Organizational quantification between perlocutionary and illocutionary performativity: insights from six HR projects in France

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Abstract :

The use of quantification such as metrics, analytics and algorithms has increased in Human Resource Management (HRM) in the last years. This paper applies Austin's speech act theory to analyze the performativity of quantification uses in organizations, according to their producers and users. Based on a qualitative study involving participant observation, organizational documents and semi-structured interviews, this study theorizes quantification acts in HRM using Austin's three speech acts – locutionary, perlocutionary and illocutionary. Our work complements the sparse but growing literature on metrics, analytics and algorithms (including artificial intelligence) in HRM showing that these socio-technological phenomena are not monoliths but use specific performativities depending on the speech act they emulate.
Mots-clés : organizational quantification, performativity, HRM, analytics, algorithms

Résumé :

L'utilisation de la quantification, telle que les metrics, les analytics et les algorithmes, a considérablement crû dans la gestion des ressources humaines (GRH) au cours des dernières années. Cet article applique la théorie d'Austin pour analyser la performativité des utilisations de la quantification dans les organisations, en fonction de leurs producteurs et de leurs utilisateurs. Fondée sur une étude qualitative impliquant une observation participante, des documents organisationnels et des entretiens semi-structurés, cette étude théorise les actes de quantification en GRH en utilisant les trois actes de langage d'Austin - locutoire, perlocutoire et illocutoire. Notre travail complète la littérature peu abondante mais croissante sur les metrics, les analytics et les algorithmes (y compris l'intelligence artificielle) dans la GRH en montrant que ces phénomènes sociotechniques ne sont pas monolithiques mais correspondent à des performativités spécifiques.

Mots-clés : quantification en organisation, performativité, GRH, analytics, algorithmes

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INTRODUCTION

Organizations manage huge amounts of employees' personal data (Angrave et al., 2016; Levenson, 2018; Simón & Ferreiro, 2018), , data that is increasingly used in quantification processes – by constructing metrics, analytics, and algorithms (sometimes using artificial intelligence) to improve organizational processes, especially in Human Resource Management (HRM). The hope associated with this use of data is that it will improve organizations' personnel decision-making. This hope is mainly based on the fact that quantification is perceived as a neutral tool that brings an objective knowledge into organizations (Kryscynski et al., 2018; Ulrich & Dulebohn, 2015). Recently, the idea of using this data within algorithms has emerged (Christin, 2017), and been applied to organizations (Caplan & boyd, 2018; Leonardi & Treem, 2020; Newlands, 2021) and within HRM (Angrave et al., 2016). Algorithms are linked to the ability to automate and predict tasks that normally require human cognition (Faraj et al., 2018; Mayer-Schönberger & Cukier, 2014; Tambe et al., 2019), often using artificial intelligence (AI). Little research is considering quantification in HRM specifically (Lee, 2018), investigating ways to improve the performance of quantification projects (Tambe et al., 2019; Yano, 2017), contrasting the seeming 'objectivity' provided by quantification with the 'subjectivity' of human beings (Elish & Boyd, 2018), or calling for a more comprehensive approach to quantification (Greasley & Thomas, 2020; Kellogg et al., 2020). There is a lack of research investigating how quantification based on employee data in its many forms, be it metrics, analytics, algorithms or even AI, acts within organizations.

People expect the use and production of numbers to have an effect on what is gauged, as the the sociology of quantification has shown (Desrosières, 2008b; Espeland & Stevens, 1998, 2008). Statistics create new ways of thinking about the world and acting on it (Desrosières, 1993), similar to how speech and language do act (Espeland & Stevens, 2008). This performativity of quantification has been studied in relation to analytics, AI and algorithms, mostly outside of employee organizations (Roscoe & Chillas, 2014). Sparse literature has investigated how numbers are used in organizations in general and HRM specifically. Extant studies found that previous research does not pay enough attention to the expected effects of quantification and the interplay with actors (Greasley & Thomas, 2020). Notably, a missing puzzle is what intended and non-intended effect quantification artefacts introduce in organizations. The academic literature about the performativity of quantification informed the following research question:

Which type of performativity is expected and produced with HRM quantification in organizations?

Answering this research question will allow us to complement the growing literature about HRM quantification, with a more critical point of view and analysis than what has been mostly done in previous research. Indeed, previous HRM research has mostly adopted a positivist view on quantification, based on the idea that quantification brings objectivity and rigor (Kryscynski et al., 2018; Ulrich & Dulebohn, 2015).

In line with Espeland and Stevens (2008), we apply Austin (1975) speech act theory to answer this question. Espeland and Stevens (2008) in their sociology of quantification proposed that quantification acts like language and therefore speech act theory can be used to analyse the expected as well as realized effects of quantification artefacts. Speech act theory suggests that certain linguistic acts (speech) have performative effects that can be analysed by looking at the speech act itself within its context (Austin, 1975; Butler, 1997). Therefore, we find it necessary, when analysing quantification acts along the lines of speech acts, to include the context of where quantification artefacts are embedded. As such quantification artefacts like algorithms and analytics are increasingly situated in organizations, we study them within an organizational context. We use data from a long-term ethnographic field project in a French telecommunications company where the first author worked as 'AI and HR project manager' to answer the research question.

