Quantifying Human Resource Management: A Literature Review

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Abstract

Purpose. With a focus on the evolution of human resource management (HRM) quantification over 2000–2020, this study addresses the following questions: (1) What are the data sources used to quantify HRM? (2) What are the methods used to quantify HRM? (3) What are the objectives of HRM quantification? (4) What are the representations of quantification in HRM?

Design/methodology/approach. This study is based on an integrative synthesis of 94 published peer-reviewed empirical and non-empirical articles on the use of quantification in HRM. It uses the theoretical framework of the sociology of quantification.

Findings. The analysis shows that there have been several changes in HRM quantification over 2000–2020 in terms of data sources, methods, and objectives. Meanwhile, representations of quantification have evolved relatively little; it is still considered as a tool, and this ignores the possible conflicts and subjectivity associated with the use of quantification.

Originality/Value. This literature review addresses the use of quantification in HRM in general and is thus larger in scope than previous reviews. Notably, it brings forth new insights on possible differences between the main uses of quantification in HRM, as well as on artificial intelligence and algorithms in HRM.

Keywords: HR metrics, HR analytics, HR scorecard, algorithms

Introduction

The concepts of measurement and data are not new in the field of human resource management (HRM). At the beginning of the nineteenth century, Taylor introduced the idea that measuring work could increase the productivity of workers and thus, the performance of the organization. At the end of the century, the work on the 'balanced scorecard' (Kaplan and Norton, 1992) developed the idea that firms should consider both financial and non-financial metrics. Subsequently, the books *How to Measure Human Resources Management* (Fitz-enz and Davison, 2002) and *The HR Scorecard* (Becker *et al.*, 2001) marked a turning point in measurement by proposing metrics to measure the activity, performance, and impact of HRM.

Even though the HR function lags behind other corporate functions in using figures and quantified data (Lismont *et al.*, 2017), new terms and concepts have, of late, emerged and have led to a burst of fresh thinking and research in the field; these include HR metrics (Lawler *et al.*, 2004), HR Scorecard (Beatty *et al.*, 2003), HR analytics (Marler and Boudreau, 2017; Vargas *et al.*, 2018), workforce analytics (Simón and Ferreiro, 2018), and talent analytics (Davenport, 2019), as well as big data (Garcia-Arroyo and Osca, 2019; Tambe *et al.*, 2019), algorithms (Duggan *et al.*, 2020), and artificial intelligence (Huang *et al.*, 2019). All these concepts refer to processes involving the use of quantification and quantified data in HRM, however, existing literature is found to be somewhat vague in their definitions (Marler and Boudreau, 2017).

This article deals with the notion of quantification in HRM on a broader level. The notion of quantification is wider than that of metrics or analytics; it is derived from the sociology of quantification (Desrosières, 1993; Espeland and Stevens, 2008) and refers to the use and production of figures. Desrosières (2019, p. 36) gives the following definition of the verb 'to quantify': *'to express and bring into existence in numerical form what was previously expressed in words and not numbers'*[1]. This notion, thus, covers a wider field than metrics and analytics. In particular, it covers all the key concepts mentioned in the paragraphs above: metrics, analytics, big data, algorithms, and artificial intelligence.

The use of these key concepts has evolved over 2000–2020, as shown in the following graph made with Google Trends below.[2]

[Insert Figure 1 about here]

Figure 1 shows a decreasing trend in keyword searches around the notion of metrics and a growing or upward trend for the concept of HR analytics, which clearly stands out from other

[1] Author's own translation.

[2] Google Trends data begin in 2004.

concepts and has become very much in demand in recent years. Contrary to what might have been expected, it also shows a declining trend for searches around algorithms, but a growing trend for the notion of big data related to HR. Finally, searches concerning HRM and artificial intelligence are found to follow a U-shaped curve.

This literature review therefore seeks to analyse the evolution of the uses of quantification in HRM over the past years (2000-2020). The period considered seems particularly interesting; it comes just after the publication of two seminal books by Fitz-enz (1984) and Becker *et al.* (2001), and sees the emergence of new notions related not only to analytics, but also to algorithms and big data. Finally, a 20-year period seems appropriate to study the evolution of literature on a given subject, in view of the time required for research and publication.

Four systematic literature reviews have recently brought to light new insights on the use of figures and quantified data in HRM (Chalutz Ben-Gal, 2019; Garcia-Arroyo and Osca, 2019; Marler and Boudreau, 2017; Tursunbayeva *et al.*, 2018). However, three of these focus only on HR metrics and HR analytics (Chalutz Ben-Gal, 2019; Marler and Boudreau, 2017; Tursunbayeva *et al.*, 2018), and the last one focuses only on big data (Garcia-Arroyo and Osca, 2019). This gives a fragmented view of the different uses of data, metrics, and quantification tools in human resource management. Besides, these reviews deserve to be updated because most of them do not go beyond 2016 (Chalutz Ben-Gal, 2019; Marler and Boudreau, 2017) or 2017 (Tursunbayeva *et al.*, 2018), while research on the subject has been extremely dynamic for several years (Huselid, 2018; Vargas *et al.*, 2018). This study aims at bridging these gaps.

Conceptual framework

The theoretical framework of the sociology of quantification has its roots notably in the economics of conventions (Diaz-Bone, 2016) and has proposed the concept of ‘quantification convention’ (Chiapello and Walter, 2016; Desrosières, 2008a, 2008b) to account for the fact that a quantification process is never neutral in the sense of producing a neutral reflection of reality. In other words, the sociology of quantification underlines that the process of quantifying something is much more than a merely technical process; it involves choices and negotiations at several steps, such as the choice of data sources, the choice of methods, and the way the results are used (Diaz-Bone, 2016; Espeland and Sauder, 2007; Espeland and Stevens, 1998).

Hence, this theoretical framework distances itself from the positivist paradigm (Hansen and Flyverbom, 2015), which has become increasingly important in HRM, both in practice and in research (Greasley and Thomas, 2020). The framework used for this study is part of a constructivist approach that invites one to analyse reflexively the use of quantification to gauge human phenomena. This framework seems particularly appropriate in a context of voices emerging and calling for practitioners to take a step back and adopt a more comprehensive approach in the use of data in HR (Greasley and Thomas, 2020; Harley, 2015).

