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# How to do HRM with numbers?

## A performative lens on HR metrics, HR analytics and HR algorithms

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**Abstract:** This study examines the performativity of using numbers in the context of Human Resource Management (HRM). We use performativity as a theoretical lens to understand how such quantification affects individuals and work. We theorise three performative effects of quantification based on multiple case studies using internal documents and semi-structured interviews. To do this we analysed six HRM quantification projects (including cases of algorithmic HRM) at a large French multinational corporation. Each use of quantification creates a specific form of performativity. Our work complements the sparse but growing literature on metrics, analytics, and algorithms in Human Resources, focusing not on the kind of reality numbers represent but on how they impact different stakeholders.

**Keywords:** algorithmic management, quantification, speech act theory, Human Resource Management, HR metrics, HR analytics, algorithmic HRM, sociology of quantification

## Introduction

Organisations process large quantities of employees' personal data (Hurrell et al., 2017; Jeske & Santuzzi, 2015; Taylor & Dobbins, 2021), which they increasingly use to manage their workforce through metrics, analytics and algorithms (Bechter et al., 2022; Leonardi & Treem, 2020; Newlands, 2021). Applying these technologies in organisations challenges the way Human Resource Management functions (Angrave et al., 2016; Tambe et al., 2019) and opens up new possibilities for managing and controlling work and workers (Faraj et al., 2018; Kellogg et al., 2020; Wood et al., 2021). The use of employee data – such as for HR metrics, HR analytics, and algorithmic HRM – belongs to the field of quantification, that is, transforming certain ideas and realities into numbers (Desrosières, 2008b). While HR metrics correspond to the production of basic numerical indicators, HR analytics refer to the use of more sophisticated statistical methods to analyse existing phenomena, and HRM algorithms enable certain tasks to be automated, including using AI (artificial intelligence) tools (Coron, 2022). These quantification technologies are used to improve organisational processes and decision-making (Jeske & Santuzzi, 2015; Lloyd & Payne, 2019). These purported improvements are based on the perception the members of an organization have of quantification technologies as neutral representations that can objectify decision-making in organisations by accurately measuring economic, organisational or social phenomena (Huselid, 2018; Vassilopoulou et al., 2022).

Former research has in particular studied the circumstances under which organisations use such quantification (Bechter et al., 2022), how the economic efficiency of these technologies can be improved (Tambe et al., 2019), how worker acceptance of quantification technologies can be influenced (Hurrell et al., 2017; M. K. Lee, 2018), the skills HR specialists require to make use of these technologies (Angrave et al., 2016; Strohmeier & Parry, 2014), and how employee voice and unions are affected (Flanagan & Walker, 2021). While there is a consensus that quantification technologies, such as metrics, analytics and algorithms, are increasingly used in organisations and have far-reaching consequences for HRM and employees (Jeske & Santuzzi, 2015; Spencer, 2018; Taylor & Dobbins, 2021), there is a lack of research investigating *how* employee-based quantification, in its many forms, *performs* in organisations. This can be explained by the predominance of the positivist paradigm in HRM research on quantification (Greasley & Thomas, 2020; Harley, 2015), the scarcity of qualitative research in this area, and the neglect of the role of performativity. This lens is used more frequently in other areas of organisational research. Moreover, the existing literature has mainly distinguished uses of quantification in HRM by the type of technology employed (namely, HR metrics, analytics

or algorithms; see Coron, 2022), suggesting that these technologies enact different forms of performativity. Research on these differences, though, remains scarce. We therefore aim to study in detail the relationships between the uses of quantification and the type of performativity they enact to answer the following research questions: *How do different HRM quantification technologies (HR metrics, HR analytics, and algorithmic HRM) perform in organisations?*

To answer this question, we draw on the sociology of quantification, a perspective that has revealed that quantification, that is, the use and production of numbers, has a threefold effect on what is being measured (Desrosières, 2008b; Espeland & Stevens, 1998, 2008). First, quantification requires transforming phenomena into a common metric to be able to compare them (Espeland & Stevens, 2008). Second, statistics create new ways of thinking about and acting on the world (Desrosières, 1993), which can be conceptualised as a form of performativity. Finally, quantification is also used to make decisions (Desrosières, 1993). In their introduction of quantification as a sociological phenomenon, Espeland and Stevens (2008) established an analogy between speech acts and the action (or act) of producing numbers. We follow their proposition that Austin's speech act analysis of performative utterances (Austin, 1975) can be used to analyse quantification technologies. Austin distinguishes three types of performative utterances: locutionary utterances (saying something, using grammar and vocabulary in order to make sense to interlocutors, for example, to describe or assert something), perlocutionary utterances (causing an action or a change by saying something), and illocutionary utterances (situations where saying something is the same as doing something). Just as Austin distinguishes between different speech acts, we distinguish between different quantification acts.

Our analysis focuses on six use cases of quantification in a large French telecommunications company where the first author worked as an 'insider researcher' (Brannick & Coghlan, 2007) in the role of 'AI and HR project manager' and was able to collect internal documents and conduct interviews.

Based on our empirical study, we show that quantification acts perform in three ways: (1) locutionary quantification, where quantification uses specific conventions to make a 'fact' visible, (2) perlocutionary quantification, where quantification influences decision-making or encourages a course of action and (3) illocutionary quantification, where quantification and decision-making happen at the same time, as in the case of algorithmic management. We also identify differences between quantification acts and speech acts, mainly concerning the human agency involved and the position (human) actors can occupy in quantification acts. Following

this analysis, we develop a typology of quantification in HRM based on how different uses of quantification function in organisations and how they influence human agents.