Drawing on the work of Austin (1975) on the performativity of speech acts, our study shows the mechanisms of how quantification can act similar to speech in organizations. We find quantification acts like speech in three forms through (1) locutionary speech acts, e.g. making meaningful statements, (2) perlocutionary speech acts, e.g. by influencing decision-making or persuading a course of action, and, (3) illocutionary speech acts, e.g. by deciding *through* quantification as in the case of algorithmic management. In providing a performative theory of organizational quantification as speech, we contribute to the literature investigating the manifold effects of metrics, analytics, and algorithms (including AI) in organizations, challenging the pervasive positivist conception of analytical tools as neutral and non-performative. Specifically, we show how quantification phenomena, such as metrics, analytics, and algorithms, act through perlocutionary and illocutionary quantification acts. When the performativity is institutionalized within the code, as in the case of illocutionary speech acts, the difference between informing and performing are subsequently collapsed. Our research has important managerial implications through understanding how numbers are and can be used in organizational contexts (Angrave et al., 2016). With that we contribute to the sparse research addressing organizational algorithms (George et al., 2014)and HR analytics (Marler & Boudreau, 2017). Finally, as the quantification phenomenon is becoming more and more widespread, it is important to look more closely at its possible transposition into organizational processes and HRM practices (Huselid, 2018).

1. LITERATURE REVIEW

1.1. THE RISE OF QUANTIFICATION OF HRM IN ORGANIZATIONS

The use of numbers and data in HRM is not a recent phenomenon. At the beginning, employee data was analysed using metrics: Frederick Taylor, at the beginning of the nineteenth century, introduced the idea that measuring work could increase the productivity of workers and thereby organizational performance (Taylor, 1919). Later, key performance indicators were used to assess personnel costs and individual performance. At the end of the century, tools like the balanced scorecard (Kaplan & Norton, 1992) promoted the inclusion of non-financial metrics including employee metrics when assessing organizational performance. With the availability of personal data through the internet, books by HR practitioners proposed metrics to measure the activity and performance of HRM and employees (Becker et al., 2001; Fitz-enz & Davison, op. 2002). Later, at the beginning of the 21st century, HR analytics has emerged, which refers to *"[an] HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making."* (Marler & Boudreau, 2017, p. 15). Just recently, algorithms entered the conversation as previous research has suggested that 'Big Data' has to be analysed or used in algorithms in order to make sense (Campion et al., 2018; Mayer-Schönberger & Cukier, 2014; Rieder & Simon, 2016). Algorithms are *"computational formula that autonomously makes decisions based on statistical models or decision rules without explicit human intervention"* (Duggan et al., 2020, p. 119). This definition underlines the fact that algorithms allow the automation of tasks and decision making in HRM, e.g., job scheduling, identification of motivated employees, or job analysis (Canós-Darós, 2013; Malinowski et al., 2008; McEntire et al., 2006; Yano, 2017). This corresponds to the aims of artificial intelligence (AI), which refers to the automation of human reasoning capabilities (Tambe et al., 2019). Very little research has been done specifically on the use of algorithms or AI in management generally and HRM specifically, for that matter (Campion et al., 2018; Lee, 2018). However, a growing trend toward the use of recommendation algorithms by major digital players has also created new opportunities and uses of algorithms within organizations: algorithms to provide employees with automated personalized recommendations or personalized job offers – as Amazon or LinkedIn offers to their customers and users (Coron, 2020). Technically, these analytical phenomena are all based on quantification procedures (e.g. by calculating an adequacy score between a job description and an employee's profile). Overall, this development over time results in three different types of quantification – metrics, analytics and algorithms (under which we subsume those algorithms using AI) (Coron, 2022).

The academic literature on the use of data and numbers in HRM remains rooted in the positivist paradigm (Greasley & Thomas, 2020; Harley, 2015). Indeed, most research considers quantification as a neutral tool that brings objectivity, transparency and rationality to HRM, and offers insights to improve organizational decision-making (Kovach et al., 2002; Shrivastava & Shaw, 2003). In this vision, quantification in organizations is perceived as promising more objective decisions (Huselid, 2018; Strohmeier & Parry, 2014) and decreased administrative costs for HRM (Ruël et al., 2007). This vision is deeply connected with the evidence-based management approach with its ideal of bringing scientific methods into management (Cossette et al., 2014; Pfeffer & Sutton, 2006; Rousseau, 2006). Lawler et al. (2010), for example, argue that evidence-based management and the use of numbers are central to making HR a business partner in the organization. Subsequently, research on HR and evidence-based management has shown that using data to inform decisions can have positive business impacts (Hota & Ghosh, 2013; Huselid, 2018; Kryscynski et al., 2018; Marler & Boudreau, 2017; Momin & Mishra, 2015). Some authors even present the effective use of employee data as a strategic organizational resource (Huselid, 2018).

