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Factors Affecting HR Analytics Adoption: A Systematic Review Using Literature Weighted Scoring Approach

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A B S T R A C T

In the era of disruptive change, a data-driven approach is vital to Human Resource Management (HRM) of any leading organization, for it is used to gain a competitive advantage. HR analytics (HRA) has emerged as innovative technologies since advanced analytics, i.e., predictive or prescriptive analytics, were widely used in the High Performing Organizations (HPOs). Therefore, many organizations elevate themselves to become HPOs through Data Science on the “people side.” This paper proposes a systematic literature review using the Literature Weighted Scoring (LWS) to develop a conceptual framework based on three adoption theories, which are the Technology-Organization-Environment (TOE), Diffusion of Innovation (DOI), and Unified Theory of Acceptance and Use of Technology (UTAUT). The results show that a total of 13 theory-derived factors are determined as influential factors affecting HRA adoption, and the top three factors are “Quantitative Self-Efficacy,” “Top Management Support,” and “Data Availability.” The conceptual framework with hypotheses is proposed to provide a foundation for further studies on organizational HRA adoption.

Keywords: HR Analytics Adoption, Innovation Adoption, TOE Framework, Systematic Literature Review, Weighted Scoring

Ⅰ. Introduction

Currently, Human Resource (HR) is playing a vital role in aligning HR strategies with organizational strategies (Gupta, 2017; Momin and Mishra, 2015; Reddy and Lakshmikeerthi, 2017). Many organizations believed that HR was not a “profit center” because HR practitioners lacked the HR metrics to evaluate the employee value (Becker and Gerhart, 1996; Masese and UttaM, 2016; Stuart, 2005). Furthermore, Friedman (2017) presented the graph to explore that technology increased at a faster rate

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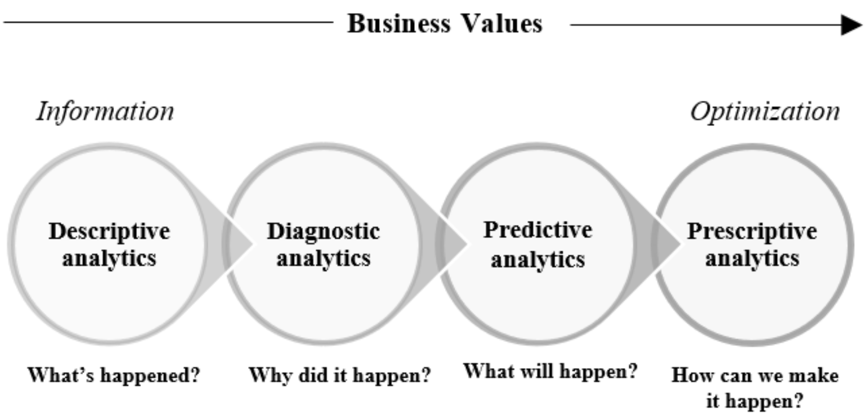
while HR has changed at a slower rate (Deloitte University, 2017). Therefore, HR needs to transform itself and tangible HR activities. HR must turn their roles into professionals or experts, and position themselves as a strategic partner through data analytics. Strategic HR aims to create a competitive advantage through Business Intelligence (BI) on the "people side" (Batarliene et al., 2017; Smith, 2013). Similarly, a survey of 359 North American organizations in 2006 reported that BI or data analytics adoption was becoming one of the top five successful practices in deriving organization value from data assets (Khatri and Brown, 2010). Moreover, Deloitte University (2018) stated that HR, also known as data or information on people, generated plentiful opportunities, and Harvard Business Review (2014) reported that 48% of 230 executives would be investing in data analytics in HR. The data analytics in HR has various labels, such as HR analytics, HR intelligence, workforce analytics, talent analytics, HR research, and people analytics (Falletta, 2014). However, a widespread label is "HR analytics" or "HRA" which is defined 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 a simple report of HR metrics all the way up to predictive modelling" (Bassi, 2011). While the data analytics trend is rising in several business lines, such as Marketing and Finance, many organizations have rarely taken benefits from HRA, and the more sophisticated the analytics are, the lower percentage they use in HR (Kapoor and Kabra, 2014). Therefore, organizations must support the adoption of HRA to get an insight from the HR data, focus on the internal environment, such as existing technologies and HR practice, and promote HRA to play a strategic role in data-driven decision-making (Falletta and Combs, 2020). Mukundan (2017) presented the type of HRA, similar to Business Analytics (BA), with an analytics continuum in 2012 by Gartner Consulting, as shown in <Figure 1>.

As shown in <Figure 1>, descriptive analytics gives an idea to the question "What is happened?" or "What is happening?" This type was schemed by traditional Business Intelligence (BI) and data visualization. Diagnostic analytics answer the question "Why it happened?" These analytics types elevate the depth of the descriptive data and explain the problems' origin. Predictive analytics or analysis of future scenarios answer "What will happen?" and are based



<Figure 1> HRA Types Aligned with BA

on historical data that can predict the future. Prescriptive analytics examines data or contents to answer the question "What should be done?" or "What can we do to make it happen?" (Gartner, 2018; Mukundan, 2017).

Technology and innovation adoption have recently received more attention for more than three decades. There was a rapid change in HR research, and many studies have researched HRA topics related to technology, innovations, systems, policies, programs, processes, or services. Since an organization made a shift toward HRA, and it was defined as "innovation" many years ago. Davenport (2006) identified HRA as a "complex innovation," and several scholars defined HRA as an "innovation." The organizations have faced challenges in HRA adoption. The possible HR optimization solutions positively affected HRA rising from 12% to 40% in 2017, and HRA is a new role added to all organizations in 2020 (Sierra, 2014; Sierra, 2018). Rogers (2003) and Rogers (2010) defined adoption as "a decision to make full use of an innovation or technology in terms of both product and processes as the best course of action available." Other scholars defined it as "an attributed to the decision made to use new systems to implement in projects and organizations" (Almarri et al., 2019; Hosseini et al., 2016). HRA was related to the terms of both "Technology" and "Innovation." Renaud and Van Biljon (2008) restated the definition of technology adoption as "a multi-phase process starting with the user becoming aware of the technology, and ending with the user embracing the technology and making full use of it." In sum the existing literature confirms that HRA adoption was identified as technology innovation.

According to the previous studies of technology or innovation adoption, technology acceptability should be perceived before using it, while technology acceptance should be perceived after using it (Distler et al., 2018; Nadal et al., 2019; Wang et al., 2015). Two fundamental phases of adoption and acceptance stages (adoption awareness or adoption intention) were the prior stage to the adoption decision (accept or reject). Halper and Stodder (2015) presented five stages of data analytics adoption in the analytics maturity model by Transforming Data With Intelligence (TDWI) involving "Nascent," "Pre-Adoption," "Early-Adoption," "Corporates Adoption," and "Mature Visionary." Other scholars proposed three stages of innovation adoption: "Pre-Adoption," "Adoption-Decision," and "Post-adoption" (Rogers, 2003) that is similar to Hameed et al. (2012) who proposed the model of technology adoption in a sequence of three stages: (1) Initiation; (2) Adoption Decision; and (3) Implementation. Besides, HRA adoption processes aligning with the IT innovation adoption recognized three stages: "Initiation," "Adoption-Decision," and "Implementation" (Hameed et al., 2012; Rogers, 1995). Therefore, this study integrated the analytics maturity model of Halper and Stodder (2015) with a three stages IT innovation adoption process involving "Initiation" or "Pre-Adoption," "Adoption-Decision," and "Implementation" or "Post-adoption," as shown in <Figure 2>.

As shown in <Figure 2>, a three-stage IT innovation adoption process was presented. Firstly, "Initiation" or "Pre-Adoption," represents the analytics environment before HRA adoption. Secondly, "Adoption-Decision" is the associated decision unit in activities that result in acceptance or rejection. Lastly, "Implementation" or "Post-adoption" represents that the HRA transforms into a strategic function, and the HR employees get involved. This stage ends with the HRA becoming established in organizations and employees operate it daily (Halper and Stodder, 2015; Hameed et al., 2012; Rogers, 1983).

<Figure 2> Three Stages IT Innovation Adoption Processes

Lee et al. (2016) adverted Information System or IS research focused on individuals, teams, and organizations' adoption, such as Electronic Data Interchange, Cloud Computing, and FinTech to identify and understand the factors affecting the acceptance and actual use of IS. Davenport (2019) posited HR departments as the initiative to adopt HRA that "they are making use of advanced analytical methods like predictive and prescriptive models, and even artificial intelligence." Similarly, Huselid (2018) justified using data analytics in HR to make certain that it focuses on this analytics beyond the HR function.

There are many HRA in qualitative studies, such as case studies and interviews, while the HRA empirical studies at an organizational level are far more limited. Many case studies were proposed. For example, Fiocco (2017) explored the spread of HRA within the HR function of one a massive Swedish-based multinational corporation (MNC) based on the DOI theory by Rogers (2003). Malini (2018) conducted a case study of selected Indian organizations and focused on understanding the adoption of HRA organizations in its present scenario. Ruohonen (2015) explored and identified the possible business benefits of implementing predictive analytics in the HR area conducting four case studies. Molefe (2014) conducted the exploratory study to measure HRA usage levels through qualitative studies in 15 large organizations in South Africa. Gustafsson (2012) conducted research to gain knowledge and insight regarding its current practice of Workforce Analytics (WA) in Swedish companies. On the other hand, few empirical studies were conducted. Vargas et al. (2018) studied the individual adoption of HRA in the early stages of innovation based on an innovation theory by Rogers (2003) and Theory of Planned Behavior (TPB) by Ajzen (1991) in order to examine the individual's decision to adopt HRA in the early stages. Saraswathy et al. (2017) explored the factors contributing to the application of HRA, and the concept of HRA with contingency factors of influence. Alamelu et al. (2017) categorized the factors involved in the adoption of HRA to create a better awareness of usage of analytics in the organization and to extend the literature on the adoption of innovation at the individual level of HRA, both academics, and practitioners. Vargas (2015) studied why HR professionals did not use HRA to improve organizational performance, and the factors impacting the HRA adoption were not only individual but its extent to the organization. Barrière (2016) represented the relationship between employees' trust in management and attitude towards HRA and highlighted the need for the encouragement of employee participation in HRA. Dooren (2012) proposed the contingency factors affecting the applicability of HRA including the methods and instruments used in the field of HRA.

It is essential to mention that HRA adoption in organizations was rarely found in empirical research. Marler and Fisher (2013) stated that high-quality scientific evidence-based research was very limited in HRA. Masese and UttaM (2016) advised that further studies should address the proposed theoretical frameworks to develop a new evidence-based model by exploring both the tangible and intangible factors involving technology or innovation to solve the organizations' problems. The study by Fiocco (2017) was in agreement with the study by Kapoor and Kabra (2014) and Sjoerd and Tanya (2017). They identified that the HRA field research should create vast academic contributions possibilities even if the empirical research were extremely limited. Therefore, this study found the importance of HRA as advantageous to both business and academic viewpoints that need to be linked together via systematic evidence. Many studies showed that there are many ways to conduct the literature reviews through systematic approach. Marais et al. (2020) developed a conceptual framework for technology management in the healthcare domain using a systematic review of 44 studies to extract the key success factors, scopes of practice, and design guidelines and criteria. Oh (2020) presented advanced analyses, namely Secondary Uses of Meta-Analytic Data (SUMAD), for theoretical and practical purposes of producing new knowledge since Meta-Analytics cannot directly generate the results. Furthermore, Xiao and Cooke (2020) proposed a systematic literature review of 178 studies to capture HRM's perspective in Chinese SOEs. Similarly, Harada and Sengoku (2019) conducted a systematic review of 136 studies to derive the key success factors of the management team in biotech start-up firms.

