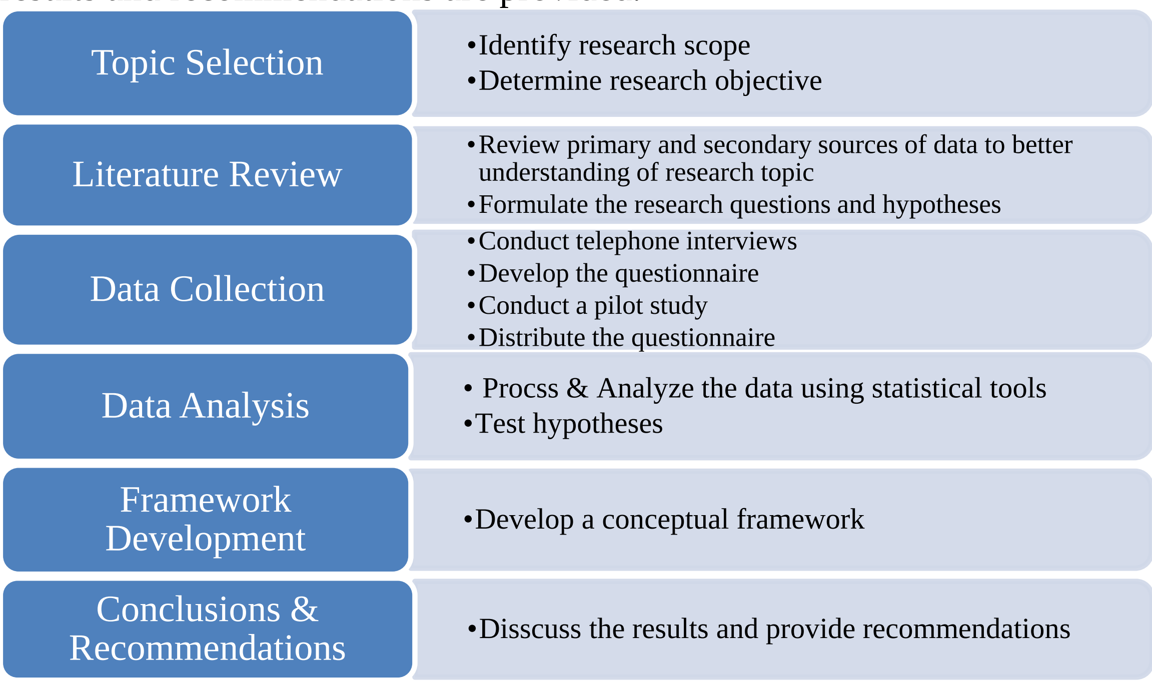

Figure (3.1): Research Methodology Framework

3.4 Research Population and Sample Size

3.4.1 Research Population

A population is defined as the whole pool from which a statistical sample is derived, from which the data are collected, and then made conclusions based on it (Roxy et al., 2008).

In this research the study population includes HR professionals in large Palestinian enterprises provided that these enterprises are using HRIS in managing their HR issues; since the integration and implementation of HRIS is considered as a significant driver of HR analytics (Carlson and Kavanagh, 2011). HR professionals are those who are currently employed in the field of HR in large Palestinian enterprises at the time this study is conducted in the years 2017/2018. Also, large enterprises in West Bank (WB) are those contain 20 employees and more (Palestinian Council of Ministers, 2011)

To determine the targeted large Palestinian enterprises in WB; the investigation is done using many internet websites such as those related to Palestine trade center (PALTRADE), eArabic Market, ArabO Palestine Directory and PCBS. Also, many brainstorming sessions are conducted with supervisors to ensure that the list of targeted enterprises is covering most of these large enterprises in WB and with different sectors. After that, many telephone interviews are conducted with all listed enterprises to ask about whether these enterprises are using HRIS in their HR departments and to ask about the number of HR employees in each enterprise. These interviews are done to guarantee the condition that will qualify these enterprises to be the proper representative sample through having the vital driver of analytics which is HRIS and to determine the population size (total number of HR professionals).

Table (3.1) shows the details of population size regarding the sector, domain and the number of HR professionals in each.

Table (3.1): Distribution of study population by sectors/domains

Enterprises' Domain	Number of HR Professionals
Service Sector	**195**
Telecommunication	60
Banking	74
Insurance	24
Internet provider	7
Logistics	3
Electricity provider	6
Cars trading	10
Hospitals	11
Manufacturing Sector	**49**
Food industry	17
Pharmaceutical industry	14
Other industries (paper, aluminum, plastic)	18
Total	**244**

3.4.2 Sample Size

The sample size represents a group of units with specific features selected from a larger group. It acts as a representative sample of the whole population to make any generalizations and to come to valid conclusions about the population (Roxy et al., 2008). The statistically representative sample size of the population, n = 150 as a result of using Daniel and Cross (2013) formula as follows:

$$n = \frac{Nz^2pq}{d^2(N-1)+z^2pq} \text{ …………………………..(1)}$$

Where:

n = the sample size.

z = is the abscissa of the normal curve which interrupts an area α at the tails (1- α equals the required confidence level) (Israel, 1992). In this research z = 1.96 for 95% confidence level.

p = the population ratio that has the required characteristic (probability of selecting an element). To give a better estimate of p, let it equal 0.5 as this will give the largest possible value for n (Daniel and Cross, 2013).

q = (1- p) and this means that q = 0.5.

d = the required confidence interval. In this research, it will equal 0.05.

N = the total population for the research, in this research it is equal 244.

Table (3.2) shows the total sample details corresponding to each industrial sector and domain. The percentage required for each sector is calculated using the following formula which is adopted by Saunders et al. (2009):

$$Strata\ sample\ size = \frac{strata\ size}{total\ population} \text{ ………………..(2)}$$

Table (3.2): Total Sample Details

Strata name	Strata size	Required %	Strata sample size
Service Sector	**195**	**80%**	**120**
Telecommunication	60	31%	37
Banking	74	38%	45
Insurance	24	12%	15
Internet provider	7	4%	4
Logistics	3	2%	2
Electricity provider	6	3%	4
Cars trading	10	5%	6
Hospitals	11	6%	7
Manufacturing Sector	**49**	**20%**	**30**
Food industry	17	35%	10
Pharmaceutical industry	14	29%	9
Other industries (paper, aluminum, plastic)	18	37%	11
Total	**244**	**100%**	**150**

3.5 Data Collection using Questionnaire Survey as a Research Tool

A questionnaire is a set of written predetermined questions, which is given to respondents to record their answers and ideas within specifically defined preferences (Sekaran and Bougie, 2010). The questionnaire is considered as the most widely used data collection method for a large sample because of its simplicity and rapidity (Saunders et al., 2009) with less effort and time. It is useful for collecting data when the researcher knows what variables are needed and how to test variable of interest (Sekaran and Bougie, 2010).

Questionnaires can be distributed either personally, mailed to the respondents, or electronically.

3.5.1 Questionnaire Design

The questionnaire is chosen as a research tool to test the research model and hypotheses which are formulated previously in chapter two. A questionnaire is designed with closed-end questions as this type of questions facilitates quick decisions for respondents and secure information coding for a researcher (Creswell, 2017). The respondents are asked to check a five-point Likert scale to rank their perceptions about the importance of each statement related to the factors that may affect the acceptance and adoption of HR Analytics. Each of the responses would have a numerical value, which would be used to measure the attitude under investigation (Likert, 1932).

The questionnaire comprised of a questionnaire cover, which consists of the purpose of the survey, definition of HR Analytics, a brief description of the body of the questionnaire and the time needed to fill it. The rest of the questionnaire consists of two major parts. Part one of the questionnaire mainly focuses on the demographic profile of respondents and general information about the enterprises. This part aims to collect data that will help in understanding the nature of both the respondents and their enterprises such as, the participants' gender, age, level of education, HR experience, industrial sector and the enterprises' size concerning the number of employees. Part two consists of several statements related to the factors that influence the acceptance and adoption of HR Analytics at the individual level. These statements aim to measure the factors that are determined by the research model and hypotheses. The respondents are asked to answer the question of “**to what extent do you think the following factors will affect your acceptance and adoption of this analytics in your HR department?**”. Each item is rated on a five-point Likert scale of 1 ‘not at all' to 5 ‘to a very great extent.'

The questionnaire has been revised with a group of experts in the field; to judge on its validity and to make sure it is appropriately designed to achieve the primary goals of the research. All of the notes related to the length, language and the number of statements have been considered and modified. The last version of the questionnaire was written in English (See Appendix B), but then it is translated into Arabic text as it is the mother language in Palestine (See Appendix C).

After that, the questionnaire is distributed over the two-month period to different large enterprises, in different sectors located in various Palestinian cities. Also, the survey is distributed in different forms based on each enterprise preferences. During the telephone interviews which are conducted at first, each enterprise is asked about its preference way for sending the questionnaire. Some enterprises preferred personal contact and filled the paper-based questionnaire, and others want to receive an electronic form via email.

Moreover, 185 questionnaires are distributed to ensure a high rate of response and obtain the required sample size of 150. At the end of distribution phase, 158 questionnaires are restored, and 7 of them are excluded since they don't fill in correctly. Some respondents fill the first part only, and others don't ask all the questions in the second part.

Table (3.3) shows the details of the questionnaire distribution. For each sector, the number of distributed and valid restored questionnaires. The last column represents the response rate for each sector. It is shown that the high percentage is 100% from logistics enterprises since the required questionnaires from them are only two, and they have limited number of HR professionals within their staff. The next high two percentages of the response rate are for telecommunication and banking in the service sector with 91%, 90% respectively; and this related to the fact that these sectors have the two highest participation in the survey as they are the most significant enterprises in size in the service sector. The lowest percentage of response rate is from the pharmaceutical industry in the manufacturing sector with 27%. These enterprises have weak participation in the survey although they are contacted much time and followed up with telephone calls and emails; unfortunately, the response is not as required.

Table (3.3): The Questionnaire Distribution Details

Sector	Distributed	Received	Response Rate	Valid
Service Sector				
Telecommunication	46	42	91%	40
Banking	55	50	90%	48
Insurance	18	16	89%	15
Internet provider	5	4	80%	4
logistics	2	2	100%	2
Electricity provider	5	4	80%	4
Cars trading	7	6	86%	6
Hospitals	9	7	78%	7
Manufacturing Sector				
Food industry	13	11	85%	10
Pharmaceutical industry	11	3	27%	3
Other industries (paper, aluminum, plastic)	14	13	92%	12
Total	**185**	**158**	**85%**	**151**

3.5.2 Questionnaire Pilot Study

The pilot study is used to refine and improve the questionnaire with the aim to examine whether the questionnaire statements are comprehensible so that the participants can understand and interpret them. Also, this study reduces the possibility of getting incomplete answers from respondents (Saunders et al., 2009).

The questionnaire is reviewed by a group of experts and arbitrators (See Appendix D), with research supervisors, academic staff, and experts in HRM. Experts and arbitrators made comments on the contents and format of the questionnaire, all of these modifications are taken into consideration to assure the validity of the survey tool.

3.5.3 Questionnaire Reliability

Reliability defines the degree to which survey tool produces similar outcomes when it is repeated in other situations or by other researchers (Saunders et al., 2009). Reliability can be determined through various methods like test-retest reliability, equivalent forms, and internal consistency.

In this research, internal consistency method is used by using Cronbach's Alpha test. Sekaran (2006) defines Cronbach's Alpha as "a reliability coefficient that indicates how well the items in a set are positively correlated to one another." Table (3.4) represents Cronbach’s Alpha coefficient for the factors affecting the acceptance and adoption of HR Analytics at the individual level. All coefficient values greater than 0.7 and for all the questions is 0.89. These values between (0.70-0.90) indicate a good internal consistency and as a result a good level of reliability of the survey tool (Cortina, 1993).

Table (3.4): Reliability Statistics of Factors Affecting the Acceptance and Adoption of HR Analytics

Factor	Cronbach's Alpha
Social Influence	0.71
Resource Availability	0.77
Data Availability	0.80
Fear Appeals	0.91
Effort Expectancy	0.86
Performance Expectancy	0.92
Self-Efficacy	0.86
Quantitative Self-Efficacy	0.74
Level of Acceptance and Adoption	0.85
All questions	**0.89**

3.5.4 Questionnaire Validity

The term validity means the extent to which a survey tool is measuring what is supposed to measure in research (Sekaran, 2006).

This research validity is achieved through the following steps:

- The questionnaire's statements are designed based on literature, where the quality standards for the research tool are already guaranteed regarding testing the validity and reliability.
- The questionnaire is revised with different arbitrators and experts in the area. Then, modifications and adjustments are made to assure the efficiency of the research tool in achieving the research objectives.
- The reliability of the questionnaire is guaranteed as shown in the previous section. So this result leads to consider the questionnaire valid also; since the reliability of a research tool is a pre-request to find it valid tool even.

3.6 Data Analysis Approach

Quantitative data collected from the questionnaire is analyzed using Minitab 18 software. The analysis is conducted in a manner that guarantees to achieve the main research objective, answering the research questions and testing the research hypotheses. The analysis methods and approaches that are used:

- Cronbach's Alpha: to measure the internal consistency of the questionnaire's constructs and assure the reliability of the questionnaire as a research tool.
- Frequency, percentage and descriptive statistics: to describe the respondents' demographic variables numerically and compare them based on their participation percentages.
- Shapiro–Wilk test: to test the data normality.
- One-way ANOVA: to test the statistical differences among respondents according to their demographic variables and regarding their perceptions to different research variables.
- Kruskal-Wallis: it is a non-parametric test works as ANOVA to test the statistical differences between different variables.
- Pearson correlation: to measure the strength and direction of the linear association between the variables.
- Regression analysis: to model the relationship between the response (dependent variable) and the predictors (independent variables). Also, regression analysis is used to test the research hypotheses.

- Box-Cox Transformation: to normalize the not-normally distributed data in regression analysis.

3.7 Summary

At the end of this chapter, the research methodology is evident. The research methodologies and approaches are outlined and explained to ensure that the data collection process and the survey tool are adequately chosen and ready to conduct the analysis needed to achieve the main research objective. The next chapter represents the results of statistical analysis, hypotheses testing and discussion regarding these results.

Chapter Four

Results and Discussion

Overview

This chapter outlines the results of the statistical data analysis. It represents and discusses the results of the analysis regarding descriptive statistics, statistical differences among respondents, hypotheses testing, proposing a proper framework for the acceptance and adoption of HR Analytics at the individual level, and also investigate the relationship between the individual and organizational acceptance and adoption of HR Analytics in large Palestinian enterprises.

4.1 Demographic and Descriptive Statistics

The total number of HR professionals participate in this survey is 151, with a response rate of 81.62 %. The following tables clarify the participants' specifications resulted from frequency tests.

1) Gender

Table (4.1) shows the gender distribution of HR professionals as participants in this survey. The representative population sample includes 67 males with a contribution of 44.37% and 84 females with 55.63%. This result indicates females have a little more roles at HR positions in large Palestinian enterprises.

Table (4.1): Sample Distribution Attributed to Participants' Gender

Variable	Characteristics	Frequency	Percent
Gender	Male	67	44.37%
	Female	84	55.63%
	Total	**151**	**100%**

2) Age

Regarding this research, age is divided into three groups. Table (4.2) shows these groups and the participants' percentages among these groups. The highest percentage of participants is young (HR professionals with age less than 35 years) who form 64.90 % of respondents. And the lowest percentage of participants is 5.96 % which represents participants with more than 45 years old.

Table (4.2): Sample Distribution Attributed to Participants' Age

Variable	Characteristics	Frequency	Percent
Age	less than 35 years	98	64.90 %
	35- less than 45 years	44	29.14 %
	more than 45 years	9	5.96 %
	Total	**151**	**100%**

3) Qualification

Qualification is divided into three levels. Table (4.3) shows the details of Educational Degree of the respondents. The highest percentage of HR professionals have a bachelor's degree and forms 80.13 %. While the lowest percentage is 5.96 % for those respondents who have an educational degree of diploma or below.

Table (4.3): Sample Distribution Attributed to Participants' Educational Degree

Variable	Characteristics	Frequency	Percent
Educational Degree	Diploma or below	9	5.96 %
	Bachelor's degree	121	80.13 %
	Master's degree	21	13.91 %
	Total	**151**	**100%**

4) Certification

As Table (4.4) presents, the majority of participants do not have HR certificates, and their percentage in participation is 84.11 %.

Table (4.4): Sample Distribution Attributed to Participants' HR Certification

Variable	Characteristics	Frequency	Percent
Certification	Yes	24	15.89 %
	No	127	84.11 %
	Total	**151**	**100%**

5) Current Position

The distribution of the participants' current position within HR department is shown in the Table (4.5). More than half of the participants are at administrative positions with a percentage of 55.63% of participation. And the lowest percentage of participants are at director position with 5.30 %.

Table (4.5): Sample Distribution Attributed to Participants' Current Position

Variable	Characteristics	Frequency	Percent
Current position	Director	8	5.30 %
	Manager	26	17.22 %
	Head of Department	21	13.91 %
	Head Unit	12	7.95 %
	Administrative	84	55.63 %
	Total	**151**	**100%**

6) Functional Area

Table (4.6) presents the distribution of the functional area of participants' current position. As the results show, the highest percentage of participants is from those HR professionals who work with employee relations issues, and their percentage in participation is 36.42 %. However, the lowest percentage is 9.93 % for respondents who work at data and information management as a functional area.

Table (4.6): Sample Distribution Attributed to Participants' Functional Area

Variable	Characteristics	Frequency	Percent
Functional Area	Training/Development	41	27.15 %
	Insurance	22	14.57 %
	Payroll	18	11.92 %
	Employee Relations	55	36.42 %
	Data and Information Management	15	9.93 %
	Total	**151**	**100%**

7) Number of years at position

The participants have a different period at their positions in HR department. Table (4.7) displays three categories of these periods and shows the highest percentage of 58.28% for those who are at their positions for less than five years. And the lowest percentage is 11.26 % for those respondents who are at their positions for more than 10 years.

