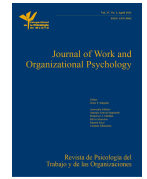




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## Human Resources Analytics: A systematic Review from a Sustainable Management Approach

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### ABSTRACT

Human Resources Analytics (HRA) is drawing more attention every year, and will be crucial to human resource development. However, the literature around the topic would appear to be more promotional than descriptive. With this in mind, we conducted a systematic literature review and content analysis with the following objectives: first, to address the current state of HRA and second, to propose a framework for the development of HRA as a sustainable practice. We analyzed 79 articles from research databases and found 34 empirical studies for subsequent content analysis. While the main results reflect the relative newness of the field of HRA, with the majority of the empirical articles focusing on financial aspects, they also reveal the growing importance given to ethics. Finally, we propose a framework for the development of sustainable HRA based on the triple bottom line and discuss the implications of our findings for researchers and practitioners.

### La analítica de recursos humanos: una revisión sistemática desde la perspectiva de una gestión sostenible

### RESUMEN

La analítica de recursos humanos (ARH) atrae cada vez más atención en los últimos años y será crucial para el desarrollo del ámbito de los recursos humanos. No obstante, la literatura sobre el tema parece ser más promocional que descriptiva. Para comprobar esto, llevamos a cabo una revisión sistemática de la literatura y un análisis de contenido con los siguientes objetivos: primero, abordar el estado actual de la ARH y segundo, proponer un marco para el desarrollo de la ARH como una práctica sostenible. Analizamos 79 artículos de investigación incluidos en las más prestigiosas bases de datos y encontramos 34 estudios empíricos para su posterior análisis de contenido. Los principales resultados reflejan la relativa novedad del campo de la ARH, estando centrados la mayoría de los artículos en los aspectos financieros. No obstante, también se observa la creciente importancia dada a la ética. Finalmente, proponemos un marco para el desarrollo de una ARH basada en la triple cuenta de resultados (económica, social y medioambiental, y se discuten las implicaciones prácticas y teóricas de nuestros hallazgos.

Human Resources Analytics (HRA) has grown in importance in recent years, but is not something new. Thirty-five years have passed since Fitz-enz (considered the father of HRA) published his book *How to measure human resources management* (Jac & Fitz-enz, 1984). Since then, HRA has received little academic interest (Marler & Boudreau, 2017). Yet, practitioners and consultants from all over the world urge their companies to invest more in sophisticated human resources information systems to collect and analyze employee data. It is striking that, according to *Deloitte Global Human Capital Trends* (2018, p. 89), 69% of organizations are building integrated systems to analyze worker-related data, 17% have already implemented real-time dashboards to crunch the avalanche of numbers in new and

innovative ways, and 84% of practitioners see the implementation of HRA as important or very important according to this same report.

The most frequently used alternative terms to refer to the concept of HRA, used interchangeably by academics and the business world, are People Analytics and Workforce Analytics (Tursunbayeva et al., 2018). We will use the lexeme HRA in the most inclusive way throughout this entire paper in order to ensure that all other lexemes are also included. To illustrate the concept, we will use Marler and Boudreau's (2017, p. 15) definition: "A practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to human resources processes, human capital, organizational performance, and external economic benchmarks to

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establish business impact and enable data-driven decision-making." This definition helps to understand how HRA could contribute to Human Resource Development (HRD). According to [Minbaeva \(2018\)](#), HRA is an organizational capability closely linked to an organization's business strategy. The author designed a three dimensional path for analytics, in which data quality, analytical competencies, and a strategic ability to act are the key elements of HRA. In this way, HRA is linked with Human Resource Management (HRM) by virtue of its strategic ability to act: its capacity to enhance the decision-making process ([Minbaeva, 2018](#)). However, [Marler and Boudreau's](#) definition also highlights one of the main problems relating to HRA literature: the adoption of an approach that solely focuses on economic outcomes and business impact fails to address the sustainable perspective, which is now a fundamental principle of smart management ([Savitz, 2013](#)). Businesses use financial, social, and environmental resources, known as the triple bottom line, so any new practice that seeks to endure should include all three as core factors. From a sustainable HRM perspective, companies must create a better future that takes into account the digital and technological challenges facing today's world, and combine them with social and environmental values that not only transfer skills to the next generation ([Aust et al., 2020](#)), but also deliver increased employee wellbeing and improved working conditions ([Aguado et al., 2019](#); [García-Izquierdo et al., 2019](#)).

Consequently, we regard sustainable human resources management (SUHRM) as the use of HR tools to assist in embedding a sustainability strategy into an organization and the creation of an HRM system that contributes to the sustainable performance of a company. That is, SUHRM creates the skills, motivation, values, and trust to achieve a triple bottom line (financial, social, and environmental objectives) that ensures the long-term health and sustainability of the organization's internal and external stakeholders through policies that reflect equity, development, and well-being, and lead to the promotion of environmentally friendly practices ([Cohen et al., 2012](#)). In this research, we aim to incorporate HRA within SUHRM. However, this first requires a review of the literature and the establishment of common ground.

Despite the importance of HRA in any organization, it remains at risk of being considered a fleeting fad. There are not enough "analytics about analytics", meaning that we know very little about how HRA functions ([Rasmussen & Ulrich, 2015](#)). In the words of [Levenson and Fink \(2017, p. 4\)](#): "The current state of HR analytics is a bit of a wild, wild, west, with too few consistent frameworks to drive powerful action and improvement for organizations." One notable exception is the framework developed by [Dulebohn and Johnson \(2013\)](#) that outlines how managers should select the type of HR metrics and decision support systems to increase organizational functioning. In addition, HR professionals are often attracted to analytics because the literature surrounding the topic is often more promotional than descriptive. There is a lack of information on how to translate ideas into practice. It has also been suggested that academics need to improve the way they elucidate this praxis ([Angrave et al., 2016](#)). A lack of definition of procedures, models, and outcomes seems to be the root of the problem. There are far too many case-studies examples in the literature ([Davenport et al., 2010](#); [Jabir et al., 2019](#); [King, 2016](#)), and the majority fail to explain their procedures carefully. This has led to a great deal of promotional information but scant evidence of HRA's advantages. This reflects the existence of another science-practice gap, a classic problem in organizational psychology and business research. For instance, the science-practice gap in e-recruitment was bridged by offering practitioners empirical evidence of the negative effects of requiring job applicants to provide information that could be used for illegal discriminatory hiring ([García-Izquierdo, Aguinis, et al., 2010](#)). As a minimum, HRA should aim to offer a solid corpus of evidence that helps to bridge this gap. In addition, [Marler and Boudreau \(2017, p. 22\)](#) conclude that there is "very limited high-quality scientific evidence-based research on this

topic." However, it should be noted that this very limited research, as well as the promotional nature of the literature, can be partially explained by the relative newness of the field of HRA ([Rasmussen & Ulrich, 2015](#)).

Another barrier that prevents the adoption of HRA is a lack of analytical thinking in the HR profession, which risks being relegated from the strategic boardroom if practitioners fail to combine analytical skills with business acumen ([Angrave et al., 2016](#)). In short, if HR professionals are unable to handle HR data, other professionals will step in to take their place. Other authors have raised similar points. [Ulrich and Dulebohn \(2015\)](#) conclude that HR professionals need to add value to HRA, and the key to achieving this added value is investment in improving their competencies. Five distinct core competencies were identified for HR professionals in the twenty-first century: technical knowledge, consultation, data fluency and analysis, storytelling and communication, and HR and business acumen ([McCartney et al., 2020](#)). Along similar lines, [King \(2016\)](#), stressed the need for academics to understand both HR and quantitative methods to play an important role in HRA. However, despite a shortage of theoretically based procedures and analytical thinking, and the lack of analytics about analytics, there is widespread academic agreement that HRA provides a perfect opportunity to bridge science and practice in the HRM arena ([Andersen, 2017](#)). As a result, there is a vital need to gather all the currently available academic research and act accordingly.

This paper therefore has two objectives: (1) to address the current state of HRA and (2) to propose a framework in which HRA becomes a sustainable HRM practice and define sustainable HRA (SUHRA).

## Method

To achieve our proposed objectives, we used a systematic literature review to collate all relevant evidence that met our eligibility criteria, using methods to minimize bias in the identification, selection, synthesis, and summary of studies, and following PRISMA-P guidelines ([PRISMA-P Group et al., 2015](#)).

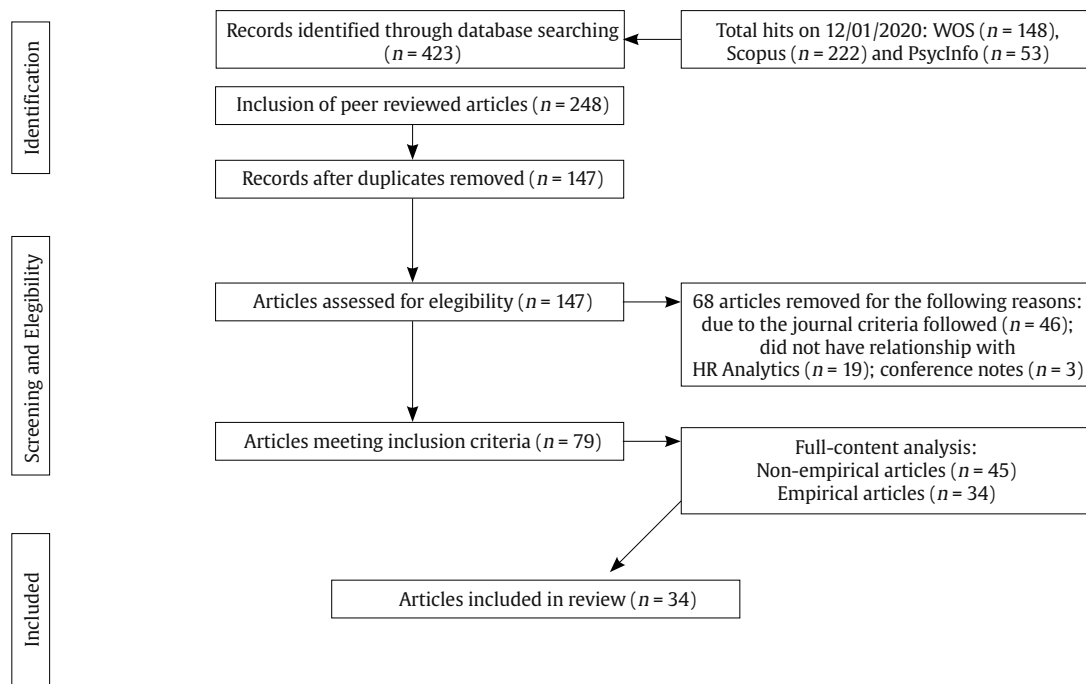
## Inclusion and Exclusion Criteria

In order to satisfy the first objective of this review, inclusion and exclusion criteria were selected to ensure replicability and adequate quality in all the articles analyzed. Bias was reduced to a minimum by using internal and external criteria. The criteria were the following:

1. The article appeared in one of three prestigious online databases (Web of Science, Scopus and PsycINFO)
2. Only peer-reviewed articles were included.
3. The article must comply with one of these two requirements:
  - The article has been published in a journal included in the last edition of the Journal Quality List (JQL) (Sixty-sixth edition, 15 February 2020), a collation of journal rankings from a variety of sources to assist academics to target papers in journals of an appropriate standard.
  - The article has been published by a journal included and ranked in the Journal Citation Report (JCR) or the SCImago Journal Rank (SCR) above Q4 quartile in the area of interest.
4. The article is in English or Spanish.
5. HRA is clearly the main topic of the article and the concept is addressed as a fundamental process or business strategy, from a practical or conceptual perspective. This will be checked during the content analysis.

