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Developing human resource data risk management in the age of big data

Thomas Stephen Calvard[a], Debora Jeske[b,*]

[a] University of Edinburgh Business School, 29 Buccleuch Place, Edinburgh, EH8 9JS, United Kingdom
[b] School of Applied Psychology, University College Cork, North Mall, Cork, TK23 K208, Ireland

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ABSTRACT

In recent years, a great deal of attention has been devoted to trying to understand the risk challenges that arise in information management, and most recently, challenges that arise due to big data. In this article, the complexities of big data for employers are explored, drawing on a risk management on Human Resources (HR) perspective and normal accident theory (NAT) to illustrate the evolving characteristics of these complexities. The paper concludes with a series of recommendations that focus on education, design in data collection, and risk management, in the hope that these recommendations enable employers to better anticipate and address emerging big data challenges.

1. Introduction

Big data collections are increasingly being made open and available by government agencies (e.g. Data.gov; Krishnamurthy & Awazu, 2016) and Internet service providers (Guzzo, Fink, King, Tonidandel, & Landis, 2015). Commercial organisations are also contributing to the bigness of data, generating it via employees' and consumers' interactions with their systems. Summarising major definitions of big data provided by authors such as Gandomi and Haider (2015), McAfee and Brynjolfsson (2012), Boyd and Crawford (2012), Kitchin (2014), Guzzo, Fink, King, Tonidandel, & Landis, 2015, Mayer-Schönberger and Cukier (2012), and Zikopoulos, Eaton, deRoos, Deutsch, and Lapis, (2012), we can assert several key characteristics that set them apart from more traditional, organised, structured and often single-source datasets. Specifically, big data can be distinguished from 'small data' in at least several main ways. First, in terms of the technical properties of big data, several aspects of which are frequently mentioned in the literature. These centre on various 'V's' (Kshetri, 2014). For instance, bigness in terms of its huge volume (i.e. the number of observations and variables), its velocity (or the speed with which data points accrue in or near real-time, as in the case of live-streaming video; Kitchin, 2014), and its varied nature (structured and unstructured). Big data can also be discussed in terms of its considerable scalability (data may expand rapidly in size), and the exhaustive and comprehensive scope of what the data captures (e.g. behavioural traces from an entire population within an organisation or system). To consolidate the sharp rise in publications over the last ten years, some reviews have sought to organise the complex connections surrounding big data, and the potential risks and benefits concerning its use. In terms of BOLD (big open linked data), for example, as many as nineteen organisational and systemic variables are relevant to understanding whether innovations and improved policy-making can result (Dwivedi et al., 2017).

The promise of data, particularly in relation to its 'big' varieties, has been promoted rapidly and heavily in recent years by various firms, commentators, and consultancies. The promised benefits typically come in several forms. At the most ambitious societal level of application, big data has been considered as a means for: learning how communities, governments and regions develop (Kshetri, 2014), studying political communication and citizenship participation (Gil de Zuniga & Diehl, 2017), and driving or improving commercial successes (e.g. Nunan & Di Domenico, 2015). At an organisational level, employers are promised novel insights and solutions that might enable them to identify measurable ways of improving financial and employee outcomes (Bania, 2015). These data-driven insights are claimed to enable employers to optimise infrastructure, operational processes, and managerial and strategic practices (Wang, Kung, & Byrd, 2018). As well as describing existing patterns of outcomes, big data proponents also claim therefore that the results may also make it increasingly possible to anticipate and predict future workplace trends and solutions, prescribing appropriate courses of action (Lytle, 2016). Despite embodying these promises and hopes, big data has inevitably thrown up new critical questions for employers too.

1.1. Big data in organisations: Ethics, embeddedness, strategy and risk

To date, theoretical development of the ethical issues surrounding

* Corresponding author.
E-mail addresses: thomas.calvard@ed.ac.uk (T.S. Calvard), d.jeske@ucc.ie (D. Jeske).

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big data and organisations has been largely neglected (Nunan & Di Domenico, 2015). Nevertheless, a number of frameworks and theoretical starting points exist that may be instructive for researchers and practitioners, and are developed further here accordingly. In terms of the general opportunities, challenges and unintended consequences arising from big data's socio-technical embeddedness in organisations and societies, these can be theoretically recognised by principles of actor-network theory (Latour, 2007), socio-technical systems approaches (Davis, Challenger, Jayewardene, & Clegg, 2014), and other, related social constructivist perspectives on technology and organising (Leonardi & Barley, 2010).