Table (4.7): Sample Distribution Attributed to Participants' No. of years at the position

Variable	Characteristics	Frequency	Percent
Number of years at the position	less than 5 years	88	58.28 %
	5-10 years	46	30.46 %
	more than 10 years	17	11.26 %
	Total	**151**	**100%**

8) HR Experience

The participants in the questionnaire have various experience in HR domain. Table (4.8) presents, the questionnaire presents three periods for HR professionals to select among them based on their HR experience. The results show the highest percentage of participants is 46.36 % of respondents whose have less than five years of HR experience. And the lowest percentage of participants is 18.54 % of respondents with more than 10 years of HR experience.

Table (4.8): Sample Distribution Attributed to Participants' HR Experience

Variable	Characteristics	Frequency	Percent
HR Experience	less than 5 years	70	46.36 %
	5-10 years	53	35.10 %
	more than 10 years	28	18.54 %
	Total	**151**	**100%**

9) Industrial Sector

As this research covers large Palestinian enterprises in both service and manufacturing sectors and in different domains, Table (4.9) shows the percentage of participants in each domain. The highest percentage is for the banking sector that forms 31.79 % followed directly by telecommunication with a percentage of 26.49 % of participants. While the lowest two percentages are for pharmaceuticals industry that forms 1.99% and logistics with 1.33 %.

Table (4.9): Sample Distribution Attributed to Participants' Industrial Sector

Variable	Characteristics	Frequency	Percent
Industrial Sector	Telecommunication	40	26.49 %
	Banking	48	31.79 %
	Insurance	15	9.93 %
	Internet Provider	4	2.65 %
	Logistics	2	1.33 %
	Electricity Provider	4	2.65 %
	Cars Trading	6	3.97 %
	Hospitals	7	4.64 %
	Food Industry	10	6.62 %
	Pharmaceuticals Industry	3	1.99 %
	Other Industries (Paper, Aluminum, Plastic)	12	7.95 %
	Total	**151**	**100%**

10) Number of Employees

The number of employees is an essential element in this research; since it talks about large enterprises. This element is classified into five categories to investigate the effect of them on the research objective. The results in Table (4.10) display the highest two percentages of participants are in enterprises which consist of more than 1000 employees and 500-1000 employees and these categories form 30.46 % and 29.80 % respectively. And the lowest percentage of participants is 1.32 % which relates to the respondents who are working in enterprises consist of less than 50 employees.

Table (4.10): Sample Distribution Attributed to Participants' Firm Size regarding the Number of Employees

Variable	Characteristics	Frequency	Percent
Number of Employees	Less than 50	2	1.32 %
	50- less than 100	22	14.57 %
	100- less than 500	36	23.84 %
	500- 1000	45	29.80 %
	More than 1000	46	30.46 %
	Total	**151**	**100%**

11) The application of Data Analytics in Organization

The results in Table (4.11) show that approximately all of the participants' firms are applying data analytics in their businesses in general with a percentage of 95.36 %. These results indicate that the enterprises are familiar with data science applications and they are using them in some of their departments. This may facilitate more the acceptance and adoption of this science in HR department.

Table (4.11): Sample Distribution Attributed to Participants' firm usage of Data Analytics

Variable	Characteristics	Frequency	Percent
The use of Data Analytics in general	Yes	144	95.36 %
	No	7	4.64 %
	Total	**151**	**100%**

4.2 Statistical Differences among Survey Participants

This section outlines the statistical differences among participants in this research. Different tests and procedures are used within Minitab 18 software to analyze the data. For example, One-way ANOVA is used at first as a test to check the statistical differences among respondents according to their demographic and descriptive variables. ANOVA compares means of independent variables, which has two or more levels, with those means of dependent variables to examine the significant differences between these variables.

Moreover, Shapiro–Wilk test is the most powerful tool for normality distribution testing (Yap and Sim, 2011) and it is used here to check the normality of the residuals resulted from ANOVA. Testing data normality is a crucial step; it is used as a guide to know what to do in the next step of the analysis. Also, therefore, if the result from normality test indicates the residuals data are normal and at the same time ANOVA indicates a significant difference, the next step will be to use Fisher test within

ANOVA to see where the statistical differences among the levels of independent variables are.

On the other hand, if Shapiro–Wilk test reveals a non-normal distribution of residuals data, nonparametric methods are used to check the statistical significant difference among respondents according to their demographic and descriptive variables. One of these non-parametric methods is Kruskal-Wallis test. This test is a median test (H statistic test) and is an overall test statistic that enables one to test the general hypothesis that all population medians are equal. Kruskal-Wallis test works well with non-normally distributed data as ANOVA do with normal data.

Furthermore, Kruskal-Wallis is used to test a general hypothesis about whether there are statistical significant differences or not between dependent and independent variables. Often, the investigator needs to know more about where these differences occur among the levels of independent variables. To do so, Macro functions within Minitab 18 are used to perform multiple comparisons in a non-parametric data through using Bonferroni test.

Finally, it is important to mention that all statistical and analysis are based on the statistical concepts in the book of ‘Applied Statistics and Probability for Engineers’ by (Montgomery and Runger, 2010).

4.2.1 Statistical differences According to Gender

4.2.1.1 Statistical Differences among Respondents According to their Gender in Social Influence

At first, one-way ANOVA test is conducted to get the residuals. Then, Shapiro–Wilk test is performed to check the normality of these residuals and to decide whether to stay at ANOVA as a decision test for significant differences or there is a need to a non-parametric test.

The following Figure (4.1) shows the normality of the residuals data with P-value greater than the significance level α of 0.05.

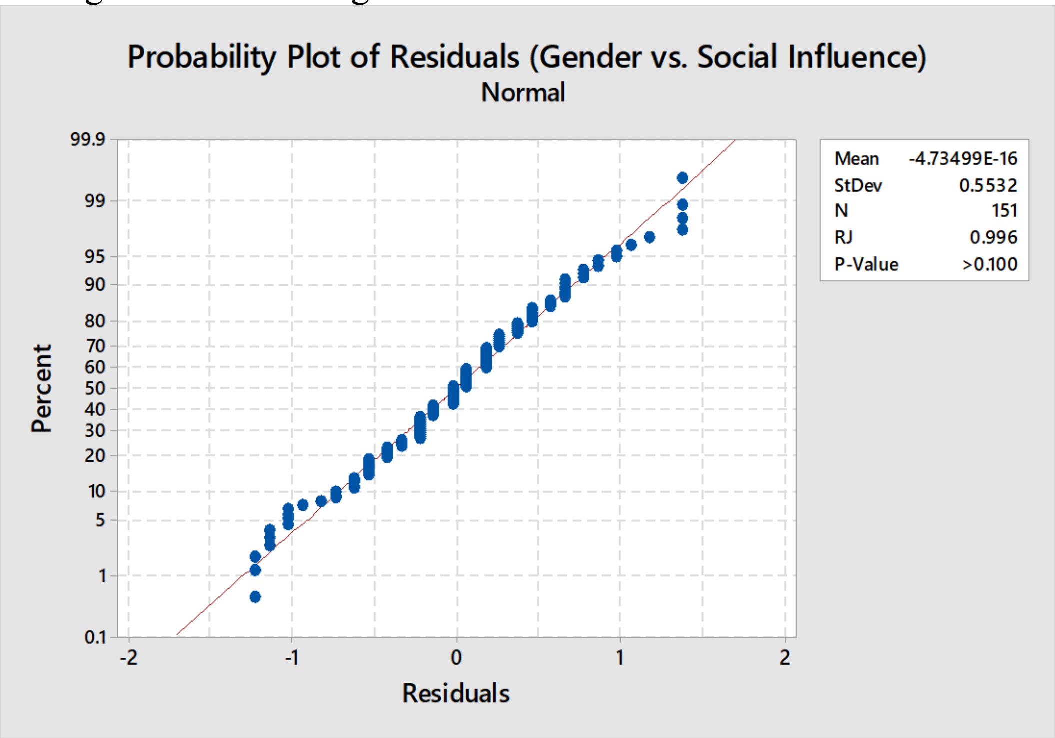

Figure (4.1): Probability Plot of Residuals (Gender vs. Social Influence)

Since the residuals have a normal distribution, ANOVA is used to examine the statistical differences among respondents according to their gender groups in recognizing social influence as a factor affecting the individual acceptance and adoption of HR Analytics. The following states the general hypotheses of ANOVA test:

Null hypothesis H_0: All means are equal

Alternative hypothesis H_1: Not all means are equal

Significance level $\alpha = 0.05$

* Equal variances were assumed for the analysis.

Table (4.12) displays the results from ANOVA. It is evident from the P-value = 0.211 which is greater than the significance level $\alpha = 0.05$; there are no statistical significant differences for gender differences among participants in social influence as a factor affecting the individual acceptance and adoption of HR Analytics.

This result agrees with Talukder and Quazi (2011) since they found that there are no differences between men and women in adopting innovation based on social influence factors.

Table (4.12): ANOVA for Gender Differences among Participants in Social Influence

Source	**DF**	**Adj Sum of Squares**	**Adj Mean of Squares**	**F-Value**	**P-Value**
Gender	1	0.4853	0.4853	1.58	**0.211**
Error	149	45.9036	0.3081		
Total	150	46.3889			

4.2.1.2 Statistical differences among Respondents According to their Gender in Resource Availability

As a beginning step, one-way ANOVA is executed to obtain the residuals. After that, the normality test is done to test the normality of resulting residuals. Figure (4.2) shows the non-normality distribution of residuals with P-value < 0.05.

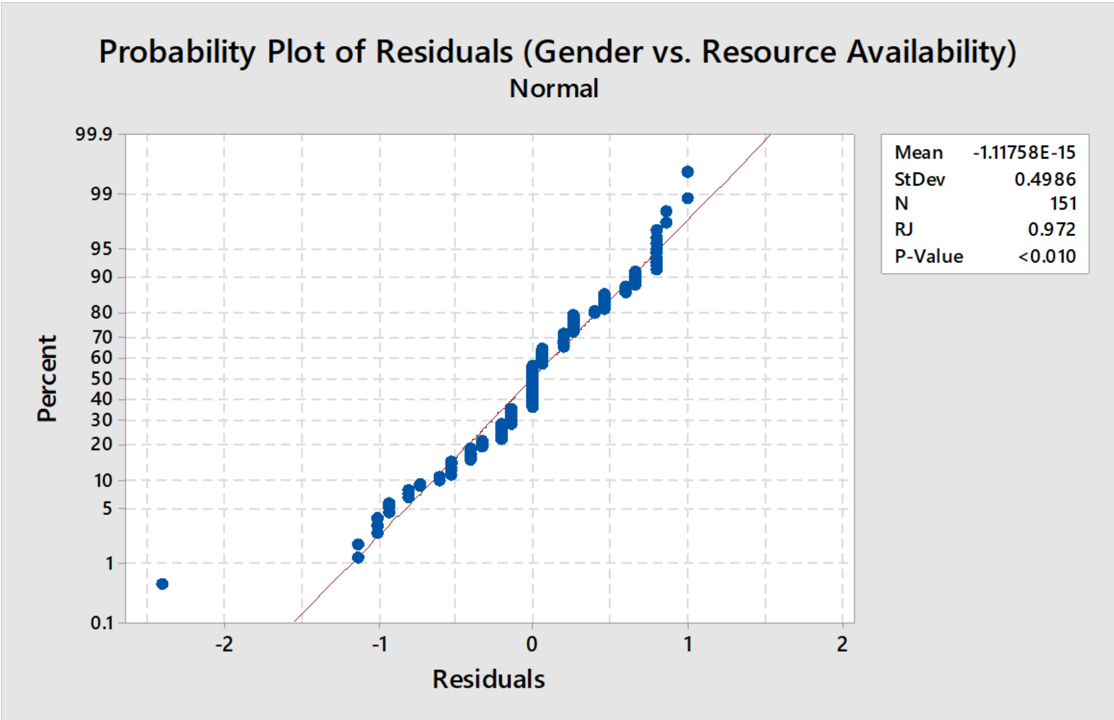

Figure (4.2): Probability Plot of Residuals (Gender vs. Resource Availability)

Based on the result of the normality test, ANOVA is not appropriate here, and there is a need for a non-parametric test. So, Kruskal-Wallis test is used to examine the existence of statistical differences among respondents according to their gender in the factor of resource availability.

As mentioned earlier Kruskal-Wallis test examines medians of statistical samples, and it forms the following general hypothesis:

Null hypothesis H_0: All medians are equal

Alternative hypothesis H_1: At least one median is different

Table (4.13): Descriptive Statistics for Gender Differences among Participants in Resource Availability

Gender	N	Median	Mean Rank	Z-Value
1	67	4	73.6	-0.60
2	84	4	77.9	0.60
Overall	151		76.0	

Table (4.14): Kruskal-Wallis test for Gender Differences among Participants in Resource Availability

Method	DF	H-Value	P-Value
Adjusted for ties	1	0.37	**0.545**

The P-value resulting from Kruskal-Wallis test is equal to 0.545 which is greater than the significance level α of 0.05, so the differences between the medians are not statistically significant and you do not have enough evidence to reject the null hypothesis that the population medians are all equal. In other words, there are no statistical differences among respondents according to their gender in the factor of resource availability.

This result is expected as chapter 2 discuss the importance of resource availability concerning both IT software and analytical skills to conduct HR Analytics properly.

4.2.1.3 Statistical Differences among Respondents According to their Gender in Data Availability

The normality test for the residuals resulting from ANOVA indicates a non-normal distribution of residuals with P-value < 0.05. Thus, there is a need to use Kruskal-Wallis test which works like ANOVA but for a non-normal data.

Kruskal-Wallis gives a P-value = 0.276 which is greater than the significance level value of 0.05. This means there are no statistical differences found among respondents according to their gender groups in the factor of data availability.

Gale (2012) argues that there are many studies have shown that many enterprises still use spreadsheets and other manual methods of collecting and exploring data. The debate proposed here about whether the use of old-fashion techniques to collect and examine data is as a result of lack of data or lack of computational skills. This issue is connected to gender differences since Boyd and Crawford (2011) found that there is a significant gender difference regarding the computational skills.

If data availability, as a factor affecting the individual acceptance and adoption of HR Analytics, is evaluated concerning computational skills, the result of this investigation contradicts Boyd and Crawford (2011) study since it founds that nowadays the majority of who have computational skills are male.

4.2.1.4 Statistical Differences among Respondents According to their Gender in Fear Appeals

Following ANOVA test, Shapiro–Wilk test has resulted in a not normal distribution of residuals which leads to a decision of using Kruskal-Wallis to test the statistical significant differences among respondents according to their gender in the factor of fear appeals.

Kruskal-Wallis outputs a P-value = 0.018 < significance level $\alpha = 0.05$ which implies that there are statistical significant differences among respondents. As mentioned earlier, Kruskal-Wallis is a general test to see whether there are statistical significant differences or not between the response and the independent variables. Also, it does not specify where the significance is precisely located among the levels of the independent variable.

A compulsory step following Kruskal-Wallis test, if it signifies differences, is to conduct Kruskal-Wallis multiple comparisons to define where the differences are located between the levels of the independent variable. However, since there is a particular case here for the variable of gender as it has only two levels, general Kruskal-Wallis test is sufficient because multiple comparisons work for three or more levels.

From Table (4.15) which shows descriptive statistics of Kruskal-Wallis test, it can be concluded that male’s respondents have more significance on the response factor of fear appeals since Mean Rank for males = 85.3 > Overall Mean Rank = 76.0.

Table (4.15): Descriptive Statistics of Kruskal-Wallis test (Gender vs. Fear Appeals)

Gender	N	Median	Mean Rank	Z-Value
Male	67	2	**85.3**	2.32
Female	84	2	68.6	-2.32
Overall	151		76.0	

Since the fear appeal is described as a persuasion method, this result disagrees with O'Keefe (2002) study which indicates that gender plays a role in convincing, and it is easier to convince females to change their mind about something than males.

4.2.1.5 Statistical Differences among Respondents According to their Gender in Effort Expectancy

Shapiro–Wilk test is revealed a non-normality distribution of the residuals resulting from ANOVA with P-value < 0.05. So, there is a need to use Kruskal-Wallis as a non-parametric test to discover the statistical significant differences. This test outputs a P-value = 0.339 which is greater than the significance level $\alpha = 0.05$, and this leads to the conclusion that there are no statistical significant differences among HR Professionals according to their gender in recognizing effort expectancy as a factor affecting the individual acceptance and adoption of HR Analytics.

This result conflicts many prior studies which indicate that women are considering effort expectancy more than men do (Bem and Allen, 1974; Bozionelos, 1996; Venkatesh et al., 2012).

4.2.1.6 Statistical Differences among Respondents According to their Gender in Performance Expectancy

Using Shapiro–Wilk test, a not normal distribution of the residuals resulting from ANOVA with P-value < 0.05. Then, Kruskal-Wallis test generates a P-value = 0.340 > 0.05 and this value indicates no statistical significant differences are found between males and females respondents in recognizing performance expectancy as a factor affecting the individual acceptance and adoption of HR Analytics.

4.2.1.7 Statistical Differences among Respondents According to their Gender in Self- Efficacy

Shapiro–Wilk test results in a not normal distribution of the residuals resulting from ANOVA with P-value < 0.05. Besides, Kruskal-Wallis test with a P-value = 0.123 > significance level of 0.05 denotes the differences between the medians are not statistically significant, and you do not have enough evidence to reject the null hypothesis that the population medians are all equal. So that, there are no statistical differences among respondents according to their gender in the factor of self-efficacy.

4.2.1.8 Statistical Differences among Respondents According to their Gender in Quantitative Self-Efficacy

ANOVA results in normally distributed residuals (P-value > 0.05). So, this leads to the decision of using ANOVA to test the statistical differences. Table (4.16) shows a P-value = 0.001 which is less than the significance level α of 0.05, and this indicates there are statistical significant differences.