1.2. The performativity of quantification

The notion of performativity has been used to study various phenomena in a variety of fields (Butler, 1990; Roscoe & Chillas, 2014), including organization studies (Gond et al., 2016; Kornberger & Clegg, 2011). Most of this research is based on Austin (1975) speech act theory that introduced and developed the concept of speech acts that have a performative effect. Austin's speech act theory is well-known in organization studies, particularly in work grounded in critical management studies (Spicer et al., 2009) and where discourse analysis (Gond et al., 2016; Kornberger & Clegg, 2011) is used. However, it has hardly been applied to study the performative effects of quantification in organizations.

Statistics are often used strategically to create new ways of thinking, measuring, and acting on society (Coyle, 2016; Espeland & Stevens, 1998; Lave, 1984; Lorino et al., 2017; Stevens, 2008; Sunstein, 2000; Vollmer, 2007). Espeland and Stevens (1998) describe how to 'do things with numbers', such as marking things or actors (with numerical codes, e.g. social security numbers) and creating categories (e.g. unpaid work, sexual orientation). Additionally, people change their behavior in reaction to quantification as in the case of evaluations and rankings. This reactivity blurs the distinction between the object that is measured by quantification and the act of quantifying said object. Therefore, science itself has been described as performative by some authors (Callon, 2008). The mechanism of performativity of numbers have been described as self-fulfilling prophecies and commensuration (Espeland & Stevens, 1998). These models have been extended to differentiate between generic performativity, i.e. how some aspects of a quantification (e.g. statistical model, ranking) are used in practice, and effective performativity, i.e. how the use of quantification (e.g. statistical model) affect the underlying process (e.g. economic mechanism) (MacKenzie, 2006).

Some research on quantification, i.e. the production and use of data and numbers, adopt a form of reflexivity both methodologically (focusing on measurement questions, bias, error, etc.), and epistemologically (what can we actually capture through quantification and thereby what is possibly entering our conceptualization of a phenomenon). In some of those works, quantification tools and their diffusion are conceptualized as based on conventions (Diaz-Bone, 2016; Diaz-Bone & Didier, 2016), social constructs and compromises (Chiapello & Walter, 2016; Desrosières, 1993, 2008b; Hansen & Flyverbom, 2015; Salais, 2016). Such conceptualization of quantification is usually rooted in more overarching academic fields such as sociology (Espeland & Stevens, 1998) or economics (Callon, 2008; MacKenzie, 2006), while

studies rooted in actual experiences with quantification and their immediate effects are found more often in more specialized fields (e.g. Roscoe & Chillas, 2014 who study online dating services).
What is apparently missing in these approaches to performativity of quantification is the organizational context where analytical phenomena are embedded and situated and the mechanism of how a quantification artefact (e.g, a specific algorithm) is exercising performativity. We therefore propose to use the original Austin's (1975) speech act theory to investigate this question.

1.3. Quantification acts

Within the field of studies dealing with the performativity of quantification, Espeland and Stevens (2008) build and use a specific conceptual toolkit. They extend Austin's (1962) analysis of language to quantification. They propose that quantification tools such as metrics, analytics and algorithms can be understood like speech acts: "Our extension of Austin's analyses of speech acts to quantification is intended to highlight important parallels between his approach for investigating utterances and strategies for advancing sociological analyses of numbers" (Espeland & Stevens, 404). Austin's (1975) speech act theory analyses how human's act through language. First, Austin distinguishes between utterances that describe or state a fact (constative utterance) and statements that accomplish an action (performative utterance). Performative utterance cannot be true or false, whereas constative utterance can. Performative utterance on contrast are either happy or unhappy, what Austin (1975)terms the felicity condition. Second, Austin points out the limits of this distinction and the different types of performative utterances. Some performative utterances are explicit, as they correspond unambiguously to actions (e.g. utterances beginning *"I want you to buy me icecream*"); others are implicit, as their performativity depends on how the recipient interprets them (e.g. *"I want icecream"* could be interpreted as a suggestion). Finally, Austin highlights three types of performative speech acts, i.e. were words are used to do something.
(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"*). Thereby locutionary speech acts are those where for example (social) facts are presented in a statement. Espeland and Stevens (2008)explain that numbers can be compared to locutionary acts when they are used in mathematics, numeracy, statistics, and related fields. There statements using quantification have to respect certain rules and conventions in order to

make sense. They also refer to locutionary acts when they are used to describe a fact or phenomenon, which can happen through quantification.

(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"* in order that a bystander will shut the window. Quantification can also act in this way, for example when underlining inequalities, or social issues 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 closes the window. This can be applied to cases where data is used to both describe a situation (e.g. the gender pay gap) and make a request (data about the gender pay gap are used to advocate for policies addressing the gender pay gap).