In strategic and economic terms, the resource-based view of the firm (e.g. Grant, 1991) and other strategic frameworks may also be helpful to identify the costs and benefits for organisations associated with big data efforts, such as the degree to which their efforts will generate the hoped-for insights that could contribute to a sustained competitive advantage. However, here we will consider more specifically the possibility of big data risks and accidents, such as data leaks and other misuses and mishandlings of information by employers and organisations. Risk analysis, and how best to apply it to information systems security, has long been a concern in information management, along with the importance of considering risk from the perspectives of various organisational stakeholders (e.g. Jayaratna, 1994). Greater consideration towards HR, managers and employees as users of big data is therefore another iteration of this holistic relationship between risk management and information security management (Soomro, Shah, & Ahmed, 2016).

1.2. Risk management and big data in human resources

In human resources (HR) practice, risk management and (big) data management intersect in a number of areas, most notably in terms of how HR and data risks and practices may result in or mitigate corresponding reputational or legal risks (Becker & Smidt, 2016). We wish to extend the arguments of Becker and Smidt (2016) by urging that they be applied more specifically to how big data is collected, managed and stored. From a risk management perspective, the use of big data may be related to levels of unpredictability in business contexts and the priorities around managing organisational and environmental uncertainty. Becker and Smidt (2016) do not explicitly pick up on big data as a source of risk or how HR practices could help mitigate big data risks in their review. However, several of their conclusions are pertinent to managing risks around big data in at least three main ways.

First and foremost, we suggest that big data actually reinforces the need for an overall informed risk management strategy and appropriate HR practices for preventing certain risks to individuals, employers and the organisation at large. HR functions and professionals have a key role to play here, due to the data they are responsible for managing internally. Through their responsibility for employee data, HR can participate in risk management and ensure the development and adoption of best practices when dealing with big data challenges that arise due to internal as well as external stakeholders and interdependencies (e.g. with data storage providers and consultants). Performance management and effective communication are two HR mechanisms noted by Becker and Smidt (2016) as ways of reducing risks associated with unethical or illegal behaviour. These risk management responses will unfold in important ways in the future, given that the monitoring of employees will far exceed previous levels due to simultaneous increases in both the breadth and depth of monitoring engendered by big data. Along these lines, ethical lapses in data sharing and curation, and the relationship of big data monitoring practices to whistleblowing and data leaks will likely be worthy topics of future research on big data, information management and HR (Kayes, Stirling, & Nielsen, 2007).

Second, HR has traditionally been at the forefront of ensuring employee health and safety, as reflected most recently in employee well-being agendas. Accordingly, Becker and Smidt (2016) recognize labour turnover and burnout as major HR risks, due to the negative impacts they can have on the individual and organisation. We would therefore argue that big data efforts within organisations represent an emergent risk factor in this area, as they may undermine employees' health and ability to maintain a healthy work-life balance, due to continuous and pervasive monitoring and the increased performance pressures and work intensification that could arise. Such outcomes can be reasonably assumed by extrapolating from the negative effects demonstrated by research conducted on electronic performance monitoring over the last thirty years (Jeske & Santuzzi, 2015; Karim, Willford, & Behrend, 2015). Currently, however, it is unclear how absenteeism versus presenteeism, or counter-productive work behaviours (e.g. manipulation of systems or recording devices by employees), relate to the implementation of internally-focused big data efforts. Future research should therefore certainly try to establish whether big data employee monitoring reinforces and exacerbates presenteeism and work-life conflict, and through which mechanisms and under which contextual conditions.

Third, Becker and Smidt (2016) also note risks arising in relation to staffing decisions, such as the decision to outsource HR or reduce headcount. Such decisions may then lead to new provider risks, disappointing costs savings due to the provider not delivering the predicted savings, and the loss of confidential information (Becker & Smidt, 2016). All of these outsourcing and workforce risks are inherently reproduced in big data collection efforts, which involve both internal and external stakeholders in the form of entities that replace internal analysts, data management services, and so on. Furthermore, as has been the case with the implementation of HR information systems (HRIS), associated risk analysis might need to cover security, legal and financial risks (Becker & Smidt, 2016). It is unclear, however, whether or not this approach is actually being adopted by organisations who pay third parties to collect data on their behalf from a number of different sources.