Our results contribute to two streams of literature. First, we expand existing theories on performativity and quantification by identifying the differences between speech acts and quantification acts. For example, quantification requires the transformation of ideas into numbers, which calls for specific conventions that are simultaneously shaped by technical and political constraints (Desrosières, 2008a). Contrary to speech acts, quantification acts do not engage only speakers and listeners, but also individuals whose data is used. We call them ‘the quantified’, as they are subject to quantification (Espeland & Stevens, 2008). Hitherto, this third position has not been identified and studied in previous research (Sousa et al., 2010). This third position raises questions about the agency of human actors when it comes to quantification. As our results show, the agency of the quantified is lower than the agency of both speakers and listeners. Second, our research complements existing theory on the uses of quantification in organisations. Usually, this literature distinguishes between HR metrics, HR analytics, and HR algorithms (Coron, 2022). Our empirical results suggest a more differentiated perspective, especially on HR algorithms, because the performativity of algorithms depends on both technical *and* organisational factors. Therefore, we develop a typology underlining the uses of HRM quantification technologies. Empirically, our study investigates a poorly documented phenomenon, that is, the ways in which employee-based quantification performs in organisations. Our results also have important practical implications, as the developed typology underlines how certain HR algorithms result in very low agency for human actors, raising questions of responsibility and decision-making by algorithms.

## **Literature review**

### **The rise of quantification of HRM in organisations**

Quantification in HRM can be used in different ways (Coron, 2022). HR practitioners use HR metrics to measure the activity and performance of HRM and employees (Becker et al., 2001; Fitz-enz & Davison, op. 2002). HR analytics emerged in the early 21st century, and refers to “[an] HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organisational performance.” (Marler & Boudreau, 2017, p. 15). More recently, algorithms have been introduced in HRM (Campion et al., 2018; Mayer-Schönberger & Cukier, 2014; Rieder & Simon, 2016). They are “computational formulas that autonomously make decisions based on

*statistical models (...) without explicit human intervention*” (Duggan et al., 2020, p. 119). This definition stresses how quantification allows the automation of tasks and decision-making in HRM through algorithms (Canós-Darós, 2013; Malinowski et al., 2008; McEntire et al., 2006; Meijerink et al., 2021; Yano, 2017). This corresponds to the use of artificial intelligence (AI), which refers to the automation of human reasoning capabilities (Tambe et al., 2019).

Most research considers quantification to be a process that brings objectivity, transparency, and rationality to HRM (Kovach et al., 2002; Shrivastava & Shaw, 2003). This ‘measurement as representation’ approach has been contested by the performative turn in organisation studies, which presupposes that numbers affect reality more than they represent it (Fauré et al., 2010; Gond et al., 2016). New quantification technologies have been associated with new intrusive forms of worker surveillance and control, as well as excessively authoritative management, effects that the positivist paradigm ignores (Heiland, 2022; Kidwell & Sprague, 2009; Newlands, 2021; Taylor & Dobbins, 2021; Weiskopf & Hansen, 2022). Research into such quantification technologies also questions how much agency is left to (human) actors in such a context (Upadhya, 2009).

### **The performativity of quantification**

A performativity lens has been used to study various phenomena in a variety of fields (Butler, 1990; Roscoe & Chillias, 2014), including organisation and management studies (Hayes & Westrup, 2012; Kenny, 2018; Learmonth et al., 2016). At its core, performativity is concerned with effects, with bringing the world into being (Butler, 2010).

Espeland and Stevens (1998) describe how to ‘do things with numbers’, such as identifying things or actors (with numerical codes, e.g., social security numbers) and creating categories (e.g., unpaid work, sexual orientation). Additionally, people modify their behaviours and change their cognitions in reaction to quantification (Espeland & Sauder, 2007; Scheibmayr & Reichel, 2023; Sousa et al., 2010). Espeland and Stevens (1998) provide the example of how law schools offer scholarships to students who score well on LSAT, a law school admission test, even if they may not be ideal candidates. Schools continue this practice because LSAT results are a key criterion for ranking law schools themselves. The fact that quantification influences people’s behaviours and decisions (in other words, the performativity of quantification) blurs the distinction between the object that is quantified and the act of quantifying and underlines that quantification is not only a neutral mirror of a pre-existing world.

These examples show how quantification acts are tightly related to human agency, that is, human capability to choose an action where they could have acted otherwise (Giddens, 1984) and to manage goals (Meyer & Jepperson, 2000). In the example provided by Espeland and Stevens, this agency seems to be guided and somehow reduced by quantification acts. However, previous research has shown how technologies can both enable and constrain individual agency (S. K. Lee et al., 2019). In the same article, Espeland and Stevens (1998) show how feminists have used quantification to demonstrate the existence of inequalities and thereby enhanced individuals' agency to address these inequalities.

## **Quantification acts**

Performativity developed from speech act theory, first introduced by Austin (1975), which analyses how humans act through language (see also Searle, 1969). Austin introduced language and speech as important prerequisites for human agency, which is the capacity of humans to act and thereby reproduce as well as transform social structures (Emirbayer & Mische, 1998). We suggest that quantification artefacts such as metrics, analytics, and algorithms can be understood like speech acts, following the theoretical proposal put forward by Espeland and Stevens (2008), who link speech act theory to the understanding of the 'doing' of numbers, and thus their capacity to alter social reality – and human agency – or in other words their performativity. Espeland and Stevens (2008) mention that language can be understood in its strict sense, the uttering of words, or in a broader sense, a system of signs interconnected to give meaning. In the latter sense, quantification constitutes a form of speech act, as numbers represent a language.

Austin distinguishes between utterances that describe or state a fact (constative utterance) and statements that accomplish an action (performative utterance). Constative utterances can be considered true or false, while performative utterances cannot be interpreted that way: they do something rather than merely describing something. For a performative utterance to act we have to consider the social context, such as the position of the speaker, the audience, the rituals involved, etc. Performativity cannot occur in just any context and certain conditions have to be met.

Austin highlights three types of performative speech acts.