(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 conditions. Promises (where the promise is made the instance someone says "*I promise*"), court sentences and marriage vows (where the marriage is legal the moment when "*I do*" is said) are good examples. They only work in certain spatial contexts (courtroom, city hall, chapel) under certain conditions (sobriety and legal age, volume, etc.). Such contextual conditions are ritualized and institutionalized to make the illocutionary speech act perform. According to Espeland and Stevens (2008), numbers 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 through measuring something that is termed 'unemployment' the social category of unemployment was created.

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 and performance). We argue that the same is true for quantification: measuring the unemployment rate simultaneously describes the phenomenon of not being employed in the labour market (locutionary act), creates the categories of thought 'the unemployed' and 'unemployment' (illocutionary act), and encourages individuals and public authorities 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 to differentiate perlocutionary from illocutionary speech acts, studying how different vocabulary, especially specific verbs, are tied to each form of speech act. Thereby one can distinguish between what is said (locutionary speech act), what is forced into being by being stated (illocutionary speech act) and what is affected, convinced and inspired (perlocutionary speech act).
Mobilizing this framework and notably the distinction between illocutionary and perlocutionary acts to understand the use of numbers allows analytics in organizations to be conceptualized *"as social action that, akin to speech, can have multiple purposes and meanings"* (Espeland & Stevens, 2008, p. 405). We propose that it is possible to investigate the performativity of quantification artefacts through their quantification acts that can be analysed just like speech acts.

2. RESEARCH MATERIAL AND METHODOLOGY

2.1. Empirical site

The results are based on ethnographic fieldwork (Zilber, 2020). The ethnographic approach was chosen to gain a deeper understanding of the performative effects of quantification in HRM (Lange et al., 2019; Schouten & McAlexander, 1995; Seaver, 2017). The first author worked as Big Data and HR project manager at Telecom, a French telecommunication company with 90,000 employees listed in the CAC40[1] between January 2016 and August 2017. This involved directly working on two quantification projects (absenteeism analytics and training recommendation algorithm). More globally, during the period, six HR projects were conducted at Telecom using quantification, which are discussed in the next section. We combined the ethnographic data from participant observation with ten semi-structured interviews and company documents (see Table 2). This triangulative approach allowed for an in-depth study of the performativity of quantification (Roscoe & Chillas, 2014). The aim was to better

[1] The benchmark index of the French stock exchange

understand the visions and perceptions of the actors involved (HR, data scientists, solution providers…). Therefore, the interviews focused on their visions of the different projects, their perception of quantification, and their perception of the HR changes due to quantification. The material therefore reflects the practices, representations, and discourses of actors, a choice rooted in the sociology of quantification conceptualizing the technical aspects of quantification as social conventions (Desrosières, 2008a; Espeland & Sauder, 2007; Espeland & Stevens, 1998, 2008)

Table 1: Material

Project	Material
Training report	Participant observation interview with HR specialized in training (training manager) (1h30)
Gender equality report	Participant observation interviews with two representatives of Labour Unions (~1h30) interview with representative of the Social Relations Direction (1h30)
Absenteeism 1	Participant observation in the role of consultant on the projects interview with data scientist working on this study (1h)
Absenteeism 2	interview with solution provider (1h)
Training recommendation	Participant observation in the role of project lead Interview with data scientist working on this project (0h50)
Pre-selection	Participant observation Interview with data scientist working on this project (1h10)

2.2. HR QUANTIFICATION PROJECTS

An overview of the six projects can be found in Table 1. Two projects established reporting standards within the organization (training report, gender equality report) and are therefore examples of organizations' establishing HRM metrics. Two projects aimed to analyse absenteeism by using the data from the HRM information system (HRIS) (absenteeism 1 and 2) and are therefore HR analytics projects. Two projects enlisted machine-learning algorithms to aid HR processes (training recommendation engine, pre-selection engine), and therefore represent algorithms. From a methodological perspective, the first two projects 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

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	understand absenteeism by identifying explanatory factors, later: using these as action-levers	HRIS, external data	all employees	multiple linear regression, factor analysis
Absenteeism 2	analytics	understand absenteeism by benchmarking, measuring the cost & finding explanatory factors	HRIS	all employees	multiple linear regression,
Training recommendation engine	algorithms / AI	improve employee experience, respond 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	improve recruitment efficiency and gain time for HR managers	job offers, candidate CVs	all candidates & jobs in 2-month-period	semantic analysis

2.3. ANALYSIS

The ethnography produced a number of documents, such as meetings, e-mails exchanges and formal or informal oral exchanges with several actors, and even included inter-organizational events (e.g. salons about Big Data in HR) that were collected and subsequently used for analysis. The aim was to better understand the visions and perceptions of the actors (HR, data scientists, solution providers…) concerning the performativity of those artefacts.