In this study, not only the systematic literature review approach was focused on, but the new approach, namely Literature Weighted Scoring (LWS), is also used to identify the factors of HRA adoption in organizations. At the same time, white and commercial papers are brought in to broaden the review and make the research findings valid and systematic. The study proposes a systematic literature review based on the LWS to identify the factors of HRA adoption and possible conceptual framework in the organizations.

Ⅱ. Related Theories

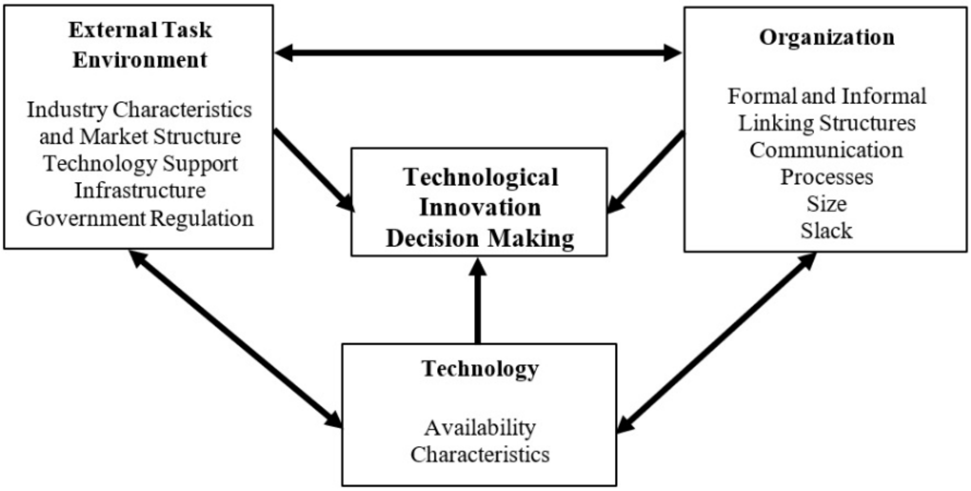
This study selected the Technology-Organization-Environment (TOE) framework (Tornatzky et al., 1990) as the core theory, and the factors in each context were derived from two theories: Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) and Diffusion of Innovation (DOI) Theory (Rogers, 1983). These theories are described as follows:

2.1. Technology-Organization-Environment (TOE) Framework

The TOE framework is an organization-level theory, described in Tornatzky and Fleischer's technological innovation processes (Tornatzky et al., 1990).

As displayed in <Figure 3> the TOE framework consists of three contexts that affect technological innovation: technological, organizational, and environmental context. The technological context refers to all of the technologies that are relevant to two important factors: "Availability," and "Characteristics." The organizational context refers to the characteristics and resources of the organization: "Linking structure between employees," "Intra-organization communication processes," "Organization size," and "Slack resources." The environmental context refers to the internal and external environment: "Structure of the Industries and Markets," "Technology Infrastructure Supports," and "Government regulations."

In the previous empirical researches, the TOE framework has been used with slightly different factors in each context. Zhu et al. (2004) indicated that three relevant factors: "Technology Readiness," "Global Scope," and "Financial Resources" affect the e-business adoption in the technological and organizational contexts. Similarly, the "Competition



<Figure 3> TOE Framework

Intensity" is a new factor influencing the e-business adoption in the environmental context. Regarding the Electronic Data Interchange (EDI) adoption, Kuan and Chau (2001) offered the pertinent factors, namely, "Perceived Financial Costs," in an organizational context. In the same vein, Zhu et al. (2004) and Zhu and Kraemer (2005) proposed "Financial commitment" and "Financial Resource" factors, respectively, affecting e-business adoption. Zhu et al. (2003) proposed that the second-order factor influences the e-business adoption, "Technology competence," consisting of IT infrastructure, Internet skills, and E-business know-how. Moreover, Tushman and Anderson (1986) reported that "Competence-Enhancing" or "Competence-Destroying" must be considered when the organization evaluates the technologies. Ka and Kim (2014) organized a theoretical base to understand the main factors affecting the intention of introducing big data and verifying their validity for the empirical studies. Hereby, those three contexts affect the technology adoption, and the scholars may need to consider the technology or context that is being studied and set the unique factors or measures fitting their studies. Finally, this study chose three fundamental factors of the TOE framework: "Technology Availability," "Government Regulation," and "Formal and Informal Linking Structures."

2.2. Diffusion of Innovation (DOI) Theory

The DOI Theory has been developed by Rogers (1983). This theory presents five main factors that influence individual innovation adoption: (1) "Relative Advantage" was defined as "the degree to which an innovation is seen as being better than the idea, program, or the product it replaces;" (2) "Compatibility" was defined as "how consistent the innovation is with the values, experiences, and needs of the potential adopters;" (3) "Complexity" was defined as "how difficult the innovation is to understand and/or use;" (4) "Trialability" was defined as "the extent to which the innovation can be tested before a commitment to adopt is made," and (5) "Observability" was defined as "the extent to which the innovation provides tangible results" (Rogers, 1983). Although the DOI

Theory was not directly applicable to organizational adoption, Vargas (2015) studied both organization and individual HRA adoption, and the results showed that "Tool Availability" affects HRA adoption at the organization level. In short, those two factors match well with the characteristics of organizations: "Compatibility" or "Technology - System Fit" and "Complexity" or "Tool Availability." As a result, these two factors were added in this study.

2.3. Unified Theory of Acceptance and Use of Technology (UTAUT) Model

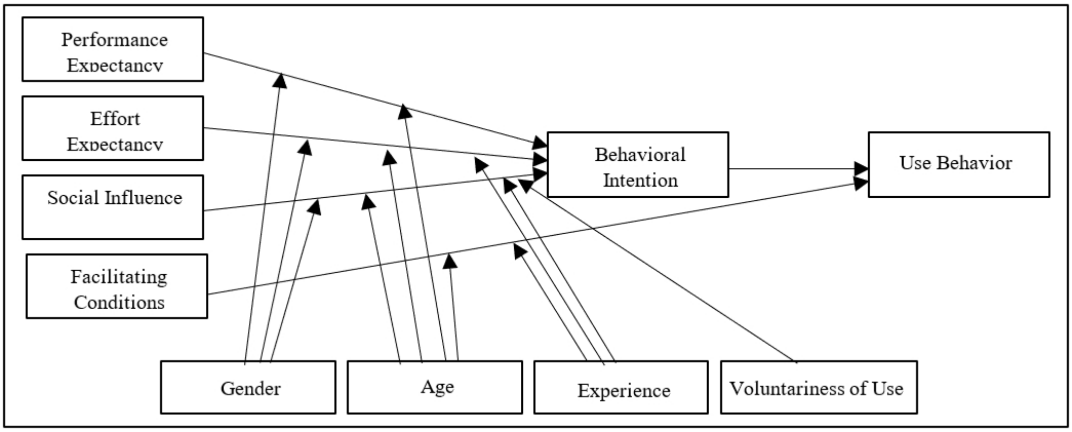
The UTAUT Model by Venkatesh et al. (2003) was consolidated from eight models which are Theory of Reasoned Action (TRA), Theory of Planned Behaviour (TPB), Technology Acceptance Model (TAM), Technology Acceptance Model (TAM), Motivational Model, Model of Personal Computer Use, Diffusion of Innovations (DOI), and Social Cognitive theory. The UTAUT model is shown in <Figure 4>.

<Figure 4> shows user intention's model of using IT and usage behavior which consists of four constructs: (1) "Performance Expectancy;" (2) "Effort Expectancy;" (3) "Social Influence;" and (4) "Facilitating Conditions." The key moderating factors were identified as experience, voluntariness, gender, and age. However, the whole UTAUT Model was not directly applied to organizational study. "Social Influence" proposed by Vargas (2015) positively influences the organizational HRA adoption. Thus, many previous studies showed that the three factors: "Performance Expectancy," "Social Influence" and "Facilitating Conditions" were the predictors of HRA adoption (Alamelu et al., 2017; George and Kamalanabhan, 2016; Vargas, 2015; Vargas et al., 2018).

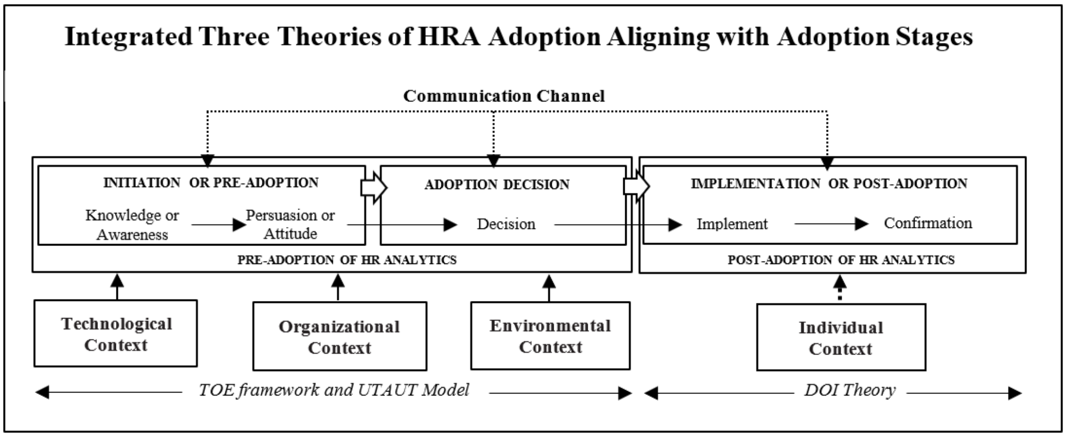
2.4. Integration Theories Approach

According to three theories described in the previous section, the Technology-Organization-Environment (TOE) framework, Unified Theory of Acceptance and Use of Technology (UTAUT), and Diffusion of Innovation (DOI) Theory are integrated to develop the structure of organizational HRA aligning with technology or innovation adoption processes by Hameed et al. (2012) as shown <Figure 5>.

As illustrated in <Figure 5>, the integration of the structure of organizational HRA aligning with



<Figure 4> UTAUT Model



<Figure 5> Integrated Three Theories of HRA Adoption Aligning with Adoption Stages

technology or innovation adoption processes is a combination of three grand theories: Organizational adoption theory (TOE framework and UTAUT model), and individual adoption theory (DOI Theory), and a ground theory: the conceptual model for IT innovation adoption process according to Hameed et al. (2012). The ground theory is categorized into three stages: "Initiation" (innovation awareness, attitude toward adoption and proposal for adoption), "Adoption Decision" (adoption decision, resource allocation for implementation), and "Implementation" (user acceptance of innovation and actual use of innovation). The factors that affect the HRA adoption in each stage are technological, organizational, and environmental context. They are derived from two grand theories: TOE framework, and UTAUT model while the individual context is derived from DOI Theory.

Based on the literature review, as shown above, three related theories have discovered the factors influencing the HRA adoption in organizations. The next section presents the designs and methods that identify the factors affecting HRA adoption from previous studies.