## Selection of Keywords

We wished to go further than [Marler and Boudreau's \(2017\)](#) evidence-based review, which used the keywords "HR Analytics",



**Figure 1.** Article Selection (PRISMA-P) Flow Diagram.

“Talent Analytics”, “Workforce Analytics”, “People Analytics”, and “Human Resource Analytics”, and decided to follow [Tursunbayeva et al. \(2018\)](#), who added more keywords to improve accuracy. Our search strategy included article title, abstract, and keywords. The keywords finally selected were: “HR analytics” OR “Human Capital analytics” OR “Human Resource analytics” OR “People analytics” OR “Talent analytics” OR “Workforce analytics” OR “Employee analytics.”

### Article Selection Process

An initial search process carried out in the three previously mentioned databases on December 1 2020 resulted in a total of 423 hits (Scopus, 222; WOS, 148; PsycInfo, 53). However, 175 were eliminated because they were not peer reviewed articles. Following the elimination of duplicate articles (101), inclusion and exclusion criteria were applied on the remaining 147 articles ([Figure 1](#)). We discarded 46 articles because they were not included in the JQL or the JCR, or the SCR above Q4. A further 19 articles were eliminated from this total, as they were not essentially focused on HRA. This decision was made after a thorough reading of the article. Three articles were subsequently identified as “conference notes”, and were duly excluded. A total of 79 articles were incorporated into our final content analysis. This classification is shown in [Figure 1](#) (the full list of included and excluded publications can be obtained from the corresponding authors upon request).

### Categorization and Content Analysis

The first step to achieving all the objectives of this research was to code and tabulate the full list of included articles using Excel 2016 software. The following information was extracted from each article: title, author, journal, inclusion or non-inclusion in the JQL, ranked in the JCR, ranked in the SCImago, subject area of the journal (Management & Economics, Computer Science, Applied Psychology or Health Sciences), empirical or non-empirical, HRA as

a general process (business strategy or used as a general method) or as a specific process or purpose (recruitment, performance, ethics, etc.), results, conclusions, and definition of HRA (original, if they use their own definition, and non-original when another author’s definition is cited). The second step was a thorough reading of all the empirical articles, and subsequent coding of the results and statistical support and conclusions, following evidence-based practice (SPICE) ([Booth, 2006](#)). In addition, several articles supported their findings with applied tools and graphics showing how they worked in a specific context (i.e., company). The results were then compared and analyzed from the sustainable HRM perspective, as explained below.

### The Sustainable HRM Framework

To fulfill the second objective, it is necessary to establish the theoretical framework around SUHRM. We used the triple bottom line described in the introduction ([Savitz, 2013](#)), which was compared with the empirical HRA literature. [Table 1](#) shows how we tabulated the results. Every article was analyzed on the basis of the aim pursued and the relevant criteria, and then grouped as economic, social, environmental or N/A (not applicable) (see [Table 1](#)). We reserved the tag N/A for empirical studies that were not conducted in companies or organizations (e.g., an article focusing on HR professionals).

**Table 1.** The Triple Bottom Line (adapted from [Savitz & Weber, 2006](#)).

Economic	Social	Environmental
Sales, profits, ROI	Labor practices	Air quality
Taxes paid	Community impacts	Water quality
Monetary flows	Human rights	Energy usage
Jobs created	Product responsibility	Waste produced

The second step focused on how to transform HRA into SUHRA. With this in mind, we decided to use the classification developed by [Barrena-Martínez et al. \(2019\)](#), who defined a set of socially

responsible human resources practices reached by academic consensus. These practices are key to every company that aims to be socially responsible, and are divided into eight areas that can be linked with the HRA metrics used: 1) attraction and retention (e.g., “performs specific processes for the adaptation and integration of new candidates”), 2) training and continuous development (e.g., “periodically detects training needs of staff”), 3) management of employment relations (e.g., “cares about achieving a comfortable work environment”), 4) communication, transparency and social dialogue (e.g., “facilitates social dialogue”), 5) diversity and equal opportunities (e.g., “creates diverse teams”), 6) fair remuneration and social benefits (e.g., “ensures the principles of justices and fairness”), 7) prevention, health and security at work (e.g., “minimizes physical and emotional risks”), and 8) work-family balance (e.g., “facilitates modification of working conditions”).

**Table 2.** Descriptive Data Analysis

		Number of articles
Methodology ( <i>N</i> = 79, all)	Empirical	34
	Non-Empirical	45
Journal field ( <i>N</i> = 79, all)	Management & Economics	45
	Applied Psychology	18
	Computer Science	14
	Health Science	2
Topic of empirical articles ( <i>n</i> = 34 <sup>1</sup> )	General HR Analytics	8
	HR processes	18
	HR Analyst Competencies	5
	Ethics	3

Note. <sup>1</sup>Only empirical articles are included in “Topic of empirical articles”.

The third step was to analyze HRA definitions and compare them with the SUHRM definition mentioned in the introduction, that of “the utilization of HR tools to help embed a sustainability strategy in the organization...” (Cohen et al., 20212). For this purpose, we recorded all the explicit definitions of HRA found in the included articles and coded the following information: the definition, the purpose of HRA (according to the definition), and the triple bottom line objectives this perspective helps to accomplish. Once the tabulation was complete, the authors individually noted the objectives seen in each definition and reached consensus.

## Results

We divided this section into three different parts. First, we use descriptive data to address the current state of HRA literature (*n* = 79). Second, we present the findings of the empirical articles (*n* = 34), comparing the HRA framework with the sustainable HRM framework. Third, we analyze all the explicit definitions found in the content analysis from a sustainable perspective.

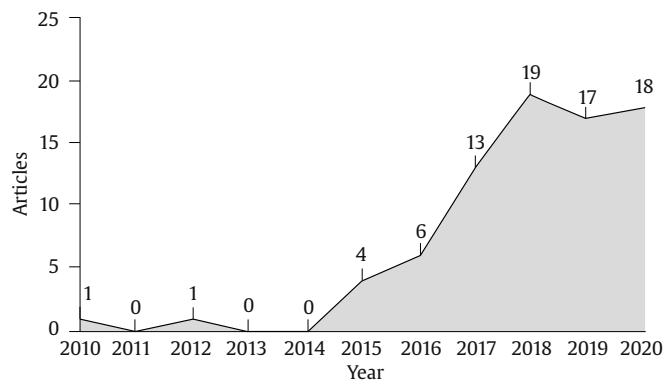
### HR Analytics: Descriptive Data

This section presents general information about the final list of HRA articles included in this review and provides details on authors, subject matter, and date and place of publication.

The first article in the review was published in 2010 (Davenport et al., 2010). Only 12 articles were published between 2010 and 2016. The remaining 67 articles were published between 2017 and 2020 (see Figure 2). The fact that 84.8% of the articles included in this review were published in the last three years reflects the growing interest in HRA.

Descriptive data extracted from the content analysis can be seen in Table 2. Of the total number of articles, 58.22% (45) are non-empirical

and 41.78% (34) are empirical. The articles included in the final list were published in Management and Economics journals (56.96%), followed by Applied Psychology journals (22.78%), and Computer Science (17.72%) and Health Sciences journals (2.54%).



**Figure 2.** Number of HRA Articles Published per Year.

Regarding the most influential authors and articles in the field, Table 3 lists all the articles with more than 50 citations (according to Scopus and WOS, 13 March, 2021). The most cited article in the field is also the oldest, in which Davenport et al. (2010) explain the well-known DELTA model, with 125 cites in Scopus and 94 in WOS. The acronym DELTA stands for access to high-quality data, enterprise orientation, analytical leadership, strategic targets, and analysts. This is widely considered to be the first reference to Talent Analytics (i.e., HRA). Among the most cited articles, there is only one empirical paper (Aral et al., 2012), in third place with 174 cites (102 in Scopus and 72 in WOS). Dave Ulrich is the most cited author in the area, with two articles in the list (Rasmussen & Ulrich, 2015; Ulrich & Dulebohn, 2015) (with a total number of 290 cites, 159 cites in Scopus and 131 in WOS) of the top six most influential articles in HRA. We have coded and grouped all of the empirical articles (*n* = 34) into four different categories: (i) General HRA, (ii) HR Processes, (iii) HR Analyst Competencies, and (iv) HRA Ethics. HR processes are very important for authors addressing HRA, 52.9% (18), with articles covering the following topics: turnover (*n* = 6), performance (*n* = 5), recruitment (*n* = 5), learning and development (*n* = 1), and stress at work (*n* = 1); and represents an even higher number of articles than general HRA which accounts for 23.5% of the articles (*n* = 8). The other topics addressed in the sample are HR Analyst Competencies (14.7%, *n* = 5), and Ethics (8.9%, *n* = 3), which is emerging as a promising new topic in HRA.

### Findings of HR Analytics

To fulfil the first objective, we need to draw attention to the empirical findings of the final list of included articles (*n* = 34) that were synthesized in the four previously mentioned categories: General HRA, HR Processes, HR Analyst Competencies, and HRA Ethics. We followed SPIDER recommendations (Cooke et al., 2012) for these analyses, whose results are shown in Tables 4, 5, 6, and 7.