The data analysis was rooted in an interpretivist approach. In the first step, a thematic analysis of the interviews, and then the participation notes (in this order) was conducted. The coding thus consisted of identifying 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 (1975) speech act theory was identified, the analysis was refined with deductive coding according to the three types of speech acts – locutionary, perlocutionary, illocutionary. The coding was conducted on broad "analysis units", mainly on the paragraph level.

3. RESULTS: DIFFERENT USES OF AI IN HR, WITH DIFFERENT EXPECTED EFFECTS

Before delving into the specific results, we give a thick description of the six projects analysed in the study. As can be seen from this description below, the projects represent different kinds of quantification (metrics, analytics, algorithms), involving different degrees of data analysis (from descriptive statistics to machine learning) as well as different data sources (organizational employee data & external data, structure & unstructured data) and different stated objectives (information, prediction, automation). Austin's (1975) speech act framework enabled us to characterize the different uses of the six projects as well as the subsequent performative effects.

3.1. THICK DESCRIPTION OF CASES

Training report: In France, large companies have the obligation to present their training plan and its implementation to the labour union. This plan and the associated overview contains a number of indicators (e.g. number of hours of training by type, number of trained employees, etc.) required by law. Additionally, the labour union defined additional indicators to review the company's training policy and implementation. In total, Telecom reported more than 100 indicators. As a consequence, the training report is viewed as an important part of HR work.

Gender equality report: In France, large companies are mandated to report on gender equality every year. In Telecom, next to the 25 indicators mandated by law, 60 indicators were defined together with the labour union to identify persisting gender inequalities.

Absenteeism 1: Two projects aim at HR analytics using the HRIS data to identify the explanatory factors of absenteeism. The first project was conducted in 2016 in-house by an employed data scientist. The data came from the HRIS, containing information on gender, job field, level in the hierarchy, wage, wage augmentation, paid vacation, etc. This data was combined with external data (seasonal and geographical epidemiology data on flu and chickenpox occurrence). The initial objective, as stated by Telecom, consists in reducing absenteeism by finding action-levers. For example, if the commuting time is found to explain absenteeism, developing teleworking can be a solution. The methods used were multiple linear and logistic regression complemented by a 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. In this project only HRIS data was used and the methods contained multiple linear and logistic regression. The objectives were stated by the provider as following: benchmarking with competitors, assessing the cost of absenteeism and identifying the explanatory variables.

Training recommendation: The project was launched following an employees' request, expressed during focus groups about employee experience conducted in 2015 with workers: Some participants expressed the wish to get personalized training recommendations within the training platform. Therefore, the project was initialized to send automatized training recommendations to the employees, based on their profiles. Data from employees' history of training, the HRIS (job field, level in the hierarchy), and the in-house social network (followed communities and employees) was used. An opt-in system was set up: From the 10,000 employees that were offered participation via email, 1,700 employees subscribed. The training recommendation is based on three machine-learning algorithms, collaborative filtering (if A followed the same training as B and B followed one additional training than A, this additional training suits A), semantical analysis (key-words of trainings already followed to suggest new trainings), and profile clustering (training taken by most similar profiles in terms of job, hierarchical level, etc.).

Pre-selection engine: This project uses a matching algorithm to pre-select candidates for recruitment. In Telecom, the recruitment process involved three actors: the research officer, who is in charge of the pre-selection of CVs, the recruitment officer, who conducts the interviews with the shortlisted candidates and reduces the list, and the manager, who makes the final choice. The objective of the pre-selection engine was to save time for the research officers[2] so that they could devote more time to proactive recruiting practices (e.g. head-hunting). Another aim was to test the possibility of detecting useful information from unstructured data. Two research officers volunteered to test the algorithm on external candidates. The engine, as it is called within the organization, was built in three steps: First, the algorithm was trained with a very limited number of job postings and CVs. The machine-learning algorithm uses semantic

[2] There are 10 research officers for the 90,000 employee-company

analysis based on unstructured data from the job proposals and the CVs: It produced word clouds from the job offers and the respective applications and compares the frequencies of words. Second, during a two-month period, every job posting and every candidate was analysed to improve the algorithm (around 1,000 job postings and 10,000 candidates were used). Third, two voluntary research officers compared their own ranking with the results from the algorithm. At the end, they noted a high adequacy of the algorithm: an average similarity of 84 % between the 20 first CVs shortlisted by the research officer and the ones shortlisted by the algorithm.