Table (4.16): ANOVA Test for Gender Differences among Participants in Quantitative Self-Efficacy

Source	DF	Adj Sum of Squares	Adj Mean of Squares	F-Value	P-Value
Gender	1	4.797	4.7975	12.12	**0.001**
Error	149	58.977	0.3958		
Total	150	63.774			

As aforementioned, ANOVA is a general test used to decide if there are statistical differences or not and it does not pinpoint where do precisely these differences occurred among respondents. This leads up to use Fisher Pairwise Comparisons as a subtest within ANOVA to specify the differences. Table (4.17) figures the results of Fisher Test.

Table (4.17): Fisher Pairwise Comparisons Test Gender Differences among Participants in Quantitative Self-Efficacy

Gender	N	Mean	Grouping
Male	67	3.5473	A
Female	84	3.1885	B

*Means that do not share a letter are significantly different

As shown in Table (4.17), there are significant differences between male and female in recognizing quantitative self-efficacy as a factor affecting the acceptance and adoption of HR Analytics. Male HR professionals are realized quantitative self-efficacy as a factor affecting acceptance and adoption of HR Analytics a little more than female HR professionals; as the Mean (Male) = 3.5473 > Mean (Female) = 3.1885.

This result contradicts the study done by Hendel (1980) that suggest there are no differences based on gender when using quantitative measures. On the other hand, the result agrees with other studies that indicate males are better in quantitative performance than females (Boyd and Crawford, 2011; Talukder and Quazi, 2011).

4.2.2 Statistical differences According to Age

4.2.2.1 Statistical Differences among Respondents According to their Age in Social Influence

First, One-way ANOVA test is conducted. Then, Shapiro–Wilk testing the normality of residuals resulting from ANOVA and it reveals a P-value > 0.05 which means a normal distribution of residuals and a decision to stay at ANOVA to test the statistical differences.

The results in table (4-18) show that there are no statistical significant differences between the three age groups of respondents in recognizing social influence as a factor affecting the acceptance and adoption of HR Analytics with P-value = 0.549 > 0.05.

Table (4.18): ANOVA Test for Age Differences among Participants in Social Influence

Source	DF	Adj Sum of Squares	Adj Mean of Squares	F-Value	P-Value
Age	2	0.3746	0.1873	0.60	**0.549**
Error	148	46.0143	0.3109		
Total	150	46.3889			

4.2.2.2 Statistical Differences among Respondents According to their Age in Resource Availability

As Shapiro–Wilk test for normality of residuals resulting from ANOVA finds out a non-normal distribution with P-value < 0.05, Kruskal-Wallis test is conducted as a non-parametric test to discover the significant differences. This non-parametric test with P-value = 0.238 > 0.05, points the result that there are no statistical significant differences among respondents according to their age in recognizing resource availability as a factor affecting the acceptance and adoption of HR Analytics.

4.2.2.3 Statistical Differences among Respondents According to their Age in Data Availability

One-way ANOVA test is used at first and then Shapiro–Wilk test is applied to check the normality of resulting residuals. The normality test gives a P-value < 0.05 which means a non-normal distribution of residuals and this results leads to using Kruskal-Wallis test. This test is resulting in a P-value = 0.901 > 0.05, and this value indicates that there are no statistical significant differences among respondents according to their age groups in recognizing data availability as a factor affecting the acceptance and adoption of HR Analytics.

4.2.2.4 Statistical Differences among Respondents According to their Age in Fear Appeals

Shapiro–Wilk test is used after ANOVA to test the normality of residuals resulting from ANOVA. This normality test reveals a not normally distributed residuals, and this result indicates the need for using Kruskal-Wallis as a non-parametric test to outline the statistical differences among respondents. The results from Kruskal-Wallis indicate that there are no statistical significant differences between age groups in recognizing fear appeals as a factor affecting acceptance and adoption of HR Analytics (P-value = 0.069 > 0.05).

4.2.2.5 Statistical Differences among Respondents According to their Age in Effort Expectancy

One-way ANOVA test is used to outline the statistical differences among respondents as the normality test indicates a normal distribution of residuals resulting from ANOVA.

Table (4.19): ANOVA Test for Age Differences among Participants in Effort Expectancy

Source	DF	Adj Sum of Squares	Adj Mean of Squares	F-Value	P-Value
Age	2	1.891	0.9454	2.84	**0.061**
Error	148	49.225	0.3326		
Total	150	51.116			

The results in Table (4.19) show that P-value = 0.061 > 0.05, which means there are no statistical significant differences among respondents according to their age groups in recognizing effort expectancy as a factor affecting the acceptance and adoption of HR Analytics.

4.2.2.6 Statistical Differences among Respondents According to their Age in Performance Expectancy

The normality test of residuals resulting from ANOVA resulting in a not normal distribution with P-value < 0.05. This result leads to the decision of using Kruskal-Wallis test to outline the statistical differences among respondents. Kruskal-Wallis test gives a P-value = 0.164 > 0.05 and this pinpoints the result that there are no statistical significant differences between age groups of respondents in recognizing performance expectancy as a factor affecting the acceptance and adoption of HR Analytics.

4.2.2.7 Statistical Differences among Respondents According to their Age in Self-Efficacy

Shapiro–Wilk test is used after ANOVA to test the normality of residuals resulting from ANOVA. This normality test reveals a not normally distributed residuals, and this result indicates the need for using Kruskal-Wallis as a non-parametric test to outline the statistical differences among respondents. The results from Kruskal-Wallis indicate that there are statistical significant differences between age groups in recognizing self-efficacy as a factor affecting acceptance and adoption of HR Analytics (P-value = 0.011 < 0.05). Table (4.20) shows the descriptive statistics of Kruskal-Wallis test and also it shows the different median values for each age group as this test is a non-parametric test (median test).

Table (4.20): Descriptive Statistics of Kruskal-Wallis test Age Differences among Participants in Self-Efficacy

Age	**N**	**Median**	**Mean Rank**	**Z-Value**
less than 35 years	98	4.0	69.1	-2.62
35- less than 45 years	44	4.1	84.9	1.61
more than 45 years	9	4.4	107.1	2.20
Overall	151		76.0	

As mentioned earlier, Kruskal Wallis is an overall test statistic that enables one to test the general hypothesis that all population medians are equal. On the other hand, the researcher is not extremely interested in this general hypothesis but is interested in comparisons amongst the individual groups. The macro function performs multiple comparisons in a nonparametric setting through conducting Bonferroni test. The following data and tables show the results from Kruskal-Wallis all pairwise comparisons (Bonferroni test).

Number of Comparisons being made: 3

Number of Ties: 137

The Family Alpha: 0.2

The Bonferroni Individual Alpha (works as the significance level here): **0.067**

Bonferroni Z-value (2-sided): 1.834

Table (4.21): Descriptive Statistics of Kruskal-Wallis all pairwise comparisons for Age Differences among Participants in Self-Efficacy

Sample	N	Median
Self-efficacy_ less than 35 years	98	4.0
Self-efficacy_ more than 45 years	9	4.4
Self-efficacy _35- less than 45 years	44	4.1

Table (4.22): Conclusions of Kruskal-Wallis all pairwise for Age Differences among Participants in Self-Efficacy

Groups	Z vs. Critical value	P-value
less than 35 years **vs.** more than 45 years	2.52350 >= 1.834	**0.0116**
less than 35 years **vs.** 35- less than 45 years	2.01124 >= 1.834	**0.0443**

The results in Table (4.22) show that there are statistical significant differences between respondents in the age group of (less than 35 years) and the third age group of (more than 45 years) since the P-value = 0.0116 < the Bonferroni individual alpha = 0.067. Also, there are statistical significant differences between respondents in the age less than 35 years and the second age group of (35- less than 45 years) as the P-value = 0.0443 < the Bonferroni individual alpha = 0.067 in recognizing self-efficacy as a factor affecting the acceptance and adoption of HR Analytics.

4.2.2.8 Statistical Differences among Respondents According to their Age in Quantitative Self-Efficacy

One-way ANOVA test is used. Then, Shapiro–Wilk test is conducted to check the normality of residuals resulting from ANOVA. It reveals a P-value > 0.05 which means a normal distribution of residuals and a decision to stay at ANOVA to outline the statistical differences.

The results in Table (4.23) show that there are no statistical significant differences between the three age groups of respondents in recognizing quantitative self-efficacy as a factor affecting the acceptance and adoption of HR Analytics P-value = 0.055 > 0.05.

Table (4.23): ANOVA Test for Age Differences among Participants in Quantitative Self-Efficacy

Source	DF	Adj Sum of Squares	Adj Mean of Squares	F-Value	P-Value
Age	2	2.452	1.2260	2.96	**0.055**
Error	148	61.322	0.4143		
Total	150	63.774			

4.2.3 Statistical differences According to Qualification

Following the same procedure, as the two previous main sections, in analyzing the statistical differences among respondents, Table (4.24) summarizes the results for statistical differences among respondents according to their qualification.

Table (4.24) shows there are statistical differences among respondents according to their qualification in recognizing the both factor: effort expectancy (P-value = 0.017 < 0.05) and performance expectancy (P-value= 0.043 < 0.05) as factors affecting the acceptance and adoption of HR Analytics.

Regarding the statistical differences among respondents according to their qualification in effort expectancy, Kruskal-Wallis Pairwise Comparisons conclude that there are statistical differences between the respondents who hold a Bachelor's degree qualification and those respondents who hold Diploma or below qualification in recognizing effort expectancy as a factor affecting the acceptance and adoption of HR Analytics (P-value = 0.0057 < the Bonferroni individual alpha = 0.067). Also, the comparisons found there are statistical differences between respondents who hold Master's degree qualification and those respondents who hold Diploma or below qualification (P-value = 0.0084 < the Bonferroni individual alpha = 0.067).

Related to the statistical differences among respondents according to their qualification in performance expectancy, Kruskal-Wallis Pairwise Comparisons point out that there are statistical differences between the respondents who hold a Bachelor's degree qualification and those respondents who hold Diploma or below qualification in recognizing performance expectancy as a factor affecting the acceptance and adoption of HR Analytics (P-value = 0.0136 < the Bonferroni individual alpha = 0.067). In the same vein, the comparisons found there are statistical differences between respondents who hold Master's degree qualification and those respondents who hold Diploma or below qualification (P-value = 0.0240 < the Bonferroni individual alpha = 0.067).

Table (4.24): Independent Samples test for Qualification Differences

Independent variable	Qualification	
	P-Value	**Test**
Social Influence	0.075	One-way ANOVA
Resource Availability	0.997	Kruskal-Wallis
Data Availability	0.497	Kruskal-Wallis
Fear Appeals	0.454	Kruskal-Wallis
Effort Expectancy	**0.017**	Kruskal-Wallis
Performance Expectancy	**0.043**	Kruskal-Wallis
Self-Efficacy	0.258	Kruskal-Wallis
Quantitative Self-Efficacy	0.613	One-way ANOVA
Note: the difference is significant at the 0.05 level		

4.2.4 Statistical differences According to Certification

The results in Table (4.25) show that there are no statistical significant differences are found among respondents according to having a certification in HR or not in any factor affecting the acceptance and adoption of HR Analytics. This table shows this result as the P-values > 0.05 for all mentioned factors.

Table (4.25): Independent Samples test for Certification Differences

Independent variable	Certification	
	P-Value	**Test**
Social Influence	0.390	One-way ANOVA
Resource Availability	0.818	Kruskal-Wallis
Data Availability	0.950	Kruskal-Wallis
Fear Appeals	0.084	Kruskal-Wallis
Effort Expectancy	0.893	Kruskal-Wallis
Performance Expectancy	0.631	Kruskal-Wallis
Self-Efficacy	0.738	One-way ANOVA
Quantitative Self-Efficacy	0.111	One-way ANOVA
Note: the difference is significant at the 0.05 level		

4.2.5 Statistical differences According to Current Position

Table (4.26) shows that there are no statistical significant differences between respondents' current position groups in recognizing each factor affecting the acceptance and adoption of HR Analytics (all P-values > 0.05).

Table (4.26): Independent Samples test for Current Position

Independent variable	Current Position	
	P-Value	**Test**
Social Influence	0.895	One-way ANOVA
Resource Availability	0.308	Kruskal-Wallis
Data Availability	0.420	Kruskal-Wallis
Fear Appeals	0.691	Kruskal-Wallis
Effort Expectancy	0.169	Kruskal-Wallis
Performance Expectancy	0.214	Kruskal-Wallis
Self-Efficacy	0.160	One-way ANOVA
Quantitative Self-Efficacy	0.545	One-way ANOVA
Note: the difference is significant at the 0.05 level		

4.2.6 Statistical differences According to Functional Area

There are no statistical significant differences among respondents according to their functional area at their position in recognizing each factor affecting the acceptance and adoption of HR Analytics. Table (4.27) shows this result since P-values > 0.05 for all factors.

Table (4.27): Independent Samples test for Functional Area

Independent variable	Functional Area	
	P-Value	**Test**
Social Influence	0.795	One-way ANOVA
Resource Availability	0.087	Kruskal-Wallis
Data Availability	0.243	Kruskal-Wallis
Fear Appeals	0.104	Kruskal-Wallis
Effort Expectancy	0.247	Kruskal-Wallis
Performance Expectancy	0.312	Kruskal-Wallis
Self-Efficacy	0.476	Kruskal-Wallis
Quantitative Self-Efficacy	0.467	One-way ANOVA
Note: the difference is significant at the 0.05 level		

4.2.7 Statistical differences According to Number of Years at Position

The results in Table (4.28) show that there are statistical significant differences between respondents according to their years at the position in the factors of social influence, effort expectancy and quantitative self-efficacy since all the P-values for these three factors are less than the significance level of 0.05.

To specify the statistical differences among respondents according to their number of years at the position in the factor of social influence, Fisher Pairwise Comparisons are used as a post hoc test in ANOVA. Fisher test outlines that both respondents who are at their positions for more than 10 years (Mean =3.882) and for less than 5 years (Mean =3.7500) are recognized social influence as a factor affecting the acceptance and adoption of HR Analytics more than those who are at their positions for the period between 5 to 10 years (Mean = 3.4609).

To investigate more the statistical differences among respondents according to their number of years at the position in effort expectancy, Kruskal-Wallis all pairwise comparisons are used as a post hoc test in the non-parametric Kruskal-Wallis test. These pairwise comparisons reveal statistical differences between respondents who are at their positions for the period between 5 to 10 years and those respondents who are at their positions for more than 10 years (P-value = 0.0184 < the Bonferroni individual alpha = 0.067) and between respondents who are at their positions for the period less than 5 years and those who are at their positions for the period between 5 to 10 years ((P-value = 0.0611 < the Bonferroni individual alpha = 0.067) in recognizing effort expectance as a factor affecting the acceptance and adoption of HR Analytics.

Related to the statistical differences among respondents according to their number of years at position in quantitative self-efficacy, Kruskal-Wallis all pairwise comparisons result in a conclusion that there are statistical significant differences between respondents who are at their positions for less than 5 years and those who are at their positions for more than 10 years in recognizing quantitative self-efficacy as a factor affecting the acceptance and adoption of HR Analytics (P-value = 0.0033 < the Bonferroni individual alpha = 0.067).

Table (4.28): Independent Samples test for Number of Years at Position

Independent variable	Number of Years at Position	
	P-Value	**Test**
Social Influence	**0.004**	One-way ANOVA
Resource Availability	0.933	Kruskal-Wallis
Data Availability	0.433	Kruskal-Wallis
Fear Appeals	0.681	Kruskal-Wallis
Effort Expectancy	**0.039**	Kruskal-Wallis
Performance Expectancy	0.871	Kruskal-Wallis
Self-Efficacy	0.232	One-way ANOVA
Quantitative Self-Efficacy	**0.007**	Kruskal-Wallis
Note: the difference is significant at the 0.05 level		

4.2.8 Statistical differences According to HR Experience

The results in Table (4.29) indicate that there are statistical significant differences among respondents according to their HR experience in recognizing effort expectancy as a factor affecting the acceptance and adoption of HR Analytics (P-value = 0.029 < 0.05).

Kruskal-Wallis pairwise comparisons are conducted to outline these differences between the HR experience groups. The results indicate that the statistical differences are between the respondents who have less than five years' experience and those who have years of experience between five and ten years in recognizing effort expectancy as a factor affecting the acceptance and adoption of HR Analytics (P-value= 0.008 < the Bonferroni individual alpha = 0.067).

Table (4.29): Independent Samples test for HR Experience

Independent variable	HR Experience	
	P-Value	**Test**
Social Influence	0.236	One-way ANOVA
Resource Availability	0.795	Kruskal-Wallis
Data Availability	0.094	Kruskal-Wallis
Fear Appeals	0.936	Kruskal-Wallis
Effort Expectancy	**0.029**	Kruskal-Wallis
Performance Expectancy	0.284	Kruskal-Wallis
Self-Efficacy	0.142	Kruskal-Wallis
Quantitative Self-Efficacy	0.094	One-way ANOVA
Note: the difference is significant at the 0.05 level		

4.2.9 Statistical differences According to Industrial Sector

There are statistical significant differences among respondents according to their industrial sector in recognizing fear appeals as a factor affecting the acceptance and adoption of HR Analytics. Table (4.30) shows this result with P-value = 0.000 < 0.05 corresponds to fear appeals factor.

Following ANOVA, Fisher Pairwise Comparisons are used to outline the differences between industrial sectors. Table (4.31) shows the results of Fisher test. Since this test depends on the conclusion that Means that do not share a letter are significantly different, the results indicate that there are statistical significant difference between telecommunication and the other industries of (paper, aluminum, plastic industries) since these sectors have the same group of letter A and the sectors of hospitals, food industry, cars trading, internet provider as these industries have the same group of letter D.

