Power Perspectives on Data Visualization in Workforce Analytics

Problem-focused workforce analytics[1] with advanced data visualization techniques[2] can significantly improve managers' ability to achieve operational and strategic objectives through more effective workforce management (Huselid, 2018). Yet, while offering a powerful advancement in rationalization and speed in decision-making and communication processes, workforce analytics can also marginalize human reasoning, devalue managerial decision-making competencies, and decrease the level of autonomy managers have to make their own decisions (Giermindl et al., 2021). When managers over-rely on the decisions prescribed by workforce analytics and communicated through data visualization displays, they run the risks of making themselves redundant (Giermindl et al., 2021). These aspects may unconsciously lead managers to distrust information and data visualization produced in the process of workforce analytics and deem the process of workforce analytics unnecessary. Indeed, some senior executives don't require or expect workforce analytics from their HR professionals (Bassi, 2011), while organisations are struggling to deliver strategic outcomes despite access to endless employee statistics (Deloitte University Press, 2017).

Thinking about the psychological discomfort, fears of incompetency and threat to power that managers may encounter as they are presented with smart and interactive data visualization displays brings us to the question of why effective data visualization may not be well-perceived by the decision-makers it serves to support. A possible answer looms as a puzzle: maybe it is not effective (at reaching its goal) precisely because it is so effective (persuasive and powerful) and threatening to those in power. This study looks at data and information visualization as a powerful tool that may shatter decision-makers' confidence about their own role in the business problem and decision-making process. It takes a power perspective on why effective visualization may be distrusted and rejected by decision-makers. Through an experiment, the study explores whether progressive data visualization displays are perceived as a power threat by decision-makers, and how decision-maker participation in the workforce analytics process and their individual trait dominance may affect their distrust response to the analytics visualization. By drawing on the research in human perception, distrust, power and dominance, the study addresses the gap in the workforce analytics and data visualization literatures as to why effective information visualization may stumble implementation of workforce analytics.

This study addresses the call for more research on theory-based relationships and the role of contextual factors in adoption of predictive workforce analytics (Gurusinghe et al., 2021).

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[1] Following Huselid (2018), I use the term 'workforce analytics' to emphasize the focus of analytics on understanding and enabling the impact of the workforce in general (not limited to the HR function alone) on organizational success. The literature offers a variety of terms referring to analytics of human resource data, i.e. HR analytics, Big Data analytics, people analytics, talent analytics, human capital analytics, HR metrics. These other terms are more specific or embrace a particular perspective, compared to a more overarching and general term 'workforce analytics'. Although I use the term 'workforce analytics' for focus and consistency in this paper, I draw on the existing research and theory related to all other variations of human resource analytics terminology.

[2] The term 'advanced data visualization techniques' refers to a move from descriptive to inferential (predictive, prescriptive and autonomous) workforce analytics as a sign of increased effectiveness and maturity of the workforce analytics process (Giermindl et al., 2021; Gurusinghe et al., 2021; Huselid, 2018).

While the literature offers some insights on the role of technological, organizational and environmental factors that affect workforce analytics adoption (Gurusinghe et al., 2021), little attention has been paid to psychological factors that promote or impede the implementation process. This study contributes to a small but growing body of quantitative empirical research on workforce analytics by exposing the role of decision-makers' power motives in accepting or rejecting workforce analytics visualization, and the mitigating effects of individual trait dominance and participation in the workforce analytics process. While importance of decision-makers' buy-in and co-creation in workforce analytics has been recognized in theory (Al-Kassab et al., 2014) and proved to be effective in practice (Coco et al., 2011; Rasmussen & Ulrich, 2015), this is the first study to provide a theoretical explanation for this phenomenon and test it empirically in an experiment.

Workforce analytics

Workforce analytics refers to "processes involved with understanding, quantifying, managing, and improving the role of talent[3] in the execution of strategy and the creation of value" (Huselid, 2018, p. 680). It is concerned both with metrics (e.g., what do we need to measure about our workforce?) and analytics (e.g., how do we manage and improve the metrics we deem to be critical for business success?) (Huselid, 2018). Most common relevant alternative concept is that of HR analytics defined as "an HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organisational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making" (Marler & Boudreau, 2017, p. 15). Compared to alternative terms used in the literature, the concept of workforce analytics encompasses a focus on understanding and enabling the impact of the workforce on organizational success, without restricting it to the HR function alone (Huselid, 2018). There is a consensus among scholars that effective workforce analytics should start with a clearly defined question to solve a particular business problem, and then data is collected, analyzed and visualized to support in decision-making (Huselid, 2018). The goal is to move beyond descriptive reporting to data-driven future-oriented decision-making (Huselid, 2018; Marler & Boudreau, 2017).