3.2. Locutionary acts

Locutionary speech acts are those speech acts where some statement is made that is meaningful. This performative aspect of a speech act deals with the content of a statement and therefore with the meaning of a speech act (Austin, 1975, Lecture XII). In the case of HR quantification, locutionary speech acts can be seen when a statement of fact about a (present) situation are made. Therefore, metrics such as key performance indicators or statements using descriptive statistics are performing locutionary quantification acts. The training report and the gender equality report both made such performative speech acts, they aimed at describing the status quo, as exemplified by this quote:

> *"Our first struggles were the* ***situation analysis****, obtaining new indicators. If not, it's a philosophical debate and we don't progress on the situation objectification. […] It necessitates to give precise elements which permit to analyse the situation, which conduct the employer to* ***acknowledge the inequalities****. And objectifying, if the inequality is demonstrated, it can conduct to progresses on the correction measures. If we don't do that, a lot of gender equality agreements are 'philosophical', as we say, we don't have precise engagements."*
>
> *(Union Labour representative on the Gender Equality report, emphasis added)*

As can be seen in the quote, stating facts is not non-performative. It acts by making a meaningful statement about some object (the situation) and acknowledging or ascribing its truth resp. its social fact quality (in this case, the inequalities). As the union labour representative states, the locutionary act is tied to a performative aim, to further implement policy measures and to commit the organization to the goal of gender equality. Austin describes such speech acts as 'commissives' (Austin, 1975, Lecture XII p.3), that act through committing a speaker. While locutionary speech 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 exemplified by this quote on the absenteeism project:

> *"The first belief (of the HR employees) is that numbers are not useful at all. We demonstrate that we* ***highlight a certain number of problematics****. 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 to understand****, 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" – focuses on the locutionary quantification act: that by using numbers the projects aim to make meaningful and true statements and nothing more. However, as we demonstrate in the next section, locutionary acts are often bound to perlocutionary acts.

3.3. Perlocutionary acts

In the material, we also find clear indications of perlocutionary speech acts. As Austin (1975) demonstrates in his examples, many speech acts try to perform on both levels, locutionary (stating something) and perlocutionary (persuading the audience). All six projects analysed aim at the same time at analysis (i.e. locutionary speech) and improvement of HR practices (i.e. perlocutionary speech acts). The most obvious examples can be found in the analytics projects (absenteeism 1 and 2), that focus on these quantification acts, as exemplified by this quote:

> *"The purpose was to analyse the absenteeism causes within Telecom, to establish preventive actions, to better understand what's happening, in order this **to help decision making**. The expected benefit was a better understanding of causes and effects, and **define actions to reduce absenteeism**."*
> *(Data Scientist, Absenteeism 1, emphasis added)*

But even in the other projects we find this form of quantification act. The training recommendation is a good example. The aim of the algorithm in this project is to send personalized recommendations to employees, and the expected effect is to generate a certain behaviour among employees (i.e. actually taking the recommended training). This corresponds to perlocutionary acts (bringing change, having an effect on others *by* saying something, in this case *by* recommending training). This is consistent with the fact that the algorithm aims at providing a new service instead of enhancing productivity or gaining time. The performance of the training recommendation algorithm itself is contingent on employees' take-up of the training recommended to them:

> *The accuracy of the training suggestion engine is measured in part by its ability **to predict users' tastes, i.e. to suggest training that users would like to take.** Thus, a feedback questionnaire sent to all participants contained the following question: "Do you think you will follow the suggestions you received? (Yes/No)."*
> *(Observation notes on Training recommendation engine, emphasis added)*

Perlocutionary quantification acts are often tied to prediction, which in itself featured prominently in the interviews and the observation notes. Prediction of employee behaviour is seen as the cornerstone of measuring the quality of a quantification project. Prediction can be conceptualized as independent of the reactivity of employers 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 conceptualized even further, by predicting the unusual and even inconceivable. When such training is predicted (and thereby recommended to the employee) and the employees is taking up the suggested training, even if s/he would not have considered it without the analytical tool, in a self-referential twist, it is 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****, what is strong is when you manage to predict things you don't already know about. That's why you also have to look to see if you increase usage, if people click on contents they wouldn't have clicked on otherwise."*
>
> *(Data scientist, Training recommendation engine, emphasis added)*

3.4. ILLOCUTIONARY ACTS

Illocutionary speech acts are those where speaking equals acting. In our analysis of organizational quantification projects we found specific examples where quantification brought material performativity into being through illocutionary illocutionary speech acts. The pre-selection engine is the most obvious example of an illocutionary act: using the engine (for pre-selection) is the same as acting (i.e. selecting). By automating certain decisions directly after quantification through the AI algorithm, the differentiation between quantification insights and decision-making is collapsed. In the pre-selection algorithm all three quantification acts are performed, but their analytical difference is collapsed in its application. In this case the difference between locutionary (saying), perlocutionary (persuading) and illocutionary act (stating) are perceived at the same moment by the user. Even though the he algorithm analyses (locutionary quantification act), ranks (perlocutionary quantification act) and pre-selects (illocutionary quantification act) the CVs in subsequent steps, for the research officer these steps are collapsed into one illocutionary quantification act, the shortlist, which is the result of the algorithm. Also, because this process is done behind the veil of the AI algorithm, it is as if "the engine" decides through quantification acts, i.e. analysing the CV's using semantical analysis and matching them to the jobs offered, ranking the CVs accordingly and pre-selecting job candidates. Indeed, by attributing a matching score to each CV, the algorithm chooses between them. Human intervention is neither necessary nor expected. It is precisely the absence of human intervention that allows a productivity gain in this example, as exemplified by the following quote:

> *"There were three issues in the hands of the hiring director: how can I reduce the time spent reading resumés, how can I reduce the time it takes to publish a job description (because one day of publication corresponds to x hundred more applications to qualify), and the third essential element is* ***to no longer undergo the flow of resumés****, and to be part of a headhunter approach where we will source people, and for that, we must free time for recruiters. So our project was born from this triple challenge."*
>
> *(Data scientist on pre-selection engine, emphasis added)*

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

4. DISCUSSION

Our results contribute to understanding quantification within organizations in three ways.