Table (4.30): Independent Samples Test for Industrial Sector Differences

Independent variable	Number of Years at Position	
	P-Value	**Test**
Social Influence	0.448	One-way ANOVA
Resource Availability	0.934	Kruskal-Wallis
Data Availability	0.377	Kruskal-Wallis
Fear Appeals	**0.000**	One-way ANOVA
Effort Expectancy	0.056	Kruskal-Wallis
Performance Expectancy	0.209	Kruskal-Wallis
Self-Efficacy	0.198	Kruskal-Wallis
Quantitative Self-Efficacy	0.497	One-way ANOVA
Note: the difference is significant at the 0.05 level		

Table (4.31): Fisher Pairwise Comparisons Test Industrial Sector Differences among Participants in Fear Appeals

Industry sector	N	Mean	Grouping			
Telecommunication	40	**2.700**	**A**			
Electricity Provider	4	2.667	A	B	C	
Other industries (paper, aluminum, plastic industries)	12	**2.583**	**A**			
Logistics	2	2.167	A	B	C	D
Banking	48	1.924			C	D
Insurance	15	1.822		B	C	D
Pharmaceutical industry	3	1.778	A	B	C	D
Hospitals	7	**1.571**				**D**
Food industry	10	**1.567**				**D**
Cars trading	6	**1.389**				**D**
Internet provider	4	**1.333**				**D**

*Means that do not share a letter are significantly different.

4.2.9 Statistical differences According to Number of Employees

The results in Table (4.32) show that there are statistical significant differences among respondents according to the number of employees in their enterprises in recognizing the following factors; resource availability, fear appeals, performance expectancy, self-efficacy, and quantitative self-efficacy as factors affecting the acceptance and adoption of HR Analytics.

Kruskal-Wallis pairwise comparisons are used to outline the differences between the number of employees' groups in recognizing the factor of resource availability. The results indicate that there are statistical significant differences between the respondents whose enterprises size is (100-less than 500 employees) and those whose their size of enterprises is (less than 50 employees). This result is concluded since the comparison between these two groups of enterprises' sizes gives a P-value = 0.0122 < Bonferroni individual alpha = 0.02.

Since there are many significant differences between comparisons according to the respondents' enterprises size (in terms of number of employees) in recognizing fear appeals as a factor affecting the acceptance and adoption of HR Analytics, Table (4.33) summarizes these significant differences between the number of employees groups that are resulted in P-values < Bonferroni individual alpha = 0.02.

Table (4.34) shows the results of Kruskal-Wallis all pairwise comparisons between the number of employees groups in recognizing the factor of performance expectancy. All the P-values are less than Bonferroni individual alpha of 0.02 which means there are statistical significant differences between the listed groups related to the number of employees.

The results in Table (4.35) show Fisher pairwise comparisons test between the numbers of employees groups in recognizing self-efficacy as a factor affecting the acceptance and adoption of HR Analytics. Fisher test indicates that Means that do not share a letter are significantly different and this appears in the table as the result of three letters groups A, B, and C as these groups have significant statistical differences.

Related to the factor of quantitative self-efficacy, Table (4.36) summarizes the results of Fisher pairwise comparisons test regarding the number of employees' groups' differences. The results indicate there are statistical significant differences between respondent in enterprises size of (1000 and more) employees, (500- less than 1000) employees (these two groups have a Mean group A) and those works at the enterprises with the size of (100- less than 500) employees (with Mean group B).

Table (4.32): Independent Samples Test for Number of Employees Differences

Independent variable	**Number of Employees**	
	P-Value	**Test**
Social Influence	0.347	One-way ANOVA
Resource Availability	**0.040**	Kruskal-Wallis
Data Availability	0.745	Kruskal-Wallis
Fear Appeals	**0.000**	Kruskal-Wallis
Effort Expectancy	0.107	Kruskal-Wallis
Performance Expectancy	**0.002**	Kruskal-Wallis
Self-Efficacy	**0.009**	One-way ANOVA
Quantitative Self-Efficacy	**0.039**	One-way ANOVA
Note: the difference is significant at the 0.05 level		

Table (4.33): Conclusions of Kruskal-Wallis all pairwise comparisons for Number of Employees Differences among Participants in Fear Appeals

Groups (Number of Employees)	**Z vs. Critical value**	**P-value**
(100- less than 500) **vs.** (1000 and more) employees	4.49772 >= 2.326	**0.0000**
(500- less than 1000) vs. (1000 more) employees	4.36566 >= 2.326	**0.0000**
(50- less than 100) vs. (1000 more) employees	3.42870 >= 2.326	**0.0006**

*Bonferroni Z-value (2-sided) = 2.326, Bonferroni Individual Alpha = 0.02

Table (4.34): Conclusions of Kruskal-Wallis all pairwise comparisons for Number of Employees Differences among Participants in Performance Expectancy

Groups (Number of Employees)	**Z vs. Critical value**	**P-value**
(100- less than 500) **vs.** (500- less than 1000) employees	3.06062 >= 2.326	**0.0022**
(100- less than 500) **vs.** (1000 and more) employees	2.98316 >= 2.326	**0.0029**
(50- less than 100) **vs.** (500- less than 1000) employees	2.46165 >= 2.326	**0.0138**
(50- less than 100) **vs.** (1000 and more) employees	2.39120 >= 2.326	**0.0168**

*Bonferroni Z-value (2-sided) = 2.326, Bonferroni Individual Alpha = 0.02

Table (4.35): Fisher Pairwise Comparisons Test Number of employees Differences among Participants in Self-Efficacy

Number of Employees	N	Mean	Grouping		
(50- less than 100) employees	22	4.218	**A**		
(100- less than 500) employees	36	4.1167	**A**		
(500- less than 1000) employees	45	3.9689	A	B	
(1000 and more) employees	46	3.8696		**B**	
(less than 50) employees	2	3.100			**C**

*Means that do not share a letter are significantly different.

Table (4.36): Fisher Pairwise Comparisons Test Number of employees Differences among Participants in Quantitative Self-Efficacy

Number of Employees	N	Mean	Grouping	
(1000 and more) employees	46	3.4928	**A**	
(500- less than 1000) employees	45	3.4148	**A**	
(50- less than 100) employees	22	3.394	A	B
(less than 50) employees	2	3.083	A	B
(100- less than 500) employees	36	3.065		**B**

*Means that do not share a letter are significantly different.

4.2.10 Statistical differences According to Various Demographic Variables on the Acceptance and Adoption of HR Analytics at the Individual level among HR Professionals.

The results in Table (4.37) show that there are no statistical significant differences among respondents according to the demographic variables, on the individual level of the acceptance and adoption of HR Analytic, except for gender, age and functional area, since these three variables have P-values < 0.05.

Kruskal-Wallis test with P-value = 0.004 < 0.05 indicates that there are statistical differences between respondents according to their gender on the individual level of the acceptance and adoption of HR Analytics. The test also shows male respondents are more interested in the individual acceptance and adoption of HR Analytics (Mean Rank = 87.2 > Overall Mean = 76.0) than female respondents (Mean Rank = 67.1).

To some extent, this result regarding the effect of gender concurs with Talukder and Quazi (2011) since this study reveals that there is no typical pattern about the effect of gender role on the acceptance and adoption of an innovation in the workplace. Also, this study indicates that this result may be varying if there other factors affecting the acceptance and adoption, for example, if the perception of innovation is considered concerning social factors, males and females have the same perceptions. While if the acceptance and adoption depend on computational skills, males have these skills more than females (Boyd and Crawford, 2011). Hence, the gender differentiation plays a role in the acceptance and adoption of HR Analytics based on the factor that takes place.

Related to the age as another demographic variable, and following ANOVA, Fisher Pairwise test shows that there are statistical differences between respondents on the individual level of the acceptance and adoption of HR Analytics. The respondents in the age group (from 35-45 years) are a little more interested in the acceptance and adoption of HR Analytics at the individual level (Mean = 4.318) than the respondents whose ages are less than 35 years (Mean = 4.0561).

Moreover, one-way ANOVA test indicates that there are statistical differences between the respondents according to their functional area at

HR department on the individual level of the acceptance and adoption of HR Analytics. Fisher Pairwise Comparisons reveal that there are differences between the respondents who work at training/development as a functional area (Mean = 4.3476) and those who work at both employee relations (Mean = 4.0455) and data and information Management (Mean = 3.867).

This result may reflect that the individuals who are working at training/ development are more familiar with innovations and technologies since there work needs to do that; to improve their employees' skills and update them to enhance the business performance.

Table (4.37): Statistical differences Test According to Demographic variables on the Individual level of the Acceptance and Adoption of HR Analytics

Demographic Variable	**The individual level of the Acceptance and Adoption Individual level of the Acceptance and Adoption**	
	P-value	**Test**
Gender	**0.004**	Kruskal-Wallis
Age	**0.029**	One-way ANOVA
Qualification	0.121	One-way ANOVA
Certification	0.753	One-way ANOVA
Current position	0.310	Kruskal-Wallis
Functional area	**0.021**	One-way ANOVA
Number of years at the position	0.492	One-way ANOVA
HR experience	0.150	One-way ANOVA
Industry sector (service vs. manufacturing)	0.514	One-way ANOVA
Number of employees	0.087	Kruskal-Wallis
Note: the difference is significant at the 0.05 level		

4.3 Hypotheses testing and HR Analytics' Acceptance and Adoption Framework in Large Palestinian Enterprises

Daniel and Cross (2010) define the hypothesis as a clear expression concerning one or more population. This expression is used to guide the researchers to get a conclusion belonging to the population after testing a sample of it.

In this research, both correlation and multiple regression are used as analysis types to test the research hypotheses that were formulated in Chapter 2.

4.3.1 Correlation Analysis

To determine if there is a significant relationship between the factors and whether they influence the acceptance and adoption of HR Analytics in Large Palestinian Enterprises among HR Professionals; the questionnaire's responses are analyzed in accordance with the research. For this purpose, Pearson Correlation Matrix and Coefficients are used.

The results in Table (4.38) show the values of Pearson correlation coefficient (r) which indicate the strength of correlation between the dependent and independent variables, from these values it is evident that the highest correlation is with self-efficacy while the lowest correlation is with social influence. This table also presents the significant P-values, all the P-values are less than the significant level of 0.05 except for the factor fear appeals which means there is no correlation only between this factor and the individual acceptance and adoption of HR Analytics. All other seven factors have significant and positive correlations as the last column shows the type of correlation.

Table (4.38): Correlation Coefficients of the Factors (Individual Level of the Acceptance & Adoption)

Independent variable	**Dependent variable**		
	Individual Acceptance & Adoption of HR Analytics		
	Pearson corr. (r)	**P-value**	**Type of Correlation**
Social Influence	0.202	**0.013**	Positive
Resource Availability	0.335	**0.000**	Positive
Data Availability	0.264	**0.001**	Positive
Fear Appeals	-0.118	0.149	No correlation
Effort Expectancy	0.359	**0.000**	Positive
Performance Expectancy	0.417	**0.000**	Positive
Self-Efficacy	0.519	**0.000**	Positive
Quantitative Self-Efficacy	0.306	**0.000**	Positive
Note: correlation is significant at the 0.05 level (2-tailed)			

Figure (4.1) and Table (4.39) show the results of Pearson Correlations Matrix mainly between the independent variables and at the last row between these independent and dependent variables. The purpose of investigating the correlations between the independent variables is to ensure that there is no multicollinearity exists between them before developing the conceptual framework of the acceptance and adoption of HR Analytics at the individual level. The results in Table (4.39) show that at the given significance level of 0.05, all the independent factors are significantly correlated to each other and to a reasonable degree that does not affect the validity. The correlation coefficients values between the independent variables are less than 0.9, so this leads to the conclusion that there is no multicollinearity exist between them (Hair et al., 2010; Chong et al., 2009).

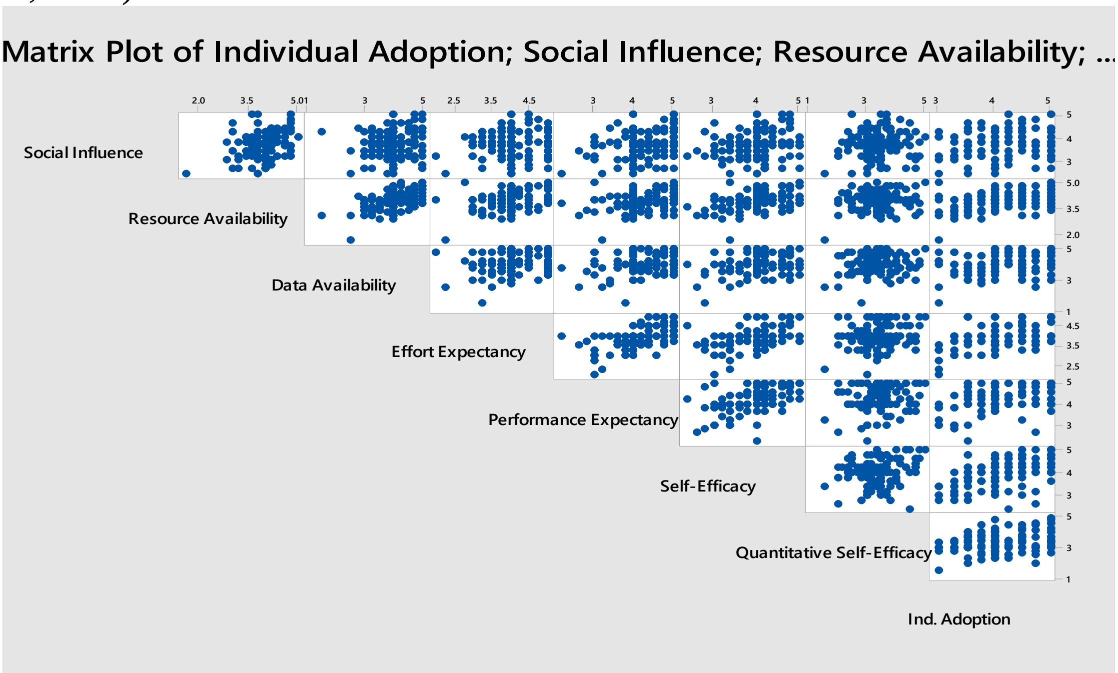

Figure (4.1): Matrix Plot of Relationships among the Variables

Table (4.39): The Pearson Correlations Matrix

Factor	Social Influence	Resource Availability	Data Availability	Fear Appeals	Effort Expectancy	Performance Expectancy	Self-Efficacy	Quantitative Self-Efficacy
Resource Availability	0.293 0.000							
Data Availability	0.131 0.110	0.551 0.000						
Fear Appeals	0.031 0.704	-0.116 0.155	-0.205 0.012					
Effort Expectancy	0.087 0.286	0.342 0.000	0.144 0.078	-0.081 0.325				
Performance Expectancy	0.269 0.001	0.350 0.000	0.283 0.000	-0.252 0.002	0.625 0.000			
Self-Efficacy	0.174 0.033	0.432 0.000	0.275 0.001	-0.186 0.022	0.565 0.000	0.574 0.000		
Quantitative Self-Efficacy	0.070 0.394	0.117 0.152	0.097 0.238	0.188 0.021	0.189 0.020	0.119 0.145	0.231 0.004	
Individual Acceptance & Adoption	**0.202** **0.013**	**0.335** **0.000**	**0.264** **0.001**	**-0.118** **0.149**	**0.359** **0.000**	**0.417** **0.000**	**0.519** **0.000**	**0.306** **0.000**

*Cell Contents

Pearson correlation

P-Value

While the basis of this study is to investigate the individual level of the acceptance and adoption of HR Analytics among HR professionals, it is important to note the effect of the studied factors on the organizational level of the acceptance and adoption. Table (4.40) shows the correlation between the independent variables and organizational level of the acceptance and adoption of HR Analytics.

The results show that there is a correlation between the organizational level of the acceptance and adoption and the factors of resource availability, data availability, effort expectancy, performance expectancy, self-efficacy and quantitative self-efficacy. To some extent, these results are logical since the organization plays an essential role in enhancing the availability of resources regarding adequate skills, systems and software. Besides, the organizational contribution may affect the improvement of an existing general IT system to be integrated with HRIS to ensure proper data availability and facilitate the process of data analysis. Regarding the effort expectancy, self-efficacy, and quantitative self-efficacy, the organization also may contribute in improving the skills of their HR professionals through training them in different skills including analysis, statistical skills besides continuous learning to be updated with new technologies. Moreover, performance expectancy is correlated to organization level of acceptance and adoption since this factor is associated with the effectiveness of work and the organizational performance.

Otherwise, there is no correlation regarding social influence and fear appeals since these factors are linked to the individual behaviors; as to some extent he or she is affected by the surrounding social environment such as peers and managers, besides their ability to change their opinions and being convinced with something new.

Table (4.40): Correlation Coefficients of the Factors (Organizational Level of the Acceptance & Adoption)

Independent variable	**Dependent variable**		
	Organizational Acceptance & Adoption of HRA		
	Pearson corr. (r)	**P-value**	**Type of Correlation**
Social Influence	0.138	0.090	No correlation
Resource Availability	0.322	**0.000**	Positive
Data Availability	0.297	**0.000**	Positive
Fear Appeals	-0.047	0.570	No correlation
Effort Expectancy	0.404	**0.000**	Positive
Performance Expectancy	0.377	**0.000**	Positive
Self-Efficacy	0.365	**0.000**	Positive
Quantitative Self-Efficacy	0.270	**0.001**	Positive
Note: correlation is significant at the 0.05 level (2-tailed)			

Returning to the individual level of adoption, and based on the correlation analysis in hypotheses testing results. The hypotheses related the factors: social influence, resource availability, data availability, effort expectancy, performance expectancy, self-efficacy, quantitative self-efficacy are all supported except the hypothesis related to the factor fear appeal is rejected (P-value = 0.149 > 0.05). These results from correlations can lead to developing the framework for the acceptance and adoption of HR Analytics among HR professionals.

On the other hand, Abu-Shanab and Haider (2015) state that depending only on Pearson correlation analysis to test if all the independent variables jointly predict the dependent variable is not favorable. A typical demonstration of variance will be missing, and some factors will be less significant than others when variables are combined in the analysis. Furthermore, it is preferable to use multiple regression when the study has one dependent variable and various independent variables. The following section will clarify the regression analysis.