The sociology of quantification suggests looking at the following three dimensions (Chiapello and Walter, 2016): the sources of data, methods, and objectives. These allow the breaking down of the initial research question into three sub-questions, which follow the steps of a quantification process (Vargas *et al.*, 2018):

(1) What are the data sources used to quantify HRM and how have they evolved over 2000–2020?

Previous research mentions different data sources; first, it distinguishes between HR data sources, covering personnel data, but also employee surveys and individual performance reviews (Tootell *et al.*, 2009), and non-HR data, corresponding for example, to economic or financial data (DiBernardino, 2011). A second distinction is made between internal company data (Eveborn *et al.*, 2006) and external data taken from social networks, such as LinkedIn, or other companies (Tarulli and DeLuca, 2019). Answering this sub-question will help specify which of the sources of data are used most and how this has evolved over the 20 past years.

(2) What are the methods used to quantify HRM and how have they evolved over 2000–2020?

Previous research mentions several types of methods: production of relatively basic indicators (basic metrics and simple outcome metrics, such as in Beatty *et al.*, 2003), use of more sophisticated statistical models and methods (Beddoe and Petrovic, 2006), predictive models (Davenport, 2019), and qualitative methods, which in most cases are cited in addition to the quantitative approaches (Fink, 2010). Answering this sub-question will help articulate which of the methods are used most and how this has evolved over the 20 past years.

(3) What are the objectives of HRM quantification and how have they evolved over 2000–2020?

Following the success of the concept of evidence-based management (Briner and Barends, 2016), the literature on HRM quantification puts forth the notion of evidence-based human resource management (EBHRM), which is based on the idea that using data and metrics is a way to improve knowledge and decision making in HR (Wolfe *et al.*, 2006). Therefore, the main objective assigned to HRM quantification seems to be improving decision-making. A second objective is based on the idea that data make it possible to measure the performance of the HR function and its contribution to organizational performance (Chhinzer and Ghatehorde, 2009). Therefore, quantification can be used to demonstrate the link between the HR function and organizational performance (Mondore *et al.*, 2011). Other objectives can be found in the literature, notably predicting phenomena (Shah *et al.*, 2017) and automating (Huang *et al.*, 2019). Answering this sub-question will help specify which of the objectives are most assigned to HRM quantification, and how this has evolved over the 20 past years.

Further, the sociology of quantification also suggests focus on the representations of quantification. Indeed, as the concept of the quantification convention suggests, quantification is a practice that involves certain beliefs and representations (Espeland and Sauder, 2007; Espeland and Stevens, 1998).

This leads to the fourth sub-question:

(4) What are the representations of HRM quantification, and how have they evolved over 2000–2020?

Previous research helps identify different representations of HRM quantification. The first one sees quantification as a technical tool (Sexton *et al.*, 2005) which is neutral and whose quality depends on technical criteria. The second one sees quantification as a way to answer questions (Fink, 2017); this representation underlines the need to start by defining questions, and to identify the right method and data to answer them. The third one sees quantification as a form of proof (Doherty and Norton, 2014), which helps support some ideas or hypotheses. Answering this sub-question will help articulate which of the representations are widely present concerning HRM quantification, and how this has evolved over the 20 past years.

These sub-questions will help answer the broader question of the evolution of HRM quantification over 2000–2020, and in addition, offer the possibility of providing more precise insights on various key concepts mentioned in the introduction (metrics, analytics, big data, algorithms, and artificial intelligence), in relation to the HR function. This is in response to the requirement of being able to identify the boundaries and bridges between these different notions. This is a major challenge, given the significant growth in research and managerial discourse using these terms. As Marler and Boudreau (2017) point out, there are still definitional ambiguities surrounding these terms that need to be resolved.

Methodology

Sample systematic search

This article seeks to identify scholarly research on the use of quantification in HR. The research design follows the integrative and systematic synthesis procedure (Briner and Denyer, 2012; Rousseau *et al.*, 2008) as do Marler and Boudreau (2017), Haq (2016), or Parris and Peachey (2013). This procedure is based on a comprehensive accumulation, transparent analysis, and reflective interpretation of all relevant studies on a given issue (Parris and Peachey, 2013). It also involves the use of questions predetermined by a theoretical framework and selection criteria defined in advance (Haq, 2016). It is used to provide transparency and impartial inclusive coverage on a specific topic (Parris and Peachey, 2013).

The search to build the sample was done on the Business Source Complete database. This research focuses on scholarly business journals, referenced in the Journal Quality List (JQL) database; this list allows researchers to identify journals of a sufficiently high academic level. This criterion, which has not been used by Chalutz Ben-Gal (2019), for example, is even more important in this study because the search terms are diverse, leading to a wide variety in the types of research and scientific production. The publication dates were restricted to 2000–2020, because the sampling was conducted in March-April 2020, and very few articles were found for 2020.

The choice of the keywords was based on a three-step procedure. First, the most common keywords concerning quantification as identified in the introduction, were mobilized: 'human resource (or 'HR') metrics', 'HR scorecard', 'HR analytics', 'HR + algorithms'. Next, reading the keywords associated with this first selection helped identify other keywords: 'HR accounting', 'workforce metrics', 'talent metrics', 'talent analytics', 'workforce analytics', 'HRM (or 'Human resource management' or 'HR' or 'Human Resource') + Big data', 'HRM + artificial intelligence' (or 'AI'). Finally, the Google Trend tool and the 'related requests' functions were used to check that the list of keywords covered all fields, and that it was unnecessary to search for other terms such as 'personnel metrics', 'manpower metrics', 'personnel analytics', or 'manpower analytics' (Tursunbayeva *et al.*, 2018). Indeed, these different terms did not return any results.

Finally, the following keywords were searched: 'HR (or 'Human resource') metrics', 'HR scorecard', 'HR accounting', 'HR dashboards', 'Workforce metrics', 'Talent metrics', 'HR analytics', 'Workforce analytics', 'Talent analytics', 'HRM' (or 'Human resource management' or 'HR' or 'Human resource') + Big data', 'HRM + artificial intelligence (or AI)', 'HRM + algorithms', and 'HRM + algorithmic management'. The sample was broadened by searching not only the title, abstract, or keywords, but also the whole text. Finally, the sample contained 103 articles.