(1) Locutionary acts correspond to the fact of saying something, using grammar and vocabulary in order to make sense to interlocutors, for example, to describe or assert something ("*This dress is red*"). Locutionary speech acts are those where, for instance, (social) facts are presented in a statement. Numbers, as primary elements of quantification, can be compared to

locutionary acts when used in mathematics, numeracy, statistics, and related fields. In these fields, statements using quantification must respect specific rules and conventions in order to make sense to the audience. An example would be, “*It is 38 degrees Celsius outside*”. Locutionary quantification acts refer to situations when numbers are used to describe a social fact or phenomenon (Espeland & Stevens 2008). For example, feminist movements have quantified time spent on unpaid work in order to define household activities as work and to quantify their importance relative to other types of work (Espeland & Stevens 1998).

(2) Perlocutionary acts correspond to the fact of producing an action or a change *by* saying something; for example, when someone says “*It’s cold*” so that a bystander will shut the window. Quantification can also act this way, for example, when presenting social issues or inequalities through data (Espeland & Stevens, 2008). A statement can be both locutionary and perlocutionary, as in the case of “*It’s cold*”. It can be both a statement of a (social) fact describing the temperature and a demand requesting that someone close the window. This can be applied to cases where data is used to both describe a situation (e.g., the amount of household work), and simultaneously make a request (advocating for policies addressing the unequal distribution of household work).

(3) Illocutionary acts correspond to situations where saying something is the same as doing something. For example, when someone says, “*I bet you won’t do that*”, the person is betting *in* using the words “*I bet*”. In the illocutionary speech act, the actual deed is performed “at the moment of the utterance” (Butler, 1997, p. 3), but only under certain felicity conditions. Promises (where the promise is made the instant someone says “*I promise*”), court sentences and marriage vows (where the marriage is legal the moment the words “*I do*” are uttered) are good examples. They only work in specific spatial contexts (courtroom, city hall, chapel) under certain conditions (sobriety and legal age, volume, etc.). Such contextual conditions are ritualised and institutionalised to make the illocutionary speech act perform the deed (Butler, 1997). According to Espeland and Stevens (2008), quantification acts can be compared to illocutionary acts when they are used to create new categories for approaching phenomena: “*Numbers often help constitute the things they measure by directing attention, persuading, and creating new categories for apprehending the world.*” (p. 404). For example, by measuring something termed ‘unemployment’, the social category of unemployment was created in the very moment of measurement.

Note that the same utterance can correspond to different speech acts. For example, the statement “*It’s cold*” can be both a locutionary and perlocutionary act and the statement “*I promise to clean the dishes*” is both locutionary (a statement about my intentions),



perlocutionary (it will persuade me to do the dishes) and illocutionary (the promise is made, independent of my actual intentions or performance). We argue in this article that the same is true for quantification acts. For example, measuring the unemployment rate simultaneously describes the phenomenon of not being employed in the labour market (locutionary act), creates the categories ‘unemployed people’ and ‘unemployment’ (illocutionary act), and encourages individuals and public authorities to act, for example to reduce unemployment (perlocutionary act). Even though a quantification act, just like a speech act, can employ all three forms of performativity, the difference is valuable from a conceptual perspective. Therefore, Austin (1975) spent considerable time differentiating perlocutionary from illocutionary speech acts, studying how different words, especially specific verbs, are tied to each form of speech act. Thereby, one can distinguish between what is said (locutionary speech act), what is inspired (perlocutionary speech act), and what is forced into being (illocutionary speech act) by speech.

Mobilising this framework to understand the performativity of different uses of quantification allows HRM quantification in organisations to be conceptualised “*as social action that, akin to speech, can have multiple purposes and meanings*” (Espeland & Stevens, 2008, p. 405). Embedding our empirical material consisting of six types of HRM quantification in Austin's (1975) speech act theory, we (1) demonstrate how different forms of quantification act in various ways, (2) conceptualise the difference between speech and quantification acts and (3) develop a typology of quantification acts to theorise the performative effects of quantification based on their consequences for (human) agency.

## **Research material and methodology**

### **Data collection**

To synthesise how different forms of quantification based on employee data perform within organisations, we conducted multiple case studies following Yin's (1981) approach. Six HRM projects (cases) representing the different forms of quantification identified in the literature review (metrics, analytics, algorithms) were analysed and compared to show how the quantification of employee data acts in organisations. More precisely, two cases were chosen for HR metrics, two for HR analytics, and two for HR algorithms. Concerning HR analytics and HR algorithms, the four cases studied correspond to the main ongoing projects in the company when the material was collected (2016-17). Concerning the two cases of HR metrics, they were chosen because it was possible to access various related internal documents.

The primary data used consists of numerous internal company documents. The first author acted as insider researcher (Brannick & Coghlan, 2007) when working as ‘Big Data and HR project manager’ at ‘Telecom’, a French telecommunication company with 90,000 employees listed in the CAC40<sup>1</sup> between January 2016 and August 2017. This involved directly working on two of the six quantification projects (absenteeism analytics and training recommendation algorithm, see Cases). To avoid the ethical issues related to covert observation (even though this method does not require ethical approval in the French academic system, see Stenger & Roulet, 2018), the researcher involved did not observe the behaviours and discourses of people in the organisation, but used her position to collect documents (for example, presentations, framing and summaries of the projects, as well as two reports for the two metrics projects) concerning the different projects (Table 1).

We combined this data with eight semi-structured interviews (see Table 1) to triangulate the analysis. The interviews were conducted with different HRM quantification actors: HR practitioners (2), Unions (2), Data scientists (3), and a solution provider (1). The aim was to obtain a comprehensive and exhaustive overview of the viewpoints of various stakeholders (not limited to data scientists or HR practitioners). The interviews sought to provide an understanding of the visions and perceptions of the actors involved. They therefore focused on their visions of the different projects, their perception of quantification, and their perception of HRM development influenced by quantification technology. Overall, our material reflects the practices, representations, and (written and oral) discourses of actors, conceptualising quantification as a result of social conventions (Desrosières, 2008a; Espeland & Sauder, 2007; Espeland & Stevens, 1998, 2008).