4.3.2 Multiple Regression Analysis

The multiple regression model is expressed as follows:

Response = constant + β1 predictor 1 + β2 predictor 2 + β3 predictor 3 + ... + βn predictor n + ε

In this research, the response is the individual acceptance and adoption of HR Analytics, and the predictors are the eight factors that affect the individual acceptance and adoption of HR Analytics.

The following will examine different models of multiple regression to find the best one that represents the response regarding the predicted factors.

- **Model 1: Individual Acceptance and Adoption of HR Analytics = Constant + β1 Social Influence+ β2 Resource Availability+ β3 Data Availability+ β4 Fear Appeals+ β5 Effort Expectancy+ β6 Performance Expectancy+ β7 Self-Efficacy+ β8 Quantitative Self-Efficacy+ ε**

Table (4.41) shows that this multiple regression, Model 1, with the eight factors: social influence, resource availability, data availability, fear appeals, effort expectancy, performance expectancy, self-efficacy and quantitative self-efficacy explain 30.91% from the variability in the acceptance and adoption of HR Analytics at the individual level (R^2 = 34.60%, Adjusted R^2= 30.91%).

Table (4.41): Model 1 Summary

Model number	S	R^2	Adjusted R^2	Predicted R^2
1	0.457011	34.60%	30.91%	24.35%
Regression Equation				
Individual Acceptance and Adoption = 0.990 + 0.0710 social influence + 0.0631 resource availability + 0.0616 data availability - 0.0274 fear appeals + 0.0195 effort expectancy + 0.1156 performance expectancy + 0.3252 self-efficacy + 0.1708 quantitative self-efficacy				

As an essential condition to approving the regression model, in addition to the regression coefficient R^2 value, is the normality of residuals resulting from the regression analysis. Shapiro–Wilk test is used to check the normality and Figure (4.2) shows non-normality distribution of residuals since the P-value = 0.038 < 0.05. So, this Model 1 is not considered as one of the candidate models that may represent the relationship between the response and the predicted variables.

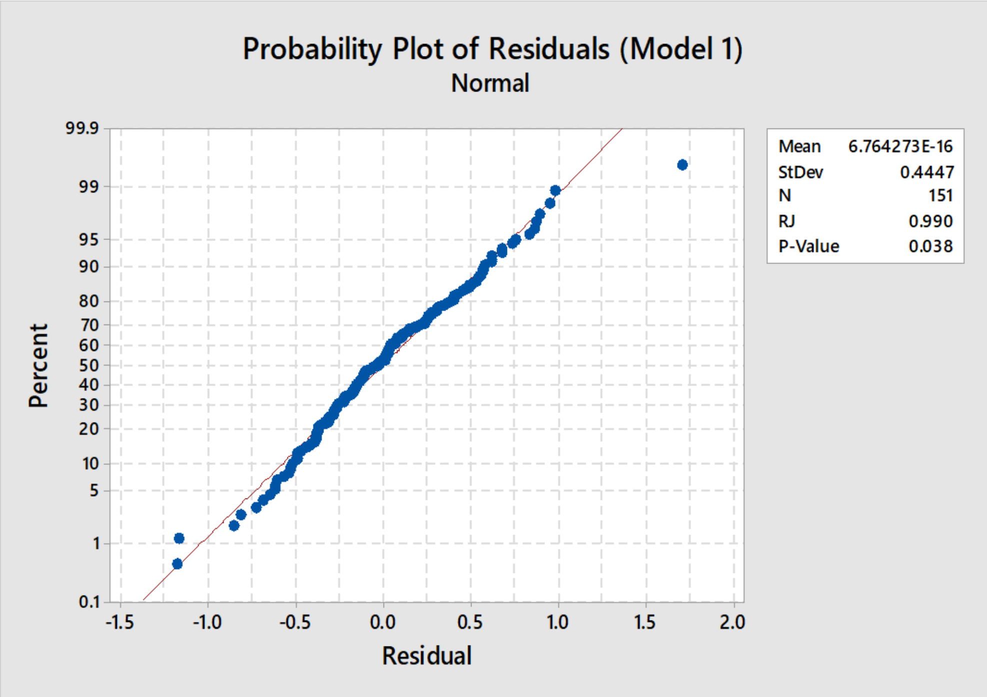

Figure (4.2): Normality Plot of Residuals (Model 1)

- **<u>Model 2</u>: Individual Acceptance and Adoption of HR Analytics = Constant + β1 Social Influence+ β2 Resource Availability+ β3 Data Availability+ β4 Effort Expectancy+ β5 Performance Expectancy+ β6 Self-Efficacy+ β7 Quantitative Self-Efficacy+ ε**

This multiple regression, Model 2 is developed by removing the factor fear appeals since the results from the correlation analysis indicate that there is no correlation exists between this factor and the response variable. This developed Model 2 with the seven factors: social influence, resource availability, data availability, effort expectancy, performance expectancy, self-efficacy and quantitative self-efficacy explain 31.22% from the variability in the acceptance and adoption of HR Analytics at the individual level (R^2 = 34.43%, Adjusted R^2= 31.22%). These results are shown Table (4.42).

Table (4.42): Model 2 Summary

Model number	**S**	**R^2**	**Adjusted R^2**	**Predicted R^2**
2	0.455995	34.43%	31.22%	25.18%
Regression Equation				
Individual Acceptance and Adoption = 0.907 + 0.0659 social influence + 0.0621 resource availability + 0.0681 data availability + 0.0139 effort expectancy + 0.1272 performance expectancy + 0.3316 self-efficacy + 0.1620 quantitative self-efficacy				

After that, Shapiro–Wilk test is conducted to check the normality of residuals. Figure (4.3) shows a not-normally distribution of the residuals resulting from regression model 2 with P-value = 0.032 < 0.05. So, this Model 2 is also not valid to be a candidate model to represent the relationship between the individual acceptance and adoption of HR Analytics and the suggested factors.

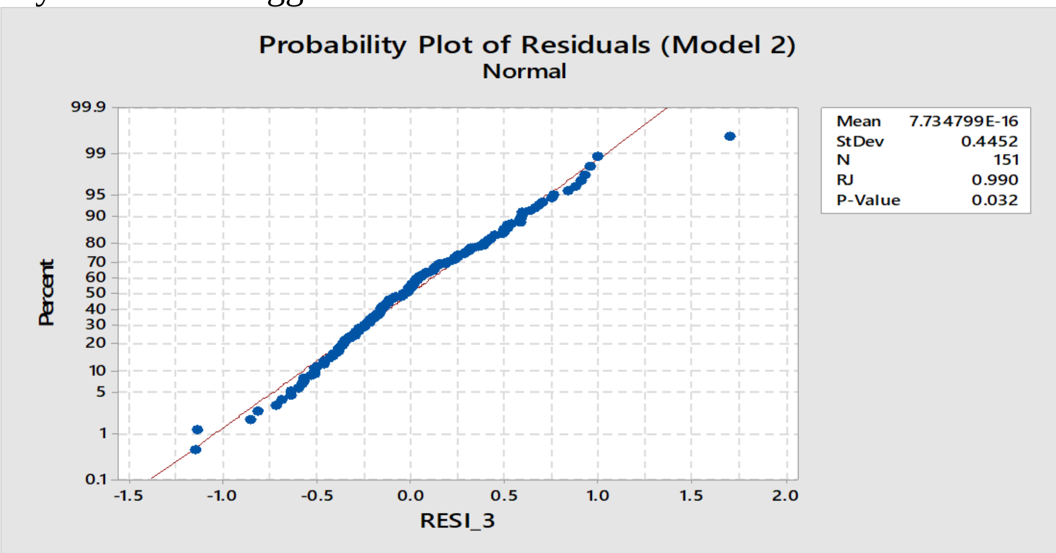

Figure (4.3): Normality Plot of Residuals (Model 2)

- **<u>Model 3</u>: Individual Acceptance and Adoption of HR Analytics = Constant + β1 Social Influence+ β2 Resource Availability+ β3 Data Availability+ β4 Effort Expectancy+ β5 Performance Expectancy+ β6 Self-Efficacy+ β7 Quantitative Self-Efficacy+ ε**

This multiple regression, Model 3 is similar to Model 2 but with one difference which is removing the outlier point that can be shown in the top right corner in the Figure (4.3) which is related to the residuals resulting from regression Model 2. This developed Model 3 with the seven factors: social influence, resource availability, data availability, effort expectancy, performance expectancy, self-efficacy and quantitative self-efficacy explain 38.26% from the variability in the acceptance and adoption of HR Analytics at the individual level (R^2 = 41.16%, Adjusted R^2= 38.26%). The results are shown in Table (4.43)**.**

Table (4.43): Model 3 Summary

Model number	**S**	**R^2**	**Adjusted R^2**	**Predicted R^2**
3	0.431652	41.16%	38.26%	34.00%
Regression Equation				
Individual Acceptance and Adoption = 0.487 + 0.0488 social influence + 0.0716 resource availability + 0.0981 data availability - 0.0362 effort expectancy + 0.1924 performance expectancy + 0.3622 self-efficacy + 0.1958 quantitative self-efficacy				

To approve the adequacy of Model 3. Shapiro–Wilk test is used to check the normality the normality of the residuals. Figure (4.4) shows the normal distribution of residuals with P-value > 0.1 and greater than the significance level 0.05. This makes Model 3 as a good candidate model for representing the relationship between the response (individual acceptance and adoption) and the independent variables. Tables (4.44) and (4.45) explain more about Model 3.

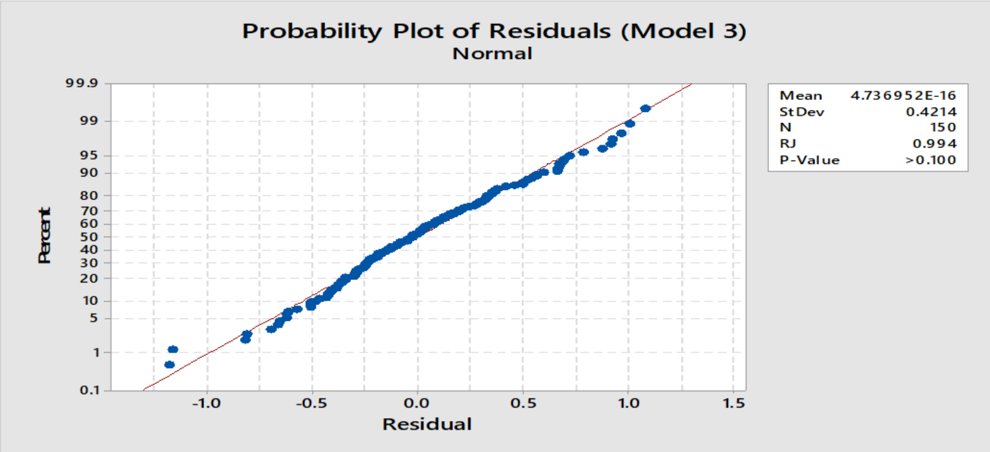

Figure (4.4): Normality Plot of Residuals (Model 3)

ANOVA test for the regression Model 3 is presented in Table (4.44). This test is conducted to test the null hypothesis for the overall regression Model 3 which is: the model does not explain any of the variations in the response variable (individual acceptance and adoption). The P-value is used to determine whether the model explains variation in the response. Since the P-value = 0.000 < significance level of 5 %, the null hypothesis is rejected and its concluded that the listed seven factors in Model 3 can explain the variation in the response and have an effect on it.

Table (4.44): ANOVA for Model 3

Source	**DF**	**Adj Sum of Squares**	**Adj Mean of Squares**	**F-Value**	**P-Value** (Significance level = 0.05)
Regression	7	18.5071	2.64386	14.19	**0.000**
Error	142	26.4579	0.18632		
Total	149	44.9650			

To investigate if there is a statistically significant association between the response variable (the acceptance and adoption of HR Analytics at the individual level) and each factor listed in Model 3, t- statistic test is used.

In other words, this t-test will determine which of the factors' coefficients β equal zero and consequently have no effect on the model.

Table (4.45) shows the P-value associated with T-value for each coefficient of all factors in the regression Model 3. Since the P-values are greater than the significance level of 5 % for the factors: social influence, resource availability, data availability and effort expectancy, the null hypothesis that the regression coefficients of these factors are equal zero can't be rejected, and it is concluded that there is no statistically significant association between the response variable and each term of these factors. Also, this means it is possible to refit the model without these factors.

On the other hand, the P-values are less than the significance level of 5 % for the factors: performance expectancy, self-efficacy and quantitative self-efficacy, this leads to rejecting null hypothesis that the regression coefficients of these factors are equal zero and concludes that there is a statistically significant association between the response variable and these three factors.

Also, Table (4.45) shows that the values of the Variance Inflation Factor (VIF). These values are used to describe how much multicollinearity (which is the correlation between the factors or the predictors) exists in a regression analysis. Multicollinearity is considered as a problematic indicator because it can increase the variance of the regression coefficients, making it difficult to evaluate the individual impact that each of the correlated predictors has on the response. All the values of VIF in Table (4.45) are ranging from 1.06 to 2.00, which indicate the reliability of the results; since these values do not exceed the upper limit value 5 (as the increase of VIF may suggest that the regression coefficient is poorly estimated due to severe multicollinearity).

Table (4.45): Regression Coefficients Results (Model 3)

Term	**Coefficient**	**SE Coefficient**	**T-Value**	**P-Value** (Significance level = 0.05)	**VIF**
Constant	0.487	0.411	1.18	0.238	
Social Influence	0.0488	0.0687	0.71	0.479	1.17
Resource Availability	0.0716	0.0944	0.76	0.449	1.74
Data Availability	0.0981	0.0729	1.35	0.181	1.46
Effort Expectancy	-0.0362	0.0852	-0.42	0.672	1.98
Performance Expectancy	0.1924	0.0876	2.20	**0.030**	2.00
Self-Efficacy	0.3622	0.0871	4.16	**0.000**	1.77
Quantitative Self-Efficacy	0.1958	0.0565	3.47	**0.001**	1.06

- **Model 4: Stepwise Regression**

Stepwise Regression is an automated tool used in the exploratory stages of model building to identify a useful subset of predictors. It consists of various steps. In each step, the process evaluates each variable inside the model to ensure that this variable will remain in the model based on a specific standard (Daniel and Cross, 2013)

As a first step, the factors; social influence, resource availability, data availability, effort expectancy, performance expectancy, self-efficacy and quantitative self-efficacy are entered into the stepwise regression process.

This process systematically adds the most significant variable or removes the least significant variable during each step.

This stepwise regression Model 4 adds the most significant variables (data availability, performance expectancy, self-efficacy and quantitative self-efficacy), and removes the least significant variables (social influence, resource availability and effort expectancy). Model 4 explains 38.85% from the variability in the acceptance and adoption of HR Analytics at the individual level (R^2 = 40.49%, Adjusted R^2= 38.85%). The results are shown in Table (4.46)**.**

Table (4.46): Model 4 Summary

Model number	**S**	**R^2**	**Adjusted R^2**	**Predicted R^2**	**α to enter**	**α to remove**
4	0.429572	40.49%	38.85%	36.65%	0.15	0.15
Regression Equation						
Individual Acceptance and Adoption = 0.660 + 0.1307 data availability + 0.1908 performance expectancy + 0.3684 self-efficacy + 0.1949 quantitative self-efficacy						

Furthermore, the normality of the residuals is checked using Shapiro–Wilk test. Figure (4.5) shows that the residuals from Model 4 have a normal distribution since the P-value is greater than 5 %. So, this Model 4 is qualified to be a proper candidate.

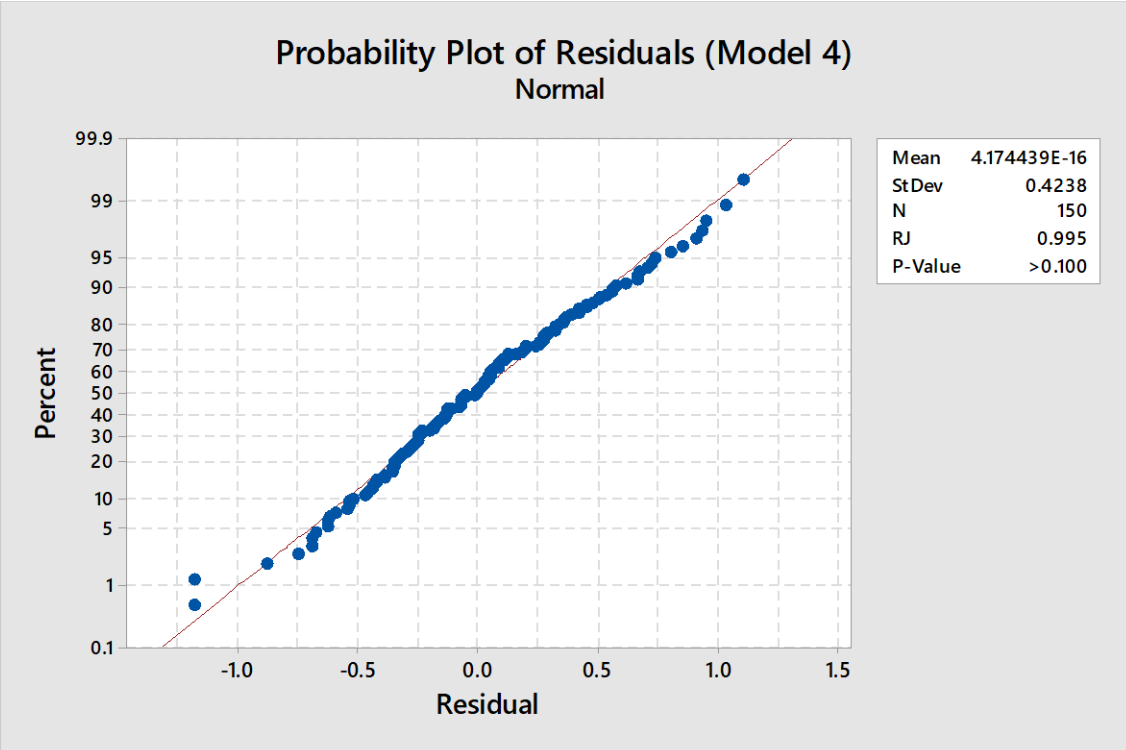

Figure (4.5): Normality Plot of Residuals (Model 4)

Moreover, Table (4.47) shows the results from ANOVA test for the regression Model 4. This test is conducted to check the null hypothesis for the overall regression model which is: the model does not explain any of the variations in the response. The P-value is used to determine whether the model explains variation in the response. Since the P-value = 0.000 < significance level of 5 %, the null hypothesis is rejected as this value means that the listed factors in Model 4 can explain the variation in the response and have an effect on it.