Ⅲ. Designs and Methods

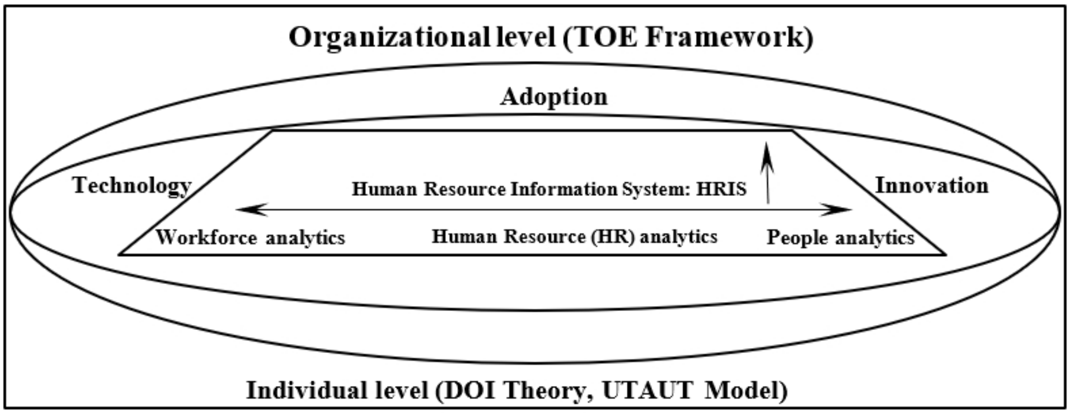
This section explains the concepts and methods of this study to extract the factors affecting the HRA adoption in organizations, including the systematic literature reviewing, the importance of Literature Weighted Scoring (LWS), the concept of LWS, and the application of LWS for HRA adoption as follows:

3.1. Systematic Literature Reviewing

The two steps of systematic literature reviewing HRA scope identification and searching literature's process are described as follows:

3.1.1. HRA Scope Identification

The HRA adoption scope is shown in <Figure 6>. As shown in <Figure 6>, the scope of the HRA terms in this study consisting of five groups: (1) the core terms: "Human Resource (HR) analytics," "Workforce analytics," "People analytics," or other similar terms, such as "Talent analytics" and "Workforces Science;"

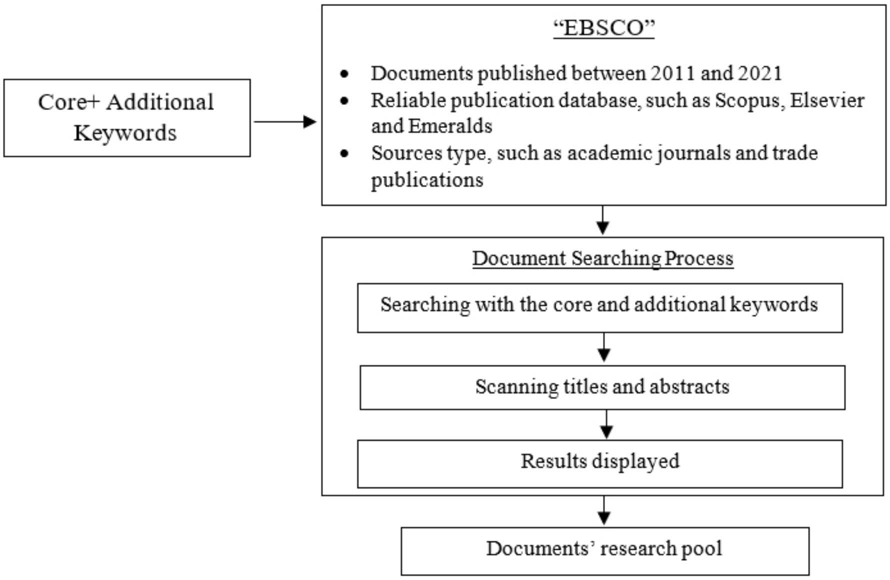


<Figure 6> Scope of the HRA Terms

(2) the related term: "Human Resource Information System or HRIS;" (3) the two terms: "Technology" and "Innovation" in which HRA adoption is a subset of them (Davenport, 2006; Vargas, 2015; Vargas et al., 2018); (4) the term "the use of HRA" is replaced by "HRA Adoption" and (5) the two adoption level terms: "Individual-level" and "Organizational-level." In sum, this HRA scope proposes the keywords to prepare for the literature-searching process so that the researcher can use them in the reliable publication database in the next step.

3.1.2. Literature-Searching Process

Literature-Searching process is illustrated in <Figure 7>. The EBSCO was used to search literature from reliable publication databases, such as Scopus, Elsevier, Emeralds, Taylor and Francis, and Web of



<Figure 7> Literature-Searching Process

<Table 1> Results of the Document Selection Process

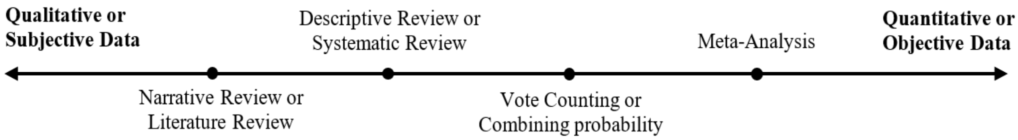
Types of Keywords	Keywords	Number of resulted documents						
		Academics Journals	Trade Publications	Books	e-books	Conference Materials	Dissertations or Theses	Total
Core Keyword	"HR analytics" or "Human Resource analytics" or "HR Intelligence" or "Talent Analytics" or "Workforce Analytics" or "HR Research", "People Analytics" or "Human Capital Analytics"	5,736	855	903	415	281	102	8,782
Core+ Additional Keywords	"Innovation" or "Technology"	3,804	379	62	920	191	63	5,659
	"Adoption"	1,337	**44**	181	727	45	**19**	2,344
	"Organizational level" or "Individual-level"	**309**	-	**18**	**354**	**3**	-	706
Selected Literatures		309	44	18	354	3	19	**789**
Full Text Availability		240	10	3	139	3	18	**413**
Detailed Literatures Evaluation		20	10	3	5	3	18	**64**

Science. The English source types included are academic journals, trade publications, books, eBooks, conference materials and dissertations or theses. The scope of publication was limited between the years 2011 and 2021. The core assigned keywords are "HR analytics," "Human Resource analytics," "HR intelligence," "Talent analytics," "Workforce analytics," "HR research," "People analytics" and "Human Capital analytics." A total of 8,782 articles were found. Consequently, the additional assigned keywords which are "Human Resource Information System," "HRIS," "Innovation," "Technology," "Adoption," "Organizational level," and "Individual-level."

After the 789 articles were selected by systematic literature approach, 413 articles were used in terms of full-text availability. The process for the final selection of relevant literature consists of three steps. First, the titles and abstracts were scanned using the keywords: "HRA adoption or acceptance," "HRIS or e-HRM adoption or acceptance," "Technology or innovation adoption or acceptance," and "HRA concept." Second, the step uses the fast reading technique to select the articles related to the factor affecting HRA adoption or acceptance, a total of empirical studies was selected in terms of grand theory, and a total of case studies was selected in terms of grand theory. Other articles (theses, books, conferences paper, review papers, white or commercial papers) was selected in following section: HRA adoption determinants, problem and obstacles, HRA challenges. The detailed literature reviewing evaluation was used for the final selection of relevant literature consisting of 15 empirical studies, 12 case studies, 21 systematic review articles, 8 white or commercial articles, and 8 books or e-book. In sum, a total of 64 articles were chosen for the LWS process in the next section.

3.2. Importance of Literature Weighted Scoring (LWS)

There are many literatures reviewing approaches according to King and He (2005), such as narrative review or literature review, descriptive review or systematics review, vote counting or combining probability, and meta-analysis as demonstrated in <Figure 8>. Those approaches are used to improve the liter-



<Figure 8> Literature Review Approaches

<Table 2> Advantages and Disadvantages of Literature Review Approaches

	Advantages	Disadvantages
Narrative Review or Literature Review	- Suitable for qualitative research - Creating classification and typology to organize the results	- No commonly accepted or standardized procedure - Lack of seeking generalization or cumulative knowledge from literature - Subjectivity and lack of explicit intent to maximize the scope or analyses of data collected can lead to biased interpretations or inferences.
Descriptive Review or Systematic Review	- More rigorous review of existing literature - Simple qualification, frequency analysis supporting a particular proposition - Systematic search for select paper to identify the distinct pattern - Enabling the in-depth systematic literature reviews within the broader literature	- Findings represent the state of the art in a particular domain - Only using for characterizing studies only not focus on a quality assessment process - Time constraints and lack the synthesis and analysis of more considered approaches.
Vote Counting	- Repeating the results in the same direction across multiple studies. - Economic reasons, such as time and cost	- Selecting the empirical studies that report significant effects only - Differential weights of each study are not considered. - Size of the effect, sample size, and are not included.
Meta Analysis	- Enabling the researchers to sample studies that show insignificant effects - Size of the effect, sample size, and are included - Enabling the researchers to search for moderator variables in the subjective data.	- Avoiding the type I error with restricted at least 15 empirical studies that are very difficult - Applicable to quantitative studies only - Researchers may select studies that 'almost' the same, and they conclude searching the studies with 'exact replications' and 'precisely the same' are almost impossible.
Literature Weighted Scoring (LWS)	- Combining the frequency analysis and weighted scoring calculation - Enabling the components of scoring, such as type of papers, publication databases, level of data analysis, and paper relevance. - Enabling the researchers to consider the previous studies that report statistically insignificant effects - Increasing the analysis and synthesize the papers with a wider perspective through multiple sources, such as review paper, and white or commercial papers not only focus on research paper - Suitable for a newly emerging research topic or limited empirical study	- Requiring academic improvement since it is a new method and not yet widely used. - Still using researchers' judgment for the total score criterion in the final step. - A small number of related papers (<50) to make the results inaccurate and unreliable.

ature review and research synthesis processes to bring in more breadth, appropriateness, and reliability, and sometimes the combination of two or more approaches has been used.

As illustrated in <Figure 8>, the literature reviewing approaches ranging from qualitative or subjective data to quantitative or objective data. A narrative review is a traditional approach for systematic qualitative review, while meta-analysis is considered the most rigorous approach (Wiles et al., 2011). Those approaches have both advantages and disadvantages as listed in <Table 2> (Bushman and Wang, 1994; Grant and Booth, 2009; King and He, 2005; Paré and Kitsiou, 2017).

As listed in <Table 2>, both advantages and disadvantages of the four existing literature reviewing approaches were considered for this study. Although the most popular criteria for factor selection was the conventional vote-counting procedure that summarizes the capriciousness in the first step, this method has many flaws, for example, it is beneficial only when the null hypothesis is true, not when it is false, and sometimes, it can confuse the treatment effect, sample size, and the results (Bangert-Drowns and Rudner, 1990; Hunter and Schmidt, 2004; Kulik and Kulik, 1989). Similarly, Bushman and Wang (1994) recommended that vote-counting was not a procedure to select since it requires a large group of studies in which effect size estimates cannot be calculated. Besides, the qualitative systematic reviewing approach lacks a quality assessment process. The other approaches, "Narrative Review" or "Literature Review," do not use generalization results. The meta-analysis, a rigorous approach, appears to be suitable for this study, but this approach requires at least 15 empirical studies that are very difficult for HRA adoption topics. HRA adoption research, particularly empirical research, is extremely limited (Fiocco, 2017; Kapoor and Kabra, 2014; Sjoerd and Tanya, 2017). Similarly, Marler and Boudreau (2017) identified that high-quality scientific evidence-based research is very limited regarding the HRA topics. Therefore, a new approach, namely Literature Weighted Scoring (LWS), was presented, and this approach was developed by combining the existing approaches: "Descriptive Review or Systematic Review," and a new approach, "Literature Weighted Scoring (LWS)" based on quality assessment approach, "Weighted Scoring." This approach was presented to align with the systematic review in the next section.

3.3. Literature Weighted Scoring (LWS) Concept

The Literature Weighted Scoring (LWS) approach is developed. It is derived from the Arithmetic mean as illustrated in Equation 1. This approach was used to analyze and synthesize the related factors with a wide perspective based on various sources. This approach was developed to reduce bias and increase data validity, as illustrated in Equation 2.