### *Table 1: Material*

#### **Analytical steps**

The data analysis was rooted in an interpretivist approach using within-case and cross-case analysis. Before the totality of the material was coded, a detailed description of each case was prepared. In the first step, a thematic analysis of the interviews and the internal documents was carried out. The coding thus consisted of identifying tentative themes, first of all sustained by descriptive codes, then by analytical codes (Anderson, 2013; Corbin & Strauss, 2015). In the second step, once the theoretical framework of Austin's (1975) speech act theory was identified,

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<sup>1</sup> The benchmark index of the French stock exchange

the analysis was refined with deductive coding based on the three types of speech acts – locutionary, perlocutionary, illocutionary. The coding was conducted on broad “analysis units”, mainly at the paragraph level. In the third step, the coding of each case was systematically compared to the other cases and relevant patterns were noted. We then triangulated back to the material to find meaningful explanations for these patterns. Notably, we incorporated the notion of (human) agency at this stage, which seemed important to understand the differences between the six cases. In the last step, the description of the cases was refined, and we were able to produce a typology of the six cases, linking the type of performativity, and the type of quantification use with the agency dimension.

### **Study context and cases**

All six cases are from the same organisation, allowing us to systematically compare them while controlling for organisational context. An overview of the six cases can be found in Table 2 and more detail on each case is presented below. The first two cases establish reporting standards within the organisation (training report, gender equality report) and are, therefore, examples of HR metrics. Two cases seek to analyse absenteeism by using the data from the HRM information system (HRIS) and external data (absenteeism 1 and 2) and are, therefore, examples of HR analytics projects. Two cases use machine-learning algorithms to aid HR processes (training recommendation engine, pre-selection engine), and are therefore examples of algorithmic HRM. From a methodological perspective, the first two cases use descriptive statistics, the second two use multivariate statistical models, and the last two use artificial intelligence.

*Table 2: Main characteristics of the six projects*

*Training report:* In France, large companies must present their training plan and its implementation to the labour union. This plan and the associated report contain many indicators (for example, number of hours of training by type, number of trained employees, etc.) required by law. Further, the labour union defines additional indicators to evaluate the company’s training policy and implementation. In total, Telecom reported more than one hundred indicators. Consequently, the training report is viewed as a central feature of HRM work at the company.

*Gender equality report:* In France, large companies must report annually on gender in/equality. In Telecom, besides the 25 indicators mandated by law, 60 were agreed upon with the labour union to identify persisting gender inequalities.

*Absenteeism 1:* Two cases deal with HR analytics using the Human Resource Information System's (HRIS) data to identify explanatory factors of absenteeism. The first case consists of an in-house project conducted in 2016 by an employed data scientist. The data came from the HRIS, including information on gender, job field, level in the hierarchy, wage, wage increases, paid vacation, etc. This data was combined with external data, for example, seasonal and geographical epidemiology data on flu and chickenpox outbreaks. As stated by Telecom, the initial objective was to reduce absenteeism by identifying action levers for the organisation. For example, if commuting time is found to explain absenteeism, developing a model for teleworking might be a solution. The methods used in this HR analytics project were multiple linear and logistic regressions complemented by factor analysis.

*Absenteeism 2:* A follow-up project was conducted with a small-business consulting firm that developed a tool to measure and analyse absenteeism. Only HRIS data was used in this project, and the methods included multiple linear and logistic regressions. In addition to identifying explanatory variables for absenteeism, the objectives of the project communicated to the consulting firm were benchmarking with competitors and assessing the cost of absenteeism.

*Training recommendation:* This case consists of a project launched following employees' requests expressed during a focus group on employee experience conducted in 2015. Some participants expressed the desire to receive personalised training recommendations within the training platform. Therefore, the project was designed to send automatised training recommendations to employees, based on their profiles. Data from employee training history, the HRIS data (job field, level in the hierarchy), and the in-house social network (which communities and employees the person followed) were used. Of the 10,000 employees that were invited to participate via email, 1,700 employees subscribed via an opt-in system. The training recommendation is based on three machine-learning algorithms: collaborative filtering (if A followed the same training as B and B followed one training course more than A, this additional training suits A), semantic analysis (using the keywords of training modules already followed to suggest new modules), and profile clustering (training taken by most similar profiles in terms of job, hierarchical level, etc.).

*Pre-selection engine:* In this project, Telecom used a matching algorithm to pre-select candidates for recruitment. The objective of the pre-selection engine was to save time for the

recruiters so they could devote more time to proactive recruiting practices (e.g., head-hunting and active sourcing). Another goal was to test the possibility of detecting useful information from unstructured data. The algorithm was developed in three stages. First, it was trained with a minimal number of job postings and CVs. The machine-learning algorithm used semantic analysis based on unstructured data from the job proposals and the CVs, producing word clouds from the job offers and the respective applications, and comparing the frequencies of words. Second, over a period of two months, every job posting and every candidate's CV was analysed to improve the algorithm. For this step, around 1,000 job postings and 10,000 candidates were used. Third, two voluntary recruiters compared their ranking with the algorithm's results. At the end, they noted a high adequacy of the algorithm with an average similarity of 84 % between the first 20 CVs shortlisted by the research officer and those shortlisted by the algorithm.

## Results

We used Austin's (1975) speech act framework to characterise common patterns between the six projects and subsequently identify the performative effects structured by the three quantification acts (locutionary, perlocutionary, illocutionary). We thus identified (human) agency as an important dimension of quantification acts.

### Locutionary acts

Metrics, such as key performance indicators or statements using descriptive statistics, correspond to locutionary quantification acts. Both the training report and the gender equality report carried out such performative quantification acts, as they aimed to describe the situation using indicators. These indicators are presented almost without any written interpretation and only exist per se. Their mere existence creates a form of performativity.