In sum, there appears to be greater risk cognizance in HR research building up over time (Becker & Smidt, 2016); however, it is currently unclear to what extent this is feeding into big data initiatives and the digital ecosystems of providers involved in these efforts.

2. Theoretical perspective

Normal accident theory (NAT; Perrow, 1984) is a conceptual framework we wish to draw on in the context of risk management. The focus of this framework is not on risk prevention; rather it deals with and is applied to the outcomes of 'data accidents', a phrase coined by Nunan and Di Domenico (2015) that extends NAT to reflect the heightened levels of complexity, tight coupling and catastrophic potential of big data ecosystems.

Like normal accidents but more so, these data accidents are defined in terms of their being less tangible, less predictable in terms of long-term consequences, more likely to remain unknown unless carefully detected, and due to the way in which they may emerge, impossible to prevent. The use of NAT is helpful here to understand the *inevitable* challenges employers may face when trying to regulate the use of big data in their organisations. Key to the theory is the recognition that accidents will eventually arise as a function of complex systems responsible for collecting big data. The 'system' here concerns the distribution and storage of big data, which may be enabled by multiple entities internal and external to the organisation, as well as various technologies. Nunan and Di Domenico (2015) therefore explicitly emphasize the importance of more proactive, careful design of data management mechanisms within organisations: "the ethical issues with big data lie not so much with its collection but with the weaknesses in organisational processes and systems that enable it" (Nunan & Di Domenico, 2015, p. 10).

Many physical and virtual work environments, for example, are merging via an increasing range of computerised devices and objects that have the capabilities to self-configure and link to each other using interoperable communication protocols. This generates big data about employees' behaviours and locations, reflecting part of a wider trend labelled the 'Internet of Things' (Li, Da Xu, & Zhao, 2015; Whitmore, Agarwal, & Xu, 2014), a network infrastructure not limited by location, supporting the seamless integration of physical and virtual objects within information networks (Kiritsis, 2011). As long as the devices have the means to communicate over the Internet, the data can be captured and transmitted, raising questions about its security.

Data accidents are therefore likely to arise as a function of both unanticipated and unfamiliar events occurring within the overall system, also referred to in NAT terms as its interactive complexity (Pidgeon, 2011). Big data is relatively new, so organisations currently still lack an extensive history of legal precedents to consult, while they may also lack knowledge of how such events may arise or how to recognise antecedents to critical failures. When employers collate information from different sources, the vulnerabilities that arise due to the number of actors and partners involved, internal and external to the organisations, may therefore combine in ways that lead to accidental data leaks. Some significant examples of accidental effects leading to catastrophic failures have been reported in organisations and are continuing to emerge, where the behaviour of one individual has an unexpected and far-reaching effect on the processes and operability of interconnected services (see Nunan & Di Domenico, 2015). The effects of such data accidents on employees depends on the extent to which they are directly involved in the data-driven decision-making. However, accidents that reveal personal information about individual employees or employee groups are highly likely to undermine trust, group cohesion and commitment to the employer.

Another key aspect of NAT concerns the recognition of tight coupling in predicting incidents (Pidgeon, 2011). In other words, rather than being sequential, related and observable, some interactions of systems and actors occur in tandem and independently from one another in a system (e.g. internal departments versus external data storage centres). A combination of organisational events taking place across coupled entities, while not problematic in its own right, may eventually lead, from small beginnings, to the emergence of catastrophic accidents. This complexity also means that when data accidents occur, a discrete culprit will not be readily identifiable. This lack of easily identifiable system weaknesses may further undermine employee trust in their employer and organisational and HR systems, devices and platforms that the employers provide them with.