The *mean* of a sample of n measured responses $y_1, y_2, \ldots, y_n$ is given by

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{1}$$

Equation 1. Arithmetic Mean

The LWS is given by

$$LWS = \frac{e}{n}\sum_{\mathbf{k=m}}^{\mathbf{j}}\sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{S_i} \tag{2}$$

Equation 2. LWS Equation

"LWS" = *Literature Weighted Scoring;*
"S" = *LWS components relevant to a research topic;*
"j" = *upper bound of LWS literature, e.g., j=64 literatures;*
"k" = *index of LWS literature;*
"m" = *lower bound of LWS literature;*
"i" = *index of LWS component;*

"n" = *upper bound of LWS component, e.g., n=4 components;*
"e" = *effect of factors (statistically significant)*

3.4. The Application of LWS for HRA Adoption

According to this study, the index of LWS (*i*) value equals 1 to 4, and the effect of factors (*e*) consists of statistically significant equals to 1 and not statistically significant equals to 0.5. The LWS components (*S*) and scores are listed in <Table 3>.

According to <Table 3>, the LWS components (*S*) and scores can be differently applied to suit each other studies. The increasing of those components and the number of related articles make the research more valid and reliable in extracting factors from literature. Consequently, the 13 extracted factors by the LWS approach have been grouped into four contexts: technological, organizational, environmental, and individual contexts. A total of 13 influential factors affecting HRA adoption in each context are described as follows:

3.4.1. Technological Context

This context focuses on existing and new technologies, both internal and external, influencing the organizations to adopt HRA. There are previous studies that discovered the three technological factors affecting HRA adoption as follows:

Tool Availability: This factor appears in the study by Vargas (2015), and it showed that "Tool Availability" has a positive impact on both the individual and organizational HRA adoption. Venkatesh et al. (2003) stated that "Tool Availability" entails the organization's belief that an existing technical infrastructure supports system usage. Vargas (2015) reported that appropriate systems and pro-

<Table 3> LWS Components and Scores

S_i	Component Scores				
S_1: Type of Papers	Research journals	Theses or Books	Conferences	Review journals	White or Commercial papers
Scores	1.00	0.85	0.65	0.45	0.25
S_2: Publication Databases	Both of Web of Science (JIF) and Scopus (SJR)	Web of Science (JIF)	Scopus (SJR)	Others	
Scores	1.00	0.50	0.50	0.00	
S_3: Level of Data Analysis Levenson (2011)	Advanced multivariate models (Structural Equations Models (SEM), Hierarchical Linear Models (HLM), Bivariate or multivariate choice models, Cross level models)	Basic multivariate models (ANOVA or ANCOVA, Regression, Factor analysis, and Path analysis)	Intermediate data analysis (Correlation, Statistically Significant Differences, and Standard Deviation)	Basic data analysis (Mean, Median, Minimum and Maximum Range, Percentiles and Frequency)	
Scores	1.00	0.75	0.50	0.25	
S_4: Paper Relevance	HRA adoption or acceptance	HRIS or e-HRM adoption or acceptance	Technology or innovation adoption or acceptance	HRA Review	
Scores	1.00	0.75	0.50	0.25	

grams were necessary. Moreover, the skills to understand data and the ability to analyze and interpret them are required. On the other hand, both skill sets and the ability to access data were necessary and important factors.

Data Availability: This factor was derived from the study by Vargas (2015) and this study reported that "Data Availability" has a positive impact on the organizational adoption of HRA. According to (Alamelu et al., 2017), it was reported that "Data and Tool Availability" is significant in the estimation of overall HRA adaptability. Johnston (2006) described "Data Availability" as the data that is seen as the ability to generate a correct assumption. Molefe (2014) recommended that centralized and good quality data enables success to HRA adoption in organizations. The last factor in the technological context is "Compatibility" which is known as one of the five traits of innovation in the diffusion process of DOI Theory.

Compatibility: Rogers (2003) explained "Compatibility" as recognizing innovation corresponding with existing values, past experiences, and the needs of potential users. Tornatzky et al. (1990) reported that the suitability between existing and new technology drives the main adoption driver. Compatibility was used in a wide variety of studies. The study by Awa et al. (2017) showed a significant negative relationship between perceived compatibility and technology adoption, and the inverse relationship points to the fear of compatibility with existing technologies, processes, and structures.

3.4.2. Organizational Context

This context refers to the descriptive characteristics of the organizations, including firm structures and strategies, managerial support, and other types of supports. The four factors driving the organizational HRA adoption in previous studies were "Top Management Support," "Facilitating Conditions," "Organization's Strategy" and "Organization's Structure." The first factor, "Top Management Support," was extracted from the TOE Framework. Kamal (2006) and Kim and Bretschneider (2004) stated it as the support from administrative departments that play an important role in technological efforts, whether unsatisfied or completed. Other terms similar to "Top Management Support" found in previous studies are "Top Management Acumen" (Vihari and Raoa, 2013) and "Top Management Influence and Visionary" (George and Kamalanabhan, 2016). The empirical research by Awa et al. (2017) showed the significant relationship between "Top Management Support" and technology adoption, particularly executives with knowledge and experience. Kumar et al. (2020) studied multi-Stage of Business Analytics or BA adoption, and the finding showed that "Top Management Support" is most important in the evaluation and adoption stage than in the assimilation of BA similarly Pudjianto et al. (2011) reported that "Top Management Support" is significant factors on e-government assimilation. The second factor, "Facilitating Conditions," was derived from the UTAUT Model. Venkatesh et al. (2003) stated that the system was believed to be supported by continual organizational and technical infrastructure. The third factor was the modified factor based on the TOE Framework, namely "Formal and Informal Linking Structures" or "Organization's Structure" in this study. Fiocco (2017) and Molefe (2014) defined it as the redesigned organizational structure, and any department will be adjusted to adopt the new technology. Saraswathy et al. (2017) found that the team building or "dedicated HR team" significantly influences the HRA application. Dooren (2012) suggested that an organic structure is required for HRA adoption. The last factor derived from the study by Saraswathy et al. (2017) is "Organization's Strategy" which is defined as the organizations that focus on planning and controlling and enhancing the opportunity to use complex technology. The empirical study by Wanyoto (2016) showed that an organizational strategy is a strong predictor of the degree of adoption of HRA. In contrast, although the study by Saraswathy et al. (2017) showed that the "Organization's Strategy" does influence the application of HR analytics. Other studies revealed the importance of the "Organizations' Strategy." For example, Lakshmi and Pratap (2016) affirmed that the key goals of HRA align HR strategies with "Organizations' strategy." Witte (2016) also pointed out that HRA is strongly positioned in organizational HR strategies.

3.4.3. Environmental Context

This context focuses on the environment of the organizations or the external industrial factors that may affect the organizations. The environmental factors from previous studies' evidence were "Competitive Intensity," "Government Regulation," and "Data Governance." The two factors based on the TOE Framework were "Competitive Intensity" and "Government Regulation," which are the critical adoption factors in organizations. Zhu and Kraemer (2005) defined "Competitive Intensity" as the pressure which the organizations sense from competitors within the industries similarly Pudjianto et al. (2011) proposed that "Competition Environment" is a significant factor in e-government assimilation. HRA is assured of acting as a basis of competitive advantage and enhancing HR professionals' images of organizations (Bassi, 2011). Kamal (2006) proposed that the high level of external pressures can positively influence IT innovation adoption in governmental organizations. Zheng (2014) stated that "Government Regulation" or "Regulatory Environment" is essential for leaders to take the environment and its strategies into account. similarly, Pudjianto et al. (2011) proposed that "Regulatory Environment" is significant factors on e-government assimilation. Bingham and McNaught (1976) presented inter-governmental influence, such as grants and technical support on the innovation adoption in government organizations. The last environmental factor was "Data Governance" which was derived from Spahic (2015) suggestion stating that the topic of ethics in HRA requires further study because the vital ethical issues are concerned with HRA practices. Ladley (2012) defined "Data Governance" as information management that should comply with executive command policies. The governance dimension features how coherent the data governance strategy in organizations is and how it supports the analytics process to ensure that Data Analyst has relevant and appropriate data for analysis, and the privacy data is protected (Halper and Stodder, 2014).

3.4.4. Individual Context

This context was based on beliefs, values, and impacts on particular innovations and individual perception. The research evidence explores the three individual factors: "Quantitative Self-Efficacy," "Social Influence" and "Performance Expectancy" as follows:

Regarding "Quantitative Self-Efficacy" or "Mathematical Self-Efficacy," this factor was derived from some previous studies (Vargas, 2015; Vargas et al., 2018). Ozgen (2013) defined "Quantitative Self-Efficacy" as the quantitative skills that involve the discernment of one who believes. There are other terms in specific

HRA adoption studies, such as "Quantitative Efficacy" (Alamelu et al., 2017), "Analytical Skills" (George and Kamalanabhan, 2016), and "Analytical Competencies" (Lydgate, 2018). George and Kamalanabhan (2016) reported that the term "Analytical Skills" was cited as the top individual-level factor influencing HRA adoption. Conversely, Alamelu et al. (2017) reported that "Quantitative Efficacy" is not significant in estimating overall HRA adoption. "Analytical Skills" in many case studies were treated as the barriers to adopt HRA, such as lack of analytical skills and competences among HR practitioners, lack of analytical knowledge and experience to adopt HRA, lack of the ability to understand statistical terminology among HR professionals and insufficient skills and ability of HRA area among HR (Anturaniemi, 2018; Cascio and Boudreau, 2011; Dooren, 2012; Witte, 2016).

Regarding "Social Influence" and "Performance Expectancy," these factors were derived from the UTAUT Model. "Social Influence" was the behavior of an individual mutually affected by people in the community as the adoption occurs (Rice et al., 1990; Venkatesh and Brown, 2001). "Social Influence" has also been highlighted as a behavioural factor in prior studies. Rogers (1995) identified "Social Influence" as the information from secondary sources that affect the decision to adopt innovation or technology in an early stage. Venkatesh and Brown (2001) proposed that "Social Influences" are the most significant considering decision to adopt for non-adopters. Venkatesh et al. (2003) defined "Performance Expectancy" as a personal belief in which the use of the system will encourage any organization to achieve profit depending on organization performance. It is also noted that "Performance Expectancy" appears to be a determinant of adoption intention. There are similar terms, such as "Usefulness and Relative Advantage" (Davis, 1989) and "Job-Fit and Outcome Expectation" (Compeau and Higgins, 1995). In contrast, Alamelu et al. (2017) reported that "Social Influence" and "Performance Outcome and Effort" are not significant in the estimation of overall HRA adaptability.

Those 13 factors in four contexts have been continually conducted and improved by previous studies which gained empirical validity for technology or innovation adoption. The summary of extracted factors, definitions, and other terms and references are listed in <Table 4>.

In conclusion, each extracted factor is significant

<Table 4> Summary of Extracted Factor, Definitions and Other Terms and References

Factors	Definitions	Other Terms and References
Technological Context		
Tool Availability (Alamelu et al., 2017; Vargas, 2015)	"The degree to which an organization believes that a technical infrastructure exists to support the use of the system" (Venkatesh et al., 2003)	Technology Availability (Tornatzky et al., 1990), Data and Tool Availability (Alamelu et al., 2017)
Data Availability (Vargas, 2015)	"The degree to which information (data) is perceived as competent in producing correct assertions" (Johnston, 2006)	Data and Infrastructure (Anturaniemi, 2018), Data Variability or Accessibility (Fiocco, 2017)
Compatibility (Rogers, 1983)	"The degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters" (Rogers, 2003)	Perceived Compatibility (Awa et al., 2017), Innovation or Technology-System Fit (Rogers, 1983)

<Table 4> Summary of Extracted Factor, Definitions and Other Terms and References (Cont.)