*“Our first difficulties were the **situation analysis**, obtaining new indicators. Without them, it's a philosophical debate and we don't progress with regard to the situation **objectification**. [...] This requires the provision of precise elements allowing an analysis of the situation, which leads the employer to **acknowledge the inequalities**. In terms of objectifying, if the inequality **is demonstrated**, it can lead to progress in terms of corrective measures. If we don't do that, many gender equality agreements are 'philosophical', as we say, we don't have precise commitments.”*

*(Union Labor representative on the Gender Equality report, emphasis added)*

As can be seen in the quote, stating facts is in itself performative by making a meaningful statement about an object (the situation) and its social fact quality (in this case inequalities). It makes the social fact visible to the organisation, which allows individuals to assess a situation and then act. While locutionary quantification acts are most obvious with the metrics used in the reporting projects, they can also be found in other quantification artefacts and other projects, as demonstrated by this quote on the absenteeism project:

*“The first belief (of the HR employees) is that numbers are of no use at all. We demonstrate that we **highlight a certain number of problems**. On absenteeism, we cover so many aspects of demography, etc., **it’s impossible not to learn anything**. There is something else, it’s that analytics is **a tool for understanding**, and discussion is more peaceful **when there are numbers, than when there are dogmas.**”*

*(Solution provider on Absenteeism 2, emphasis added)*

The last sentence – “a discussion is more peaceful when there are numbers, than when there are dogmas” – indicates a locutionary quantification intention: by using numbers, the projects make meaningful and true statements (and supposedly nothing more). However, the earlier statements, that the analysis should highlight problems or is carried out to ‘learn anything’ from it, suggest a perlocutionary act. Therefore, the performativity of quantification acts seems to contain a paradox, which differs from what happens with speech acts: the locutionary act is bound to a perlocutionary aim, and it is precisely *because* numbers are supposedly neutral and exist *per se* (which corresponds to the sole aim of a locutionary act) that they can be used with a perlocutionary aim – but as they have a perlocutionary aim, they cannot be neutral.

Notably, metrics empower union representatives to discuss the problem. As the union labour representative states, metrics can be used to further implement policy measures and commit the organisation to the goal of gender equality. Here, a second paradox appears. Metrics are presented as neutral and objective, existing *per se*, which supposedly does not give much agency to the actors. However, these numbers can then be used by actors (for example, unions during negotiations), which means that numbers increase actors' agency, in this case, giving them the ability to increase their bargaining power.

### **Perlocutionary acts**

We also find clear indications of perlocutionary quantification acts in the material. They are most apparent in the analytics projects (absenteeism 1 and 2) that seek to analyse the situation to improve HRM practices, as exemplified by this quote:

*“The purpose was to analyse the causes of absenteeism within Telecom, to establish preventive actions, to better understand what’s happening, in order to **help decision making**. The expected benefits were a better understanding of causes and effects and to **define actions to reduce absenteeism**.”*

*(Data Scientist, Absenteeism 1, emphasis added)*

We also find this type of perlocutionary act in the other projects. The training recommendation algorithm is a good example. The aim of the algorithm in this project is to send personalised recommendations to employees, and the expected effect is to generate a certain behaviour among employees (taking the recommended training). This corresponds to perlocutionary acts (influencing others *by* saying something, in this case, *by* recommending training). The algorithm seeks to provide a new service to employees, in which they receive new information that can influence their behaviour (their training choice). The performance of the training recommendation algorithm itself is contingent on whether or not the employees choose to take the suggested training:

*The accuracy of the training suggestion engine is measured, in part, by its ability to **predict users’ tastes, that is, to suggest training that users would like to take**. Thus, a feedback questionnaire sent to all participants includes the following question: “Do you think you will follow the suggestions you received? (Yes/No).”*

*(Internal report on Training recommendation engine, emphasis added)*

Perlocutionary quantification acts are often tied to the prediction ability of the algorithm, which featured prominently in the interviews and the internal documents. Prediction of employee behaviour is perceived as the cornerstone of algorithm quality evaluation. Prediction can be conceptualised as dependent on the reactivity of employees to the suggestion by the analytical tool, as exemplified in the quote above. However, as the following quote shows, the ideal of prediction can be further conceptualised by predicting unusual and even inconceivable choices, and is hence independent of employee behaviour. When such training is predicted (and thereby recommended to the employees) and the employees take up the suggested training, even if they would not have considered it without the analytical tool, this is, in a self-referential twist, interpreted as the height of predictive power:

*“This is why we include in the questionnaire ‘Would you have thought about it without the tool or not?’. This is the **predictive power**, which is strong **when you manage to predict things you don’t already know about**. That’s why you also have to check whether you increase usage, if people click on content they wouldn’t have clicked on otherwise.”*

*(Data scientist, Training recommendation engine, emphasis added)*

In terms of agency, the examples of perlocutionary quantification acts, and notably the training recommendation algorithm, show that the actors still have a high level of agency in perlocutionary quantification acts: notably, they can decide whether or not to follow the recommendations made by the algorithm. In this specific case, employees were informed of how the algorithm works, and also of the type of data used, which also gives them the power to change the results of the algorithm.

*Training suggestions are sent to employees. At the same time, a message is sent to them with a link to a text explaining how the algorithm works (data and algorithms used). Employees can then ask questions by email to obtain further details on the subject.*

*(Internal working document on Training recommendation engine)*

### **Illocutionary acts**

In our analysis of organisational quantification cases, we also found examples of illocutionary quantification acts. The pre-selection engine is the most obvious example of acting through quantification: using the engine (for pre-selection) is the same as acting (pre-selecting).

*Description of the pre-selection engine: “**matching** job offers and CVs via an analysis of the semantic content of job offers and CVs”*

*(Internal presentation of pre-selection engine, emphasis added)*

In the quote above, the word “matching” refers to the illocutionary act: quantifying is the same as pairing job offers and CVs.