Table (4.47): ANOVA for Model 4

Source	DF	Adj Sum of Squares	Adj Mean of Squares	F-Value	P-Value (Significance level = 0.05)
Regression	4	18.2079	4.5520	24.67	**0.000**
Error	145	26.7571	0.1845		
Total	149	44.9650			

Table (4.48) shows the results of T-test and corresponding P-values. These results show that the null hypotheses that the regression coefficients are equal zero, for the factors data availability, performance expectancy, self-efficacy and quantitative self-efficacy, can be rejected since the P-values for the β coefficients are less than the significance level of 5 %.

Also, Table (4.44) shows that the VIF values are ranging from 1.04 to 1.52, which indicate the reliability of the results since the multicollinearity between the independent variables is in small values.

Table (4.48): Regression Coefficients Results (Model 4)

Term	Coefficient	SE Coefficient	T-Value	P-Value (Significance level = 0.05)	VIF
Constant	0.660	0.368	1.79	0.075	
Data Availability	0.1307	0.0626	2.09	**0.039**	1.08
Performance Expectancy	0.1908	0.0747	2.55	**0.012**	1.47
Self-Efficacy	0.3684	0.0803	4.59	**0.000**	1.52
Quantitative Self-Efficacy	0.1949	0.0558	3.49	**0.001**	1.04

- **Forward Selection**

This method of selection depends mainly on the correlation strength between the dependent and the independent variables while developing the model. The independent variable with the highest strength of correlation with dependent variable will be the first selected variable to stay in the model if it achieves the required standard in this method. This procedure is repeated with all the independent variables until ending with the developed model that have all independent variables with a strong correlation with the dependent variable and at the same time guarantee the standards needed for this method of selection (Daniel and Cross, 2013).

This method of selection is used the value $\alpha = 0.25$ to enter each of the independent variables. This value of α is used to ensure that the forward selection procedure ends when none of the candidate independent variables have a p-value smaller than the value specified in α to enter. The independent variables that are entered into this model are the social influence, resource availability, data availability, effort expectancy, performance expectancy, self-efficacy and quantitative self-efficacy.

Forward selection is resulted in the same model terms and values as in Model 4 (Stepwise regression). The same independent variables are retained in the model which are: data availability, performance expectancy, self-efficacy and quantitative self-efficacy. And the same value for R^2 = 40.49%, Adjusted R^2 = 38.85% and Predicted R^2 = 36.65%.

- **Backward Elimination**

This method used the contrast process of forward selection. The independent variable with the lowest correlation with the dependent variable and does not meet the required standards will be eliminated first from the model. This procedure is repeated with all the independent variables that entered to the model until all the variables that do not meet the standards are eliminated from the model (Daniel and Cross, 2013).

Backward elimination method is used the value $\alpha = 0.1$ to remove the independent variables that don't meet the criteria. This value of α is used to guarantee that backward elimination processed ends when none of the variables included in the model have a p-value greater than the value specified in α to remove. This method starts with the model that contains the variables: social influence, resource availability, data availability, effort expectancy, performance expectancy, self-efficacy and quantitative self-efficacy.

Also, this method results in a regression model contains the same terms and values as in Model 4 (Stepwise regression). The same independent variables are retained in the model which are: data availability, performance expectancy, self-efficacy and quantitative self-efficacy. And the same value for R^2 = 40.49%, Adjusted R^2 = 38.85% and Predicted R^2 = 36.65%.

Finally, Model 3 and Model 4 will be used in the final decision about the best model that is considered as a representative framework for the acceptance and adoption of HR Analytics at the individual level. Model 4 is chosen only, since it is a result of stepwise regression, and this type represents a combination of forward selection and backward elimination procedures.

4.4 The Framework of the Acceptance and Adoption of HR Analytics at the Individual Level in Large Palestinian Enterprises

Comparing both Model 3 and Model 4, as good candidates to represent the relationship between the response and predicted variables in this study. For Model 3 the values of R^2 = 41.16% and Adjusted R^2 = 38.26%. While for Model 4 the values of R^2 = 40.49% and Adjusted R^2 = 38.85%. It is noticed that both models are having a little difference in value; they are approximately equal. Furthermore, for Model 3 the value of Predicted R^2 = 34.00%, while for Model 4 Predicted R^2 = 36.65%. Predicted R^2 is also used as an indicator of regression model fitness. Models that have a larger value of predicted R^2 have the better predictive ability. So, Model 4 is considered a better candidate in predicting the response variable (the individual acceptance and adoption of HR Analytics).

As a result, Model 4 is adopted. This model reveals a significant prediction of the response variable with explanation percentage up to 38.85% (R^2 = 40.49% and Adjusted R^2 = 38.85%). Such value of the explanation of the variability in the acceptance and adoption of HR Analytics at the individual level shows that it is a good model.

Moreover, the results from the regression Model 4 indicate that data availability, performance expectancy, self-efficacy and quantitative self-efficacy are the significant factors that predict the acceptance and adoption of HR Analytics at the individual level among HR professionals. While the factors of social influence, resource availability, fear appeals and effort expectancy do not contribute significantly to the model. Besides, the values of factors' coefficients β point out that self-efficacy ($\beta = 0.3684$) is more significant in affecting the individual acceptance and adoption of HR Analytics than quantitative self-efficacy ($\beta = 0.1949$), performance expectancy ($\beta = 0.1908$) and data availability ($\beta = 0.1307$). Also, Multicollinearity between the independent variables is in small values. The VIF values are ranging from 1.04 to 1.52, which point out the reliability of the results.

Based on this result, regression Model 4 is choosing as a representative framework of the acceptance and adoption of HR Analytics at the individual level, the hypotheses testing results for this research are shown in the Table (4.49):

Table (4.49): Hypotheses Testing Results (Based on Regression model 4)

Hypothesis	Result
H1: Social Influence affects the individual acceptance and adoption of HR Analytics positively in large Palestinian enterprises.	Rejected
H2: Resource Availability affects the individual acceptance and adoption of HR Analytics positively in large Palestinian enterprises.	Rejected
H3: Data Availability affects the individual acceptance and adoption of HR Analytics positively in large Palestinian enterprises	Accepted
H4: Fear Appeals affects the individual acceptance and adoption of HR Analytics positively in large Palestinian enterprises	Rejected
H5: Effort Expectancy affects the individual acceptance and adoption of HR Analytics positively in large Palestinian enterprises	Rejected
H6: Performance Expectancy affects the individual acceptance and adoption of HR Analytics positively in large Palestinian enterprises	Accepted
H7: Self-Efficacy affects the individual acceptance and adoption of HR Analytics positively in large Palestinian enterprises.	Accepted
H8: Quantitative Self-Efficacy affects the individual acceptance and adoption of HR Analytics positively in large Palestinian enterprises	Accepted

Hence, the conceptual framework describing the acceptance and adoption of HR Analytics at the individual level in large Palestinian enterprises is proposed. Thus, this framework is represented by Model 4 from the regression analysis. This Model 4 reveals that H3, H6, H7, and H8 are accepted. While, H1, H2, H4, H5 are rejected. So the affecting factors are:

- Self-Efficacy: the results reveal that self-efficacy is the most significant factor that affects HR Analytics' acceptance and adoption. Hence, hypothesis 7 is supported. This means that the extent to which individuals believe in their competences to succeed and perform well at their positions through using HR Analytics; will affect their decision about the acceptance and adoption of HR Analytics. This finding coincides with the studies of Bandura (1982) and Boyd and Crawford (2011). So, this result assures that if HR professional's beliefs are weak about their competences of accomplishing their work in the best way using HR Analytics, they will not accept and adopt it.

- Quantitative Self-efficacy: is the second factor that affects the individual acceptance and adoption of HR Analytics positively. Hypothesis 8 is supported. This result means that HR professionals believe in that having quantitative skills such as mathematical and statistical analysis skill; will increase their chance to accept and adopt HR Analytics. This result is logical; since HR analytics is dealing mainly with data science techniques which require specific skills in the mathematical and statistical computation to perform the analysis in a proper way that guarantees to achieve the required objectives of the data analysis. Also, this result ensures that individuals who are capable of connecting between mathematics and real life concerning comprehend the problems and find the best solutions for them will succeed and perform well at work. Moreover, having the ability to make a connection between computational skills and HR problems through using HR Analytics; will enhance the work of HR issues. Besides, this agrees with the studies of Baki et al. (2009) and Ozgen (2013).

- Performance Expectancy: the results show that performance expectancy has a significant and positive effect among HR professionals when they are asked to decide on the acceptance and adoption of HR analytics. Hypothesis 6 is supported. This result is in accordance with UTAUT theory which argues that performance expectancy is affecting the behavior of individuals towards the acceptance and adoption of innovation (Venkatesh et al. 2003, Venkatesh et al., 2012). Also, this result indicates that HR professionals who consider HR Analytics as an innovative technology comes to enhance their job performance and reinforce their work effectiveness, unconditionally they will accept and adopt this innovation.
- Data Availability: the regression analysis shows that data availability is affecting the acceptance and adoption of HR Analytics at the individual level positively. Hypothesis 3 is supported. This is a reasonable outcome; since data is a primary requirement to conduct HR analytics. Furthermore, the importance of this factor appears in Techopedia (2017) definition of data availability as “it is the extent to which data is readily usable along with the necessary IT and management procedures, tools and technologies required to enable, manage and continue to make data available." Besides, this result is consistent with Van den Heuvel and Bondarouk (2017) study which explores the opinions of HR Analytics practitioners about the future of this innovation. The study indicates the importance of data availability, the integration of different data sources and the integration of IT systems as essential factors for HR Analytics

to stay and develop. In this research, HR professionals have nearly the same opinion as they suggest data availability as a significant factor to accept and adopt HR Analytics.

On the other hand, the factors that do not affect the response variable in this investigation are:

- Social Influence: unexpectedly, the results show that social influence does not affect the individual acceptance and adoption of HR Analytics. Hypothesis 1 is not supported. This means that HR professionals are not influenced by their social environment opinions such as their peers or their supervisors to change their behaviors towards accepting and adopting HR Analytics. This result contradicts the results of Hsu et al. (2004), Talukder (2012), Talukder and Quazi, (2011) and Vargas (2015). The reason for this result may be that HR professionals in large Palestinian enterprise, until now, don’t see the benefits of the acceptance and adoption of HR Analytics among their social influencers to emulate them in using this innovation (Frambach and Schillewaert, 2002).
- Resource Availability: the hypotheses testing through regression analysis reveal that resource availability has no effect on the individuals' decision regarding the acceptance and adoption of HR Analytics. Hence, Hypothesis 2 is not supported. This is unexpected result; because conducting HR Analytics needs the availability of specific skills and tools to concern this new technology. Besides, this result differs from Carlson and Kavanagh (2011) who argue that individuals with the

requisite skills and competencies are a significant factor since they will need to know what data is needed, how to collect and analyze the data, and interpret the results of the analysis for reporting purposes and decision making.

- Fear Appeals: the results indicate that there is no effect of fear appeals as a factor affecting the acceptance and adoption of HR Analytics among HR professionals. Hypothesis 4 is not supported. This result means that individuals' fear of losing their jobs or replacing them with others having the essential skills to conduct HR Analytics does not influence their decision regarding the acceptance and adoption of this new technology. To some limit, this result agrees with Rogers (1975) study which indicates that there is no common conclusion about the effect of fear appeals on conviction decisions and it depends on other factors such as the social environment or other existing situations. While, fear appeals approve a significant positive effect on persuasion regarding health issues (Schneider et al., 2001; Sherer and Rogers, 1984).
- Effort Expectancy: this factor has no significant effect on the individual acceptance and adoption of HR Analytics. Hence, Hypothesis 5 is not supported. This means that HR professionals do not consider the degree of ease associated with using HR Analytics when they decide to accept and adopt this innovation. This result disagrees with the UTAUT theory of Venkatesh et al. (2012) which argues that effort expectancy is an important behavioral factor affecting the use of new technology.

By identifying the affecting and non-affecting factors regarding the acceptance and adoption of HR Analytics, the first two questions in this research are answered; what are the main factors that may influence the individual acceptance and adoption of HR Analytics in large Palestinian enterprises? What is the significance of each factor in affecting the individual acceptance and adoption of HR Analytics in large Palestinian enterprises?

4.5 The Relationship between the individual and the organizational Acceptance and Adoption of HR Analytics in Large Palestinian Enterprises

With the aim of answering the last question of this research; what is the relationship between the individual and the organizational acceptance and adoption of HR Analytics? The correlation between these two variables are checked first and results in a P-value = 0.000 < 0.05 and a Pearson correlation value = 0.678 which indicate there is a significant relationship between the individual and organizational level of acceptance and adoption.

Since the result from correlation analysis indicates a significant relationship between these two variables, there is a good chance to develop a regression model that can describe the relationship between the individual and organizational level of acceptance and adoption of HR Analytics.

As a first step, a simple regression model is tried to be developed as there is only one independent variable (organizational level of the acceptance and adoption) correlated to the response variable (individual level of the acceptance and adoption). The analysis of this simple regression model results in a not-normally distributed residuals which leads to invalid model as the normality of residuals resulting from the regression is a crucial condition to validate the proposed model.

Then, Box-Cox transformation is used as a technique to solve the problem of the not normally distributed residuals. The regression analysis with this transformation tool also results in a not-normally distribution of residuals.

Moreover, many trials are conducted to gain a good representative regression model with a normally distributed residuals. These trials include removing various outliers from the data points to improve the distribution of residuals. As Tabachnick and Fidell (2007) stated , there is an opportunity to remove outliers from the data set as the total number of data set points are more than (104 + k), ‘k’ represents the number of independent variables and in this simple regression model is equal to one, so (104+1= 105).

Finally, the regression analysis produces a normally distributed residuals in model 5 with P-value = 0.066 > 0.05, as shown in Figure (4.6). Also, Table (4.50) shows that this developed model 5 explains 73.00% from the variability in the acceptance and adoption of HR Analytics at the individual level (R^2 = 73.21%, Adjusted R^2= 73.00%).

Table (4.50): Model 5 Summary

Model number	S	R^2	Adjusted R^2	Predicted R^2	λ
5	0.266759	73.21%	73.00%	72.33%	1
Regression Equation					
Individual Acceptance and Adoption = 0.904 + 0.7889 organizational acceptance and adoption Note: λ- value which is used in Box-Cox transformation is equal to 1. This means no need for transformation and is the same result for the simple linear regression model.					

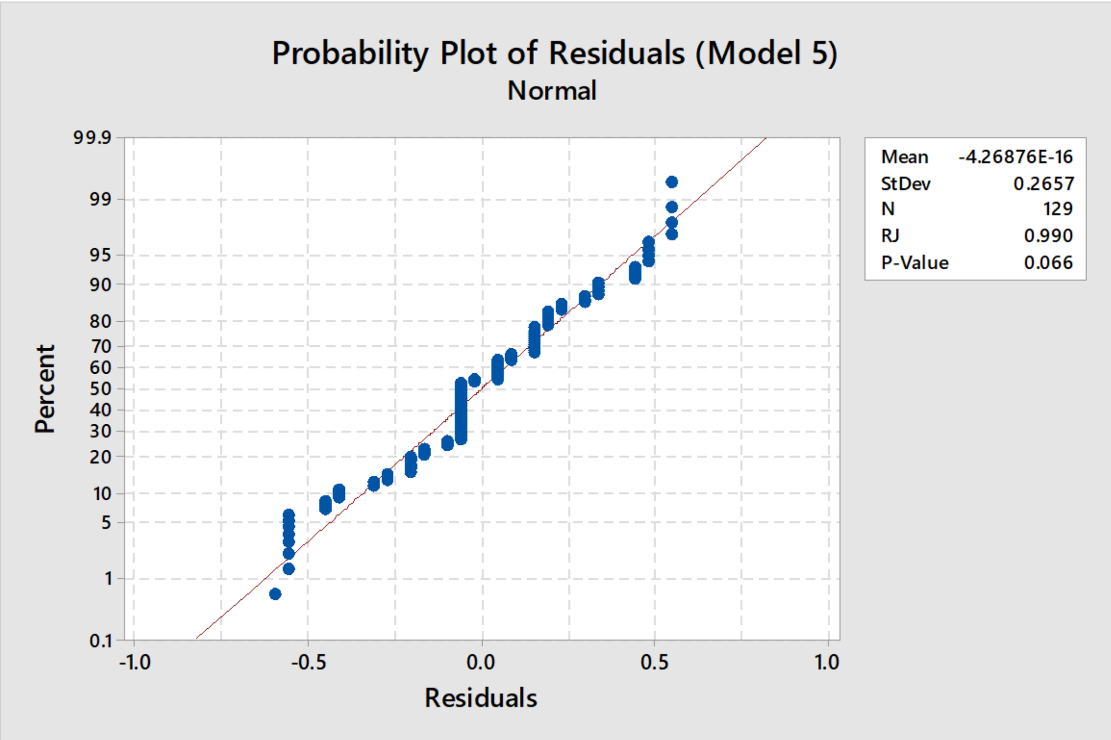

Figure (4.6): Normality Plot of Residuals (Model 5)

ANOVA test for the regression model 5 is presented in Table (4.51). This test is conducted to test the null hypothesis for the overall regression model 5 which is: the model does not explain any of the variations in the response variable (individual acceptance and adoption). The P-value is used to determine whether the model explains variation in the response. Since the

P-value = 0.000 < significance level of 5 %, the null hypothesis is rejected and its concluded that the organizational level of acceptance and adoption can explain the variation in the response and have an effect on it.