### Results for General HRA

**General HR Analytics.** This includes all the articles offering an overview of the field (see Table 4). In this section, productivity (i.e., store performance or productivity at a company level) is the main dependent variable, and is present in 50% of the articles in this category. As independent variables, the authors based the predictions on HR metrics in 87.5% of the cases, in which we can distinguish between ad hoc measures in the form of a survey (i.e., employee



**Table 3.** Most cited Articles about HRA

Authors	Title	Year of Publication	Journal	Cites in Scopus	Cites in WOS
Davenport et al.	Competing on talent analytics	2010	Harvard Business Review	125	94
Angrave et al.	HR and analytics: why HR is set to fail the big data challenge	2016	Human Resource Management Journal	104	77
Aral et al.	Three-way complementarities: performance pay, human resource analytics, and information technology	2012	Management Science	102	72
Ulrich et al.	Are we there yet? What's next for HR?	2015	Human Resource Management Review	96	83
Marler and Boudreau	An evidence-based review of HR Analytics	2017	International Journal of Human Resource Management	72	54
Rasmussen and Ulrich	Learning from practice: how HR analytics avoids being a management fad	2015	Organizational Dynamics	63	48

alignment, capabilities and engagement), and objective data (i.e., number of calls and duration).

A survey analysis conducted by Aral et al. (2012) found that human capital management, performance pay, and HR analytics generate a productivity premium when they are implemented simultaneously ( $R^2 = .871$ ,  $\beta = .165$ ,  $p < .05$ , fixed effects;  $R^2 = .876$ ,  $\beta = .170$ ,  $p < .05$ , random effects). Lismont et al. (2017) used survey analysis methodology to establish the current application of analytics in companies, which led to four broad categories of company: no analytics, analytics bootstrappers, sustainable analytics adopters, and disruptive analytics innovators. Gelbard et al. (2018) used sentiment analysis to evaluate several human factors (e.g., performance, employee satisfaction, withdrawal intentions). For this purpose, they conducted the sentiment analysis on all internal emails within the organization and gave a score for vitality and satisfaction, which are explanatory factors of the engagement key performance indicator (KPI). Leaving ethical implications to one side, they claim that “this model enhances its (the organization’s) capacity of tracing and predicting emerging behavioral patterns”. They found a KPI that can be used in the organization to measure HR factors, but no evidence to support that this KPI is in any way connected with improved people data-driven decisions. Schiemann et al. (2018) is a fine example of how to use HR analytics in a business framework from an academic perspective. Using the service-profit chain and a people equity model, they are able to forecast turnover and productivity. They used alignment, capabilities and engagement (ACE) metrics in each of the restaurants in their chain in order to predict success in any specific restaurant. They provide a full operative model, in which, in their words:

Restaurants with the Optimized Talent profile experience 21% less turnover and 10% higher productivity than sites with the High-Risk profile (in correlation terms, ACE accounts for 51% of the variance in turnover and 26% of the variance in productivity). The financial impact is substantial: \$27,000 in reduced turnover costs (cost-to-hire and train) and \$72,000 in increased profits per restaurant per year (Schiemann et al., 2018, p. 6).

Using a similar strategic analytics approach, Simón & Ferreiro (2018) describe an HR analytics initiative in a large fashion company. The study aimed to predict store performance through the use of HR metrics. They concluded that hiring each extra supervisory assistant would increase sales by €1.89 per hour ( $R^2 = .41$ ). Hazarika et al. (2019) found that HR metrics have financial implications linking HR metrics with revenue and passengers carried in a statistically significant model and very high explained variance (adj.  $R^2 = .92$  and adj.  $R^2 = .97$ , respectively). Al-Ayed (2019) demonstrated how different strategic human resources practices (and their metrics) had an impact on an organization’s resilience. Finally, Koriat and Gelbard (2019) analyzed the importance of hiring internal or external workers and their behaviors, concluding

that the higher the number of hired external workers, the lower the likelihood that knowledge is shared.

### Results for HR Processes

**HR Processes.** The topics included in this section (see Table 5) are the following: turnover ( $n = 6$ ), performance ( $n = 5$ ), recruitment ( $n = 5$ ), learning & development ( $n = 1$ ), and stress at work ( $n = 1$ ).

**HRA and Turnover.** Five of the six articles selected turnover as the dependent variable, but one article used “intention to leave”. Authors predominantly used logistic regression (50%). Two authors (33.33%) adopted an algorithmic approach to the problem (e.g., random forest), and one of the articles (16.67%) used a Bayesian approach. As independent variables to predict turnover, we found that authors used demographic factors in 50% of the cases (pay, seniority, position, education, etc.). Job satisfaction is also an important variable included in a third of the cases.

Results indicate that there is a way to predict quit rates complementing personnel records with information from job satisfaction surveys, with 92.61% of the employees classified correctly (Frederiksen, 2017). Along similar lines, Rombaut and Guerry (2018) found that gender, seniority, partner status, nationality, salary, work percentage, company car, and company phone are significant predictors of turnover. Nandialath et al. (2018) used a Bayesian approach, in which job satisfaction is present in 80% of the simulated models, and perceived organizational support in 75%. Rombaut and Guerry (2020) investigated retention strategies using a data-driven approach. Employing a random forest algorithm, they found that retention strategies including compensation and recognition have a positive average treatment effect on the entire population ( $N = 1,606$ ,  $p < .05$ ), while training and flexibility do not ( $p > .05$ ). Ryan (2020) attempted to shed light on the use of bibliometric indicators as a people analytics tool for examining research performance outcome differences in faculty turnover. Using bibliometric information from research databases, the publication, citations, h-index and the newly developed individual annualized h-index (hla), Ryan found that the hla metric is a predictor of terminated employment status ( $\chi^2 = 25.35$ ,  $p < .001$ ). Finally, Sri Harsha et al. (2020) concluded that the fundamental explanation for attrition is an effort-reward imbalance related factors, and compare algorithms that correctly classified more than 83% of the employees.

**HRA and Performance.** The main methodology in the performance category is regression analysis (60%). However, new methods have emerged, such as latent ability models and the network data science approach. The most frequently used dependent variable in this case was individual performance (60%). Team performance was chosen in 20% of the articles, and the remaining 20% selected employee productivity (although this term does not match perfectly with performance, their definition led us to include these articles in this

**Table 4.** Results for General HRA

Ref	Main Finding	Method	General HR Analytics (N = 8)			Sustainable HR Analytics		
			IV/CV	DV	Statistical Support	TBL outcomes mentioned	Potential TBL outcomes	Related sustainable HR practices
Aral et al. (2012)	Human capital management software adoption, performance pay and HR Analytics generate a productivity premium when they are implemented simultaneously	Linear Regression	Human Capital Management Software, performance pay and HR Analytics	Productivity (at a company level)	$R^2 = .871, \beta = .165, p < .05$ (fixed effects); $R^2 = .876, \beta = .170, p < .05$ (random effects)	Economic	Social	[Performance Pay] 6. Fair remuneration and social benefits [HR Analytics] 4. Communication, transparency and social dialogue
Lismont et al. (2017)	An analytics maturity path with 4 clusters (of companies) from no analytics to experts	Cluster Analysis	HR Analytics survey (analytics techniques and applications used)	HR Analytics usage	"No analytics" 5.5%, "Analytics bootstrappers" 20.6%, "Sustainable analytics adopters" 38.4%, "Disruptive analytics innovators" 35.6%; (chi-squared $p$ value < .001)	N/A	N/A	N/A
Gelbard et al. (2018)	Sentiment Analysis can enhance HR capacity of predicting an ontology of HR factors	Sentiment Analysis (text mining algorithm)	Email digital footprints (vitality and satisfaction)	Engagement KPI	Digital footprints of changing	Economic and Social	N/A	N/A
Schiemann et al. (2018)	Restaurants with the Optimized Talent profile experience 21% less turnover and 10% higher productivity than sites with the High Risk profile	Linear Regression	Employee alignment, capabilities and engagement	Return of Investment	Alignment, capabilities and engagement account for 51% of the variance in turnover and 26% in productivity	Economic	Social	[Capabilities] 2. Training and continuous development [Engagement and Alignment] 6. Fair remuneration and social benefits and 7. Prevention at work and 8. Work-family balance
Simón and Ferreiro (2018)	The number of supervisory clerks obtained the largest effect size related to store productivity	Linear Regression	HR indicators (e.g., absenteeism, job tenure, supervisory clerks, the age of store managers)	Store Performance	Hiring each extra supervisory assistant would increase sales by 1.89 euros/hour ( $R^2 = .41, \beta = .241, p < .001$ )	Economic	Social	[Absenteeism, job tenure] 7. Prevention, health and security at work
Hazarika et al. (2019)	HR Metrics have financial implications and can improve performance	Linear Regression	Employee Strength (Retention)	(1) Company revenue and (2) passengers carried	(1) Adj $R^2 = .921, \beta = 1.777, p < .01$ ; (2) Adj $R^2 = 0.974, \beta = .871, p < .01$ and (1) $r = .962, (2) r = .988 (p < .01)$	Economic	Social	[Retention] 1. Attraction and retention of employees
Al-Ayed (2019)	Strategic Human Resources Practices have a significant impact on organization resilience	Structural equation modeling	Strategic Human Resources Management (strategic value of human resource practices, human resource analytics and high-performance work practices)	Organizational resilience: (1) cognitive, (2) behavioral, and (3) contextual	(1) $\beta = .31, p < .05$ ; (2) $\beta = .40, p < .05$ ; (3) $\beta = .38, p < .05$	N/A	N/A	N/A
Koriat and Gelbard (2019)	The more external workers are hired, the less knowledge sharing analytics	t-test and ANOVA	Employment contract: external vs. internal	Knowledge sharing analytics (duration of the call, assuming shorter as more effective interactions)	$t = 21.64, p < .05$	Economic	Social	[Employment Contract] 6. Fair remuneration and social benefits

Note. IV = independent variable; CV = control variable; DV = dependent variable; TBL = triple bottom line; N/A = not applicable.

section). A variety of independent variables were used. For example, Zuo and Zhao (2020) established the h-index as one of the predictors of future research performance, and Wang and Katsamakos (2019) established the number of repositories (a specific task) on which an employee works.