The differentiation between the provision of insights by quantification technologies and decision-making is eliminated by directly automating certain decisions through the AI algorithm. This element distinguishes quantification acts from speech acts. Indeed, in the pre-selection engine for example, all three quantification acts are performed simultaneously, dissolved in the application and therefore not analytically distinguishable for human actors, that is, users. Even though the algorithm analyses (locutionary quantification act), ranks (perlocutionary quantification act), and pre-selects (illocutionary quantification act) the CVs in subsequent steps, for the recruiter these steps are dissolved into one illocutionary quantification act – the shortlist – which is the ‘product’ of the algorithm. Because this process takes place behind the veil of the AI algorithm, the algorithm seems to decide directly. Indeed, by attributing a matching score to each CV, the algorithm chooses between them. Human intervention is neither necessary nor expected in this process. For the organisation, it is precisely



this absence of human intervention that is perceived as a productivity gain, as exemplified by the following quote:

*“There were three issues for the hiring director: how can I reduce the time spent reading resumes, how can I reduce the time of publishing a job description (because one day of publication corresponds to x hundred more applications to assess), and the third essential element is **to no longer undergo the flow of resumes**, and to be part of a head-hunter approach where people are actively sourced, and for that, we need to free up time for recruiters. So, our project was born out of this triple challenge.”*

*(Data scientist on pre-selection engine, emphasis added)*

Here ‘the engine’ ‘frees’ the HR manager from locutionary acts (describing candidates) and illocutionary acts (choosing whom to invite) by performing these quantification acts itself.

In this case, the agency of the individuals whose data is used (applicants) is very low: they do not even know that their data is used and processed by an algorithm.

## **Discussion**

Our results contribute to understanding quantification technologies and their effects when used for HRM in organisations. The empirical material allowed us to identify three theoretical contributions of our research, which we present below. First, we contribute to the literature on the performativity of quantification by demonstrating the importance of specific conventions as felicity conditions for the performativity of quantification acts. Second, we contribute to this literature by focusing on agency and identifying three different actor groups (quantifier, receiver and quantified), which allows us to question the agency of the quantified individuals in the case of HR quantification. Furthermore, the quantifier (that is, speaker) role can be inhabited by a non-human entity or by a collaboration between humans and technology. Third, based on this, we develop a typology of quantification acts in HR underlining different aspects of agency linked to different types of performativity (see Table 3), thus contributing to the literature on HR quantification and HR algorithms.

### **First theoretical contribution: Performativity of quantification acts and conventions**

Performativity refers to bringing reality into being (Butler, 2010). For Austin, language, when used in speech, acts in different ways: through locutionary, perlocutionary and illocutionary speech acts. In our analysis, we used the three main types of speech acts to compare and describe how different forms of HR quantification impact humans. Since

quantification is a language of its own, it differs from speech acts, mainly through the work required to quantify something. While words are pronounced without mediation, quantification requires the transformation of ideas into numbers. This follows specific technical and social conventions established by humans beforehand (Desrosières, 2008a).

Locutionary quantification acts bring social facts into being by quantifying and thereby bringing a social phenomenon into being (e.g., the gender pay gap). When compared to locutionary speech acts, we find that quantification acts perform using the same mechanism of bringing social facts into being that affect cognition. They make a social reality visible to those who may not believe in it beforehand, allowing change to happen. However, locutionary acts require the effort of human quantification work (Espeland & Stevens, 2008), while words and grammar are rarely subject to debate. Notably, producing numbers requires a certain technicity (mastering technical conventions), which is not (or is less) required to produce speech. As a result of this technicity, locutionary quantification acts are tied to the illusion of the objectivity and neutrality of numbers (Porter 1996). This makes it difficult to question them, which is not the case for speech acts.

Perlocutionary acts perform by convincing the listener. The interviews suggest that certain myths, for example the belief that numbers are neutral and objective, irrespective of the context they are produced in and irrespective of the intentions of the people who produce them (Porter, 1996), are prevalent when perlocutionary quantification acts are invoked. This illusion of objectivity enhances the performativity of numbers (Elish & boyd, 2018; Hacking, 1991; Vassilopoulou et al., 2022). We suggest that these quantification myths act as necessary social conventions for quantification acts to function. This means that the felicity conditions highlighted by Austin (1975) for the performativity of speech acts (status of the speaker, form of the statement, appropriate circumstance) may be different for quantification acts (e.g., faith in the objectivity of numbers, perceived professionalism and technicity of the producer of numbers, etc.). Moreover, the performativity of quantification acts is specific in the sense that it is precisely *because* numbers are supposedly neutral and exist *per se* (which corresponds to a locutionary aim) that they can be used with a perlocutionary aim—but as they have a perlocutionary aim, they cannot be neutral. Concerning our empirical case, the results suggest that the perlocutionary performativity of quantification is stronger than that of speech acts as it is more difficult to debate numbers than words or ideas.

Illocutionary quantification acts perform by mere utterance, as do illocutionary speech acts. However, we find that the felicity conditions for their performativity include technical and managerial aspects, which are not prevalent in speech acts. In speech acts, the social context

matters, including the sincerity of the speaker, or legal conditions (for example, for marriage, propositions, transactions), etc. In quantification acts, these social norms can be embedded in the technology, through technical conventions. This is what Muniesa (2000) shows when explaining the performativity of the French stock exchange algorithm: It is because the algorithm is programmed with the Walrasian approach to economics that the French stock exchange follows a Walrasian mechanism. In our case, the CV parsing algorithm indicates which applicants are invited. But, and this is an essential difference with respect to illocutionary speech acts, the technological conditions are embedded in the technology itself. In this case, some applicants are not invited, because the algorithm is programmed in such a way that it does not invite them. This is a step further from illocutionary speech acts that can only assert, direct, commit, declare or express (Searle & Vanderveken, 1985). In the case of automatic decisions made by AI, illocutionary quantification acts result in programmed decisions, something that is very rare in illocutionary speech acts and only exists in specific and highly institutionalised contexts (e.g., in marriage vows or court decisions). Technology therefore replaces the social context in certain illocutionary quantification acts. In speech acts, the performativity of the speech act is determined by the context. The felicity conditions of illocutionary quantification acts are, however, not (only) based on the social context but (also) on the technical conventions.