Recognising these interdependencies and extensions of the tenets of NAT reflected in big data systems, as well as the related pitfalls of processing such big data, will be key for employers wishing to use such data for to improve work processes and employee and organisational effectiveness. Not only will data accidents be more likely to arise due to how complex systems operate in general, but there are also inherent risks around big data practices being compromised by the very same system that helps employers to generate the data and insight in the first place (Vaughan, 1999). It seems reasonable to assume that no one department or function such as HR can control the extensive flow or mass of big data (Rynes & Bartunek, 2017). The interdependencies created due to the nature of big data, particularly across external providers such as third party data centres, create new vulnerabilities and system-specific interactions that are hard to anticipate, resulting in data accidents as the new 'normal' predicted by NAT (Perrow, 1984). Based on this state of affairs, in the next section we therefore outline some new learning domains that employers face in the age of big data.

3. New lessons for employers

The following five sub-sections below summarise some of the main impacts that big data has had on information management and organisation, as well as areas of capability for employers and HR to focus their learning activities around. Many of these will be familiar in general terms, but equally, big data analytics raises the stakes for many organisations.

3.1. Responsible and democratic data sampling

The social, legal and ethical concerns and controversies around big data have created an urgent need for organisations to appreciate the *power* attached to the use of employee data, representation on analytic projects, and the inequalities (re)produced at work and in employment through big data-driven solutions. The inherently big, continuous, and automated aspects of big data create heightened risks of the associated technology becoming too deterministic, and even a tool that distances and silences organisational dissenters (Morrison & Milliken, 2000). Overreliance on big data algorithms, in the absence of contextual analysis, risks threatening employee agency and autonomy in situ. Greater appreciation is needed of big data and analytics becoming potentially undemocratic to the extent that their precise workings remain an obscure black box to those employees and stakeholders who can be affected by them in unforeseen ways. Only by designing systems imbued with more transparency, accountability and trust can stakeholders ensure that big data delivers on its promises to help tackle overarching challenges facing modern workplaces and under wider societal conditions. While it may be difficult, if not impossible, to prevent potential data accidents in an absolute sense (Nunan & Di Domenico, 2015), employers do have control over how they collect information in the future, as well as how they respond to accidents. As a result, there is significant merit in expanding existing, or implementing new, (digital) ethics and risk management programs so as to take account of the ethical and risk-related issues that may arise due to the use, production, analysis and storage of big data for an employer (e.g. Ferrell & Ferrell, 2011).

3.2. Preventative data risk management and data accident handling

As has been noted, relatively little is known about the risks that big data tools may generate when such data also enables employers to monitor and track union activity, infringe employee rights, and limit or manipulate employee voice within the modern workplace. Nevertheless, employers still have the option to prospectively and *preventatively* prepare their risk strategy in advance by consulting experts in the various departments dealing with ethical issues in HR, the legal domain, and marketing, among many other functions. Such pre-emptive cross-functional consultation will aid in exploring and reflecting on strengths and limitations of relevant legal frameworks for organisations, while drawing attention to many crucial big data ethical conundrums. In particular, risks and threats that emerge when data about employees is triangulated may affect incentives around internal whistleblowing and union activity, which may need to be identified and anticipated. A guided examination of legal assumptions and frameworks can therefore be the first step toward encouraging an informed discussion around how, when and why big data is collected and used. This may then lead to more proactive networking among organisational representatives responsible for employee legal affairs, data security and information management (e.g. HR, IT and marketing).

3.3. Reputational risk management

While not widely promoted by those advertising analytics solutions, big data is far from perfect, and it may require numerous iterations of methodological intervention to make sense of and gain helpful insight from what is essentially "very imperfect data" (Ducey et al., 2015, p. 557). This means that 'more data' is not necessarily giving employers more useful information at all, but can actually result in more noise, as well as requiring more demanding data screening and transformations than would be the case for structured, comprehensive, carefully collected and usually more complete (high-quality) data records. Ultimately, recommendations based on poor quality data are unlikely to result in optimal decisions and outcomes for employers or the employees themselves – and big data can exacerbate rather than eliminate these scenarios.

Crucially, and in line with NAT, we suggest that preventive risk management can only go so far. It is entirely possible that due to the complexities of what big data analytics could capture about organisations and their suppliers and customers, big data 'findings' will provide highly political and sensitive windows onto an organisation's systematic inter-dependencies with internal and external actors. This is information which may then be used to systematically cripple the business and also have a significant, negative impact on its reputation. Many existing risk management strategies will probably fall short of predicting these accidents, as the nature of new complexities are currently unknown and most likely indeterminable. However, this should not stop risk management and proactive strategizing at all levels of the organisation. If anything, these developments make these more critical in order to engender resilience and the ability to bounce back from critical or widespread infrastructure or system failures.