Regarding performance results in HRA, Ozgur et al. (2017) made a contribution to performance appraisals when concluding that we can evaluate nurses (work habits scale) based on the proportion of perfect scores. Wang and Cotton (2018) offer an example of HRA to improve workforce strategy by analyzing performance. They found evidence of the influence of experience ties on team performance in

various competency areas (organizational experience ties: fielding:  $\beta = -.039, p < .01$ ; competitor experience ties: pitching  $\beta = -.054, p < .01$ , and fielding  $\beta = -.027, p < .05$ ). Wang and Katsamakos (2019) demonstrated how a network data science approach can help companies gain useful insight into employee effort and productivity, and the likelihood of future collaborations. Luo et al. (2019) employed a latent ability model (LAM) to map employees and their activities. They created a vector, in which ability of the employee is on one side and the set of required skills on the other side in order to create a model for employee performance prediction. Zuo and Zhao (2020) attempted to understand and predict researcher career trajectories

**Table 5.** Results for HR Processes

Ref	Main Finding	Method	HR processes (N = 18) Turnover (N = 6) HR Analytics			Sustainable HR Analytics		
			IV/CV	DV	Statistical Support	TBL outcomes mentioned	Potential TBL outcomes	Related sustainable HR practices
Frederiksen (2017)	The ability to predict quits improves with job satisfaction surveys and reduce turnover costs	Logistic Regression	Job satisfaction surveys and Personnel Employee record	Turnover	92.61% employees correctly classified (ability to correctly predict quits: 39.26%)	Economic	Social	[Job Satisfaction] 3. Management of employment relations and 7. Prevention, health and security at work
Rombaut and Guerry (2018)	Data in the personnel system (i.e., gender, age, seniority, partner, nationality, salary, work percentage, company car and company phone) are significant predictors of turnover	Logistic Regression	Demographic and workforce specific factors (i.e., gender, pay)	Turnover	AUC = .743	Economic	Social	[Demographic factors] 5. Diversity and equal opportunities
Nandialath et al. (2018)	Bayesian Model Averaging approach provides less model dependent results and only Perceived Organizational Support and Job Satisfaction determine who is likely to leave the organization	Bayesian Model Averaging	Job satisfaction, organizational commitment, perceived organizational support, leader-member exchange, professional, national and religious identity centrality, individual and company growth expectation, organizational and campaign identification, work stress and demographic information	Intention to leave	Inclusion probability (most robust): Perceived Organizational Support, 75%; Job Satisfaction, 80% Adj $R^2 = .46$ Stress: $\beta = .111, p < .01$ ; Job Satisfaction: $\beta = -.103, p < .05$ ; Industry Growth Expectations: $\beta = -.107, p < .1$ ; Perceived Organizational Support: $\beta = -.074, p < .1$ Non-significant relations found with: Leader Member Exchange, Organizational Commitment, National Identity, Professional Identity, Religious Identity, Identification with Organization, Company Growth Expectations, Organizational Tenure, Industry Tenure, Age, Gender, Marital Status	N/A	N/A	N/A
Rombaut and Guerry (2020)	An uplift model shows that recognition and compensation retention strategies have a significant effect on the population	Causal conditional inference forests algorithm	Retention strategies: (1) Recognition, (2) Compensation, Training and Flexibility	Turnover	(1) $p < .01$ ; (2) $p < .01$	Economic	Social	[Pay] 6. Fair remuneration and social benefits. [Training] 2. Training and continuous development
Ryan (2020)	The hla metric is a predictor of terminated employment status	Multinomial logistic regression	Bibliometric indicators of paper counts, citation counts, h-indices and hla scores GROUP: terminated, retained and resigned faculty	Turnover	$\chi^2 = 25.35, p < 0.001, df = 8$ (Between-group difference for the h-indices Cohen's f statistic: $f = 0.14$ ; between-group difference in hla: $f = 0.24$ )	Economic and Social	N/A	N/A
Sri Harsa et al. (2020)	A model which will predict employee attrition rate dependent on HR analytics dataset	Algorithms (Naïve Bayes, Support Vector Machine, KNearest Neighbour, Random Forest) and Logistic regression	Demographic factors (i.e., gender) and workforce specific factors (i.e., pay) GROUP: Algorithms (Naïve Bayes, Support Vector Machine, KNearest Neighbour, Random Forest) and Logistic regression	Turnover	More than 0.83 accuracy (classification) and Accuracy/AUC: Logistic regression: 0.880/0.706; Naïve Bayes: 0.839/0.5; Support Vector Machine: 0.884/0.709; KNearest Neighbour: 0.832/0.524; Random Forest: 0.850/0.581	Economic	Social	[Demographic factors] 5. Diversity and equal opportunities [Pay] 6. Fair remuneration and social benefits

**Table 5.** Results for HR Processes (continued)

Ref	Main Finding	Method	Performance (N = 5) HR Analytics			Sustainable HR Analytics		
			IV	V	Statistical Support	TBL outcomes mentioned	Potential TBL outcomes	Related sustainable HR practices
Ozgur et al. (2017)	Nurse anesthetists can be evaluated validly based on the proportions of perfect scores	Mixed effects logistic Regression	Work habits scale	Individual Performance	When the rate was treated as a random effect, the estimated logit was no different from zero (0.44 ± 0.66, $p = 0.32$ )	N/A	N/A	N/A
Wang and Cotton (2018)	Team performance would be higher for teams having strategic roles with a moderate (vs. low or high) level of organizational and competitor experience ties	Regression (fixed effects)	(1) Organizational and (2) competitor experience ties (strategic roles for pitcher, batter, and fielder)	Team Performance	Adj $R^2 = .396$ ; (1) fielding ( $\beta = -.039, p < .01$ ); (2) pitching ( $\beta = -.054, p < .01$ ) and fielding ( $\beta = -.027, p < .05$ )	Economic	Social	[Experience] 2. Training and continuous development
Wang and Katsamakias (2019)	Network data science can be used to derive a broad spectrum of insights about employee effort and collaboration in organization	Network data science approach	The number of repositories an employee work on and contributions	Employee's productivity	Graphs: power-law relationships on project sizes	Economic	Social	[Contributions made] 2. Training and continuous development
Luo et al. (2019)	They map employee and activity to create a model for employee performance prediction	Latent Ability Model	Latent Variables: the set of abilities provided by employees and the set of abilities required by activities	Individual Performance	Match up score for employee and activity in graphic form	Economic	Social	[Latent Variables] 2. Training and continuous development; 6. Fair remuneration and social benefits; 5. Diversity and equal opportunities.
Zuo and Zao (2020)	Working with highstanding collaborators is a significant predictor for future impact (3-years) of early-stage researchers	Regression analysis	Betweenness eigenvector, Collaboration Betweenness, Collaboration h-index, h-index and network degree GROUP: Researchers at different career stages (early-stage, mid-career, and senior researchers) Citations for past papers in the past time window	Researchers future impact (Individual Performance); (1) three, (2) five and (3) ten years into the future	Collaboration h-index ( $\beta = .106, 95\% \text{ CI } [0.06, 0.15]$ ); h-index ( $\beta = .349, 95\% \text{ CI } [.31, .39]$ ) and Early-stage: (1) $r = .385 (p = .000)$ ; (2) $r = .419 (p = .000)$ ; (3) $r = .376 (p = .000)$ ; Mid-career: (1) $r = .478 (p = .000)$ ; (2) $r = .471 (p = .000)$ ; (3) $r = .380 (p = .000)$ ; Senior researchers: (1) $r = .466 (p = .000)$ ; (2) $r = .454 (p = .000)$ ; (3) $r = .426 (p = .000)$	Economic and Social	N/A	N/A
Recruitment (N = 5) HR Analytics								
Ref	Main Finding	Method	IV	DV	Statistical Support	TBL outcomes mentioned	Potential TBL outcomes	Related sustainable HR practices
Hoang et al. (2018)	They improved a skill tagger, which uses properties of semantic word vectors to recognize and normalize relevant skills in resumes	Monte Carlo Markov Chain Clustering Algorithm	Skills in resumes and relevancy and approval scores by users	Skill tagging	Skill tagging: 90% precision, 73% recall; relevancy and user approval rate: $r = .81$	N/A	N/A	N/A
Necula and Strimbei (2019)	Mining data from people résumés brings to surface relations between résumés data and employability	Data science and Semantic Web technologies (J48 algorithm)	Resumes (work experience -responsibilities and position held-, education and skills) GROUP: Algorithm: (1) Classification via Regression, (2) Support vector machine, (3) k-NN, (4) Naïve Bayes, (5) Random forest, (6) Decision tree	Skills that a job seeker has	Overall accuracy of the classifier: 80.83%; area under ROC (with aggregate features): .822 and Area under ROC for the Dataset Containing Aggregated Features: (1) .836, (2) .661, (3) .936, (4) .784, (5) .998, (6) .822	N/A	N/A	N/A



**Table 5.** Results for HR Processes (continued)

Ref	Main Finding	Method	Recruitment (N = 5)			Sustainable HR Analytics		
			IV	DV	Statistical Support	TBL outcomes mentioned	Potential TBL outcomes	Related sustainable HR practices
Brandt and Herzberg (2020)	The less prepositions used in cover letters, the more negative/critical words in CV and complete application, and the more written words in the cover letter, the greater the chance of rejection	Linguistic Inquiry and Word Count and Logistic Regression	(1) Prepositions used in cover letters (2) Negative/critical words in CV and complete application (3) The written words (count) in the cover letter	Application Success	Odds ratio and <i>p</i> value: (1) 0.84 (< .001); (2) 0.69 (.011) and 0.66 (.016); (3) 1.43 (.001) and Omnibus Likelihood Ratio Tests: (1) $\chi^2 = 14.65$ , $p < .001$ (2) CV model $\chi^2 = 31.14$ , $p < .01$ ; complete application model $\chi^2 = 6.31$ , $p < .05$ . (3) $\chi^2 = 10.81$ , $p < .001$	N/A	N/A	N/A
Xu et al. (2019)	Stock price information is potentially beneficial in predicting talent flow	Deep Sequence Prediction	Stock Price and Historical Talent Flow Record	Job Transitions (talent flow into and out of targeted organizations)	More than 89% of top 1,000 companies show the predicting ability of stock price to talent flows and Out/In $r = .603$ ( $p = 9e-28$ ), $r = .590$ ( $p = 5e-27$ )	N/A	N/A	N/A
Pessach et al. (2020)	The Variable-Order Bayesian Network (VOBN) model it is feasible to predict the successful placement of a candidate in a specific position at a pre-hire stage	Machine Learning Models	Lifestyle, family details, interview and test scores, demographics, diversity measures, background record, professional preferences questionnaires and details about the positions	Successful placement (future performance)	VOBN AUC = .705	Economic	Social	[All metrics] 1. Attraction and retention of employees and 5. Diversity and equal opportunities.
Learning and Development (N = 1)								
Hicks (2018)	A significant percentage of professional learning activity is predictable based on employee demographics	Regression Model	Job level, organizational function, overall satisfaction score, the use or not of the Profile tool and the use or not of the Real-Time Feedback tool	Employee's learning activity	$F(20, 39,849) = 1.742.92$ , Adj $R^2 = .41$ , $p < .0001$	Economic and Social	N/A	N/A
Stress at work (N = 1)								
Jabir et al. (2019)	The new working program with flexible hours reduces stress at work	<i>t</i> -Test	GROUP: The new program of work: Stress at work vs Stress at work	Stress at work	$t = 22.36$ , $p < .001$ ; $d = 1.115$	Economic and Social	N/A	N/A

Note. IV = independent variable; CV = control variable; DV = dependent variable; TBL = triple bottom line; N/A = not applicable; CI = confidence interval.