### **Second theoretical contribution: Redefining the place of human agency in performativity theory**

We can also derive consequences for human agency from these conceptualisations of quantification acts that differ from speech acts. In speech act theory authors usually distinguish two types of actors – speakers and listeners. In the quantification acts we studied we find three different actors. First the quantifier (equivalent to the speaker), who is the actor who builds the quantification tool and produces the results, or an assemblage of technical and human actors in the case of algorithms where algorithms actively contribute to the production of results. Second, the receiver (equivalent to the listener), usually a human actor who receives the results of the quantification act; and third, the person whose data is used to produce the quantification act. In quantification acts, especially in the context of HRM, these components are human actors, mostly employees and applicants, who are *subject to quantification*. We term these actors *the quantified*. The emergence of this third agentic position, the quantified, raises new questions concerning quantification in organisations, that have not yet been studied (Sousa et al., 2010). Notably, the agency of the quantified in the quantification process is usually restricted and lower than that of quantifiers and receivers. In our material, the human actors might have agency

and this agency differs considerably between cases, depending on their roles, on how the technical aspects enable and constrain the agency of the quantified, and the extent to which automation is a central aim of the quantification act (Howcroft & Taylor, 2022). In the CV parsing case, for example, quantified individuals (applicants) have very low agency, they do not even know that their data is used for a quantification act that is highly relevant to them (being invited to an interview or not). It is quite possible that if they were aware of the quantification act, for example if they would know how the algorithm parses the CVs, which keywords it looks for, they could ‘game the system’ (Strohmeier, 2022). Playing the quantification game may restore agency to those who are usually surveyed and controlled, which shows the limitations of the “technological fatalist perspective” (Upadhy, 2009). The case of the training recommendation engine, on the other hand, shows high agency for the quantified individuals, as they are also the listeners. As employees can choose to follow the recommendation and are also aware of the algorithmic principles behind them, they can influence the quantification act itself.

Overall, the agency of the quantified depends on the context and the technical aspects, which often conceal managerial decisions. Technology provides an aura of determinism (‘that is just how the technology is’), obscuring the actors and agency behind it (management, data scientists, etc., whoever programmed the quantification to ‘be that way’) but also the agency of quantified individuals and individuals who receive the results of the quantification act. However, the fact that technology conceals it does not mean that there is no agency at all (Upadhy, 2009). Finally, these elements open a breach in the traditional boundary between structure and agency (Steen et al., 2006).

### **Third theoretical contribution: A typology of quantification artefacts by use**

Rather than generally discussing the use of quantification technologies in HRM (Tambe et al., 2019; Yano, 2017), we suggest that it is better to classify quantification artefacts. We also find that the typology identified by previous research (Coron, 2022; Marler & Boudreau, 2017), which distinguishes between metrics, analytics, and algorithms, is inadequate if we want to understand *how* quantification acts within HR management because it accounts neither for the performativity produced nor for who is being addressed by the technology (Schaupp, 2022). Instead, we use the following criteria to build a typology more adequate to understanding the performativity of HRM quantification: (a) why is the quantification act performed, (b) who is involved in the process and how they are involved, (c) what agency do actors have in shaping and/or manoeuvring the quantification artefact and (d) what type of performativity is at stake.

We use the empirical elements provided in the case presentations and in the results section to build our typology (Table 3).

Table 3: Typology of quantification technologies by performativity

The criteria (a) to (d) allow us to distinguish (a) HR metrics and analytics, (b) HR algorithms when the results are sent to the employees, that is, the individuals whose data is used (quantified individuals), in this case, the training recommendation engine, and (c) HR algorithms when the results are sent to people other than those whose data is used, in this case, the pre-selection engine. For example, we have shown that metrics and analytics can be used to describe a situation as well as improve both HR policies and decision-making. They also involve employees (whose data is used: quantified individuals), HR practitioners and unions (who receive the results: receivers), data scientists and an external consulting firm (who work with HR practitioners to produce the quantification act: quantifiers). In case 5 (training recommendation), the aim was to personalise the employee experience, and the quantification act was done by HR practitioners and data scientists based on employees' data. Employees whose data was used were the ones who received the results. This was not the case for case 6 (preselection engine), in which the data came from the applicants, whereas recruiters received the results of the quantification act. Additionally, the agency of quantified individuals varies from very low, when they do not even know that their data is used (case 6), to high when they can influence the algorithm (case 5). The agency of receivers varies depending on the degree of automation of decision-making. The distinction between locutionary, perlocutionary, and illocutionary performativity can shed light on the performative effects of quantification in organisations. Notably, HR metrics and HR analytics are characterised by *both* locutionary *and* perlocutionary performativity, whereas HR algorithms are characterised by *either* perlocutionary *or* illocutionary performativity, depending on who receives the results and the extent to which the decision-making is automated (cases 5 and 6). The typology indicates that it is necessary to distinguish between different types of HR algorithms, depending on which actors are involved, how performativity impacts them, and their level of agency.

### **Practical implications**

Our study investigates a poorly documented phenomenon: how employee-based quantification performs in organisations. Detailed investigation of our empirical data demonstrates the variety of quantification acts within organisations. The typology developed

has major practical ethical implications. The distinction between cases 5 and 6 is crucial because these cases differ in their ethical consequences, notably related to the agency of employees as a result of illocutionary or perlocutionary performativity. The agency of the receivers and the quantified is very low in case 6, which corresponds to a situation where individuals provide their data without receiving anything in return. Besides, such quantification acts carried out by an algorithm and with low human agency raise the question: who is responsible and liable for this decision within the organisation? This question is particularly relevant for illocutionary speech acts performed by quantification technologies.