	Definition of Factors	Other Terms and References
Organizational context		
Top Management Support (Tornatzky et al., 1990)	"The degree to which the support from administrative authorities play a significant role in whether technology efforts are frustrated or completed" (Kamal, 2006; Kim and Bretschneider, 2004)	Top Management Influence and Visionary (Anturaniemi, 2018; Awa et al., 2017; George and Kamalanabhan, 2016), Top Management Acumen (Vihari and Raoa, 2013)
Facilitating Conditions (Venkatesh et al., 2003)	"The degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" (Venkatesh et al., 2003)	-
Organization's Strategy (Saraswathy and Premakumari, 2016)	"The degree to which the organizations are meticulous in terms of planning and controlling and the chance to adopt the sophisticated technology will probably be higher" (Saraswathy et al., 2017)	-
Organization's Structure (Anturaniemi, 2018; Saraswathy and Premakumari, 2016)	"The degree to which the organizational structure is redesigned and their departments are transformed for new technology adoption" (Fiocco, 2017; Molefe, 2014)	Formal and Informal Linking Structures (Tornatzky et al., 1990)
Environmental Context		
Competitive Intensity (Tornatzky et al., 1990)	"The degree of pressure that the organization feels from competitors within the industry" (Zhu and Kraemer, 2005)	Competitive Pressures (Awa and Ojiabo, 2016), Number of Competitors (Saraswathy et al., 2017)
Data Governance (Spahic, 2015)	"The use of authority combined with policy to ensure the proper management of information assets" (Ladley, 2012)	Governance Dimension (Halper and Stodder, 2014)
Government Regulation (Tornatzky et al., 1990)	"The only way to get leaders to react to environmental concerns and incorporate it into their organization strategies, which are usually mandatory, but are also in the form of guidelines sometimes" (Zheng, 2014)	Government support (Alhammadi et al., 2015), Regulatory Environment (Zhu et al., 2006)
Individual context		
Quantitative Self-Efficacy (Vargas, 2015; Vargas et al., 2018)	"The individual's personal believed judgment in relation to their quantitative skills" (Ozgen, 2013)	Quantitative Efficacy (Alamelu et al., 2017), Analytical Skills (George and Kamalanabhan, 2016), Analytical Competencies (Lydgate, 2018)
Social Influence (Venkatesh et al., 2003)	"The extent to which members of a social network influence one another's behavior in adoption" (Rice et al., 1990; Venkatesh and Brown, 2001)	Subject Norm (Alamelu et al., 2017; Awa et al., 2017)
Performance Expectancy (Venkatesh et al., 2003)	"The degree to which an individual believes that using the system will help his or her organization to attain gains in organization performance" (Venkatesh et al., 2003)	Performance Outcome and Effort (Alamelu et al., 2017), Perceived values or Extrinsic motivation, Job-fit (Awa and Ojiabo, 2016; Awa et al., 2017)

with adoption level or adoption intention depending on differences in each context and the type of innovation or technology. The results of those 13 factors identifying by the LWS approach are presented in the next section.

Ⅳ. Results

This section describes the results of the factors of the HRA adoption identification and proposed conceptual framework with hypotheses as follows:

4.1. Identifying the Factors of the HRA Adoption

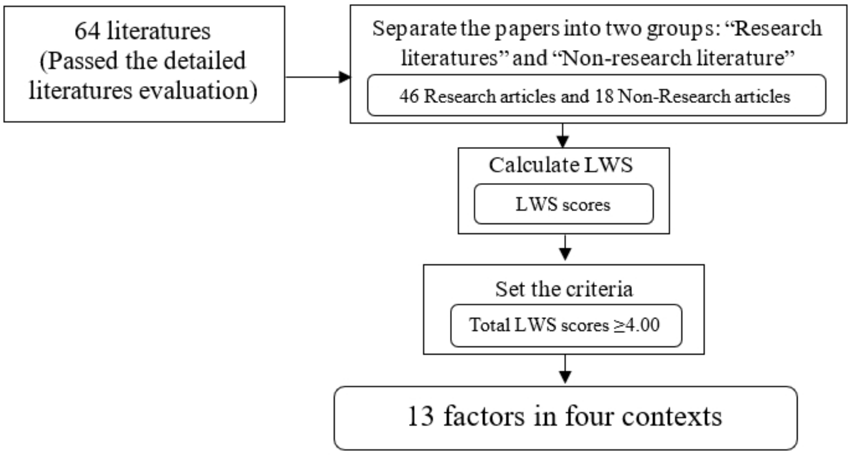
The 13 factors were extracted using four steps of the LWS approach: (1) Separate the literature into two groups (research literature and non-research literature); (2) Calculate the LWS; (3) Set the criteria for factor selection, and (4) Select and rank the factors by the LWS Scores. The factors extraction procedure is shown in <Figure 9>.

As shown in <Figure 9>, a total of 64 articles received a pass from the detailed literature evaluation and entered the first step of the LWS. Then they were separated into two groups: 46 research articles and 18 non-research articles. Next, the LWS scores of those works of literature were calculated, and the results showed the total LWS scores. Then the factors were selected when the total LWS score was more than 4.00. Finally, 13 factors were identified and ranked by the total LWS scores. The results of the LWS are listed in <Table 5>.

According to <Table 5>, a total of 13 factors were selected and ranked by the total LWS scores, and the top three factors are "Quantitative Self-Efficacy," "Top Management Support," and "Data Availability." Those factors were grouped into four contexts to develop the HRA adoption structure in the following section.

4.2. Structure of HRA Adoption Processes

According to the previous section, IT adoption processes by Hameed et al. (2012) were applied for specific organizational HRA adoption processes. This section presents the structure of organizational HRA



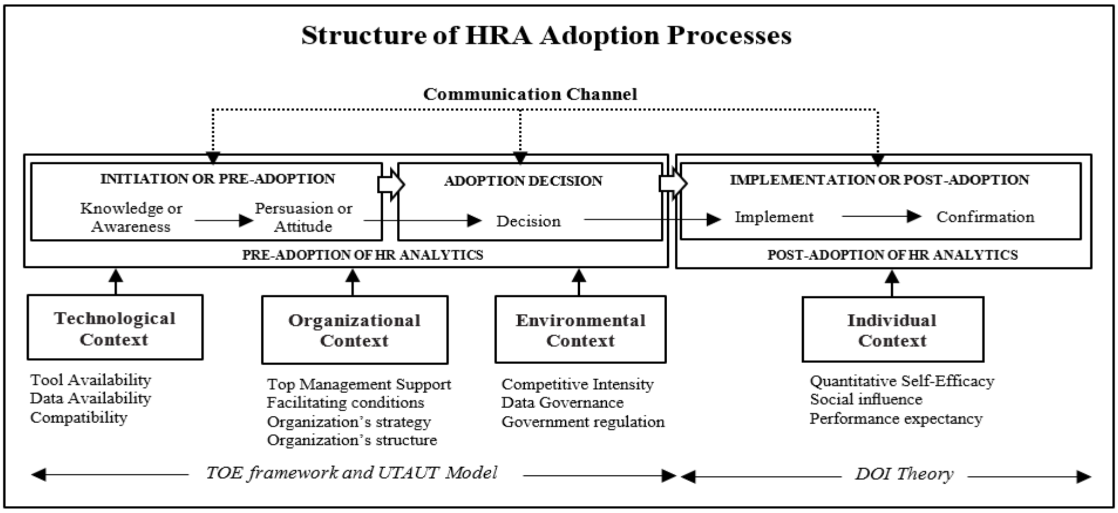
<Figure 9> LWS Calculation Step

adoption processes, as shown in <Figure 10>.

As illustrated in <Figure 10>, the specific organizational HRA adoption processes are a combination of both grand theories: the Technology-Organization-Environment (TOE) according to Tornatzky et al. (1990), and Unified Theory of Acceptance and Use of Technology (UTAUT) according to Venkatesh et al. (2003); and ground theories: the conceptual model for IT innovation adoption process according to Hameed et al. (2012) and the five stages of innovation decision-making process according to Rogers (2003). According to the results of this study,

<Table 5> Results of Identification of the HRA Adoption's Factors by LWS

Contexts	Factors	LWS Scores (Total LWS Scores ≥4.00)			Rank
		Research literature	Non-Research literature	Total	
Technological Context	Tool Availability	6.33	0.64	6.97	4
	Data Availability	**4.47**	**2.88**	**7.35**	**3**
	Compatibility	3.20	0.81	4.01	11
Organizational Context	**Top Management Support**	**4.97**	**2.80**	**7.77**	**2**
	Facilitating Conditions	4.22	1.96	6.18	6
	Organization's Strategy	3.42	2.84	6.26	5
	Organization's Structure	4.12	-	4.12	9
Environmental Context	Competitive Intensity	4.36	-	4.36	8
	Data Governance	2.47	1.22	4.05	10
	Government Regulation	2.34	1.67	4.01	11
Individual Context	**Quantitative Self-Efficacy**	**5.38**	**4.08**	**9.46**	**1**
	Social Influence	3.97	0.54	4.51	7
	Performance Expectancy	4.00	-	4.00	12



<Figure 10> Structure of HRA Adoption Processes

13 first-order factors were grouped into four second-order factors, and those factors were included in the structure of organizational HRA adoption processes. Those 13 first-order factors were grouped into four second-order factors and were used to establish the proposed second-order conceptual framework as shown in the following section.

4.3. Conceptual Framework Establishment and Propositions

Total 13 factors were grouped into four contexts of conceptual framework based on TOE framework, and this study modified the structure of TOE framework to identify the four contexts as the second-order factors, namely "Technology Availability," "Organization Competence," "Environment Force" and "Individual Driven." The four second-order factors are detailed as follows:

4.3.1. Technology Availability

Previous studies discovered the second-order factor, namely "Technology Availability," affecting HRA Adoption Level." Other names of these factors are "Technology Readiness," "Technology Competence," and "Technological Context." Three first-order factors are grouped: "Tool Availability," "Data Availability," and "Compatibility." The previous studies indicated that "Technology Availability" directly positively influences "Technology Adoption." According to the study by Vargas (2015) showed that the two technological factors affecting HRA adoption are "Tool Availability," and "Data Availability." Daradkeh (2019) stated that "Technology Readiness" is a predictor of the main factor influencing the visual analysis acceptance. Oliveira et al. (2014) found that "Technology Readiness" is the influential determinant of cloud computing adoption in the service and manufacturing sectors. Zhu et al. (2006) reported that "Technology Competence" significantly impacts the use of e-business. Some other scholars support this finding that "Technology Readiness" will positively influence the IT adoption decision (Puklavec et al., 2018; Wang and Wang, 2016). "Technology Competence" is a significant adoption facilitator of e-business (Zhu et al., 2002; Zhu et al., 2003). Pan and Jang (2008) found that "Technology Readiness" is moderately positively associated with ERP adoption. Awa and Ojiabo (2016) proposed that "ICT infrastructures" and "Perceived Compatibility" were found statistically significant adoption determinants.

Zhu et al. (2006) found that the factors namely "Technology Readiness" and "Technology Integration" are positive factors for e-business adoption in both developed and developing countries. On the other hand, other previous studies suggested that "Technology Readiness" does not influence technology adoption. Hmoud and Várallyai (2020) asserted that "Technology Readiness" did not affect the intention to use AI-HRIS. Other studies stated that "Technology Readiness" did not find it as a critical factor of the ERP adoption (Premkumar and Ramamurthy, 1995; Thong, 1999). Oliveira and Martins (2009) concluded that "Technology Readiness" did not affect e-commerce adoption. In summary, these findings from previous studies can be summarized that the future HRA adoption studies should focus on "Organizational Competence" with four first-order factors: "Tool Availability," "Data Availability," and "Compatibility." proving that those factors have a positive significant influence the HRA adoption that supports an increase to adopt it in the organizations. The proposed hypothesis is listed in Proposition 1.

Proposition 1: (H1) Technology Availability will have a positive significant influence on HRA Adoption Level.