(future performance) by considering the research community as a social network. They found evidence that the research impact of current collaborators has a positive effect on future impact ( $\beta = .106$ , 95% CI [.06, .15]).

**HRA and Recruitment.** Regarding recruitment, all five of the articles are based on algorithms and a computer science approach. Monte Carlo Markov chain, semantic web analysis, linguistic inquiry and word count (LIWC), logistic regression, and deep sequence prediction and machine learning are the methods chosen to study this area. Two articles (40%) focus on skill prediction or detection; one article (20%) on forecasting the success of the application, one article (20%) on predicting future performance, and one article (20%) on talent flow in the form of job transitions. Curriculum vitae (CV) is used to extract the information in 3/5 of the articles, and attempts are made to tag competencies and compare them with the competencies required for a specific job.

Hoang et al. (2018) improved the SKILL system to detect skills in human capital data such as resumes, composed of (1) a skills tagger, which uses properties of semantic word vectors to recognize and normalize relevant skills, and (2) a skill entity sense disambiguation

component, which infers the correct meaning of an identified skill, and is currently used for workforce analytics and job matching. The results show that the current skill tagging framework attains 90 percent precision and 73 percent recall. Along similar lines, Necula and Strimbei (2019) conducted a semantic web analysis of 213 CVs to extract data and create an algorithm that can predict the skills a job seeker has on the basis of their CV. The overall accuracy of their algorithm was 80.83% for certain skills detected in their CVs. In contrast, Xu et al. (2019) used a data-driven approach to model the dynamics and evolving nature of talent flows. An empirical study of the correlation between stock price, talent flow and, according to the authors, experimental results on real-world data showed that the proposed model outperforms other benchmarks in terms of prediction accuracy. Brandt and Herzberg (2020) investigated whether word categories of LIWC can predict application success in recruitment. They analyzed 581 cover letters and CVs and found no support for the main hypothesis (successful applicants are associated with more categorical language). However, they did find a correlation with the category prepositions in cover letters, concluding that the more they use, the greater the chances of success. They also found

**Table 6.** Results for HR Analyst Competencies

Ref	Main Finding	Method	HR Analyst Competencies (N = 5)			Sustainable HR Analytics		
			IV/CV	DV	Statistical Support	TBL outcomes	Potential TBL outcomes	Related sustainable HR practices
Vargas et al. (2018)	The level of HR Analytics adoption depends on HR professional competencies	Partial least squares path modeling	Competencies: (1) technology self-efficacy, (2) quantitative self-efficacy, (3) social influence, (4) the attitude towards HR Analytics, and (5) tool trialability	Level of HR Analytics adoption	Adj R <sup>2</sup> = .349; (1) β = .196, p < .01; (2) β = .126, p < .01; (3) β = .196, p < .01; (4) β = .304, p < .01; (5) β = .111, p < .05	N/A	N/A	N/A
Kryscynski et al. (2018)	There is a positive relationship between analytical competencies in HR professionals and performance	Regression Analysis	Analytical Competencies in HR professionals: (1) general business skill, (2) personal credibility and (3) analytical ability	Individual Performance (internal and external evaluation)	Adj R <sup>2</sup> internal = .05 Adj R <sup>2</sup> external = .07 (1) Internal β = .16, p < .05, external β = .24, p < .01; (2) internal: β = .01, p > .05, external: β = -.05, p > .05; (3) internal: β = .26, p < .01, external: β = 0.25, p < .01	N/A	N/A	N/A
Sripathi & Madhavaiah (2018)	Having analytical competencies is not being considered as anything unique for HR professionals	t-test	GROUP: general population, HR professionals	Analytical Competencies	t(36) = -0.69, p = .494; d = 0.11	N/A	N/A	N/A
Kalvakolanu et al. (2019)	Knowledge about software package MS-Excel obtained the first rank in HR analyst competency frame (1), followed by Performing basic statistical calculations (2) and (3) Using Advanced multivariate models	Fuzzy Logic	Analytical Competencies in HR professionals	Level of analytical competencies	Defuzzification value: (1) 1.78; (2) 1.65; (3) 1.65	N/A	N/A	N/A
McCartney et al. (2020)	A set of five distinct competency themes required by HR Analysts was found: (1) technical knowledge, (2) consulting, (3) data fluency and analysis, (4) storytelling and communication and (5) HR and business acumen	Content Analysis	Job Requirements	HR Analysts competency model	Percentage of skill references: (1) 31; (2) 27; (3) 25; (4) 12; (5) 5	N/A	N/A	N/A

Note. IV = independent variable; CV = control variable; DV = dependent variable; TBL = triple bottom line; N/A = not applicable.

evidence to support the proposal that successful candidates use less negative/critical words and written words. Finally, Pessach et al. (2020) demonstrated that it is feasible to predict the successful placement of a candidate in a specific position at a pre-hire stage, and to use predictions to devise a global optimization model (variable-order Bayesian network algorithm AUC = .705).

**HRA and Learning and Development.** Only one article is included in this section (Hicks, 2018). The author used a regression model to predict employee learning activity, and found that a significant percentage of professional learning activity is predictable, based on job level, organizational function, overall satisfaction score, the use or non-use of the Profile tool, and the use or non-use of real time feedback (RTF) tool,  $F(20, 39.849) = 1.742.92$ , adj.  $R^2 = .41$ ,  $p < .0001$ .

**HRA and Stress at Work.** The article included in this section (Jabir et al., 2019) compared two groups of employees at two different times. They tested whether a new flexible working program (less working hours and more rewards) reduced stress. The hypothesis was supported ( $t = 22.36$ ,  $p < .001$ ,  $d = 1.115$ ).

**Results for HR Analyst Competencies**

**HR Analyst Competencies.** There are five articles included in this category (see Table 6). Three articles (60%) used traditional multivariate techniques, one article (20%) used fuzzy logic, and one article (20%) used content analysis. The most important dependent variable was the level of HRA adoption (40%).

The article by Kryscynski et al. (2018) was included in this section despite the fact that its dependent variable is more associated

with performance, given that its independent variable was the level of analytic competencies. This paper made a very important contribution to establishing the set of competencies an HR analyst requires, as they found a positive relationship between an individual's general business skill (internal  $\beta = .16$ ,  $p < .05$ , external  $\beta = .24$ ,  $p < .01$ ) and analytical ability (internal:  $\beta = .26$ ,  $p < .01$ , external:  $\beta = .25$ ,  $p < .01$ ) and performance. Vargas et al. (2018) examined the individual decision of HR practitioners to adopt HR Analytics. Employing survey analysis, they measured attitudes towards HR Analytics and how a practitioner's set of competencies affects the decision to adopt HR Analytics. They found that technology self-efficacy, quantitative self-efficacy, social influence, the attitude towards HR Analytics and trialability were positively related to higher levels of adoption of HR analytics (adj.  $R^2 = .35$ ). However, Sripathi and Madhavaiah (2018) conducted research to ascertain whether analytical competencies in HR professionals were higher than in the general population, and did not find support for this hypothesis ( $p = .494$ ,  $d = 0.11$ ).

Kalvakolanu et al. (2019) used fuzzy logic to establish a ranking of analytical competencies in HR professionals. The highest ranked was "Knowledge about software package MS-Excel" (defuzzification = 1.78), followed by "Performing basic statistical calculations" (defuzzification = 1.65) and "Using advanced multivariate methods" (defuzzification = 1.65). Along similar lines, McCartney et al. (2020) explored the knowledge, skills, and abilities required for the new role of HR Analyst by performing a content analysis of 110 job advertisements in various countries. They found 1,597 skills referencing 38 KSAOs (i.e., knowledge, skills, abilities, and other requirements) critical to HR Analysts. Each of these was categorized

**Table 7.** Results for HR Analytics and Ethics

Ref	Main Finding	Method	Ethics (N = 3)			Statistical Support	Sustainable HR Analytics		
			IV/CV	DV	HR Analytics		TBL outcomes mentioned	Potential TBL outcomes	Related sustainable HR practices
Khan and Tang (2016)	Employees concerns about HR Analytics are found in "Cost Reduction" and "Information Privacy"	Regression Analysis	Employees attributions about HRA: (1) Cost reduction (2) Information privacy (3) Quality and employee enhancement attribution	Employees affective commitment		Adj $R^2 = .21$ ; (1) $\beta = -.44$ , $p < .05$ , (2) $\beta = -.37$ , $p < .05$ , (3) $\beta = -.35$ $p < .10$	N/A	N/A	N/A
Newman, et al. (2020) Study 1	Individuals will perceive algorithm-driven decisions about promotions and layoffs as less fair than human decisions	ANOVA	Decisions made by humans vs algorithms	Fairness perceptions		$F(1,197) = 12.61$ , $d = 0.50$ , $p < .001$	N/A	N/A	N/A
Newman, et al. (2020) Study 2	The HR algorithm was perceived as significantly less fair than the HR team to make performance review decisions in promotions and layoffs; and quantitatively driven algorithms led to less organizational commitment than did all other HR processes	ANOVA	(1) GROUP: The HR algorithm vs. The HR team (2) GROUP: Quantitatively driven algorithms vs. all other HR processes	(1) Fairness perceptions (2) Organizational commitment		(1) $F(1,1652) = 5.30$ , $d = 0.11$ , $p = .021$ ; (2) $t(1648) = 4.56$ , $d = 0.26$ , $p < .001$	N/A	N/A	N/A
Köchling et al. (2020)	Algorithms for classification tasks in the recruiting context still have deficits concerning inherent biases and unpredictable classifications	Video based IA algorithm	Job Interview Score, gender and ethnicity GROUP: ethnicity (Asian, Caucasian, African-American) GROUP: algorithms (BU-NKU, ROCHCI)	Fairness Measures (Disparate Impact) (1) Conscientiousness, (2) Job interview score, (3) Neuroticism		Disparate Impact $< 0.8$ and BU-NKU Asian: (1) $d = -0.38$ , ( $p = .01$ ), $M$ and $SD$ : $0.54 \pm 0.10$ ; (2) $d = -0.23$ , ( $p = .13$ ), $M$ and $SD$ : $0.50 \pm 0.08$ ; (3) $d = 0.28$ , ( $p = .03$ ), $M$ and $SD$ : $0.45 \pm 0.11$ // Caucasian: (1) $d = -0.03$ , ( $p = .07$ ); (2) $d = -0.01$ , ( $p = .45$ ); (3) $d = 0.01$ , ( $p = .50$ ) // African-American: (1) $d = 0.05$ , ( $p = .36$ ); (2) $d = -0.01$ , ( $p = .90$ ); (3) $d = -0.02$ , ( $p = .74$ ) ROCHCI Asian: (1) $d = -0.40$ , ( $p = .01$ ); (2) $d = -0.26$ , ( $p = .12$ ); (3) $d = 0.18$ , ( $p = .22$ ) // Caucasian: (1) $d = -0.05$ , ( $p = .06$ ); (2) $d = -0.06$ , ( $p = .03$ ); (3) $d = -0.03$ , ( $p = .29$ ) // African-American: (1) $d = 0.30$ , ( $p = .00$ ); (2) $d = 0.13$ , ( $p = .13$ ); (3) $d = 0.30$ , ( $p = .00$ )	N/A	N/A	N/A

Note. IV = independent variable; CV = control variable; DV = dependent variable; TBL = triple bottom line; N/A = not applicable.

into technical knowledge, consulting, data fluency and analysis, storytelling and communication, and HR business acumen. With this approach, they define KSAOs of the twenty-first century HR specialist.