### **Limitations and Future Research**

This paper has some limitations that open new research perspectives. First, it focuses on the representations and discourses of central actors in organisations. This focus is rooted in the sociology of quantification, which suggests that quantification relies on social conventions. Additionally, it would be insightful to take a deeper look at the technical and methodological characteristics of these projects. Second, by focusing the interviews on data scientists, HRM practitioners, and union representatives, this paper does not sufficiently represent the views of actors opposed to, or wary of the use of quantification in organisations, especially when employee data is concerned. Therefore, we were not able to study forms of (overt or subtle) resistance to quantification. Future research can build on such a perspective and identify cases of counter-performativity (Bamford & MacKenzie, 2018) and infelicity of quantification acts. The study could also benefit from a comparison with other forms of quantification, such as, for example, financial and accounting quantification, which focuses mainly on economic transactions and uses currencies as measurement units.

### **Conclusion**

Based on six cases, this paper shows that quantification is performative and acts similar to speech acts. However, we find notable differences between speech and quantification acts: quantification acts rely on social and technical conventions to perform, and they imply a third actor absent from speech acts, namely, the individuals whose data is used (the quantified). HRM quantification acts are therefore related to human agency. We develop a typology of quantification artefacts by use, and by the way they act on reality. Therefore, one of the main takeaways of this paper is to show that HR algorithms do not constitute a monolith but deserve

to be distinguished according to the agency granted to human actors and should include the position of those being quantified. In conclusion, if this article could contain only one message, we would like it to be the following: HR quantification performs in various ways in organisations and it is necessary to pay attention to different aspects of quantification processes, notably, who is involved and in what ways, which quantification acts are carried out, and what type of agency human actors have in the process.

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Table 1: Material

| Project                 | Material  |
|-------------------------|---|
| Training report         | Internal documents: Training report<br>interview with HR personnel specialized in training (training manager) (1h30)  |
| Gender equality report  | Internal documents: Gender equality report<br>Interviews with two representatives of Labour Unions (~1h30)<br>Interview with representative of the Social Relations Department (1h30) |
| Absenteeism 1           | Internal documents: 17 PPT and Word presentations of the project<br>Interview with data scientist working on this study (1h)  |
| Absenteeism 2           | Internal documents: 1 PPT presentation of the solution provided<br>Interview with solution provider (1h)  |
| Training recommendation | Internal documents: 20 PPT and Word presentations of the project<br>Interview with data scientist working on this project (0h50)  |
| Pre-selection           | Internal documents: 2 PPT presentations of the project<br>Interview with data scientist working on this project (1h10)  |

Table 2: Cases Characteristics

| Project                        | Type of Use     | Stated Objective  | Technical Characteristics                      |   |  |
|--------------------------------|-----------------|---|--|---|--|
|                                |                 |   | Data   | Sample                                  | Methods  |
| Training report                | metrics         | compliance with legal obligations, inform about training & policy implementation                  | HRIS   | all employees                           | frequencies, summary statistics, legally mandated & union-defined key indicators |
| Gender equality report         | metrics         | compliance with legal obligations, identify inequalities  | HRIS   | all employees                           | frequencies, summary statistics, legally mandated & union-defined key indicators |
| Absenteeism 1                  | analytics       | understanding absenteeism by identifying explanatory factors, later: using these as action-levers | HRIS, external data                            | all employees                           | multiple linear regression, factor analysis                                      |
| Absenteeism 2                  | analytics       | understanding absenteeism by benchmarking, measuring the cost & finding explanatory factors       | HRIS   | all employees                           | multiple linear regression,  |
| Training recommendation engine | algorithms / AI | improving employee experience, responding to employees' request                                   | HRIS, training report, in-house social network | 1,700 voluntary employees               | collaborative filtering, semantic analysis, profile clustering                   |
| Pre-selection engine           | algorithms / AI | improving recruitment efficiency and gaining time for HR managers                                 | job offers, candidate CVs                      | all candidates & jobs in 2-month-period | semantic analysis  |



Table 3: Typology of Quantification Uses in HRM

|  |  |  |  |
|--|--|--|--|
| Type of quantification technology  | HRM metrics & HR analytics (Cases 1 to 4)  | AI / algorithms when results are sent to individual employees (Case 5)                                   | AI/algorithms when results sent to HR practitioners such as recruiters (Case 6)            |
| Why? (main objective stated)   | Describing the situation & improving HRM policies & decision-making  | Personalise the employee experience  | Making a shortlist of candidates   |
| Who? (possible actors involved)<br>Quantified: individuals whose data is used<br>Quantifiers: quantification actor (~speakers)<br>Receivers: Actors receiving the results (~listeners) | Quantified: employees<br>Quantifiers: HRM, data scientists, external firm<br>Receivers: HRM and unions   | Quantified: employees<br>Quantifiers: HRM, data scientists<br>Receivers: employees                       | Quantified: applicants<br>Quantifiers: HRM, data scientists<br>Receivers: Recruiters (HRM) |
| Agency 1. Agency of quantifiers (quantification actor)   | High (they make the choices behind the quantification tools)   | High (they make the choices behind the quantification tools)   | High (they make the choices behind the quantification tools)                               |
| Agency 2. Agency of receivers (actors receiving the results)   | High (HRM and unions can use the results to inform company policy)   | High (individual employees can use the results to improve training)                                      | Low (if HRM automates decision making)   |
| Agency 3. Agency of quantified (the people whose data is used)   | Low (employees might not be aware that their data is used, employees can only indirectly – through union – influence how the results are used) | High (employees can subscribe to the project or not and also decide to follow the recommendation or not) | Very low (applicants are not aware that their data is used within an algorithm)            |
| Main type of performativity  | locutionary (describing facts) & perlocutionary (decision-making)  | perlocutionary (recommendations to employees)  | Illocutionary (automating decision-making)   |