Critical evaluation of the sample

After the initial search, a second screening is necessary to assess eligibility of each article (Haq, 2016; Parris and Peachey, 2013). Therefore, I read the summaries of these 103 articles in greater detail and excluded articles whose abstracts indicated content that was far removed from the theme of this literature review. I also read the introductions of articles whose abstracts left some doubt as to their relevance. Therefore, nine articles that did not have a sufficient match with the theme were deleted. The final sample thus includes 94 articles (see appendix for the complete list). Some of these articles corresponded to several keywords; in these cases, they were associated to a single key notion, depending on the content of the abstract. For example, articles containing 'HR dashboard' or 'HR accounting' also dealt with 'HR metrics' and were filed under this notion. The articles dealing with 'HRM + algorithmic management' were filed under 'HRM + algorithms'. Table 1 shows the number of articles under each key notion.

[Insert Table 1 about here]

Table 2 provides information on the number of articles per journal.

[Insert Table 2 about here]

Next, the consistency between the articles in this sample and those in other studies on similar themes (Chalutz Ben-Gal, 2019; Garcia-Arroyo and Osca, 2019; Marler and Boudreau, 2017; Tursunbayeva *et al.*, 2018) was checked. Many common articles were identified. Owing to the keywords used in the present study, this sample also contains a lot of articles—notably those dealing with artificial intelligence or algorithms—that are not present in the other four literature reviews. The cases of articles absent from this sample, but present in another literature review, were analysed. All these cases can be explained individually.

Notably, the literature review of Chalutz Ben-Gal (2019) is not restricted to the JQL list. For example, it contains an article by Zang and Ye (2015), published in the *Journal of Human*

Resource and Sustainability Studies, a journal not classified in JQL. The sample used here, therefore, does not contain this article. Similarly, Tursunbayeva *et al.* (2018) use the Scopus database without any restriction about journals classified in JQL. Marler and Boudreau (2017), on the other hand, restrict themselves to the JQL list. However, while they mentioned that the search terms should be located in the title and not in the body of the text (this is not the case for the present study), they imposed fewer constraints on the appearance of the expression as a whole. More precisely, one article out of the 14 in their sample is not in the present list (Coco *et al.*, 2011). This can be explained by the fact that the words ‘people’ and ‘analytics’ are present in the title, but the expression ‘HR/workforce/talent/people analytics’ is present neither in the title nor in the text. Garcia-Arroyo and Osca (2019) focus on big data in HRM, but also use the keywords ‘massive data’ or ‘work’. This means that some of their articles are not present in this study. For example, their sample contains articles that deal with big data and work or management but do not contain the notion of HRM (such as Evans and Kitchin, 2018, or Liu *et al.*, 2017).

Categorization

First, the key notions were grouped into thematics corresponding to similar concepts. The two articles in HR Scorecard (Schwarz and Murphy, 2008; Walker and MacDonald, 2001), thus, contain several instances of the word ‘metrics’, but none of ‘analytics’. They were, therefore, grouped within the thematic ‘HR metrics’. ‘Talent Analytics’, ‘Workforce Analytics’, and ‘HR Analytics’ were grouped together because of the proximity of the keywords (Marler and Boudreau, 2017; Vargas *et al.*, 2018). Finally, there are five thematics: ‘HR metrics’ (12 articles), ‘HR analytics’ (44 articles), ‘HRM + AI’ (14 articles), ‘HRM + Algorithms’ (15 articles), and ‘HRM + Big data’ (9 articles).

[Insert Figure 2 about here]

Figure 2 shows that ‘HR metrics’ and ‘HRM + algorithms’ tend to decrease over the period. The other concepts (‘HR analytics’, ‘HRM + Artificial intelligence’, ‘HRM + Big data’) have been addressed by many articles since 2015–2016, showing the value of updating the Marler and Boudreau literature review (2017), which does not go beyond 2016, and the need to add notions such as artificial intelligence or big data. ‘HR analytics’ generates a larger number of publications over the sample period as compared to ‘HR metrics’ (44 articles versus 12), owing mainly to publications in the last 10 years. This suggests that the notion of metrics was used more often earlier, and even before 2000, but has gradually been supplanted by that of analytics.

Second, the theoretical framework of the sociology of quantification and research questions were used to create four criteria of categorization: data sources, methods, use of results, and representations of quantification. Three other criteria were added: type of article, HR activities/processes involved, and difficulties identified. The boxes corresponding to each criterion were filled in for each article without attempting to structure this information. Subsequently—to be able to offer descriptive statistics—a second recoding step was carried out (Marler and Boudreau, 2017). For each category, 3 or 4 response modalities were identified, and each article was attached to the corresponding response modality (Table 3), and sometimes to several modalities when needed.

The type of article was categorized into empirical or non-empirical, following the typology of Marler and Boudreau (2017). The HR activities concerned were categorized according to the most common cases identified in the articles: articles dealing exclusively with workforce, talent management, planning (e.g., Giuffrida, 2014); articles dealing with a specific HR process other than workforce management, such as Gobble (2017) on recruitment, or Burnett and Lisk (2019) on well-being, and articles dealing with HRM in general (e.g., Kryscynski *et al.*, 2018).

Regarding data sources, the main distinctions mentioned in the conceptual framework were used: HR data sources (e.g., Tootell *et al.*, 2009) vs non-HR data (e.g., DiBernardino, 2011), and internal data (e.g., Eveborn *et al.*, 2006) vs external data (e.g., Tarulli and DeLuca, 2019). Note that many articles mention several data sources, and some mention these 4 data sources (e.g., Pape, 2016).

Concerning the methods used, the main methods mentioned in the conceptual framework were used to characterize the articles: basic metrics (e.g., Beatty *et al.*, 2003), use of more sophisticated statistical models and methods (e.g., Beddoe and Petrovic, 2006), predictive models (e.g., Davenport, 2019) or qualitative methods (e.g., Fink, 2010). Combinations of methods are frequent (e.g., Lismont *et al.*, 2017).

Regarding the use of results, several possibilities were identified, as mentioned in the conceptual framework: improving decision making (e.g., Falletta, 2014), demonstrating the link between the HR function and organizational performance (e.g., Mondore *et al.*, 2011), predicting phenomena (e.g., Shah *et al.*, 2017), and automating (e.g., Huang *et al.*, 2019). Again, many articles address several of these categories (e.g., Angrave *et al.*, 2016).