Table (4.51): ANOVA for Model 5

Source	**DF**	**Adj Sum of Squares**	**Adj Mean of Squares**	**F-Value**	**P-Value** (Significance level = 0.05)
Regression	1	24.7010	24.7010	347.12	**0.000**
Error	127	9.0374	0.0712		
Total	128	33.7384			

Moreover, Table (4.52) shows the results of the T-test and corresponding P-values. These results show that the null hypotheses that the regression model coefficient of the predicted variable (organizational level of the acceptance and adoption of HR Analytics) is equal to zero can be rejected since the P-values for the β coefficient are less than the significance level of 5 %. This means that there is a statistically significant association between the response variable and the predicted variable. Also, Table (4.52) shows that the VIF is equal to 1.00, which indicates the reliability of the results.

Table (4.52): Regression Coefficients Results (Model 5)

Term	**Coefficient**	**SE Coefficient**	**T-Value**	**P-Value (Significance level = 0.05)**	**VIF**
Constant	0.904	0.175	5.16	**0.000**	
Organizational Acceptance and Adoption	0.7889	0.0423	18.63	**0.000**	1.00

The regression model 5 aims at investigating the effect of organizational-level on the acceptance and adoption of HR Analytics on the Individual-level of adoption. This is an important point to shed light on it since the acceptance and adoption at the individual level needs much support from the organization. This support is represented by the resources that the organization needs to available them to facilitate the individual acceptance and adoption.

Moreover, there are various resources that the organization may support the individuals with them to ensure a proper acceptance and adoption of HR Analytics among HR professionals such as; tools like developed HRIS with continuous updating to be integrating with other IS in the organization, training the employees to improve their skills and competencies perform HR Analysis and the continuous support for HR professionals and give them the opportunity to bring HR department to the strategic table with other departments and hence affect the organizational performance.

Furthermore, HR professionals may have the willingness and the capability to perform HR Analytics, but the organizations do not provide them with the required resources. For example, Carlson and Kavanagh (2011) argue that the HRIS used in some organizations today are outdated and do not have the capabilities to integrate seamlessly with computers and infrastructures that used nowadays.

On the other hand, this result of the significant role the organization could play to facilitate the individual acceptance and adoption of HR Analytics coincides with the study of Madsen et al. (2017), which investigates the issues that may affect the developed of HR Analytics in the coming years.

Finally, based on the analysis results, Figure (4.7) shows the conceptual framework which proposed as one of this research objectives. The solid lines refer to the supported hypotheses that test the effect of each factor on the individual acceptance and adoption of HR Analytics, while the dotted lines represent not supported hypotheses of this study. Also, the numbers on the connected lines in Figure (4.7) refer to Pearson correlation coefficient as an indication of the significance of each independent factor on the response variable. This conceptual framework represents the general structure of proper acceptance and adoption of HR Analytics among HR professionals in large Palestinian Enterprises.

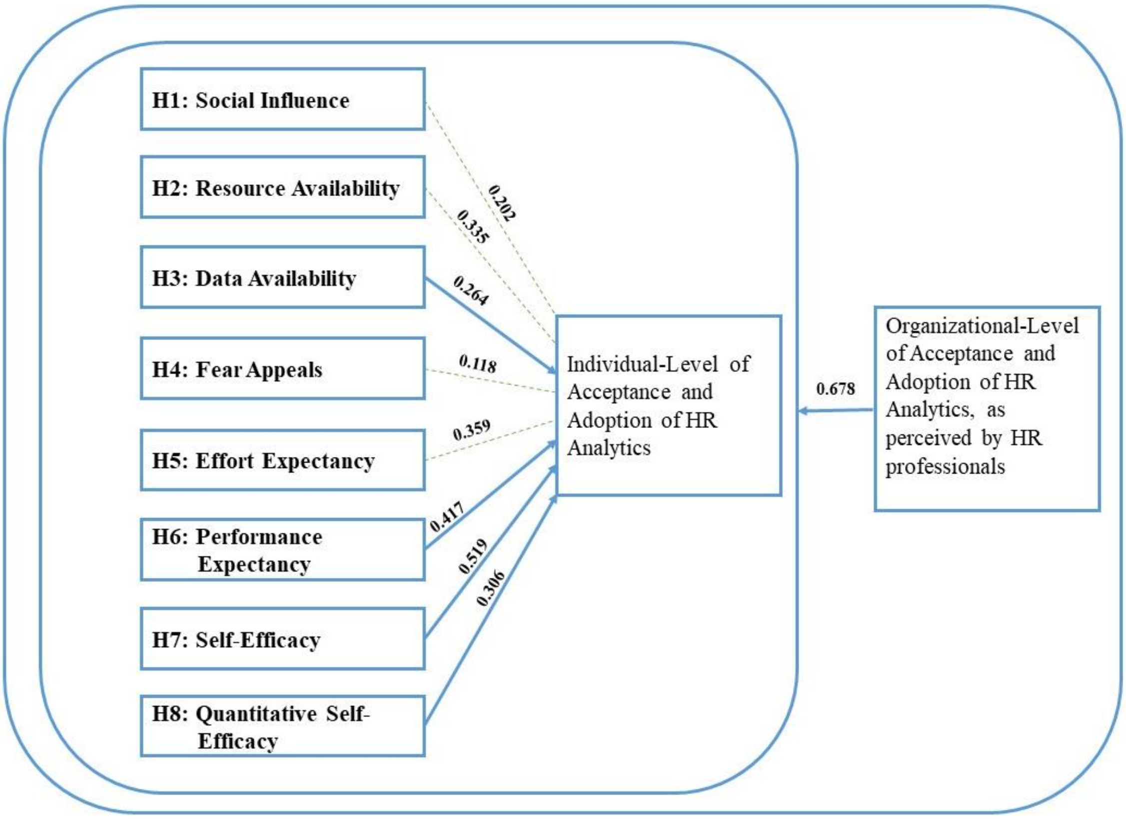

Figure (4.7) : The Managerial Conceptual Framework

4.6 Summary

This chapter shows the statistical data analysis, tests research hypotheses and discusses the results. Also, all the research questions are answered in this chapter. The conceptual framework for the acceptance and adoption of HR Analytics in large Palestinian enterprises is developed. In the next chapter, conclusion and recommendations are presented.

Chapter Five

Conclusions and Recommendations

This chapter overviews the research results where the main conclusions are explained. It also provides recommendations based on research results for the acceptance and adoption of HR Analytics at the individual level in large Palestinian enterprises. Besides, this chapter discusses the research contribution to the related literature and provides some suggestions for future research studies.

5.1 Conclusions

The primary objectives of this research are to investigate the factors affecting the acceptance and adoption of HR Analytics at the individual level in large Palestinian enterprises, develop a conceptual framework for proper acceptance and adoption of HR Analytics, and examine the relationship between the individual and organizational acceptance and adoption of HR Analytics.

To achieve these objectives, exploratory research is conducted with a questionnaire, as a survey tool, distributed among HR professionals in large Palestinian enterprises in WB; to ask about their perceptions towards the factors that may affect their acceptance and adoption of HR Analytics. After that, the questionnaire results are analyzed using Minitab 18 software.

The results show that the factors of data availability, performance expectancy, self-efficacy and quantitative self-efficacy are the most significant factors which affect the individual acceptance and adoption of HR Analytics positively in large Palestinian enterprises. While, the factors of social influence, resource availability, fear appeals and effort expectancy have no significant effect on the acceptance and adoption of HR Analytics. Moreover, the relationship between the individual (response variable) and organizational (predicted variable) acceptance and adoption is investigated. The correlation analysis indicates a strong relationship between these two variables and based on that a regression model is proposed to represent this relationship. Finally, a conceptual framework is developed representing the significant factors that affect the individual acceptance and adoption of HR Analytics. Besides, the relationship between the individual and organizational acceptance and adoption appears on the model as the organizational acceptance and adoption represents the facilitating factor to guarantee a proper individual acceptance and adoption by ensuring the availability of the required resources including skills and systems.

5.2 Recommendations

Based on the research results, this study introduces the following recommendations that can be implemented by large Palestinian enterprises to guarantee a better acceptance and adoption of HR Analytics among HR professionals, and hence gain the maximum benefit from this innovation:

- Updating the HRIS regularly to meet any new development regarding new technologies like HR Analytics.
- Integrating the organization's IT data structure as it is vital in centralizing the data source from different disciplines in a single database to ease the process of data analysis.
- Integrating the data of HR department with data from other departments inside an organization and also data from outside such as social media streams to enhance the process of data collection and collaboration between HR department and other departments.
- Consisting analytics teams from various functions within the organization, including HR, to construct a centralized analytics function with the primary aim of enhancing business performance as a whole.
- Improving employees' skills by training them in analytical competencies needed to perform HR Analytics.
- Coordinating lectures with universities to talk about the benefits of HR Analytics as a new topic in HR management. Also, encourage the universities to add new mathematical and statistical courses in HR specialization even elective ones.
- The developed conceptual framework for the acceptance and adoption of HR Analytics at the individual level is recommended as a guiding tool; to ensure a proper acceptance and adoption among HR professionals.

5.3 Research Contribution

The importance of this research is its contribution to the literature with a quantitative empirical study in HR Analytics. Also, this study is a unique one in developing countries, and it investigates the factors that affect the acceptance and adoption of HR Analytics at the individual level in large Palestinian enterprises.

Moreover, this study is considered to be significant in its contribution by identifying the most important factors that affect the acceptance and adoption of HR Analytics at the individual level in large Palestinian enterprises. Besides, it is one of the few studies that investigate practically the relationship between the individual and organizational acceptance and adoption of HR Analytics. Furthermore, it develops a conceptual framework for the proper acceptance and adoption of HR Analytics.

Finally, this research guides large Palestinian enterprises in their acceptance and adoption of HR Analytics as a new technological innovation through focusing on the most significant factors that will affect this process. Also, it sheds light on the importance of the role which organizations can play to support and facilitate the individual level of the acceptance and adoption.

5.4 Recommendations for Future Work

As the literature reveals, the concept of HR Analytics is still in its infancy, and there are many opportunities to add in this subject. Hence, more researches are needed to conduct in this domain, and especially empirical ones as the literature reveals previously.

Moreover, this research studying the acceptance and adoption of HR Analytics. Future research may concern the adopter organizations and investigate the extent of adoption, the practical benefits of adoption, the impact on the business outcomes and the difficulties that organizations and HR professionals are facing in performing HR Analytics.

Although a mixed research approach is used in this research, the primary approach used is a quantitative one. Future work may hold a qualitative research approach and use it in investigating other factors that may affect the acceptance and adoption of HR Analytics from the views of HR professionals. This process may discover other factors besides those derived in this research from literature.

On the other hand, this research is focused on the individual level of the acceptance and adoption of HR Analytics and investigate the organizational level as it is the arena where the individual is conducted. Future studies may focus only on the organizational level and investigate more in this level.

Also, the current research studies the concept of HR Analytics among HR professionals only. Other future contributions may research in other parties that may affect this innovation such as technological organizations that have a significant effect in supporting and upgrading the HRIS as a basis to perform HR Analytics.

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Appendices

Appendix A

Tables: Source of Questionnaire statements

1) Social Influence

The statement	Adopted from
People who influence my behavior think that I should use HR Analytics.	Johnston and Warkentin (2010), Venkatesh et al. (2012), Vargas (2015)
People who are important to me think that I should use HR Analytics.	Venkatesh et al. (2012), Vargas (2015)
People whose opinions that I value prefer that I use HR Analytics.	Venkatesh et al. (2012), Vargas (2015)
The senior management of this business has been helpful in the use of HR Analytics.	Thompson et al. (1991), Venkatesh et al. (2003), Vargas (2015)
In general, the organization has supported the use of HR Analytics.	Thompson et al. (1991), Venkatesh et al. (2003), Johnston and Warkentin (2010), Vargas (2015)

2) Resource Availability

The statement	Adopted from
I have the resources necessary to use HR Analytics.	Venkatesh et al. (2012), Vargas (2015)
I have the knowledge necessary to use HR Analytics.	Venkatesh et al. (2012), Vargas (2015)
Given the resources, opportunities and knowledge it takes to use HR Analytics, it would be easy for me to use HR Analytics.	Ajzen (1991), Vargas (2015)
HR Analytics are compatible with other technologies I use.	Venkatesh et al. (2012), Vargas (2015)
I can get help from others when I have difficulties using HR Analytics.	Venkatesh et al. (2012), Vargas (2015)

3) Data Availability

The statement	Adopted from
My organization's database has all the data I need to use HR Analytics software.	Vargas (2015)
My organization's HR system collects data from all HR interactions.	Vargas (2015)
My organization uses the same system/platforms for all HR activities.	Vargas (2015)
I can easily access the database in my organization so I get the data needed in HR Analytics	The arbitrators of current research

4) Fear Appeals

The statement	Adopted from
If I were forced to use HR Analytics, it would have a negative effect on my organizational commitment	Witte et al. (1996), Vargas (2015)
It is unlikely I would be forced to try or use HR Analytics to keep my job.	Witte et al. (1996), Vargas (2015)
If I were required to use HR Analytics, It would have a significant negative impact on my job performance.	Witte et al. (1996), Vargas (2015)
If I were mandated to use HR Analytics, it would have a negative effect on my job satisfaction.	Witte et al. (1996), Vargas (2015)

5) Effort Expectancy

The statement	Adopted from
Learning how to use HR Analytics is easy for me.	Venkatesh et al. (2012), Vargas (2015)
My interaction with HR Analytics would be clear and understandable.	Venkatesh et al. (2012), Vargas (2015)
I would find HR Analytics easy to use.	Venkatesh et al. (2012), Vargas (2015)
It is easy for me to become skillful at using HR Analytics.	Venkatesh et al. (2012), Vargas (2015)

6) Performance Expectancy

The statement	Adopted from
I would find the use of HR Analytics useful in my job.	Johnston and Warkentin (2010), Venkatesh et al. (2012), Vargas (2015)
Using HR Analytics enables me to accomplish tasks more quickly.	Johnston and Warkentin (2010), Venkatesh et al. (2012), Vargas (2015)
Using HR Analytics increase my productivity.	Johnston and Warkentin (2010), Venkatesh et al. (2012), Vargas (2015)
Using HR Analytics would improve my job performance.	Davis (1989), Vargas (2015)
Using HR Analytics would enhance my effectiveness on the job.	Davis (1989), Vargas (2015)

7) Self- efficacy

The statement	Adopted from
HR Analytics is easy to use	Davis (1989), Johnston and Warkentin (2010), Vargas (2015)
HR Analytics is convenient to use	Davis (1989), Johnston and Warkentin (2010), Vargas (2015)
I am able to use HR Analytics without much effort.	Davis (1989), Johnston and Warkentin (2010), Vargas (2015)
I can solve most problems if I invest the necessary effort	Davis (1989), Chau (2001), Vargas (2015)
I am confident that I could deal efficiently with unexpected events.	Davis (1989), Chau (2001), Vargas (2015)
If I am in trouble, I can usually think of a solution.	Davis (1989), Chau (2001), Vargas (2015)
When I am confronted with a problem, I can usually find several solutions.	Davis (1989), Chau (2001), Vargas (2015)
I can usually handle whatever comes my way.	Davis (1989), Chau (2001), Vargas (2015)

8) Quantitative Self-Efficacy

The statement	Adopted from
I find using mathematical and/or statistical measurements interesting.	Bai et al. (2009), Vargas (2015)
I worry about my ability to solve mathematical and/or statistical problems.	Bai et al. (2009), Vargas (2015)
I get nervous when I use mathematical and/or statistics.	Bai et al. (2009), Vargas (2015)
I enjoy working with mathematical and/or statistical measures.	Bai et al. (2009), Vargas (2015)
I find mathematical and/or statistical measures challenging.	Bai et al. (2009), Vargas (2015)
Math and/or statistics are one of my favorite subjects	Bai et al. (2009), Vargas (2015)

9) Level of Adoption

The statement	Adopted from
My organization is putting a policy in place to use HR Analytics	Vargas (2015)
I am beginning to explore using HR Analytics	Vargas (2015)
I am interested in using HR Analytics	Vargas (2015)
I am recommending my organization invest in HR Analytics	Vargas (2015)
I use HR Analytics for some specific tasks	Vargas (2015)
I have the needed training and development in my organization, so I have the ability to use HR analytics	The arbitrators of current research

Appendix B

Questionnaire of

Factors Affecting the Acceptance and Adoption of Human Resources' Analytics

Dear Respondent,

Thank you for finding time for filling in this questionnaire. The main objective of this questionnaire is to study the factors affecting the acceptance and adoption of Human Resources (HR) Analytics in Large Palestinian Enterprises. **HR Analytics defined as an area in the field of analytics that refers to applying analytic processes to the human resource department of an organization in the hope of improving employee performance and therefore getting better business outcomes.**

This questionnaire is divided into two parts. The first one is prepared to gather general information about the respondent (HR Professionals) and the enterprise. The second part is to investigate the factors affecting the acceptance and adoption of HR Analytics in Large Palestinian Enterprises.

Your participation in this survey by answering the following questions is totally appreciated. It should take around 10 minutes to complete the questionnaire. Please note that all the information in this survey will only be used for academic research purposes, and all information provided will be treated with confidence.

Researcher: Rana Abu-Tayyoun

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An-Najah National University

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<u>Part One:</u> General Information

Please check the appropriate answers for each of the following items.

1. Gender: ( ) Male ( ) Female

2. Age: ( ) less than 35 ( ) 35- 45 ( ) more than 45

3. Your Education Degree (highest level):

( ) Diploma or below ( ) Bachelor's degree ( ) Master's degree

4. Do you have any Human Resource Certification(s)? ( ) Yes ( ) No

5. Your current position:

( ) Director ( ) Manager ( ) Head of Department

( ) Head Unit ( ) Administrative

6. What is the functional area of your current position?

( ) Training/Development ( ) Insurance ( ) Payroll ( ) Employee Relations ( ) Data and Information Management ( ) Other, Please Specify ……………………..…

7. How long have you worked for your current employer?

( ) less than 5 years ( ) 5-10 years ( ) more than 10 years

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

( ) less than 5 years ( ) 5-10 years ( ) more than 10 years

9. Industry sector in which you are employed:

( ) Banking ( ) Hospitals ( ) Telecommunication ( ) Logistics ( ) Insurance ( ) Internet Provider ( ) Manufacturing, Please Specify ………...……..