4.3.2. Organizational Competence

This second-order factor consists of four first-order factors that described the organizational competence, namely: "Top Management Support," "Facilitating Condition," "Organizations' Strategy," and "Organization Structure." Some studies named this factor as "Organization Characteristics," "Organizational Readiness," and "Organizational Context." Many previous empirical studies are discussing this second-order factor. According to the study by Vargas (2015) showed that the three organizational factors affecting HRA adoption are "Social Influence," "Tool Availability," and "Data Availability" Likewise, the contingency factors influencing the degree of application of HRA at the organization level are "Dedicated HR Team," "Organizations' age," "Organizations' structure," "Organizations' Size," and "Organizations' strategy" (Dooren, 2012; Saraswathy et al., 2017). There are some other studies related to innovation or technology adoption that support this study. Williams (2011) concluded that "Organization Readiness" is essential to enhance innovation readiness by identifying some key organizational strategies to support the adoption of new ideas and services and sophisticated technologies. Nemati and Udiavar (2012) identified four main factors of "Organization Readiness" for Supply Chain Analytics (SCA) from the empirical results, which are standardized and integrated data, well-established infrastructure, sound technical and non-technical expertise, and the organizational culture and strategy. In sum, these findings from previous studies can be summarized that the future HRA adoption studies should focus on "Organizational Competence" with four first-order factors: "Top Management Support," "Facilitating Condition," "Organizations' Strategy," and "Organization Structure." to ensure that those factors have a positive significant influence on the HRA adoption in organizations. The proposed hypothesis is listed in the Proposition 2.

Proposition 2: (H2) Organization competence will have a positive significant influence on HRA Adoption Level.

4.3.3. Environment Force

This second-order factor influences the organizations' level of technological innovation (Tornatzky et al., 1990), and the three first-order factors consist of "Government Regulation," "Competitive Intensity," and "Data Governance." Some studies of literature named this factor as "Environmental Conditions," "Environment Characteristics," "Environment Pressure," and "Environmental Context." The environmental condition influences the motivation of an organization to adopt innovation, and these factors play a critical role in enabling organizations to adopt the technology (Damanpour and Gopalakrishnan, 1998; Ruder-Hook, 2018). In the competitive environment, organizations' leaders and HR managers should intend to adopt HRA to increase the potential of HR (Etukudo, 2019). There are many previous empirical studies to support this finding. The empirically investigated results found that the external environment plays any role in adopting advanced Business analytics in organizations (Grant, 2020). Other studies have focused on each type of IT adoption. Zhu et al. (2002) proposed the findings of environmental factors as "Competitive Pressure" are significant adoption facilitators of e-business. Looi (2005) examined the effect of five factors on E-commerce adoption among small and medium-sized enterprises, and the findings indicated that "Environment Characteristics," such as "Competitive Pressures," and "Government Support" are significant motivators of E-commerce adoption. Awa and Ojiabo (2016) found that "External Supports," and "Competitive Pressures" are equally important, but its negative effect suggests less obstacles to adopters than to non-adopters. On the other hand, Teo et al. (1997) explored a contingency model of internet adoption among large businesses, and they concluded that the "Environmental Factors" were less important than "Organizational and Technological Factors." In summary, these findings from previous studies can be summarized that the future HRA adoption studies should focus on the environment force including "Government Regulation," "Competitive Intensity," and "Data Governance" to ensure that those factors are ready to motivate the organizations and adopt the HRA. The proposed hypothesis is listed in the Proposition 3.

Proposition 3: (H3) Environment Force will have a positive significant influence on HRA Adoption Level.

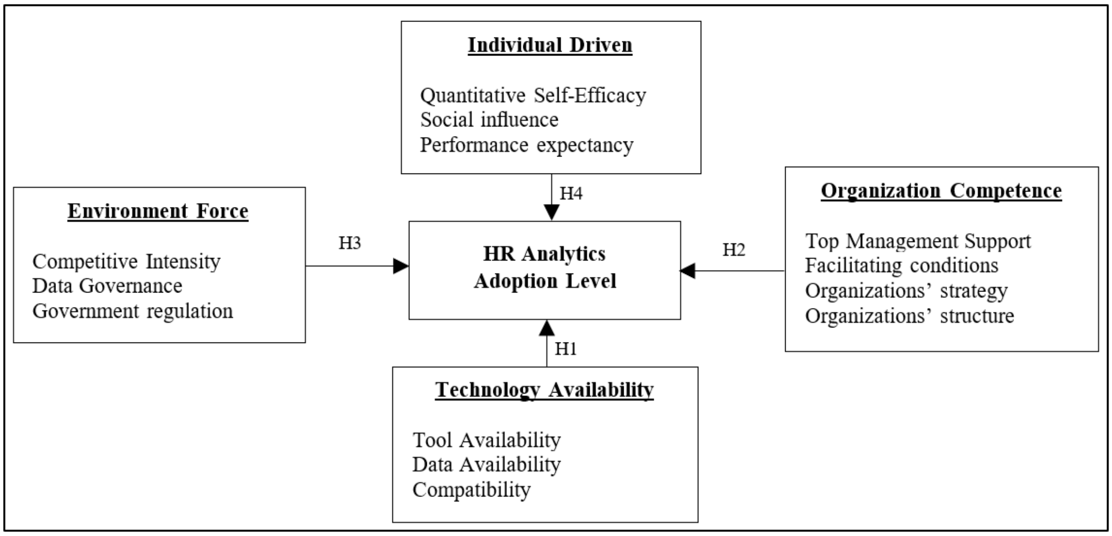
4.3.4. Individual Driven

This second-order factor consists of three first-order factors that described the individual driven, namely: "Quantitative Self-Efficacy," "Social Infl uence," and "Performance Expectancy." Previous studies of literature named this factor as "Individual Acceptance," "Individual Adoption," and "Individual Context." Many previous empirical studies are discussing this second-order factor. Venkatesh and Brown (2001) proposed that first-order factors, such as "Social Influences" are the most significant element of the decision to adopt technology for non-adopters. Similarly, Rogers (1995) identified "Social Influence" as the information from secondary sources that affect the decision to adopt innovation or technology at an early stage. Lee et al. (2016) reported that recent studies focus on "Social Influence" to encourage organizations to interact with society. Vargas (2015) reported that the attitude towards analytics predominantly drives the individual level of HRA adoption and closely followed by the first-order factors, namely "Quantitative Self-Efficacy" Similarly, George and Kamalanabhan (2016) proposed that the individual factor, namely "Analytical skills," and "Performance Expectancy" influencing the use of analytics in HR. Alamelu et al. (2017) reported that the first-order factors, namely "Data & Tool Availability" and "Fear Appeal" and "Level of Acceptance" are significant. In conclusion, these findings from previous studies can be summarized that the future HRA adoption studies should focus on the individual driven: "Quantitative Self-Efficacy," "Social Influence," and "Performance Expectancy" to ensure that those factors have a positive significant influence on the HRA adoption in organizations. The proposed hypothesis is listed in Proposition 4.

Proposition 4: (H4) Individual driven will have a positive significant influence on HRA Adoption Level.

The four second-order factors with 13 first-order factors and the four propositions (H1-H4) are proposed and those propositions can be used, as further research, in HRA adoption in organizations and tests in context as illustrated in <Figure 11>.

According to <Figure 11>, the proposed conceptual framework focusing on four contexts, and 13 factors influence the level of HRA adoption. Those factors were derived from three theories and empirical research. The first context is a technology consist-



<Figure 11> Proposed Conceptual Framework

ing of three factors: "Tool Availability" "Data Availability" and "Compatibility". The second context is an organization combining four factors: "Top Management Support;" "Facilitating Conditions;" "Organizations' Strategy" and "Organizations' Structure." The third context is an environment consisting three factors: "Competitive Intensity;" "Data Governance" and "Government Regulation." The last context is individual composing three factors: "Quantitative Self-Efficacy;" "Social Influence;" and "Performance Expectancy." The following hypotheses are proposed to provide a foundation proposition for further testing of the conceptual framework of HRA adoption. These proposed hypotheses were based on the results outlined in this paper: H1-H3 derived from the TOE framework by Tornatzky et al. (1990) and H4 derived from the empirical research by Vargas (2015) and Vargas et al. (2018). In summary, this framework is based on three contexts of the TOE framework and the 13 factors from the selected theories were noted as influential factors affecting the HRA adoption level.

In conclusion, the HRA adoption model was developed from the empirical findings of the second-order SEM analysis base on the TOE framework. Otherwise, the HRA adoption model was proved through a quantitative method for generalizing to the large populations. This model was used to establish an HRA adoption framework for management purposes.

Ⅴ. Conclusion and Future Research Directions

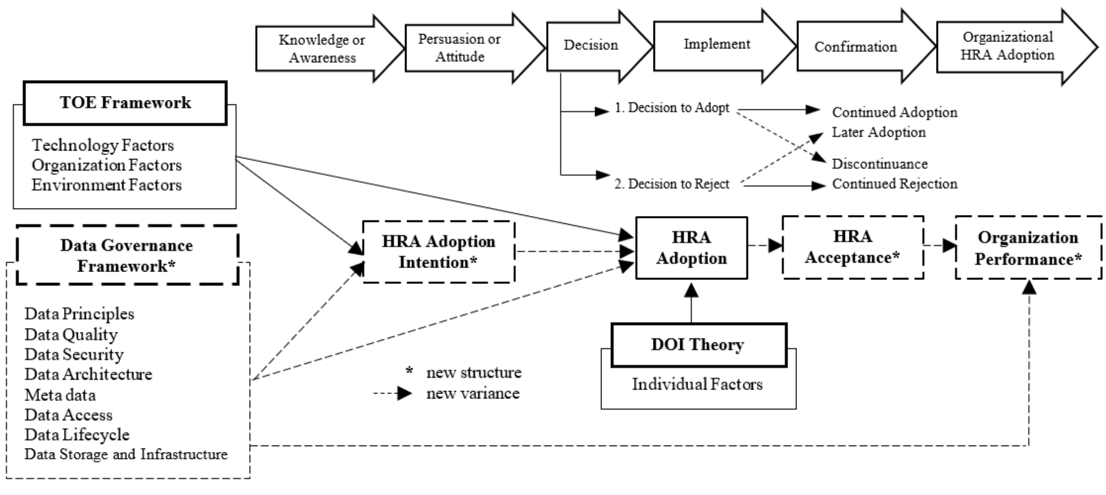
This section presents the conclusion to summarize the study results and future research directions that suggest the new structure of the HRA adoption framework as follows:

5.1. Conclusion

Although HRA is a new management domain, it will undoubtedly be the direction of future evidence-based HRM or management by the fact which is becoming a crucial role in a leading organization; nevertheless, it is still adopted at the earliest stage in organizations. Previous studies pointed out that organizational HRA adoption is needed in empirical research. Therefore, this study proposed the organizational conceptual framework of HRA adoption with four hypotheses using the Literature Weighted Scoring (LWS) based on three contexts of the TOE framework. In contrast, the new structure or the individual context was added, and those contexts were identified as the second-order factors. A total of 13 theory-derived factors are determined as influential first-order factors affecting HRA adoption, and the top three first-order factors are "Quantitative Self-Efficacy," "Top Management Support," and "Data Availability." In academic contribution, this framework is valuable for further empirical research. In the management aspect, the results of this study are beneficial to any HR professional or HR practitioner who plays the role of policymakers or enablers.