Concerning representations of quantification, the three categories mentioned in the conceptual framework were used: a technical tool (e.g., Sexton *et al.*, 2005), a way to answer questions (e.g., Fink, 2017), or a form of proof (e.g., Doherty and Norton, 2014).

Finally, according to the articles, the difficulties stemmed from five sources: HR function and practitioners (lack of capabilities, as in Vargas *et al.*, 2018); data (poor quality or non-existence of data, as in Minbaeva, 2018); organization (role of the HR function, lack of organizational support, as in Ulrich and Dulebohn, 2015); technical aspects (difficulty in modeling a complex phenomenon with heterogeneity, as in Guerry, 2011); and legal aspects (privacy, as in Calvard and Jeske, 2018, or discrimination, as in Singh and Finn, 2003).

[Insert Table 3 about here]

Of the 94 articles, 54 are empirical and 40 non-empirical. Notably, of the 44 articles on HR analytics, 26 are empirical. This shows that there has been an evolution towards more empirical work on HR analytics since Marler and Boudreau's literature review (2017).

Further, of the 94 articles, only 14 do not provide any details on the HR processes involved. The remaining 80 are split between HRM in general (25), talent/workforce management or planning (25), and others (30). The HRM category includes articles that provide several examples of the HR processes covered (Doherty and Norton, 2014). The talent/workforce management or planning category includes numerous articles on staffing (Malinowski *et al.*, 2008), but also more broadly on workforce management (Simón and Ferreiro, 2018). The 'other' category includes articles on employee engagement (Schiemann *et al.*, 2018), recruitment (Singh and Finn, 2003), and employer branding (Dabirian *et al.*, 2017).

Results

This section aims at answering the identified sub-questions 1 to 4, thanks to the conceptual framework. The results are presented following the steps of a quantification process (Vargas *et al.*, 2018): data sources, methods, objectives. The last subsection deals with representations of HRM quantification.

Data sources used in HRM quantification

This subsection is intended to answer sub-question 1: What are the data sources used to quantify HRM and how have they evolved over 2000–2020? Table 4 presents some statistics that help answer sub-question 1.

[Insert Table 4 about here]

In the full sample, 60 articles address the issue of data sources. Of these, 25 focus on internal HR data (personnel data, HRIS, employee surveys, etc.) and seven focus on external HR data (information on employees from social networks or connected objects). Seven articles address both internal and external HR data. Ten articles mention both internal HR data and internal non-HR data (finance, accounting, etc.). The rest of the articles mention other combinations of data sources, with three articles mentioning all four sources (internal HR and non-HR data, external HR and non-HR data).

The cross-referencing between the data sources and the HR processes covered shows that the articles on talent/workforce management specifically mention internal data, with HR in particular, and are sometimes combined with internal non-HR data, especially with a view to measuring the benefits of a talent management strategy (DiBernardino, 2011; Douthitt and Mondore, 2014). Articles that refer to external HR data include recruitment or employer branding (Congdon, 2016; Dabirian *et al.*, 2017).

Cross-referencing with thematics shows that six of the 12 articles about HR metrics mention internal HR and non-HR data. This may be particularly because the ‘HR balanced scorecard’ includes metrics on other areas, such as strategy or financial performance (Walker and MacDonald, 2001). On the other hand, only two articles (Doherty and Norton, 2014; Lawler *et al.*, 2004) on HR metrics mention external data, particularly for benchmarking purposes. Of the 44 articles on HR analytics, 20 do not mention any specific data source, and nine focus on internal HR data. However, 7 articles also mention external HR data. Curiously, the majority of articles on HRM and algorithms only mention internal HR data (ten out of 15). On the other hand, five of the nine articles on HRM and AI that mention data sources mostly cite external sources (Congdon, 2016; Cunningham, 2016; Dabirian *et al.*, 2017).

The data sources mentioned have evolved during 2000–2020. Indeed, the reference to external data, both HR-related and non-HR, is relatively recent. The first mention of external HR data (connected objects, professional social networks) dates from 2014 (Fox, 2014; Levenson, 2014), as the first mention of external non-HR data (Doherty and Norton, 2014; Falletta, 2014). On the contrary, the mention of non-HR data, whether internal or external, is not confined to the end of the period. Its first appearance is as early as 2000 (Murphy and Zandvakili, 2000) and it occurs regularly until 2020 (Hamilton and Sodeman, 2020).

Methods used in HRM quantification

The following step of the quantification process consists of using methods to analyse the data. Therefore, this subsection is intended to answer sub-question 2: What are the methods used to quantify HRM and how have they evolved over 2000–2020? Table 5 presents some statistics that help answer sub-question 2.

[Insert Table 5 about here]

Of the 94 articles in the sample, 66 mention methods for analysing the data. Fourteen focus exclusively on metrics; 28 on more advanced models; four on predictive models. The 28 articles on more advanced models help specify the latter category. It includes, for example, articles using regression models, but also more complex ones, such as those using network analysis (Wang and Katsamakas, 2019), or bathtub models (van der Laken *et al.*, 2018). 20 articles mention a combination of methods. Among them, ten articles discuss the combination of metrics and more advanced models, after explaining that simple metrics are sometimes insufficient (Giuffrida, 2014). Finally, five articles mention qualitative methodologies, but always in combination with other methods (Levenson, 2011).

The cross-referencing between the methods mentioned and the HR processes covered shows that most articles dealing with talent/workforce management/planning use more advanced models (14 out of the 16 that explain the methods that can be used) and that only 2 articles on these processes use metrics alone. Conversely, the articles on HRM, in general, have a more equal distribution of different methods.

Cross-referencing with thematics underlines that almost all articles on ‘HRM + Algorithms’ and ‘HRM + AI’ mention only the more advanced models. Almost all the articles on HR metrics mention only metrics. On the other hand, it is striking that five articles that are classified under ‘HR analytics’ owing to their title and keywords only mention metrics (e.g., Mason, 2017). This runs contrary to the distinction made by Marler and Boudreau (2017) between HR metrics and HR analytics based on, among other things, the methods used. However, Marler and Boudreau’s distinction is, to a large extent, reflected in the fact that while only 3 of the 12 articles in the ‘HR metrics’ thematic mention more advanced models or predictive modeling (sometimes combined with metrics), this is the case for 22 of the 27 articles in the ‘HR analytics’ thematic that mention specific methods. Another striking point is that of the 9 articles in the ‘HRM +

Big data' theme, 7 do not mention any particular method, while the others mention combinations of methods.