( ) Other, Please Specify……………………..…

10. Number of employees in your organization approximately is:

( ) less than 50 ( ) 50-less than 100 ( ) 100- less than 500

( ) 500- less than 1000 ( ) 1000 and more

11. My organization currently uses Human Resource Information System (HRIS):

( ) Yes ( ) No

13. Do you currently use analytics in your organization, in general? ( ) Yes ( ) No

<u>Part Two</u>: To study the factors affecting the acceptance and adoption of Human Resources Analytics in Large Palestinian Enterprises; for each item choose to what extent do you think the following factors will affect your acceptance and adoption for this analytics in your HR department.

Factor	The Statement	Level				
		1	2	3	4	5
		Not at all	To a slight degree	To a moderate extent	To a great extent	To a very great
Social Influence	People who influence my behavior think that I should use HR Analytics					
	People who are important to me think that I should use HR Analytics					
	People whose opinions that I value prefer that I use HR Analytics					
	The senior management of this business has been helpful in the use of HR Analytics.					
	In general, the organization has supported the use of HR Analytics.					
Resource Availability	I have the resources necessary to use HR Analytics					
	I have the knowledge necessary to use HR Analytics					
	Given the resources, opportunities and knowledge it takes to use HR Analytics, it would be easy for me to use HR Analytics					
	HR Analytics are compatible with other technologies I use					

	I can get help from others when I have difficulties using HR Analytics					
Data Availability	My organization's database has all the data I need to use HR Analytics software					
	My organization's HR system collects data from all HR interactions					
	My organization uses the same system/platforms for all HR activities					
	I can easily access the database in my organization so I get the data needed in HR Analytics					

Fear Appeals	If I were forced to use HR Analytics, it would have a negative effect on my organizational commitment					
	If I were required to use HR Analytics, It would have a significant negative impact on my job performance					
	If I were mandated to use HR Analytics, it would have a negative effect on my job satisfaction					
Effort Expectancy	Learning how to use HR Analytics is easy for me					
	My interaction with HR Analytics would be clear and understandable					
	I would find HR Analytics easy to use					
	It is easy for me to become skillful at using HR Analytics					
Performance Expectancy	I would find the use of HR Analytics useful in my job					
	Using HR Analytics enables me to accomplish tasks more quickly					
	Using HR Analytics increase my productivity					
	Using HR Analytics would improve my job performance					
	Using HR Analytics would enhance my effectiveness on the job					

Self- efficacy	HR Analytics is easy to use					
	I am able to use HR Analytics without much effort					
	I can solve most problems if I invest the necessary effort					
	I am confident that I could deal efficiently with unexpected events					
	When I am confronted with a problem, I can usually find several solutions					
Quantitative Self-Efficacy	I find using mathematical and/or statistical measurements interesting					
	I worry about my ability to solve mathematical and/or statistical problems					
	I get nervous when I use mathematical and/or statistics					
	I enjoy working with mathematical and/or statistical measures					
	I find mathematical and/or statistical measures challenging					
	Math and/or statistics are one of my favorite subjects					

Level of Adoption	My organization is putting a policy in place to use HR Analytics					
	I am beginning to explore using HR Analytics					
	I am interested in using HR Analytics					
	I am recommending my organization invest in HR Analytics					
	I use HR Analytics for some specific tasks					
	I have the needed training and development in my organization, so I have the ability to use HR analytics					

Appendix C

استبانة حول

العوامل المؤثرة في قبول وتبنَي تحليلات الموارد البشرية في الشركات الفلسطينية الكبرى

عزيزي القارئ/ القارئة :

أشكرك على تخصيص جزء من وقتك لتعبئة هذه الاستبانة, والتي تهدف إلى دراسة العوامل المؤثرة في قبول وتطبيق تحليلات الموارد البشرية في الشركات الفلسطينية الكبرى, وذلك استكمالا لمتطلبات الحصول على درجة الماجستير. **تعرَف تحليلات الموارد البشرية على أنها ذلك المجال من التحليلات الذي يهدف الى تطبيق تقنيات مختلفة ومتنوعة من التحليلات على قسم الموارد البشرية في الشركات , وذلك بهدف تحسين أداء الموظفين وبالتالي الحصول على نتائج أفضل على مستوى الشركة ومخرجاتها.**

تنقسم هذه الاستبانة إلى جزأين :

الجزء الأول : يهدف إلى جمع معلومات عامة عن القارئ/ القارئة المتخصص في مجال إدارة الموارد البشرية, إضافة إلى معلومات عامة عن الشركة التي يعمل بها.

الجزء الثاني : يهدف إلى استكشاف العوامل المؤثرة في قبول وتطبيق تحليلات الموارد البشرية في الشركات الفلسطينية الكبرى .

حسن تعاونكم في هذا البحث هو موضع تقدير كبير. هذا التقييم سوف يستغرق منك حوالي 10 دقائق لإتمامه, الرجاء التفضَل بقراءة جميع فقرات الاستبانة بدقة, ووضع الدرجة التي تراها مناسبة أمام كل فقرة بموضوعيِة وحياد , علما بأنَ كافَة المعلومات سوف تكون سرية ولن تستخدم إلا لأغراض البحث العلمي.

الباحثة : رنا أبو طيَون

برنامج ماجستير الإدارة الهندسية

جامعة النجاح الوطنية

Rana.abutayyoun@gmail.com

❖ الجزء الأول: معلومات عامة

يرجى التكرم بالإجابة عن الأسئلة التالية باختيار الإجابة التي تناسبك :

1. **الجنس:**

( ) ذكر ( ) أنثى

2. **العمر:**

( ) 35 فأقلَ ( ) من 35- 45 ( ) أكثر من 45

3. **المؤهل العلمي:**

( ) دبلوم فأقل ( ) بكالوريوس ( ) ماجستير

4. **هل تمتلك شهادات معترف بها دوليًا في مجال الموارد البشرية؟**

( ) نعم ( ) لا

5. **الموقع الوظيفي الحالي**

( ) مدير إدارة ( ) مدير دائرة ( ) رئيس قسم ( ) رئيس وحدة ( ) إداري

6. **ما هو مجال تخصصك الوظيفي لموقعك الحالي ؟**

( ) التدريب والتطوير ( ) التأمينات ( ) الرواتب ( ) شؤون الموظفين

( ) إدارة البيانات والمعلومات ( ) غير ذلك , من فضلك حدَد ....

7. **أنت تعمل في موقعك الوظيفي الحالي منذ :**

( ) أقل من 5 سنوات ( ) 5- 10 سنوات ( ) أكثر من 10 سنوات

8. **عدد سنوات خبرتك في مجال الموارد البشرية :**

( ) أقل من 5 سنوات ( ) 5-10 سنوات ( ) أكثر من 10 سنوات

9. **تعمل المؤسسة في قطاع :**

( ) البنوك ( ) المستشفيات ( ) الاتصالات ( ) شركات النقل اللوجستيَة

( ) التأمين ( ) مزوَدي خدمة الانترنت ( ) الصناعات , حدد نوع الصناعة من فضلك
....

( ) قطاعات أخرى, اذكرها من فضلك ....

10. **عدد العاملين في المؤسسة تقريبا :**

( ) أقل من 50 ( ) 50- أقل من 100 ( ) 100- أقل من 500

( ) 500- أقل من 1000   ( ) 1000 وأكثر

11. تستخدم شركتك الأن نظام معلومات الموارد البشرية : ( ) نعم   ( ) لا

12. تستخدم الشركة تحليل البيانات بشكل عام في أقسامها : ( ) نعم   ( ) لا

❖ **الجزء الثاني : إلى أيَ درجة تعتقد أن العوامل التاليَة قد تؤثرعلى مدى قبولك وتبنَيك لتحليلات الموارد البشرية في وظيفتك الحاليَة ضمن قسم الموارد البشرية في مؤسستك**

العوامل	الفقرة	بدرجة كبيرة جدا 5	بدرجة كبيرة 4	بدرجة متوسطة 3	بدرجة قليلة 2	بدرجة قليلة جدا 1
التأثير الاجتماعي	لدى الأشخاص الذين يؤثرون في سلوكي الوظيفي (الأقدم أو الأعلى مرتبة منَي في العمل) تأثيرا على استخدامي لتحليلات الموارد البشرية					
	يؤثَر الاشخاص المهمَين لي في عملي (زملائي في العمل) على استخدامي لتحليلات الموارد البشرية					
	يؤثر الأشخاص الذين أقدَر أرائهم في عملي على استخدامي لتحليلات الموارد البشرية					
	الإدارة العليا في عملي داعمة ومساندة لاستخدام تحليلات الموارد البشرية					
	بشكل عام , تدعم المؤسسة استخدام تحليلات الموارد البشرية					
توفَر الموارد	أمتلك الموارد اللازمة (أنظمة, برامج, مهارات) لاستخدام تحليلات الموارد البشرية					
	أمتلك المعرفة اللازمة لاستخدام تحليلات الموارد البشرية					
	يوجد سهولة في استخدام تحليلات الموارد البشرية عندما تتوفر الموارد والفرص والمعرفة اللازمة لاستخدامها					
	تتوافق تحليلات الموارد البشرية مع التقنيات الأخرى التي أستخدمها في عملي					
	يمكنني الحصول على مساعدة من الاخرين عندما أواجه صعوبات في استخدام تحليلات الموارد البشرية					
	تتوفر في قاعدة البيانات الموجودة في مؤسستي, جميع البيانات اللازمة و التي أحتاجها لاستخدام					

	برامج تحليلات الموارد البشرية					
توفَر البيانات	يجمع نظام معلومات الموارد البشرية المستخدم في مؤسستي البيانات من جميع أقسام دائرة الموارد البشرية					
	تستخدم مؤسستي نفس نظام المعلومات لجميع أنشطة الموارد البشرية					
	أستطيع الوصول بسهولة لقاعدة البيانات الموجودة في مؤسستي حتى أحصل على البيانات اللازمة والتي أحتاجها في تحليلات الموارد البشرية					
مشاعر الخوف والتهديد	إجباري على استخدام تحليلات الموارد البشرية في عملي , سيؤثَر سلبا على التزامي الوظيفي في المؤسسة					
	إذا كنت مكلفَا في استخدام تحليلات الموارد البشرية , فإن ذلك سيؤثر سلبا على رضاي الوظيفي					
	إذا كان مطلوبا منَي استخدام تحليلات الموارد البشرية فإنَ ذلك سيؤثَر سلبا على أدائي الوظيفي					
سهولة الاستخدام	تعلَم كيفية استخدام تحليلات الموارد البشرية أمر سهل بالنسبة لي					
	تفاعلي مع استخدام تحليلات الموارد البشرية واضحا ومفهوما					
	أجد تحليلات الموارد البشرية سهلة الاستخدام					
	من السهل بالنسبة لي أن أصبح ماهرا في استخدام تحليلاتالموارد البشرية					
الفائدة المرجوَة	استخدام تحليلات الموارد البشرية مفيد في عملي					
	استخدام تحليلات الموارد البشرية يتيح لي إنجاز المهام بسرعة أكبر					
	يؤدي استخدام تحليلات الموارد البشرية إلى زيادة إنتاجيَتي في العمل					
	استخدام تحليلات الموارد البشرية سيؤدي إلى تحسين أدائي الوظيفي (أدائي كشخص في موقع عملي)					
	استخدام تحليلات الموارد البشرية يعزز من فعاليَتي في العمل (أدائي مع الفريق على مستوى الدائرة)					
	استخدام تحليلات الموارد البشرية سهل بالنسبة لي					
	أنا قادر على استخدام تحليلات الموارد البشرية					

	دون بذل الكثير من الجهد					
الكفاءة الذاتيَة	يمكنني حلَ معظم المشاكل إذا بذلت الجهد اللازم لذلك					
	لديَ الثقة بأنَه يمكنني التعامل بكفاءة مع الأحداث المفاجئة و الغير متوقعة					
	عندما أواجه مشكلة يمكنني عادة التفكير في عدَة حلول لها					
الكفاءة الذاتية الكميَة	أجد استخدام المقاييس الرياضيَة أوالإحصائية مثيرة للاهتمام					
	أشعر بالقلق بشأن قدرتي على حلَ المشاكل الرياضيَة أو الإحصائية					
	أشعر بالتوتر عندما أتعامل مع المواضيع الرياضية أوالإحصائية					
	أستمتع بالعمل في المواضيع الرياضية أو الإحصائية					
	أجد أنَّ المواضيع الرياضية و الإحصائية مثيرة للتحدَي					
	الرياضيات و الإحصاء هي من المواضيع المفضلة لديَ					
مستوى التبنَي	تعمل مؤسستي على وضع سياسة لاستخدام تحليلات الموارد البشريَة					
	بدأت في استكشاف وتعلَم كيفيَة استخدام تحليلات الموارد البشرية					
	أنا مهتم في استخدام تحليلات الموارد البشريَة					
	أوصي مؤسستي أن تستثمر في تحليلات المورد البشرية					
	أنا أستخدم تحليلات الموارد البشرية لبعض المهام المحددة					
	تتوفَر لي آليَات التدريب والتطوير في مؤسستي, حتى أمتلك القدرة الكافية لاستخدام تحليلات الموارد البشرية					

Appendix D

Table: Arbitrators Who Reviewed the Questionnaire

Name	Position	organization
Dr. Mohmmad Othman	Head of Industrial Engineering Department. Assistant Professor in Industrial Engineering Department	An-Najah National University
Dr. Yahya Saleh	Director An-Najah Business Innovation & Partnership Center (NaBIC) Assistant Professor, Industrial Engineering Department	An-Najah National University
Dr. Ayham Jaaron	Assistant Professor in Industrial Engineering Department	An-Najah National University
Dr. Nidal Dwaikat	Deputy President for Planning, Development and Quality Assurance Director of ABET Center	An-Najah National University
Eng. Abdallah Mustafa	Human Resources Director	An-Najah National University Hospital
Ashraf AbuHantash	Training & Development Department Manager	Palestine Telecommunications Co.

جامعة النجاح الوطنية

كلية الدراسات العليا

قبول وتبنَي تحليلات الموارد البشرية في الشركات الفلسطينية الكبرى

إعداد

رنا عمر أبو طيون

إشراف

د. محمد عثمان

د. يحيى صالح

قدمت هذه الأطروحة استكمالا لمتطلبات الحصول على درجة الماجستير في الإدارة الهندسية في كلية الدراسات العليا في جامعة النجاح الوطنية، نابلس، فلسطين.

2018

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الملخص

في الآونة الأخيرة ، ومع ازدهار الاهتمام بعلم البيانات ، بدأت العديد من الشركات الناجحة تتجه نحو استخدام تحليل البيانات لتحديد فرص جديدة للترويج لمنتجاتها وخدماتها. إلى جانب ذلك ، ولضمان فوائد تحليل البيانات وتأثيرها المرغوب على أداء الأعمال ؛ فإنه يجب أن يتم تطبيقها في جميع أنحاء المنظمة. ومما لا شك فيه ، فإن هذا التطبيق يجب أن يتضمن أهم الأصول للمنظمات (الأشخاص) والتي يتم تغطيتها من خلال إدارة الموارد البشرية في المنظمة. يتوافق تحليل البيانات مع إدارة الموارد البشرية في مفهوم جديد وهو تحليلات الموارد البشرية . وسيساعد هذا الابتكار الموارد البشرية على أن تصبح شريكا استراتيجيا مع الإدارات الأخرى في جميع أنحاء المنظمة ، كما سيساعد الأعمال في تحديد احتياجات المواهب ، العثور على الأشخاص المناسبين والحفاظ عليهم ، تطوير مهارات وقدرات الموظفين ، والتخطيط للمستقبل.

على الرغم من الأهمية المثبتة لتحليلات الموارد البشرية وتأثيرها الكبير على نتائج الأعمال ، فإنه لا يزال هناك عدم اعتماد لهذه التكنولوجيا الجديدة بين المنظمات. لذا يهدف هذا البحث إلى التحقق من هذا التناقض من خلال التحقق من العوامل التي تؤثر على قبول واعتماد تحليلات الموارد البشرية بين خبراء الموارد البشرية في المؤسسات الفلسطينية الكبيرة.

لتحقيق هدف البحث الرئيسي ، تم استخدام منهج البحث المختلط (نوعي وكمي) لإجراء الدراسة الاستكشافية. وباستخدام الاستبيان كأداة بحث ، تم جمع البيانات المطلوبة من عينة طبقية مختارة عشوائياً تتكون من 151 متخصص في الموارد البشرية يعملون في مؤسسات فلسطينية كبيرة في قطاعي الخدمات والتصنيع. وقد أظهر التحليل الإحصائي للبيانات التي تم جمعها باستخدام برنامج

وتحليل الانحدار الخطي أن عوامل توفر البيانات ، الأداء المتوقع ، الكفاءة الذاتية Minitab والكفاءة الذاتية الكمية هي أهم العوامل التي تؤثر على القبول والاعتماد الفردي لتحليلات الموارد البشرية بشكل إيجابي في المؤسسات الفلسطينية الكبيرة. في حين أن عوامل التأثير الاجتماعي ، توفر الموارد ، مشاعر الخوف والجهد المتوقع ليس لها تأثير على قبول وتبني تحليلات الموارد البشرية. علاوة على ذلك ، يشير تحليل الارتباط إلى علاقة قوية بين المستوى الفردي والتنظيمي للقبول واعتماد تحليلات الموارد البشرية ، ونموذج الانحدار يمثل هذه العلاقة الهامة.

واستناداً إلى نتائج البحث ، تم وضع إطار مفاهيمي لوصف القبول والتطبيق الملائمين لتحليلات الموارد البشرية على المستوى الفردي في المؤسسات الفلسطينية الكبيرة.