First, our results show that the use of quantification in organizations using employee data is not monolithic: it corresponds to different performative effects often related to the objectives of quantification projects. Even though all quantification acts studied were assigned to the overarching goal of improving HRM, as mentioned in previous research (Huselid, 2018; Strohmeier & Parry, 2014), the specific aims differed. For example, the training and gender equality reports aim at defining HR policies and improving HR practices, but also committing the different stakeholders within the organization. The training recommendation algorithm aimed at improving employees' experiences and the pre-selection engine aimed at automating an already existing HR practice. Furthermore, the performative effects also differed. Therefore, rather than talking generally about the use of quantification in HRM (Tambe et al., 2019; Yano, 2017), it would be better to specify quantification *by use*. This can be systematically achieved by analyzing the following characteristics: (a) what are the objectives of the quantification act (b) how are the results used (reporting, analytics, recommendation, decision-making), (c) who is receiving the results (employee, HR managers, data scientists), and (d) how much agency do the actors have in shaping and/or maneuvering the quantification artefact. The combination of those different factors gives different types of performativity (locutionary, perlocutionary, illocutionary). Specifically, the distinction between locutionary, perlocutionary and illocutionary performativity can shed light on the performative effects of quantification in organizations. While all projects have locutionary performativities (saying something of meaning that can be judged), some projects also had clear perlocutionary effects (e.g., persuading for a specific action, committing the organization to something, steering decision-making, convincing an organizational audience), that were less visible on first sight. Interestingly the producers of these quantification tools claim objectivity and 'freedom of dogma' indicative of solely locutionary acts, while at the same time being quite honest about trying to influence decisions that clearly have perlocutionary performativities. Additionally, illocutionary speech acts were identifiable where stating something was the same as acting. In one project this was institutionalized into the algorithm itself: the pre-selection engine analyzed CV's aligning with job offers (locutionary), ranked them (perlocutionary) and also pre-selected CVs for job interviews (illocutionary). All three acts were performed with a machine learning algorithm and the user could not differentiate between those quantification acts. The collapse of these quantification steps was stated as an explicit objective of the project, as exemplified by the quote of the data scientist.

Callon (2008) discussed the relationship between performativity and prescription, where prescription is just a particular case of performativity and that it is "futile" to distinguish between them. However, as our results suggest, the distinction between quantification artefacts producing perlocutionary acts by stating numbers that convince an audience and quantification artefacts performing illocutionary acts in automating decision-making and acting through algorithms is crucial. In the case of the perlocutionary quantification act (e.g. training recommendation), employees and HR managers still have agency in choosing to follow the recommendations of the algorithm or not, whereas in the case of illocutionary quantification acts (pre-selection engine), the algorithm replaces the human decision-making completely. The distinction can explain how the six projects raise different issues notably concerning the interaction between quantification and humans, the possibility of human interference and control and thereby the issue of responsibility. For organizations, this difference has three important implications: motivational, legal, and ethical. Motivation theory suggests that humans have a strong desire for autonomy (Deci & Ryan, 1980), autonomy that is being completely eliminated in the case of illocutionary quantification acts such as algorithmic decision-making. Therefore, the effects on (employee and manager) motivation are proposed by self-determination theory to be negative. While past studies have analyzed how different degrees of perceived autonomy are related to motivation, the situation of no autonomy is less clear. In terms of legal implications, quantification acts raise a number of issues for organizations: Organizations already struggle with discrimination issues arising from certain forms of quantification, as in the case of AI (Harcourt, 2005; O'Neil, 2017). Illocutionary quantification acts additionally raise the question of legal liability and accountability. Who is responsible for discrimination if the pre-selection engine does it automatically? How do candidates even find out about it, given that the use of an algorithm is not known to them in the first place? These concerns are related to ethical questions arising from using illocutionary and perlocutionary quantification acts.