The study of the evolution of the methods mentioned over the period 2000–2020 shows a shift towards more sophisticated methods. Thus, 'more advanced models' only appear in 2002, and remain rare until 2005, but have become predominant since. Predictive models appear in 2008 (Malinowski *et al.*, 2008). This evolution is therefore in line with not only technological developments but also with the evolution of HR practices, which for a long time remained deaf to the call of sophisticated models, due to a lack of analytical skills, among other reasons (Lismont *et al.*, 2017; Minbaeva, 2018).

Objectives of HRM quantification

Once the data are analysed with the help of quantitative methods, the results can be used for several purposes. This subsection is intended to answer sub-question 3: What are the objectives of HRM quantification and how have they evolved over 2000–2020? Table 6 presents some statistics that help answer sub-question 3.

[Insert Table 6 about here]

Of the 94 articles, 60 mention a way of using the results, and of these 60, 25 focus on decision making. Quantification is, thus, seen as a way to improve decision making, whether it involves evaluating HR policies to improve them (Wang and Katsamakas, 2019), helping in defining HR policies (Sexton *et al.*, 2005), assisting in job analysis to help in recruitment decision making (McEntire *et al.*, 2006), or assisting in workforce planning (Harriott, 2019). 18 articles refer to both decision making and ways of demonstrating the link between HRM and organizational performance (Hamilton and Sodeman, 2020), which, in turn, lead to an underlying drive to improve the positioning of the HR function within the organization (Lawler *et al.*, 2004). Three articles focus solely on the link between HRM and organizational performance. Six mention that quantification can help to predict results or performance, for example, in the context of attribution to projects (Gobble, 2017) or turnover (Frederiksen, 2017). Finally, eight articles mention that quantification can be used to automate (Malinowski *et al.*, 2008). Among them, three mention decision making and automation at the same time; for these articles, quantification can be used to automate decision making (Zaharia and Hodoregea, 2017).

Cross-referencing with the HR processes shows that the articles on talent/workforce management/planning mainly mention decision making (13 of the 16 articles that explain the objectives of quantification do so). The underlying idea is that quantification can help to improve the decisions made about individuals and human capital management processes (Giuffrida, 2014; Hamilton and Sodeman, 2020). The articles on HRM, in general, tend to refer jointly to decision making and the demonstration of the effect of HRM on organizational performance.

Cross-referencing with thematics reveals that the articles on 'HRM + AI' and 'HRM + Algorithms' focus solely on decision making and automation, and that none of these articles mention the link between HRM and organizational performance. Most articles that do mention this link (16 out of 21) come from articles on HR analytics, therefore this link seems characteristic of the literature on HR analytics, and, to a lesser extent, of that on HR metrics.

The study of the objectives of quantification during 2000–2020 shows an evolution. During 2000–2009, there is an overwhelming focus on decision making (9 out of the 11 in the period mention a way of using the results), but from 2010 onward, there is an uptick in articles mentioning the link between HRM and organizational performance. The notion of prediction appears in 2012 (McAfee and Brynjolfsson, 2012) and again in 2017 (Shah *et al.*, 2017). The notion of automation appears in 2002 (Sniezek *et al.*, 2002), and is regularly mentioned throughout the period.

Representations of HRM quantification

Finally, this subsection is intended to answer sub-question 4: What are the representations of HRM quantification and how have they evolved over 2000–2020? Table 7 presents some statistics that help answer sub-question 4.

[Insert Table 7 about here]

The overwhelming majority of papers (51 of the 65 that mention a representation of quantification) consider quantification as a tool. This tool can have several functionalities, as per the aims presented in the previous section: decision making (Ulrich and Dulebohn, 2015), automation (Huang *et al.*, 2019) and problem solving (Canós-Darós, 2013; Cezik and L'Ecuyer, 2008). This representation of quantification, thus, emphasizes its functions and usefulness. It is sometimes combined with the idea that quantification can constitute evidence (e.g., evidence of the effect of the HR function on organizational performance) (Doherty and Norton, 2014). However, quantification is also sometimes seen as a way of answering questions, a representation that is possibly combined with another one (7 articles). This representation emphasizes the questions that are asked, and the fact that quantification is not just a neutral tool, since the questions may be subjective and of poor quality, and so on (Fink, 2017; Kryscynski *et al.*, 2018).

Cross-referencing with HR processes shows that most of the articles on talent/workforce management/planning see quantification as a tool (15 out of 19 articles that show a particular representation of quantification). Only a few articles on other processes and on HRM, in general, focus on it only as a means of answering questions (Engler *et al.*, 2016; Falletta, 2014) and not as a tool.

Cross-referencing with thematics reveals that only articles on HR analytics are interested in quantification as a means of answering questions. The articles on 'HRM + AI', 'HRM + Algorithms', and 'HRM + big data' generally consider quantification as a simple tool. Three articles on HR metrics consider quantification as both a tool and a means of evidence, and seven consider it as a tool alone.

The study of the evolution of representations of quantification during 2000–2020 shows that the understanding of quantification as a means of answering questions or even as evidence, instead of viewing it as a tool, is a rather recent phenomenon, dating from 2010, as articles during 2000–2009 all consider quantification primarily as a tool. Apart from this evolution, which remains marginal, there has been little change over the period because quantification is still essentially perceived as a tool.

Discussion and conclusions

This literature review aims at answering four questions on the use of quantification in HRM.

The first one deals with data sources. Previous research mentions four types of data sources: internal HR-related data, external HR-related data, internal non-HR data, and external non-HR data (Angrave *et al.*, 2016; Rasmussen and Ulrich, 2015; Garcia-Arroyo and Osca, 2019). However, while it is part of the numerous choices and debates that take place when trying to quantify a phenomenon, as the sociology of quantification shows (Desrosières, 2019), this aspect is scarcely discussed in existing literature, and this study brings some clarifications. It shows that internal HR data remains the main data source (Simón and Ferreiro, 2018); besides, the choice of data source depends on the HR process, with external HR data used in recruitment, with articles on talent/workforce management mainly mentioning internal data (HR or non-HR). More surprisingly, while the reference to external data remains relatively recent in the HRM literature (Fox, 2014), the reference to internal non-HR data is older. This may be because the notion of HR metrics, which is older than all the other ones (HR analytics, algorithms, artificial intelligence, and big data) is deeply linked with the notion of the HR scorecard, which includes non-HR data.