5.2. Future Research Directions

It is a concern that this study revealed the complete conceptual framework of HRA adoption in organizations that can be highly useful for technology or innovation adoption in organizations. This framework will be broadly generated in research applicable to both public and private organizations, and State-Owned Enterprises (SOEs). Those organizations should apply this framework by brainstorming among executives to select and rank all the most relevant factors to their organizations. Further studies should focus on testing influence in each context and those 13 factors that may directly influence the adoption level. On the other hand, those factors may influence the individual adoption level after HRA was already adopted in organizations to consider technology acceptance. Moreover, this study can be replicated since some factors can be insignificant in some particular contexts, and new factors may emerge. HRA takes an effort to reduce the challenges which many organizations have been facing. Lastly, further studies should use this framework to guide the HRA adoption and answer the question "How HRA affects organizational performance?" or "How do organizations use HRA to increase organizational performance?" as illustrated in <Figure 12>.



<Figure 12> Proposed HRA Adoption Conceptual Framework for Further Study

As illustrated in <Figure 12>, the proposed HRA adoption conceptual framework for further study combines two grand theories (TOE Framework and DOI Theory). Interestingly, four new structures (HRA Adoption Intention, HRA acceptance, Data Governance Framework, and Organization Performance) were added to extend the HRA adoption studies, and six variances of the new structure were proposed to mediator analysis for further study. Although this study focused on HRA Adoption, the two mediators (Adoption Intention, and Acceptance) has recently received more attention. HRA user acceptance factors should be considered, such as usefulness and quality (Davis, 1989; Delone and McLean, 2003; Phaosathianphan and Leelasantitham, 2019). Since the big data phenomenon has emerged, the data-driven approach receives more attractive attention in IS research. The new perspectives and topics on the development, adoption, and application of IS that imply the potential of data-intensive IS applications (Lee et al., 2016). Therefore, Eight components of Data Governance ("Data Principles," "Data Quality," "Data Security," "Data Architecture," "Metadata Data Access," "Data Lifecycle," and "Data Storage and Infrastructure") were derived from data governance domains according to Khatri and Brown (2010), and conceptual framework for data governance according to Abraham et al. (2019). Although the previous studies related to HRA adoption and data governance were limited, they still appear in HR strategic unit. For example, Sivathanu and Pillai (2019) found that talent analysis led to developing a high-performing talent pool that affects the organizations' performance. Several previous studies related to technology or innovation adoption found that HRA is an influential part of organizational performance. Therefore, organizations can rapidly integrate innovation into the existing infrastructure. The top management executives have a strong understanding of how technology and innovation can increase business performance (Garrison et al., 2015). In summary, the studies of innovation or technology adoption, particularly HRA adoption, including organizational performance or data governance, are increasing more attention to the research.

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<References>

[1] Abraham, R., Schneider, J., and Vom Brocke, J. (2019). Data governance: A conceptual framework, structured review, and research agenda. *International Journal of Information Management, 49*, 424-438.

[2] Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211.

[3] Alamelu, R., Nalini, R., Motha, L. C. S., Amudha, R., and Bowiya, S. (2017). Adoption factors impacting human resource analytics among employees. *International Journal of Economic Research, 14*(6), 417-423.

[4] Alhammadi, A., Stanier, C., and Eardley, A. (2015). The determinants of cloud computing adoption in Saudi Arabia. *In 2nd International Conference on Computer Science and Engineering.*

[5] Almarri, K., Aljarman, M., and Boussabaine, H. (2019). Emerging contractual and legal risks from the application of building information modelling. *Engineering, Construction and Architectural Management, 26*(10), 2307-2325.

[6] Anturaniemi, K. (2018). *Human capital analytics: Maturity evaluation and development proposal for a case company*. Metropolia Ammattikorkeakoulu.

[7] Awa, H. O., and Ojiabo, O. U. (2016). A model of adoption determinants of ERP within TOE framework. *Information Technology & People, 29*(4), 901-930.

[8] Awa, H. O., Ojiabo, O. U., and Orokor, L. E. (2017). Integrated technology-organization-environment(TOE) taxonomies for technology adoption. *Journal of Enterprise Information Management, 30*(6), 893-921.

[9] Bangert-Drowns, R. L., and Rudner, L. M. (1990). Meta-analysis in educational research. *Practical Assessment, Research, and Evaluation, 2*(1), 8.

[10] Barrière, J. M. (2016). *The influence of trust on attitude of employees towards HR Analytics in organisations*. University of Twente.

[11] Bassi, L. (2011). Raging debates in HR analytics. *People and Strategy, 34*(2), 14-17.

[12] Batarliene, N., Ciziuniene, K., Vaiciute, K., Sapalaite, I., and Jarasuniene, A. (2017). The impact of human resource management on the competitiveness of transport companies. *Procedia Engineering, 187*, 110-116.

[13] Becker, B., and Gerhart, B. (1996). The impact of human resource management on organizational performance: Progress and prospects. *Academy of Management Journal, 39*(4), 779-801.

[14] Bingham, R. D., and McNaught, T. P. (1976). *The adoption of innovation by local government*. Lexington Books.

[15] Bushman, B. J., and Wang, M. C. (1994). Vote-counting procedures in meta-analysis. In *The handbook of research synthesis* (Vol. 236, pp. 193-213). Russell Sage Foundation.

[16] Cascio, W., and Boudreau, J. (2011). *Investing in people: Financial impact of human resource initiatives.* Ft Press.

[17] Compeau, D. R., and Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly, 19*(2), 189-211.

[18] Damanpour, F., and Gopalakrishnan, S. (1998). Theories of organizational structure and innovation adoption: The role of environmental change. *Journal of Engineering and Technology Management, 15*(1), 1-24.

[19] Daradkeh, M. K. (2019). Determinants of visual analytics adoption in organizations. *Information Technology & People, 32*(3), 668-695.

[20] Davenport, T. H. (2006). Competing on analytics. *Harvard Business Review, 84*(1), 98.

[21] Davenport, T. H. (2019). Is HR the most-analytics driven function. *Harvard Business Review (Digital Article, April 2019)*, Retrieved from 19 April 2019.

[22] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340.

[23] Deloitte University (2017). *2017 global human capital trends*. Retrieved from 10 August 2018 https://www2.deloitte.com/content/dam/Deloitte/global/Documents/About-Deloitte/central-europe/ce-global-human-capital-trends.pdf

[24] Deloitte University (2018). *2018 global human capital trends*. Retrieved from 1 December 2019 https://www2.deloitte.com/insights/us/en/focus/human-capital-trends.html

[25] Delone, W. H., and McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems, 19*(4), 9-30.

[26] Distler, V., Lallemand, C., and Bellet, T. (2018). Acceptability and acceptance of autonomous mobility on demand: The impact of an immersive experience. *Paper Presented at the Proceedings of the 2018 Chi Conference on Human Factors in*

Computing Systems.

[27] Dooren, J. V. (2012). *HR analytics in practice: An overview of the influence of contingency factors on the applicability of HR analytics in Dutch organizations*. Retrieved from November 1 2018 http://arno.uvt.nl/show.cgi?fid=127276

[28] Etukudo, R. U. (2019). *Strategies for using analytics to improve human resource management*. Ph.D. Dissertation, Walden University.

[29] Falletta, S. (2014). In search of HR intelligence: Evidence-based HR analytics practices in high performing companies. *People and Strategy, 36*(4), 28-37.

[30] Falletta, S., and Combs, W. (2020). The HR analytics cycle: A seven-step process for building evidence-based and ethical HR analytics capabilities. *Journal of Work-Applied Management*. doi: 10.1108/JWAM-03-2020-0020

[31] Fiocco, E. (2017). *HR analytics at work Exploring diffusion of innovation within a Swedish-based MNC*. University of Gothenberg.

[32] Friedman, T. L. (2017). *Thank you for being late: An optimist's guide to thriving in the age of accelerations (Version 2.0, with a new afterword)*. Picador/Farrar Straus and Giroux.

[33] Gartner (2018). *Gartner IT glossary*. Retrieved from October 30 2018 https://www.gartner.com/it-glossary/prescriptive-analytics

[34] George, L., and Kamalanabhan, T. (2016). A study on the acceptance of HR analytics in organisations. *International Journal of Innovative Research and Development, 5*(2).

[35] Grant, M. J., and Booth, A. (2009). A typology of reviews: An analysis of 14 review types and associated methodologies. *Health Information & Libraries Journal, 26*(2), 91-108.

[36] Grant, N. C. (2020). *Factors influencing willingness to adopt advanced analytics in small businesses*. Cleveland State University.

[37] Gupta, S. (2017). Overview of HR analytics-past, present and future. *Journal of Research Articles in Management Science and Allied Areas(Refereed), 10*(2), 1-6.

[38] Gustafsson, D. (2012). *Business intelligence, analytics and human capital: current state of workforce analytics in Sweden*. University of Skovde.

[39] Halper, F., and Stodder, D. (2014). *TDWI analytics maturity model guide*. Retrieved from https://tdwi.org/~/media/545E06D7CE184B19B269E929B0903D0C

[40] Halper, F., and Stodder, D. (2015). *TDWI analytics maturity model guide*.

[41] Hameed, M. A., Counsell, S., and Swift, S. (2012). A conceptual model for the process of IT innovation adoption in organizations. *Journal of Engineering and Technology Management, 29*(3), 358-390.

[42] Harada, Y., and Sengoku, S. (2019). The key success factors of biotech start-up firms: Characteristics and attributes of the management teams of high-performing biotech start-ups. *Paper Presented at the PICMET 2019-Portland International Conference on Management of Engineering and Technology: Technology Management in the World of Intelligent Systems*, Proceedings.

[43] Harvard Business Review (2014). *HR joins the analytics revolution*. Harvard Business School Publishing.

[44] Hmoud, B. I., and Várallyai, L. (2020). Artificial intelligence in human resources information systems: Investigating its trust and adoption determinants. *International Journal of Engineering and Management Sciences, 5*(1), 749-765.

[45] Hosseini, M. R., Banihashemi, S., Chileshe, N., Namzadi, M. O., Udeaja, C., Rameezdeen, R., and McCuen, T. (2016). BIM adoption within Australian Small and Medium-sized Enterprises (SMEs): An innovation diffusion model. *Construction Economics and Building, 16*(3), 71-86.

[46] Hunter, J. E., and Schmidt, F. L. (2004). *Methods of meta-analysis: Correcting error and bias in research findings*. Sage.

[47] Huselid, M. A. (2018). The science and practice of workforce analytics: Introduction to the HRM special issue. *Human Resource Management, 57*(3),

679-684.

[48] Johnston, A. C. (2006). *An empirical investigation of the influence of fear appeals on attitudes and behavioral intentions associated with recommended individual computer security actions*. ProQuest Information & Learning.

[49] Ka, H. K., and Kim, J. S. (2014). An empirical study on the influencing factors for big data intented adoption: Focusing on the strategic value recognition and TOE framework. *Asia Pacific Journal of Information Systems, 24*(4), 443-472.

[50] Kamal, M. M. (2006). IT innovation adoption in the government sector: Identifying the critical success factors. *Journal of Enterprise Information Management, 19*(2), 192-222.

[51] Kapoor, B., and Kabra, Y. (2014). Current and future trends in human resources analytics adoption. *Journal of Cases on Information Technology(JCIT), 16*(1), 50-59.

[52] Khatri, V., and Brown, C. V. (2010). Designing data governance. *Communications of the ACM, 53*(1), 148-152.

[53] Kim, H. J., and Bretschneider, S. (2004). Local government information technology capacity: An exploratory theory. *Paper Presented at the System Sciences, 2004. Proceedings of the 37th Annual Hawaii International Conference*.

[54] King, W., and He, J. (2005, 13/10/2008). Understanding the role and methods of meta-analysis in IS research. Retrieved from https://doresearch.wordpress.com/

[55] Kuan, K. K., and Chau, P. Y. (2001). A perception-based model for EDI adoption in small businesses using a technology-organization-environment framework. *Information & Management, 38*(8), 507-521.

[56] Kulik, J. A., and Kulik, C. L. C. (1989). The concept of meta-analysis. *International Journal of Educational Research, 13*(3), 227-340.