**Results for HR Analytics and Ethics**

**HRA and Ethics.** Three articles have been included in this section (see Table 7). Two articles used traditional multivariate techniques, such as regression and analysis of variance. The remaining article is based on a video-based algorithm. The dependent variables are fairness perception of decision making (66.66%) and employee affective commitment (33.33%). The authors conduct an empirical test to establish if the adoption of HRA practices potentially affect employee perceptions of fairness.

One of the studies focuses on employees at the individual level. Khan and Tang (2016) conducted research on how HRA is related to employee commitment, and found that employee attributions about HRA cost reduction are negatively related to affective commitment ( $\beta = -.44$ ,  $p < .05$ ). Their results also indicated ( $\beta = -.37$ ,  $p < .05$ ) that employee commitment can be affected by concerns about data

privacy. Algorithms can help to overcome human bias in HR, but may run the risk of being perceived as less fair (Newman et al., 2020). Decision processes may be affected and perceived as reductionist and unfair when algorithms are used. To determine if their hypothesis was correct, they conducted several studies and asked employees about promotion or terminating their employment relationship with the organization. Results support their initial fears: individuals affected by personnel decisions will perceive algorithm-driven decisions as less fair than the same decisions made by a human being ( $p < .001$ ,  $d = 0.5$ ). In addition, The HR algorithm was perceived as significantly less fair than the HR team to make performance review decisions ( $p = .021$ ,  $d = 0.11$ ), and quantitatively-driven algorithms led to less organizational commitment than did all other HR processes ( $p < .001$ ,  $d = 0.26$ ). This highlights a potential problem for HR departments in the future: how can algorithms be integrated into decision-making without them being perceived as less fair? Finally, Köchling et al. (2020) examined the extent to which decision-making leads to unfair treatment in recruitment contexts. They used highly accurate algorithms to analyze 10,000 video clips of self-presentations. They use disparate impact (DI) as a criterion, and follow the 80% rule of fairness in which employment rates of one group (the unprivileged)

**Table 8.** Original Definitions of HR/People/Talent/Workforce Analytics

Authors	Definition	HRA aim embedded in the definition	Triple Bottom Line Objectives addressed (economic, social or environmental)
Davenport et al. (2010)	Track, analyze, and use data about their people-ranging from a simple baseline of metrics to monitor the organization's overall health to custom modeling for predicting future head count depending on various "what if" scenarios.	Not specified	Social
Marler and Boudreau (2017, p. 15)	An HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making.	Establish business impact and decision making	Economic
Tursunbayeva et al. (2018, p. 231)	People Analytics is an area of HRM practice, research and innovation concerned with the use of information technologies, descriptive and predictive data analytics and visualization tools for generating actionable insights about workforce dynamics, human capital, and individual and team performance that can be used strategically to optimize organizational effectiveness, efficiency and outcomes, and improve employee experience.	Organizational outcomes (efficacy and efficiency outlined) and employee experience	Economic and Social
Vargas et al. (2018, p. 3055)	HR Analytics is defined as demonstrating the direct impact of people data on important business outcomes. HR Analytics are the statistical measures that can show connections, correlations and even causality between human resource metrics and other business measures.	Business outcomes (not specified)	Economic
Levenson (2018, p. 6)	Any analyses done individually or at the role level and is the domain of what is traditionally considered workforce analytics. Specific topics include motivation, employee engagement, competencies, leadership development, training, compensation, and more. In addition, any analysis that seeks to explain business processes through the lens of individual differences falls into this category.	To explain business processes	Economic
Minbaeva (2018, p. 701)	Organizational capability that is rooted in three micro-level categories (individuals, processes, and structure) and comprises three dimensions (data quality, analytical competencies, and strategic ability to act).	Not specified	Not specified
McIver et al. (2018, p.406)	Workforce Analytics is a process - one that is continuously advanced by improving problem-solving through sound measurement, appropriate research models, systematic data analysis, and technology to support organizational decision making.	To support organizational decision making	Not specified
Leonardi et al. (2018)	People A is a new way to make evidence-based decisions that improve organizations.	Improve organizations	Not specified
Fernández and Gallardo-Gallardo (2020, p. 17)	HR Analytics is a set of principles and methods that address a strategic business concern that encompasses collecting, analyzing and reporting data to improve people-related decisions.	Address a strategic business concern	Not specified
Singh and Malhotra (2020, p. 3260)	People Analytics refers to the unification of Human Resource data from various, different but relevant sources, the implementation of people analytics or workforce analyses on the occupied data, and further the complete understanding and discernment from the analyses to bring stronger decisions into shape for finer organizational performance.	Decisions and organizational performance	Economic
Zuo and Zhao (2020, p. 1)	People Analytics is a data-driven analytics approach that improves the efficiency as well as the efficacy of talent acquisition as well as retention.	Improves efficiency and efficacy	Economic
Ryan (2020, p. 2)	HR/people analytics can be broadly categorized as the various use of big data, cloud computing and machine learning for informing HR decisions.	Decisions Not specified	Not specified

cannot be less than the other 80% of other group rates (privileged). If the unprivileged group receives a positive outcome less than 80% of their proportion of the privileged group, it is a disparate impact violation. They found that two highly accurate algorithms for classification tasks in recruitment have deficits and biases ( $DI < 0.8$ ).

**Empirical HR Analytics and Sustainability.** In this section, we address the second objective of this review, shown in Tables 4, 5, 6, and 7. The content analysis of the 34 empirical studies, 47% (16) were not conducted in a company or organization context and were therefore coded N/A (not applicable). The remaining 18 articles were analyzed from the sustainable HRM perspective. Regarding the triple bottom line, 72% (13) of the HRA articles considered economic outcomes such as store performance or revenue, whereas only 28% (5) considered both economic and social outcomes such as costs and employee experience. It is important to note that environmental objectives are not mentioned in any of the articles included in this review.

To fulfill the objective, we proposed sustainable HRM practices to enhance HRA and help the practice to become sustainable. Having suggested the inclusion of at least one sustainable HRM practice, all the articles included at least an analysis of economic and social aspects. All the articles were able to achieve both economic and social outcomes using the same HR metrics. Following the criteria

of Barrena-Martínez et al. (2019) mentioned in the method section above, Sustainable HRM Practice 6: fair remuneration and social benefits (e.g., ensures the principles of justices, fairness...) was suggested six times; Practice 2: training and continuous development (e.g.: periodically detects training needs of staff...) was suggested four times; Practice 7: prevention, health and security at work (e.g., minimizes physical and emotional risks...) was suggested three times; Practice 4: communication, transparency and social dialogue (e.g., facilitates social dialogue...); and Practice 8: work-family balance (e.g., facilitates modification of working conditions...), just once.

**Definitions of HR Analytics.** We recorded 24 explicit definitions (30.3%) in the 79 articles analyzed. Of these, 12 definitions (15.15%) were consistent with explanations, but quoted other authors. The remaining 12 definitions (15.15%) used their own original definition. The 12 definitions are listed in Table 8. Marler and Boudreau's definition (2017) is mentioned twice by other authors (Peeters et al., 2020; Tursunbayeva et al., 2018), and is the widely cited.

Regarding the original definitions of HRA, 50% do not mention any clear triple bottom line objective, with vague statements like "to support organizational decision making" (McIver et al., 2018, p. 406), or "for informing HR decisions" (Ryan, 2020, p. 2). However, 41.6% mentioned economic outcomes as one of the main contributions of HRA (e.g., "to establish business impact"; Marler & Bou-



dreau, 2017, p. 15). Tursunbayeva et al.'s (2018, p. 231) is the only definition that, apart from economic outcomes, is concerned with improving employee experience (social objective).

### **Original Definitions of HR/People/Talent/Workforce Analytics**

Finally, we make our own contribution in the form of a new definition of HRA. Our definition was based on three guiding principles. First, the definition must help to overcome the science-practice gap. Second, the scientific treatment of data (from data gathering to data analysis) must be included. Third and finally, any organizational capability (such as HRA) must consider a sustainable approach. On the basis of these three principles, the authors agreed on the final definition. Specifically, we define SUHRA as an action-research practice that uses meaningful company data and statistical analysis to enhance data-driven decisions that lead the firm to achieve economic, social, and environmental benefits. This definition takes other definitions into account (e.g., Marler & Boudreau, 2017; Tursunbayeva et al., 2018), adds the action-research method, and sets boundaries to limit the definition of HRA.

### **Discussion**

This systematic literature review examined results of all empirical studies on HRA that were currently available. In order to accomplish this objective, we used fairly restrictive criteria to include studies in our review. We realize that our very restrictive approach may have led to the rejection of several papers, but we believe this it was necessary to ensure the reliability of our conclusions. We hope to see a growing corpus of evidence in the field in the coming years.

Given the issues relating to HRA we identified in the introduction, and after performing this review we would like to particularly focus on the problem defined by Rasmussen and Ulrich (2015) – the lack of definition of procedures. One thing is clear. HRA is no longer a fledgling discipline in search of meaning. It has now established clear aims and the means to achieve them. The aims identified in this review focus on maximizing company profit, whether directly or indirectly, through return of investment (ROI) measures that can impact on a variety of business outcomes, such as performance or turnover, and lead to increased company revenue. We can see that the approach of Schiemann et al. (2018) of using a service-profit chain and a people equity model to predict turnover and productivity is a perfect example of these objectives. However, in terms of future research, we underline the need to go beyond the use of HRA to increase profit, and to link HRA with social and sustainable HRM practices. In short, HRA must consider fairness, wellbeing, and ethics. As for how to bring this about, this review reveals two different but coexisting methods. The first method results from all the work carried out to date, together with the organizational psychology methods that have become integral to companies over the last century. Here we include all the descriptive statistics and predictive approaches (such as regression methods) in a highly applied manner. The second and most innovative approach stems from computer science with rapid and accurate algorithms designed to classify or predict HR metrics and business outcomes. Both methods coexist in companies and academia under the same name: HRA. The question that needs to be addressed is why the same method is used. Having conducted this content analysis, we can corroborate that they share the same raw material, namely HR metrics, and use this raw material for the same purpose. It therefore makes sense for academia to include them in the same category. However, we should not forget that HRA stems from business analytics. This means that HRA still risks being subsumed within business analytics, with the computer science approach occupying the territory. Both perspectives will need to keep working on this same approach and join forces to achieve better results.