The second question deals with methods. This aspect is studied more extensively in the literature and is presented as a way to distinguish between HR metrics and HR analytics, with the latter involving the use of more sophisticated models and methods (Marler and Boudreau, 2017). This distinction is indeed found in this study, but with some nuances: five articles concerning HR analytics only mention metrics. The study also shows that there has been an evolution during 2000–2020 toward more sophisticated methods. It is interesting to note that advanced models remain rare in literature prior to 2005, but have become predominant since then; and predictive modeling appears only in 2008 (Malinowski *et al.*, 2008).

The third question deals with the objectives of HRM quantification. The main objective mentioned in the literature concerns decision making, as expected. This is in line with the notion of EBHRM, which underlines the necessity of making decisions based on data and evidence (Briner and Barends, 2016; Rousseau and Barends, 2011). However, since 2010, a growing number of articles have mentioned that quantification could be used to demonstrate the link between HRM and organizational performance (Chalutz Ben-Gal, 2019). This can be related to the literature on the positioning of the HR function and the ambition to become a business partner (Douthitt and Mondore, 2014). Besides, two other objectives are mentioned, albeit less frequently: the objective of automation, which quite surprisingly appeared as early as 2002, and the objective of prediction, which is much more recent (McAfee and Brynjolfsson, 2012). Besides, the prediction objective remains scarce (mentioned in six articles), whereas one of the main features associated with big data concerns prediction (McAfee and Brynjolfsson, 2012). This is consistent with the fact that predictive modeling appeared only in 2008 in the HRM literature, and this might mean that the HR function is not quite ready to incorporate this objective in its processes.

The fourth question deals with the representations of quantification. Indeed, the sociology of quantification underlines the fact that the use of quantification is based on representations of it (Chiapello and Walter, 2016; Espeland and Stevens, 2008). The main representation found in the literature sees quantification as a tool. This ignores the possible conflicts and subjectivity associated with the use of quantification (Diaz-Bone, 2016). However, this study shows that over the last decade some articles have suggested that quantification be defined as a way to answer questions; this puts the accent on the quality of those questions, and therefore on the fact that HRM quantification might be less neutral than expected, however, this type of thinking remains scarce.

Overall, these results indicate that there has been an evolution in data sources, methods, and objectives, but almost none in representations. This might constitute a danger for the literature on quantification in HRM because it can lead to a narrowing of the debate on the use of metrics, analytics, or any other type of quantification methods used in HRM; it may even lead to a 'one-best way' not only in HRM practices, but also in HRM research (Greasley and Thomas, 2020; Harley, 2015).

Furthermore, this literature review complements the literature and previous systematic literature reviews (Chalutz Ben-Gal, 2019; Garcia-Arroyo and Osca, 2019; Marler and Boudreau, 2017; Tursunbayeva *et al.*, 2018) by providing insights to define and distinguish the various notions used to speak of quantification in HRM: HR metrics, HR analytics, AI, algorithms, and big data. Table 8 characterizes each thematic by the main data sources, methods used to quantify, objectives of quantification, and representations of quantification.

[Insert Table 8 about here]

Table 8 shows that HR metrics and HR analytics differ in their data sources and methods used to quantify HRM. This result is consistent with the extant literature and previous literature reviews (Chalutz Ben-Gal, 2019; Marler and Boudreau, 2017). HR analytics also introduces the objective of prediction, which is not present in the literature on HR metrics, consistent with previous research (Tursunbayeva *et al.*, 2018). The study presented here gives original results on AI, algorithms, and big data in HRM. Indeed, these notions remain scarcely studied (Garcia-Arroyo and Osca, 2019). Table 8 shows that all these notions are linked to advanced models, and sometimes to predictive ones, as well as to representations that make quantification a technical tool. This can be because majority of the literature on AI, algorithms, and big data is technical, presenting quantitative methods and tools that can be used to model human phenomena and assist HRM, for example, in workforce planning (Eveborn *et al.*, 2006; Holder, 2005). Many of these works are published in technical journals (e.g., *Computers & Industrial Engineering*, or *Expert Systems with Applications*), and not in HRM-related journals. However, these three notions differ according to the data sources, which are: internal and external, HR-related and non-HR for AI; internal and HR-related for algorithms; and mainly external for big data. Overall, this shows that these notions are not interchangeable and must remain distinct, and that they are distinct from HR analytics because they do not make use of metrics and are focused on decision making and automation.

Overall, the literature review presented here shows that there are a lot of possibilities for each step (data sources, methods, objectives). Therefore, HRM quantification is based on choices that can be subjective, rather than being merely a technical process. This shows that the opposition posited in academic literature on EBHRM between individual subjectivity and the objectivity and rigor provided by the data and quantification (Kryscynski *et al.*, 2018; Rousseau and Barends, 2011; Schiemann *et al.*, 2018; Schwarz and Murphy, 2008) is not quite justified. Indeed, the subjectivity of individuals can be expressed in each of these four steps.

Practical implications

It is interesting to note that the most commonly mentioned difficulties in the articles from the sample are HR-related (at least 29 articles mention HR-related difficulties); the lack of analytical capabilities among HR practitioners (Angrave *et al.*, 2016; Vargas *et al.*, 2018) and low adoption of data-driven management (McAfee and Brynjolfsson, 2012) are examples. Technical difficulties are mentioned less often (22 articles), whereas data issues and legal issues are mentioned in 13 and 7 articles, respectively, that is, even less. This calls for the development of analytical skills among those in the HR function, as in other fields (Vargas *et al.*, 2018). This article aims at helping companies and HR professionals to gain some of those capabilities. Indeed, it provides insights about two dimensions that hitherto seem to have been relatively neglected by the academic literature.

First, it provides insights about the definition of each notion used in the managerial and academic discourses on the use of quantification in HRM; it shows that HR metrics, analytics, artificial intelligence, algorithms, and big data are not interchangeable and do have unique characteristics (Table 8).