Second, our results question if there is a difference between speech acts and quantification acts (Espeland & Stevens, 2008). Even though Espeland and Stevens (2008) use Austin's work to analyse the use of numbers, our results indicate that there are some important differences between speech and quantification acts. As Austin (1975) emphasized in his speech act theory (Lecture VI), speech acts can only be understood in their proper contexts when they are accompanied by clues (e.g., enunciation situation, facial expression, the circumstances of the speech act) that facilitate their interpretation and enhances their performativity. This is especially relevant for perlocutionary and illocutionary speech acts, they only work in specific contexts. For illocutionary speech acts, especially, relies on rituals and social norms embedded in a specific spatial (e.g. judge sentencing requires a court) and temporal (during a ruling) aspects using specific conventionalisted linguistic elements ("the court sentences you to…") (Butler, 1997). Butler (1997) reminds us of Austin's insight that illocutionary speech acts are always based on conventions, otherwise they do not work. In the case of quantification we are less aware of such contextual factors and they have not been systematically studied yet. For example, the results of the pre-selection algorithm are not accompanied with such contextual clues. Besides, language is based on shared conventions, which is not obvious for numbers, and notably for algorithms. Indeed, numbers necessitate technical capabilities (Thomas et al., 2018) which may not be shared by everyone in the organization. Above all, algorithms often remain black boxes which are difficult to open, sometimes even for their producers (Lange et al., 2019). This constitutes an important difference between speech acts and quantification acts. The interviews suggest that certain myths, e.g. the belief that numbers are neutral and objective irrespective of the context they are produced in (Porter, 1996), are prevalent when perlocutionary and illocutionary quantification acts are present. This illusion of objectivity enhances the performativity of numbers. We therefore suggest that these quantification myths are a necessary social convention for these 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 (e.g., faith in the objectivity of numbers, or perceived professionalism of the producer of numbers). Additionally, in the case of numbers, the speech act might arrive without a speaker (Butler, 1997, p. 34), being a second characteristic of quantification acts. Furthermore, certain technical conventions might act as necessary context for illocutionary quantification acts to work. In the case of the pre-selection engine, the illocutionary acts is written into the software. Future research might systematically investigate the role of the speaker and the contextuality of quantification acts by looking at the socio-technical boundary conditions.

Third, our results show a surprising consensus between the actors involved: different actors shared the same points of view and described the same expected effects when using or producing quantification devices, whatever their professional fields (HR practitioners, data scientists). This seems surprising given the research on professions (Ackroyd, 1996). It might indicate how one point of view manages to impose itself on others. Actually, some quotes highlight the idea that this uniform point of view comes from the following "quantification myths" (Desrosières, 2008b) that are echoed by all actors involved: faith in numbers and their objectivity and the myth of prediction. These social myths are also present in common and managerial discourse about Big Data, Artificial intelligence, and algorithms, and form part of the "Big Data premise". It is reasonable to wonder how these myths have managed to penetrate the different functions of a company and the professionals situated there. One explanation might be that quantification, especially in the case of AI algorithms, are considered "black boxes" and the persisting belief that not even the programmers themselves can reconstruct all steps in the analysis and decision-making of "the engine". Therefore, for most actors it is difficult to define exactly what the algorithm is doing. The myth of objectivity together with this inexplicability creates a certain 'magic' for everyone involved (Elish & boyd, 2018). Hence, the actors might be more open to external discourses because of the vagueness of the algorithmic object. Future empirical investigations might shed light on these quantification myths and their interaction with the 'black-boxing' of quantification artefacts in organizations.

CONCLUSION

This paper focuses on various uses of quantification in organizations, specifically in the realm of HRM using employee data, and tries to identify their expected effects through Austin's (1975) speech act theory and the notion of performativity. Beyond shared understandings, the use of quantification in organizations is not monolithic: some projects can be compared to perlocutionary acts (persuading and convincing), others to illocutionary acts (acting through quantificaiton), while at the same time a pervasive image of these artefacts is that of locutionary speech acts (objectively informing on and describing the social reality).

The main contribution of this work consists of achieving a deeper understanding of the use of quantifcation in organizations especially concerning employee data. Indeed, there are very few academic publications about quantification using employee data specifically, whereas companies are implementing such devices more and more. This paper tries to address this gap by analyzing six HR quantification projects in a large French telecommunication company. Our research has important implication for organizations and especially HR professionals, providing them with a useful analytical tool to analyze the aims of quantification tools within their professional jurisdiction. The distinction between locutionary, perlocutionary and illocutionary quantification allows to analyze HR quantification projects in terms of their objectives (e.g. reporting, prediction, automation). Furthermore our research suggest that organizations have to build the corresponding capabilities and skills in the area of metrics, analytics and algorithms (Kryscynski et al., 2018) as well as the related socio-technical understanding including a critical perspective on the different uses and forms of performativity and their consequences within organizations.

Nevertheless, this paper has some limitations that open new research perspectives. First, it is focused on the practices, representations, and discourses of actors. This choice is rooted in the sociology of quantification, which suggests that the technical aspects of quantification are to be understood as social conventions. However, it would be interesting to take a deeper look at the technical and methodological characteristics of these projects. Second, the qualitative approach preclude generalization of the results and encourage complementary quantitative research of this subject. Third, this paper does not sufficiently consider the points of view of people opposed or reluctant to the use of quantification in organizations, especially when employee data is concerned. Future research can build on such a perspective and identify cases of counter-performativity as well as the in/felicity of quantification acts.

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