Another problem relates to privacy and ethics. HRA uses metrics and employee information. The use of technology, algorithms, and black-box software to process this information represents a challenge itself, so HR departments will need to deal with negative employee perceptions of fairness when algorithms are involved in decisions. The challenge is not only to define, use, and add evidence of new HRM methods, but to establish how this method impacts on employee perception of fairness in a company.

It is important to note that sustainable HRM practices and HRA are not mentioned in any of the articles analyzed. Even though some researchers point to social objectives as well as economic benefits (e.g., Ryan, 2020), we conclude that HRA has largely focused on economic outcomes. This could result from certain traditional fears found in HR departments, such as being relegated from the strategic boardroom if they are unable to ensure ROI measures (Angrave et al., 2016). We have made our contribution by showing that, with the use of the same HR metrics, objectives can be transformed from strictly economic to sustainable (including social aspects). The HRM outcomes expected in this direction include non-business objectives such as societal fairness, workplace democracy, environmental protection, and human rights (Aust et al., 2020). In this area, the most frequently recommended sustainable practice has been fair remuneration and social benefits (e.g., ensures the principles of justices, fairness, etc.). In this respect, HRA offers a significant amount of related data that should allow organizations to make fairer decisions. It should also be noted that none of the articles mentions the environmental aspects of the triple bottom line. In this new approach, which links HRA and SUHRM, the social aspect may gain more attention than environmental issues. HRA is developed within the HR department, so it makes sense that the preliminary analysis is more focused on human capital. However, further research is required to analyze how environmental sustainability can be linked with SUHRA. This is a novel contribution that complement HRA perspectives in terms of organizational maturity, that is: descriptive, predictive, and prescriptive (e.g., Margherita, 2022).

Regarding the definitions of HRA, the fact that only 30% of the articles in this review clearly define the term suggests that the promotional aspect of HRA continues to override any genuine recognition of the true importance of HRA. We collected all the currently available definitions of HRA to provide a common framework for HRA and sustainability. Given the way in which many definitions agree that HRA allows organizations to enhance data-driven decisions, we believe it is important to clarify the term. "Enhance" should not solely refer to more accurate decisions, it should also mean fairer and sustainable decisions. This explains why we include it in our definition. It should be made clear that HRA will help to increase the fairness of procedures and improve working conditions, and therefore enable organizations to achieve not just economic but social and environmental objectives.

This review has several implications for HR professionals. Back in 2010, we believed that HRA (and Big Data in general) would lead to a complete transformation of the HR department. However, this transformation has only occurred in limited situations in specific sectors. HRA will transform the way in which HR works in two different ways. First, it will extend a wide-ranging increase in data-friendliness in companies to HR departments, and lead to the adoption of an increasingly data-driven approach for each and every process. The second transformation will relate to the HR competency model. The figure of the HR Analyst will assume much greater importance and require analytical competencies. However, these competencies will need to be accompanied by other socially related competencies. In particular, there will be a need to address concerns over privacy and the proper use of data and technology, and further progress in developing sustainable and ethical HRM practices to be included in the HR core competences framework. Following Giermendl et al (2022, p. 21), "the question is not whether people



analytics will monitor, determine, and optimize an increasing portion of our working environment in the future; rather, it is how we can reap the positive rewards this process offers, while respecting the complexity of the human condition.”

Some very promising results and HRA models have been discussed in this review, and we encourage practitioners and researchers to continue working along similar lines. Contributions and results support the use of HRA, but research should embrace this new development. What results can HRA achieve for a company? How can we be sure that HRA promotes sustainable growth of a company? How does this approach affect employee commitment? All of these questions are yet to be answered. We also underline the importance of changing the aims of HRA. This method cannot continue solely for the purposes of increasing profit. Equal importance must be given to the achievement of non-business social objectives. Although more data-driven decisions in companies should lead to fairer workplaces, further research is clearly required.

## Conclusions

We believe that the objectives of this paper established in the introduction have been achieved. A systematic literature review was performed to satisfy the first objective. The second objective was achieved by analyzing how HRA could go well beyond the achievement of strictly economic purposes. We also expanded the HRA literature to include a much broader sustainability perspective, offered a triple bottom line (financial, social, and environmental objectives) criterion, and suggested directions for future HRM research and practices.

This review has made two primary contributions. First we addressed the status of current HRA literature, and concluded that although this area is attracting ever-increasing attention, the main focus of HRA remains economic benefit, and therefore ignores the sustainable approach that has assumed importance in today's companies. In addition, we demonstrated how HRA can become SUHRA by proposing that sustainable HRM practices become important criteria, and striving to include social and environmental objectives (e.g., fairness, employee wellbeing, environmentally friendly practices) as standards.

## Limitations

Although this review met its primary objectives, it still has some potential limitations. First, the selected online databases may have ignored some, probably, adequate papers, including those published in professional journals and databases. The second limitation of this review is we used restrictive criteria to select articles. By being very restrictive, we risk excluding some good papers. We decided this was the price to be paid if we were to achieve solid conclusions and fulfill the aim of the study. In addition, the subject under discussion remains a relatively new field. As a result, HRA has sometimes gone under various names, which means that some articles may have escaped our search. A further limitation stems from the fact that some articles relate to business while others relate to computer science. As a result, the tags or names of variables in the HR domain do not always match the way this is carried out in other fields. We noticed this when we looked at performance or employee productivity. This makes it harder to group articles, and leaves the results open to interpretation. Finally, the framework proposed by Barrena-Martínez (2019) is based on socially responsible human resources practices, but fails to address environmental aspects of the triple bottom line.

Finally, since we have found a great variety of issues, frameworks, variables, measures, samples characteristics, and analyses methods, we were unable to carry out a meta-analysis. Putting all the

information together by means of a quantitative strategy would have increased the quality of the information given by our research (Oh, 2020; Rubio-Aparicio et al., 2018), but unfortunately we can only deal with all the information extracted qualitatively. We also want to call HRA researchers to give rigorous, clear, transparent, and complete information that could help other colleagues to go further following recommendations recently proposed (Aguinis et al., 2021). However, practitioners may cope with difficulties and potential political sensitivities when seeking to publish ‘within firm’ HR analytics projects (Edwards et al., 2022) or results.

In spite of these potential limitations, we hope that our paper fosters increased interest in research on HRA and helps organizations use these new techniques to enhance their performance and achieve important social and environmental outcomes (e.g., fairness, ethics, environmentally friendly practices).

## Implications and Future Research

We are now going to present the implications of the results and conclusions obtained from this study for the theory and practice of human resource management.

### Implications for Advancing HRA Theory

The results of our review revealed that there are a growing number of empirical studies on HRA, but one of the major limitations of this research is that it has not been based on an explanatory theoretical model. Thus, we believe that our review of the HRA literature has key implications for advancing theory and research on the topic. HRA was originally based on the control theory (Fitz-enz, 1984), and we believe that this framework is still a useful means for understanding HRA processes. However, it does not provide clear explanations for all elements in the process (e.g., identifying sources of problems), and does not offer predictions on how to solve these problems. As a result, we believe that the control theory should be expanded to include other models and well-established relationships in organizational behaviour and HR (e.g., employee job dissatisfaction is related to turnover) that can be used to understand the sources of problems and suggest corrective actions. For example, HRA typically uses the analysis of big data sets, algorithms, and artificial intelligence (AI) or machine learning to identify the potential causes of problems, but these methods are guided by searching the data rather than turning toward evidence-based relations that were detected through the scientific process. Thus, we maintain that the control theory should be expanded to include existing models of organizational behaviors and attitudes – e.g., Mobley et al.'s (1979) model of turnover – and well-established relationships (e.g., job dissatisfaction is related to turnover) to identify causes of problems and suggest ways to correct them. In the paragraphs that follow we describe how the control theory applies to the HRA process and indicate how the existing theory and research might be used to extend this model. The control theory model of HRA (Fitz-enz, 1984) typically consists of the following five step process: 1) establishing performance standards, 2) measuring actual performance, 3) comparing actual performance to the standards, 4) searching for causes of any discrepancy or problems, and finally 5) taking corrective actions. Although the control theory is used as the basis for HRA, we believe that it is limited because it does not provide an adequate explanation for how organizations identify causes of problems or make predictions about the appropriate corrective actions. We also maintain, as others (Fan et al., 2014) do, that analyzing big data sets, using algorithms or AI/machine learning to identify sources of problems may not always be effective or give organizations insights about their problems. As a result, some researchers have lamented that organizations are more concerned about analyzing thousands or millions of data points rather than

understanding the actual source of problems (Calude & Longo, 2017). Thus, we need organizational behaviour frameworks for HRA. Further, others have argued that there are a number of ethical, legal, or other limitations associated with mining big data sets or using AI to uncover the causes of problems (Dattner et al., 2019) which we analyze now.

In recent years, analysts have started searching big data sets for relationships and using algorithms to help organizations uncover sources of problems and identify solutions to them. The analysis of big data sets and the use of algorithms have shifted how organizations think about research and appears to assume that data-driven solutions are better than scientifically-based ones (Boyd & Crawford, 2012). Big data typically consists of datasets that are large in volume, high in velocity (i.e., created in real time), diverse in variety (i.e., being structured and unstructured in nature), and exhaustive in scope (i.e., capturing entire populations) (Kitchin, 2014). According to Bassi et al., (2012), human resource analytics is a methodology to improve all human decisions related to the causes of strengthening the individual and/or the overall impact on the corporation, being an opportunity for the emergence of a comprehensive statistics-based decision-making process and a competitive advantage for companies. According to van den Heuvel and Bondarouk (2016), HR analytics consists of the systematic identification and quantification of people factors that contribute to the improvement of decision making. This implies collecting personal data and trying to establish patterns about people. Holsapple et al. (2014) distinguishes between three guidelines: descriptive analytics, predictive analytics, and prescriptive analytics. These data are then collated using artificial intelligence algorithms. Analysts search big data sets to identify correlations or uncover causes of problems. Algorithms are also used to analyze large data sets, and can be defined as a finite sequence of well-defined instructions that are typically used to perform a computation or solve a class of specific problems (Calude & Longo, 2017). Despite the widespread use of big data sets and algorithms to identify problems and solutions to them, these authors have argued that there are a number of limitations of these new approaches, and we highlight some of them below.