Second, it uses a theoretical framework that recommends the analysis of quantification with a constructivist and reflexive approach, instead of the positivist and normative approach that is generally mobilized (Greasley and Thomas, 2020). In doing so, it provides HR practitioners with a grid to analyse their proper practices of quantification. This analytical grid includes 4 steps: (1) paying attention to the data sources; (2) analysing the methods used; (3) paying attention to the objectives of the quantification process; and (4) understanding the representations of quantification.

Limitations and research avenues

This study suffers from several limitations which open promising research avenues. First, the theoretical framework of sociology of quantification suggests that one should pay interest to the different stakeholders and their respective and potentially conflicting interests. Unfortunately, the literature review conducted here does not address this question; in future research, it would be interesting to pay attention to various players involved in the quantification processes in HRM. Second, the article does not provide insights on the idea of subjectivity, whereas one of the contributions of the research is to show that HRM quantification is based on choices and not only on technical considerations. This calls for further investigation into the individual subjectivity expressed during quantification processes. Third, the literature on quantification and HRM has been very dynamic in recent years; this would necessitate a frequent update of such a literature review. Fourth, the literature review is limited to a 20-year period, whereas the use of quantification in HRM began at the beginning of the nineteenth century and evolved before 2000 as well, which would call for a historical view of the topic, over a larger period.

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Appendix

List of references included in the literature review

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Bernstein (2016)

Burnett and Lisk (2019)

Calvard and Jeske (2018)

Canós-Darós (2013)

Cappelli (2017)

Cezik and L'Ecuyer (2008)

Chalutz Ben-Gal (2019)

Congdon (2016)

Cunningham (2016)

Dabirian *et al.* (2017)

Davenport (2019)

Davenport *et al.* (2010)

DiBernardino (2011)

Doherty and Norton (2014)

Douthitt and Mondore (2014)

Duggan *et al.* (2020)

Dulebohn and Johnson (2013)

Edwards *et al.* (2017)

Engler *et al.* (2016)

Eveborn *et al.* (2006)

Falletta (2014)

Fink (2010)

Fink (2017)

Fox (2014)

Frederiksen (2017)

Garcia-Arroyo and Osca (2019)

Gelbard *et al.* (2018)

Giuffrida (2014)

Gobble (2017)

Greasley and Thomas (2020)

Green (2019)

Guerry (2011)

Hamilton and Sodeman (2020)

Harriott (2019)

Harris *et al.* (2011)

Hedge *et al.* (2006)

Holder (2005)

Huang *et al.* (2019)

Huselid (2018)

Janiak and Kovalyov (2008)

Khan and Tang (2017)

Kryscynski *et al.* (2018)

Lawler *et al.* (2004)

Legato and Monaco (2004)

Levenson (2011)

Levenson (2014)

Levenson (2018)

Lin and Hsu (2010)

Lismont *et al.* (2017)

Lupushor (2018)

Malinowski *et al.* (2008)

Marler and Boudreau (2017)

Mason (2017)

McAfee and Brynjolfsson (2012)

McEntire *et al.* (2006)

Mehrabad and Brojeny (2007)

Minbaeva (2018)

Mondore *et al.* (2011)

Murphy and Zandvakili (2000)

Pape (2016)

Polychroniou and Giannikos (2009)

Rasmussen and Ulrich (2015)
Roland *et al.* (2010)
Rousseau (2016)
Rousseau and Barends (2011)
Schiemann *et al.* (2018)
Schwarz and Murphy (2008)
Sexton *et al.* (2005)
Shah *et al.* (2017)
Simón and Ferreiro (2018)
Singh and Finn (2003)
Sniezek *et al.* (2002)
Tambe *et al.* (2019)
Tarulli (2019)
Tarulli and DeLuca (2019)
Tavis (2016)
Tootell *et al.* (2009)
Tung *et al.* (2005)
Tursunbayeva *et al.* (2018)
Ulrich and Dulebohn (2015)
van der Laken *et al.* (2018)
Vargas *et al.* (2018)
Walker and MacDonald (2001)
Wang and Cotton (2018)
Wang and Katsamakas (2019)
Welbourne (2006)
Wright and Snell (2004)
Yano (2017)
Zaharia and Hodorogea (2017)

Tables

Table 1. Number of articles by key notion

Notion	Number of articles
HR metrics	10
HR scorecard	2
HR analytics	24
Talent analytics	7
Workforce analytics	13
HRM + AI	14
HRM + Algorithms	15
HRM + Big data	9

Table 2. Number of articles per journal

Journal	Number of articles
Business Horizons	2
California Management Review	2
Career Development International	1
Computers & Industrial Engineering	2
Computers & Operations Research	1
Decision Support System	1
Employee Relations	1
European Journal of Operational Research	5
Expert Systems	1
Expert Systems with Applications	2
German Journal of Human Resource Management	1
Harvard Business Review	5
Human Resource Management	11
Human Resource Management Journal	5
Human Resource Management Review	4
Human Resource Planning	2
Industrial Management & Data Systems	1
Information Resources Management Journal	1
International Journal of Information Management	3
International Studies of Management & Organization	1
Journal of Business Research	2
Journal of Business Strategy	1
Journal of General Management	1
Journal of Labor Research	1
Journal of Management Education	1
Journal of Management Information Systems	1
Management Decision	1
Management science	2
Operations Research	1
Organizational Dynamics	2
People & Strategy (ex-Human Resource Planning)	22
Personnel Review	1
Public Manager	1
Research Technology Management	1
The International Journal of Human Resource Management	3
The Journal of the Operational Research Society	1

Table 3. Coding for each category

Category	**Modalities**
Type of article	• Empirical • Non-empirical
HR activities	• Talent/Workforce management/planning • Other • HRM in general
Data sources	• Internal HR-related data • External HR-related data • Internal non-HR data • External non-HR data
Methods used to quantify	• Basic metrics • More advanced models • Predictive modeling • Qualitative methods (interviews, ethnographic methods, …)
Use of results—Aims	• Make better decisions (decision making) • Prove the link between HRM and organizational performance • Predict • Automate
Representations of quantification	• Tool • Way to answer questions • Proof
Difficulties	• Data (bad data quality, missing data, etc.) • HR (lack of capabilities, etc.) • Organization (role of the HR function, etc.) • Technical (difficulty in modeling a complex phenomenon, etc.) • Legal (privacy, discrimination, etc.)