Accountability for claims based on big data analysis is one point that has been raised by Guzzo et al. (2015), an issue that once again points to the importance of careful data interpretation and decision-making (Toterhi, 2014). This is still one area where the promises of big data are still largely unknown: its value is nil, or less than, if big data findings lead to inaccurate or ineffective decision-making in the workplace. The work by Illingworth (2015) on discriminatory algorithms and by Kroll et al. (2016) on accountable algorithms provide further insight into the legal complexities when employers use algorithms in relation to big data analytics. In each of these two articles, a case is made for accountability and integrity, such that it is important to understand, declare and verify the computational processes and purpose specifications inherent in algorithms. The reputational damage inflicted by not being accountable for data leakages, or the promotion of algorithms that lead to discrimination, are therefore concerns that need to be considered to a much larger degree in every organisation.

3.4. Contextual awareness

The bigger the data, the more likely other contextual factors will come into play, such as political elements around participation in the workplace and social norms about who is supported to interact with whom. These may then operate as confounds and acerbate analytical issues such as validity threats (Whelan & DuVernet, 2015), a problem which big data shares with 'small' data efforts in terms of the reliability, accuracy, availability, and accessibility of the data (Harford, 2014; Roberts, 2013). Construct validity is particularly challenging to establish, as big data sets feature numerous different types of behavioural trace data, ratings, and physiological measures (Braun & Kuljanin, 2015), which need to be converted, combined and interpreted to create valid operational variables that reflect a clear construct meaning and clearly measure what they purport to assess. Areas in need of more guidance here include topics such as the rights and privacy of those providing information, the possibility of informational harm arising due to data use, and the use or misuse of publically available information (Boyd & Crawford, 2012; Fairfield & Shtein, 2014). These concerns are also reflected in fears that predictive modelling supported by big data analytics will put limits on individuals' ability to act with acceptable degrees of freedom. This will occur as they are restricted or penalised before they engage in certain behaviours (Mayer-Schönberger and Cukier, 2012), severely limiting individual autonomy and free will due to what the data around one's past behaviours suggest.

3.5. Ethics to understand and manage data risk

As the new role of data scientist is still taking shape, the risk is that important ethical lessons will continue to be missed out. The ethical reasoning and appropriate education of those who collect and contribute to data are two main developmental issues to begin with (Dekas & McCune, 2015). Nevertheless, the challenges associated with managing ethical dilemmas are not unique to data science, or specifically relevant to big data alone. In relation to the impact of new technologies more generally, for instance, Ferguson, Thornley and Gibb (2016) have examined how library and information professionals navigate ethical dilemmas. Their overview of ethical issues and dilemmas provides a nice overview of potential tensions and pitfalls. Such tensions include contradictory demands for information access versus censorship, information access versus interests of individuals (also concerning harm to individuals, right to consent and privacy), and professional ethics versus organisational ethos/requirements (Ferguson, Thornley, & Gibb, 2016). Explicit, codified guidelines to balance those dilemmas are often missing in organisational settings.

Ethics and collaborative decision-making will become more and more important for professional analysts and managers collecting employee data, followed by their interpreting, analysing and triangulating of results that identify individuals or teams within organisations. Often, those providing data (e.g. employees), and those tasked with the analysis (e.g. analysts, HR managers), will be relatively unaware of each other's perspectives. Furthermore, in some cases, decision-makers may have no legal precedents to help them determine which way forward is considered most ethical and morally responsible (Fung, 2015; Poor & Davidson, 2016; Zwitter, 2014). In line with Gil de Zuniga and Diehl (2017), we suggest therefore that data analysts in various organisations ought to carefully report how they handled ethical concerns that arose during their analyses in a timely fashion – in order to ensure transparency of the process, accountability and replicability of the analyses.