[57] Kumar, A., Krishnamoorthy, B., and Kamath, D. B. (2020). Key themes for multi-stage business analytics adoption in organizations. *Asia Pacific Journal of Information Systems, 30*(2), 397-419.

[58] Ladley, J. (2012). *Data governance: How to design, deploy and sustain an effective data governance program*. Waltham, MA: Morgan Kaufmann.

[59] Lakshmi, P., and Pratap, P. (2016). HR analytics-a strategic approach to HR effectiveness. *International Journal of Human Resource Management and Research, 6*(3), 21-28.

[60] Lee, J., Pee, L., and Min, J. (2016). New perspectives on the development, adoption, and application of information systems. *Asia Pacific Journal of Information Systems, 26*(3), 385-392.

[61] Levenson, A. (2011). Using targeted analytics to improve talent decisions. *People and Strategy, 34*(2), 1-22.

[62] Looi, H. C. (2005). E-commerce adoption in Brunei Darussalam: A quantitative analysis of factors influencing its adoption. *Communications of the Association for Information Systems, 15*(1), 3.

[63] Lydgate, X. K. M. (2018). *Human resource analytics: Implications for strategy realization and organizational performance*. Portland State University.

[64] Malini, N. (2018). Understanding the adoption of HR analytics in Indian corporations: A case study on selected Indian private multinational company. *City College*, Retrieved from http://www.cityinstitution.com/understanding-the-adoption-of-hr-analytics-in-indian-corporations/

[65] Marais, A., Grobbelaar, S. S., and Kennon, D. (2020). A systematic review of healthcare innovation platforms towards a conceptual framework. *Paper Presented at the 26th International Association for Management of Technology Conference*, IAMOT 2017.

[66] Marler, J., and Boudreau, J. W. (2017). An evidence-based review of HR Analytics. *International Journal of Human Resource Management, 28*(1), 3-26. doi: 10.1080/09585192.2016.1244699

[67] Marler, J., and Fisher, S. (2013). An evidence-based review of e-HRM and strategic human resource management. *Human Resource Management Review, 23*(1), 18-36.

[68] Masese, O. F., and UttaM, M. K. (2016). Creating

value of human resource through analytics. *Asia Pacific Journal of Research, 1*(19), 97-103.

[69] Molefe, M. (2014). *From data to insights: HR analytics in organisations*. University of Pretoria.

[70] Momin, W. Y. M., and Mishra, K. (2015). HR Analytics as a strategic workforce planning. *IJAR, 1*(4), 258-260.

[71] Mukundan, S. (2017). Analytics in HR a snapshot view. *International Journal of Engineering Technology, Management and Applied Sciences, 5*(7), 597-601.

[72] Nadal, C., Doherty, G., and Sas, C. (2019). Technology acceptability, acceptance and adoption-definitions and measurement. *Paper Presented at the 2019 CHI Conference on Human Factors in Computing Systems*.

[73] Nemati, H., and Udiavar, A. (2012). Organizational readiness for implementation of supply chain analytics. *AMCIS 2012 Proceedings*, 26.

[74] Oh, I. S. (2020). Beyond meta-analysis: Secondary uses of meta-analytic data. *Annual Review of Organizational Psychology and Organizational Behavior, 7*, 125-153. doi: 10.1146/annurev-orgpsych-012119-045006

[75] Oliveira, T., and Martins, M. F. (2009). Determinants of information technology adoption in Portugal. *Paper Presented at the ICE-B*.

[76] Oliveira, T., Thomas, M., and Espadanal, M. (2014). Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. *Information & Management, 51*(5), 497-510.

[77] Ozgen, K. (2013). Self-efficacy beliefs in mathematical literacy and connections between mathematics and real world: The case of high school students. *Journal of International Education Research, 9*(4), 305-316.

[78] Pan, M. J., and Jang, W. Y. (2008). Determinants of the adoption of enterprise resource planning within the technology-organization-environment framework: Taiwan's communications industry. *Journal of Computer Information Systems, 48*(3), 94-102.

[79] Paré, G., and Kitsiou, S. (2017). Methods for literature reviews. In *Handbook of eHealth evaluation: An evidence-based approach[Internet]*. University of Victoria.

[80] Phaosathianphan, N., and Leelasantitham, A. (2019). Understanding the adoption factors influence on the use of Intelligent Travel Assistant(ITA) for eco-tourists: An extension of the UTAUT. *International Journal of Innovation and Technology Management, 16*(8), 1950060.

[81] Premkumar, G., and Ramamurthy, K. (1995). The role of interorganizational and organizational factors on the decision mode for adoption of interorganizational systems. *Decision Sciences, 26*(3), 303-336.

[82] Pudjianto, B., Zo, H., Ciganek, A. P., and Rho, J. J. (2011). Determinants of e-government assimilation in Indonesia: An empirical investigation using a TOE framework. *Asia Pacific Journal of Information Systems, 21*(1), 49-80.

[83] Puklavec, B., Oliveira, T., and Popovič, A. (2018). Understanding the determinants of business intelligence system adoption stages. *Industrial Management & Data Systems, 118*(1), 236-261.

[84] Reddy, P. R., and Lakshmikeerthi, P. (2017). 'HR analytics'-An effective evidence based HRM tool. *International Journal of Business and Management Invention, 6*(7), 23-34.

[85] Renaud, K., and Van Biljon, J. (2008). Predicting technology acceptance and adoption by the elderly: A qualitative study. *Paper Presented at the Proceedings of the 2008 Annual Research Conference of the South African Institute of Computer Scientists and Information Technologists on IT Research in Developing Countries: Riding the Wave of Technology*.

[86] Rice, R., Grant, A., Schmitz, J., and Torobin, J. (1990). Individual and network influences on the adoption and perceived outcomes of electronic messaging. *Social Networks, 12*(1), 27-55.

[87] Rogers, E. M. (1983). *Diffusion of innovations*. The Free Press.

[88] Rogers, E. M. (1995). *Diffusion of innovations*. New

York.

[89] Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Simon and Schuster.

[90] Rogers, E. M. (2010). *Diffusion of innovations*. New York, NY: Simon and Schuster.

[91] Ruder-Hook, M. (2018). *Organizational adoption of AI through a sociocultural lens*. Ph.D. Dissertation, University of Michigan.

[92] Ruohonen, S. (2015). *Business benefits of leveraging predictive analytics in HR*. Master's Thesis, Aalto University.

[93] Saraswathy, R., and Premakumari, P. (2016). A snapshot of HR analytics in practice in organizations in Tiruchirappalli. P*aper Presented at the National Conference on Emerging Business Strategies in Economic Development*.

[94] Saraswathy, R., Vaijayanthi, P., and Shreenivasan, K. A. (2017). A snapshot of HR analytics-An overview of the influence of contingency factors on the applicability of HR analytics in INDIAN organizations. *International Journal of Applied Business and Economic Research, 15*(11).

[95] Sivathanu, B., and Pillai, R. (2019). Technology and talent analytics for talent management-a game changer for organizational performance. *International Journal of Organizational Analysis, 28*(2), 457-473.

[96] Sjoerd, V. D. H., and Tanya, B. (2017). The rise (and fall?) of HR analytics: A study into the future application, value, structure, and system support. *Journal of Organizational Effectiveness: People and Performance, 4*(2), 157-178.

[97] Smith, T. (2013). *HR analytics: The what, why and how*. Numerical Insights LLC.

[98] Spahic, J. (2015). *Exploring HR intelligence practices in fortune 1000 and select global firms*. Drexel University.

[99] Stuart, A. (2005). *Finance is from Mars, HR is from Venus*. Retrieved from September 8 2018 ww2.cfo.com/human-capital-careers/2005/11/finance-is-from-mars-hr-is-from-venus/

[100] Teo, T. S., Tan, M., and Buk, W. K. (1997). A contingency model of Internet adoption in Singapore. *International Journal of Electronic Commerce, 2*(2), 95-118.

[101] Thong, J. Y. (1999). An integrated model of information systems adoption in small businesses. *Journal of Management Information Systems, 15*(4), 187-214.

[102] Tornatzky, L. G., Fleischer, M., and Chakrabarti, A. K. (1990). *Processes of technological innovation*. Lexington Books.

[103] Tushman, M. L., and Anderson, P. (1986). Technological discontinuities and organizational environments. *Administrative Science Quarterly, 31*(3), 439-465.

[104] Vargas, R. (2015). *Adoption factors impacting human resource analytics among human resource professionals*. Nova Southeastern University.

[105] Vargas, R., Yurova, Y. V., Ruppel, C. P., Tworoger, L. C., and Greenwood, R. (2018). Individual adoption of HR analytics: A fine grained view of the early stages leading to adoption. *The International Journal of Human Resource Management, 29*(22), 1-22.

[106] Venkatesh, V., and Brown, S. A. (2001). A longitudinal investigation of personal computers in homes: Adoption determinants and emerging challenges. *MIS Quarterly, 25*(1), 71-102.

[107] Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478.

[108] Vihari, N., and Raoa, M. (2013). *Analytics as a predictor for strategic and sustainable human resource function: An integrative literature review*. IIT, Roorkee.

[109] Wang, X., White, L., Chen, X., Gao, Y., Li, H., and Luo, Y. (2015). An empirical study of wearable technology acceptance in healthcare. *Industrial Management & Data Systems, 115*(9), 1704-1723.

[110] Wang, Y. M., and Wang, Y. C. (2016). Determinants of firms' knowledge management system implementation: An empirical study. *Computers in Human Behavior, 64*, 829-842.

[111] Wanyoto, K. (2016). *A diagnostic model for adoption of human resources analytics in local subsidiaries: Study focused on multi-national enterprises (MNEs) in Sub-Saharan Africa*. University of Pretoria.

[112] Williams, I. (2011). Organizational readiness for innovation in health care: Some lessons from the recent literature. *Health Services Management Research, 24*(4), 213-218.

[113] Witte, L. (2016). *We have HR analytics! So what?: An exploratory study into the impact of HR analytics on strategic HRM*. University of Twente.

[114] Xiao, Q., and Cooke, F. L. (2020). Towards a hybrid model? A systematic review of human resource management research on Chinese state-owned enterprises(1993-2017). *International Journal of Human Resource Management, 31*(1), 47-89. doi: 10.1080/09585192.2019.1682030

[115] Zheng, D. (2014). The adoption of green information technology and information systems: An evidence from corporate social responsibility. *Paper Presented at the PACIS*.

[116] Zhu, K., Dong, S., Xu, S. X., and Kraemer, K. L. (2006). Innovation diffusion in global contexts: Determinants of post-adoption digital transformation of European companies. *European Journal of Information Systems, 15*(6), 601-616.

[117] Zhu, K., Kraemer, K., and Xu, S. (2002). A cross-country study of electronic business adoption using the technology-organization-environment framework. *ICIS 2002 Proceedings*, 31.

[118] Zhu, K., Kraemer, K., and Xu, S. (2003). Electronic business adoption by European firms: A cross-country assessment of the facilitators and inhibitors. *European Journal of Information Systems, 12*(4), 251-268.

[119] Zhu, K., and Kraemer, K. L. (2005). Post-adoption variations in usage and value of e-business by organizations: Cross-country evidence from the retail industry. *Information Systems Research, 16*(1), 61-84.

[120] Zhu, K., Kraemer, K. L., and Dedrick, J. (2004). Information technology payoff in e-business environments: An international perspective on value creation of e-business in the financial services industry. *Journal of Management Information Systems, 21*(1), 17-54.

[121] Zhu, K., Kraemer, K. L., and Xu, S. (2006). The process of innovation assimilation by firms in different countries: A technology diffusion perspective on e-business. *Management Science, 52*(10), 1557-1576.

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