Table 4. Statistics about the sources of data used in HRM quantification

	Whole sample	HR metrics	HR analytics	HRM + AI	HRM + algorithms	HRM + big data
Internal HR data	25	2	9	3	10	1
External HR data	7	0	3	3	0	1
HR data (both int. and ext.)	7	0	4	2	0	1
Internal data (both HR and non-HR)	10	6	3	1	0	0
Other (ext., non-HR data)	11	2	5	0	0	4
No mention of data source	34	2	20	5	5	2
Total	**94**	**12**	**44**	**14**	**15**	**9**

Table 5. Statistics about the methods used in HRM quantification

	Whole sample	HR metrics	HR analytics	HRM + AI	HRM + algorithms	HRM + big data
Basic metrics	14	9	5	0	0	0
Advanced models	28	1	5	9	13	0
Predictive modeling	4	0	3	1	0	0
Combination	20	2	14	0	2	2
No mention of method	28	0	17	4	0	7
Total	**94**	**12**	**44**	**14**	**15**	**9**

Table 6. Statistics about the objectives of HRM quantification

	Whole sample	HR metrics	HR analytics	HRM + AI	HRM + algorithms	HRM + big data
Decision making	25	7	12	2	4	0
Link HRM/org. perf.	3	0	3	0	0	0
Decision making & link HRM/org. perf.	18	4	13	0	0	1
Other (automation, prediction)	14	0	5	4	2	3
No mention of objective	34	1	11	8	9	5
Total	**94**	**12**	**44**	**14**	**15**	**9**

Table 7. Statistics about the representations of HRM quantification

	Whole sample	HR metrics	HR analytics	HRM + AI	HRM + algorithms	HRM + big data
Tool	51	7	16	9	13	6
Way to answer questions	3	0	3	0	0	0
Proof	1	0	1	0	0	0
Combination	10	3	7	0	0	0
No mention of representation	29	2	17	5	2	3
Total	**94**	**12**	**44**	**14**	**15**	**9**

Table 8. Characterization of each thematic

	Data sources	Methods used to quantify	Objectives of quantification	Representations of quantification
HR metrics	Internal HR-related and non-HR data	Metrics	Decision making and demonstration of the link between HRM and organizational performance	Tool and means of evidence
HR analytics	Internal and external data, HR-related and non-HR	Metrics, more advanced models and predictive models	Decision making, demonstration of the link between HRM and organizational performance, and prediction	Tool, means of evidence, and way to answer questions
HRM + AI	Internal and external data, HR-related and non-HR	More advanced models	Decision making Automation	Tool
HRM + algorithms	Internal HR data	More advanced models	Decision making Automation	Tool
HRM + big data	External HR-related and non-HR data	More advanced models and predictive models	Decision making, demonstration of the link between HRM and organizational performance, prediction, and automation	Tool

Figures

Figure 1. Evolution of the number of Google requests (2004-2019)

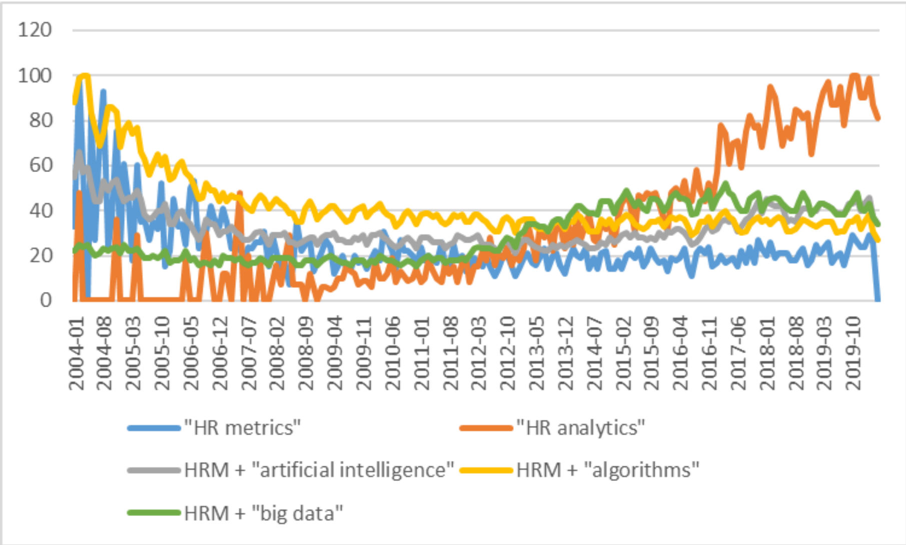
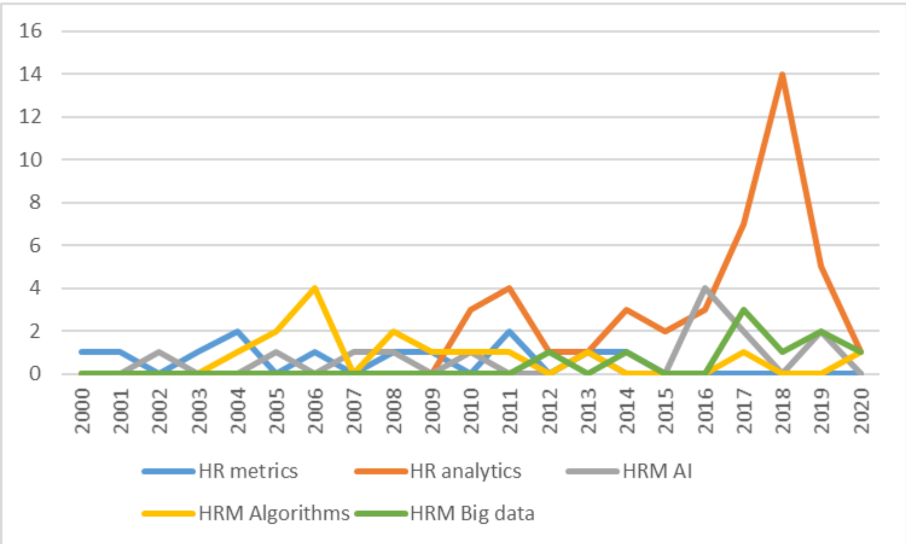


Figure 2. Evolution of the number of articles per thematic (2000-2020)*



*2020 does not correspond to a full year (review realized in March-April 2020).