### Analyzing Big Data Sets

One of the major limitations of analyzing big data sets to identify causes of problems is that the process is likely to uncover spurious correlations, and larger data sets are more likely to find spurious correlations than smaller ones (Calude & Longo, 2017). Thus, one risk of searching big data sets is that analysts may make erroneous inferences and recommendations based on spurious or misleading correlations. In this sense, statistically significant regression/correlational models may occur by chance (Fan et al., 2014) especially when there is not a well previous specified model. Thus, even though there is no actual correlation between variables, the analysis and reanalysis of big data sets may still find a statistically significant model.

Moreover, Calude and Longo (2017) have argued that with large data sets and enough computing power analysts can uncover any relationship or pattern in the data. However, these patterns may not always be meaningful or allow organizations to make valid predictions about the cause of problems, as these patterns are usually based on correlations, but these analyses do not identify the underlying causes of relationships and there could be hundreds of explanations for them. Further, Anderson (cited in Mazzocchi, 2015) warned that analysts know that correlation does not imply causation, but they often assume correlation supersedes causation and they make recommendations to organizations based on correlations to isolate sources of problems. Thus, searching big

data sets may not always identify meaningful correlations and may lead analysts to make inaccurate inferences that are not helpful for organizations. More on this, we must take into account that we can find non-linear relations between variables (e.g. García-Izquierdo, Moreno, et al., 2010; Guastello, 2013; Navarro et al., 2022; Ramos-Villagrasa & García-Izquierdo, 2011).

### Use of Algorithms

Algorithms are increasingly being used to identify organizational problems and develop effective solutions to them. Researchers have argued that the use of algorithms to identify problems has several benefits (Gonzalez et al., 2019). First, algorithms are perceived to be more objective and thorough than humans, and are viewed as more rational, efficient, and consistent than them (Davenport, 2018). Researchers also argue that algorithms have fewer biases and make fewer errors than human decision makers (Gonzalez et al., 2019), and have the ability to identify hidden patterns and trends in the data (Davenport, 2018). Thus, algorithms are often viewed as infallible, and some researchers have argued that they make better decisions than humans (Smith, 2018). However, other research has shown that algorithms are often plagued with the same errors and biases as humans because they are developed and programmed by humans (Leong et al., 2019; Raub, 2018). As a result, algorithms may not always uncover the most accurate sources of problems and may create or replicate discriminatory practices. Researchers have also argued that there are number of limitations associated with them (Osoba & Welser, 2017). Following Ryan and Deros (2019), despite the fact that technology in assessment leads to much greater efficiency, there are also untested assumptions about effectiveness and fairness, and there is little consideration of potential negative byproducts of contextual enhancement, removing human judges, and collecting more data. Consequently, we identify some of these limitations below.

First, even though some researchers contend that algorithms may reduce biases and have fewer errors than human decision-making (Gonzalez et al., 2019), others maintain that algorithms still suffer from biases and mistakes because they are developed and programmed by humans, and as a result, they may perpetuate or amplify human errors in decision making (Osoba & Welser, 2017). For example, Weizenbaum (1976) argued that biases arise in algorithms from the data used or the way it is programmed or coded, so they incorporate the programmer's biases and expectations. Consequently, he warned against trusting decisions made by algorithms that a user does not understand and suggests that these programs may result in ethical problems including unfair discrimination, invasion of privacy, or harm for humans. Thus, he cautioned that there should be limits on what computers or algorithms should be able to do. This author also noted that algorithms may use good information, but its use might result in negative ethical consequences. In this regard, van den Heuvel and Bondarouk (2016) conclude that analytics is based on historical data and may therefore lead to stereotyping and could lead, finally, to discrimination in terms of gender, racial, or age issues, for instance taking into account the digital divide. Therefore, managers should be cautious about using algorithmic decisions without checking them because they may result in negative consequences for individuals and organizations (Johnson et al., 2021), and that a system of oversight should be developed for algorithms in every organization.

Another concern with the use of algorithms is that users often perceive that they are neutral, objective, and result in the best possible answers every time (Johnson et al., 2021). However, algorithms are very complex and opaque, so managers may not always understand how the processes were performed or the final decisions were made (Lee, 2018). In spite of the lack of understanding about how algorithms work, managers often put their blind faith in decisions made by algorithms and may ascribe greater authority to

algorithmic based decisions than human ones (Johnson et al., 2021). Thus, the overreliance on algorithmic rather than human decisions may lead to a number of negative consequences (Lee, 2018). For example, algorithms are typically designed to maximize corporate profit, not social good, and the use of these new technologies may fail to consider human needs, deepen inequalities in our society, produce complacency, and displace workers (Pew Research & Elon University, 2012). One reason for this is that the use of algorithms favor those with digital expertise over others, and these individuals may gain even greater power in our society (e.g., Google, Facebook). As a result, we believe that limits should be placed on the use of algorithms for high stakes decisions or those involving human safety and organizations should create mechanisms to ensure that algorithmic failures are identified and corrected (Zerilli et al., 2019). Further, we believe, as others do (e.g., Dulebohn & Johnson, 2013), that organizations should not rely solely on algorithms to make final decisions. Instead, algorithmic outputs should serve as an input into human decision processes, and organizations should use a hybrid method of making key decisions (e.g., Johnson et al., 2021).

Taken together, our brief review indicated that the analysis of big data and use of algorithms have a number of potential advantages and limitations. However, one of our recurring concerns about the search of big data and use of algorithms is that analysts are searching for causes of problems in the dark without any direction, but there are already vast amounts of research on the reasons for some of these problems (e.g., turnover, low performance levels). Thus, analysts are spending a great deal of time searching big data bases to uncover information that is already well known in the research literature. We believe that if they started by reviewing the existing theory and research on a problem, they would be able to identify the causes and solutions more quickly.

Another concern is that analysts and managers often assume that data driven solutions are better than scientific-based ones, but scientific knowledge is based on a review of the background research, theoretical predictions, the collection of data to test those predictions, and statistical methods to test those predictions. One major difference between data-driven and scientific-based knowledge is that scientific researchers typically review the existing research literature to determine what is already known about an issue, and data-driven analysts do not always view this step as important. However, there is considerable published research on the causes of key problems in organizational settings (e.g., turnover, low performance levels), and there is no need to search for them without a specific direction. Thus, we believe that a step needs to be added to control theory that involves reviewing the existing research prior to searching for potential causes of problems. This would save analysts time and provide them with insights about potential sources of problems before they start searching big data sets or using algorithms. Of course, they can still search for insights or correlations in their big databases or use algorithms to uncover sources of problems in their particular context.

Given the problems with using big data sets, algorithms and other means noted above, we believe that the search for causes of problems in organizations should start with well-established theories and research that identifies evidence-based sources of problems. For instance, existing turnover theories (Mobley et al., 1979) typically argue that two factors affect turnover (i.e., job dissatisfaction and employment alternatives including employment, retirement, etc.). Similarly, Leventhal's (1980) principles of procedural justice identify several reasons that HR policies may be viewed as unfair (e.g., they are applied inconsistently, biased, based on inaccurate data, or there are no ways to correct unfair decisions). Thus, instead of organizations randomly searching for the cause of problems they might initiate their search by reviewing the existing causes of problems in the research literature.

In summary, we maintain that the control model of HRA should be expanded to include well established theories and

evidence-based predictors of problematic behaviors and attitudes (e.g., turnover, job dissatisfaction, beliefs that policies are unfair, destructive leadership). If organizations are faced with other challenges, we believe that they should be encouraged to review the existing theory and research on the problem before searching big data sets or using algorithms.

### Implications for HR Practice

We believe that our review of the empirical research on HRA has a number of important implications for practice in organizations. For example, results of the review suggested that an analysis of HR practices and strategies can be used to predict turnover, performance, recruitment, learning and development, stress at work, and ethical issues. Thus, we consider the practical implications of some of the HRA research on these topics in the paragraphs that follow. However, we want to caution that there are very few studies on each topic so the results noted in this review should be replicated in other contexts before generalizations are made.

**Turnover.** First, the results of our review suggested that an analysis of HR (HRA) practices and strategies can be used to predict turnover rates in organizations. For example, analyzed research revealed that when organizations evaluate employee job satisfaction levels, compensation and recognition programs, and effort-reward imbalances they can forecast turnover rates. As a result, we believe that organizations should regularly evaluate compensation and recognition systems, and employees perceived or actual effort-reward imbalances to predict and decrease attrition rates. Moreover, other variables are present in turnover intentions as mediators, mainly those related to stress (Haider et al., 2020). Consequently, not only direct relations must be taken into account.

**Performance.** Second, the findings of our review indicated that an evaluation of employee work habits, experience ties in teams, the fit between employee abilities and skill requirements of jobs, and social networks can be used to forecast performance levels. Thus, organizations may want to evaluate researchers' social networks in order to forecast and increase their career success levels. Nonetheless, not only hard and soft skills are relevant variables to forecast performance. Subjective well-being and labour health has an influence as recent research has demonstrated (Pujol-Cols & Lazaro-Salazar, 2021; Salgado et al., 2019; Moscoso & Salgado, 2021; Salgado & Moscoso, 2022).

**Recruitment.** Third, our review of research suggested that HRA may be used to predict applicant success rates in recruiting using semantic analysis. However, the words that are predictive of job success may vary for different types of jobs and organizations, so additional research is needed to determine the types of words that forecast applicants' success rates in varying contexts. Moreover, other tools related to computing with words as the fuzzy logic methods seem promising (e.g. García-Izquierdo et al, 2020).

**Learning, Development and Stress Levels.** Research has also shown that HRA can be used to predict learning, development, and employee stress levels. In view of these results, organizations may want to evaluate the impact of other interventions on employees' stress and wellbeing levels.

**Ethical Issues.** Our review of the research on HRA also revealed that it can be used to predict a number of ethical issues including employees' affective commitment, reactions to algorithm-based decisions, and perceptions that HR practices are unfair. Thus, we believe, as others do (Dulebohn & Johnson, 2013; Johnson & Stone, 2019), that rather than relying solely on algorithms to make decisions organizations may want to use algorithms as only an input to the overall human decision-making processes.

Taken together, our review of the research on HRA suggests that organizations may want to use HRA to help them identify



problems (e.g., turnover, employee stress, and negative reactions to algorithms), take actions to decrease these problems, and use the data to enhance productivity, affective commitment, recruitment success, and the methods used to make HR decisions.

### Conflict of Interest

The authors of this article declare no conflict of interest

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