4. State of existing big data research, limitations and future research directions

In their systematic review of 219 papers on big data from 152 journals published during 2009–2014, Frizzo-Barker, Chow-White, Mozafari, and Ha, (2016) find an enthusiastic growth of interest in the topic. However, the existing landscape of big data research remains in its early stages, with empirical studies still rising to catch up with conceptual work in trying to map the tools and business implications of the general domain. General benefits, challenges and risks of big data are therefore identified (Raguseo, 2018), but arguably still need to be unpacked more in relation to specific fields and functions within organisations, such as HR. From a risk and accident perspective, we do know that organisations are likely to vary in how risk-seeking or risk-averse they are in engaging big data. A study of Korean firms, for instance, suggests that organisational intentions to adopt and acquire big data tools can vary, depending on their benefit perceptions based on existing experiences using externally sourced data (Kwon, Lee, & Shin, 2014).

In some areas, progress is being made where research is linking big data to more specific accompanying technological trends and emerging technologies important to its effective use (Yaqoob et al., 2016). For example, Gupta, Kar, Baabdullah, and Al-Khowaiter, (2018), in a systematic review, found 18 papers on big data and cognitive computing, the latter domain describing processes whereby machines will independently assess data at levels too large for human actors to process. However, more research is needed to understand how to make a safe and sustainable transition to widespread cognitive computing (Gupta et al., 2018), and how it will affect employees, risk management and the nature of human interventions concerning big data in the workplace. Similarly to cognitive computing, Hashem et al. (2015) review work on cloud computing and big data, noting how cloud computing has enabled the rise of big data as an organisational concern. While cloud computing provides an infrastructure for virtually storing and sharing big data, research still needs to assess how HR and other organisational functions work with cloud vendors to address competing challenges, such as availability, integrity and governance (Hashem et al., 2015).

A key limitation of existing research, but also a potential opportunity for future research, concerns recognising more explicitly that most big data is highly unstructured and noisy, and that this requires studies into changing statistical mind-sets and analytical tools in organisations (Gandomi & Haider, 2015). In the case of HR, and many other fields involving information management, this necessitates a move away from traditional sampling-based statistics and significance testing towards a process underpinned more by the efficient and responsible use of algorithms.

More research is therefore also needed to systematically diagnose a particular organisation's big data analytic capabilities. Emerging frameworks such as Grossman (2018)Grossman's (2018) Analytic Process Maturity Model (APMM) in information management, and Dulebohn and Johnson (2013)Dulebohn and Johnson's (2013) metrics and decision support classifications framework in HR, offer promising possibilities in this regard. This is particularly important as organisations are unlikely to be equally proficient in all areas of big data processing, such as risk management or modelling, and organisations of different sizes, ages, and strategic positions may also have different levels of maturity in how comprehensively they can use big data.

The HR and management literature on big data appears to be smaller than the wider information management and information systems literatures. However, it shows the same rising emergence of case studies, critical commentaries and reviews seeking to map the domain's general organisational adoption challenges, benefits and risks (e.g. Angrave, Charlwood, Kirkpatrick, Lawrence, and Stuart, 2016; Rynes & Bartunek, 2017; Rasmussen & Ulrich, 2015). Marler and Boudreau (2017) found only 14 peer-reviewed articles on HR analytics, and note the lack of grounding in existing HR topics and frameworks as well as the slowness of adoption. Nevertheless, as big data analytics matures as an innovation, cross-fertilization of more specific theories and frameworks across HR and information management would seem a worthwhile goal.

5. Concluding remarks

It is unlikely that organisations can rely solely on existing risk evaluation and prevention strategies to deal with data accidents. On the one hand, data accident-handing strategies can focus on employee upskilling to meet new ethical, data security and data collection challenges. On the other hand, such strategies will need to also involve system-wide audits to be able to trace both complex and tightly coupled interdependencies to identify the most likely contributing factors. Identifying these may be the first step toward monitoring patterns of vulnerabilities and to reduce the likelihood of reoccurrence. The objective for organisations is therefore to ensure that specific data accidents are made more known, less ambiguous and more traceable. Such cooperation and coordination will inevitably require a closer interaction of internal and external stakeholders involved in big data efforts, including HR and its relationships with employee data and information. In sum, if the goal is to generate insight from employee data for one organisation, the benefit of carefully controlled in-house data efforts and risk management can be mobilised to outweigh and combat the costs of coordination and emergent vulnerabilities arising from big data.

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