The literature on workforce analytics highlights the critical role of HR professionals in leading this process and the associated challenges (Bassi, 2011; Huselid, 2018; Marler & Boudreau, 2017; Minbaeva, 2018). Although HR professionals collaborate with the IT department and statisticians to collect, analyze, and present relevant data, it is generally assumed that the rest of the key stakeholders and decision-makers are on the recipient end of the workforce analytics results. While successful cases of workforce analytics (Coco et al., 2011; Rasmussen & Ulrich, 2015) and theorizing on effective information visualization for managerial decision-support (Al-Kassab et al., 2014) suggest that it is critical to involve key decision-makers in the workforce analytics process from the very beginning, the literature doesn't offer a theoretical explanation on why this is important for successful workforce analytics implementation.

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[3] The term 'talent' refers to a firm's entire workforce, as per the North American context (Huselid, 2018).

Data and information visualization in the context of workforce analytics

Data and information visualization refers to graphic display of quantitative and qualitative information about employees (i.e. demographics, tenure, skills, promotion record, interview notes, performance reviews, etc.) collected and analyzed in the process of workforce analytics. For the purposes of the study, the terms are used interchangeably. Data visualization is defined as "visual representation of "data", defined as information which has been abstracted in some schematic form, including attributes or variables for the units of information" (Friendly & Denis, 2001, p. 2). Information visualization is defined as visual representations of the semantics, or meaning, of information (Chen, 2005). In contrast to data or scientific visualization, information visualization generally deals with non-quantitative, nonspatial, high-dimensional and more abstract data (Chen, 2005). While information visualization techniques include displays typical for data visualization, such as line, bar and pie graphs, flow charts and density lines, they also include distinct features such as pictures, quotes, metaphors and other textual information. Al-Kassab et al. (2014) suggested that information visualization can support managers as a communication channel, a knowledge management tool and a decision-support instrument.

While visualization acts as a catalyst for interpretation of information, the process of interpretation is influenced by existing knowledge and cultural background of the perceiver (Al-Kassab et al., 2014). Information visualization can accelerate perception and provide insight (Al-Kassab et al., 2014), spark creativity and generate new ideas by stimulating intuition and imagination (Platts & Tan, 2004), and enhance decision-makers' experience with the data and information at the core of a business problem that requires attention. However, it can also diminish decision-making progress and damage user attitudes with inappropriate level of complexity (McLain & Aldag, 2009), heighten decision-making biases by silencing critical uncertainties and cherry-picking of relevant information (Al-Kassab et al., 2014). Moreover, influential information visualization displays have a capacity to elevate distrust due to threat of power loss in the very decision-makers it is called to serve.

Distrust of data and information visualization

The concept of distrust should be understood qualitatively different from the concept of trust. This notion stems from a growing consensus in the trust literature that trust and distrust as separate and distinct constructs, with unique antecedents, development processes and consequences (Bijlsma-Frankema et al., 2015; Guo et al., 2017; Lewicki et al., 1998; Sitkin & Bijlsma-Frankema, 2018). The distinction is most eloquently captured in a contrasting statement by Lewicki et al. (1998) in that "[l]ow distrust is not the same thing as high trust, and high distrust is not the same thing as low trust" (p.444). In the context of information visualization (InfoVis), Mayr et al. (2019) defined distrust as "the user's expectation that the InfoVis aims to disinform or harm him" (p. 28).

Concerns about both trust and distrust of data visualization by managers becomes especially relevant when there is some degree of risk associated with its further use. Risk refers to uncertainty associated with digital information, i.e. it's completeness, consistency, lineage, currency, credibility, subjectivity, and interrelatedness (Mayr et al., 2019). The sense of risk especially heightens if information perceiver is "*vulnerable* to suffer some kind of loss if he or she relies on it [digital information] (e.g. taking a wrong decision, humiliation by others), but also *depends* on the information" (Kelton et al., 2008, p. 365). The issue of risk and visualization of uncertainty appears to be relevant both for trust and distrust to data visualization. While some visual analytics researchers theorized on the mediating role of data visualization in the relationship between uncertainty propagation and trust building (Sacha et al., 2016), others suggested that visualization of uncertainty may in fact increase distrust for users with limited knowledge of statistics (Mayr et al., 2019). According to Mayr et al. (2019), the link between visualization of uncertainty and trust has not been studied empirically. Moreover, no empirical research on the relationship between data visualization in workforce analytics and decision-maker distrust has been found by this author. Current study provides a novel contribution to the literatures on data visualization and workforce analytics by exploring the role of power and decision-maker's trait dominance for distrust of data visualization.

The literature on trust in information visualization (Mayr et al., 2019) highlights the role of user perceptions in the processes of elaboration about trustworthiness of data, its visualization, and how much trust (or distrust!) the user may develop for a particular piece of data or information visualization. While the user's trust perceptions will be largely driven by subjective evaluation of the quality and reliability of visualized information (Mayr et al., 2019), the user's distrust perceptions will most likely be driven by assessment of threat posed by the visualized information. In the context of powerful individuals, i.e. managers, key stakeholders, decision-makers, smart and progressive data visualization displays may trigger distrust perceptions because powerful and persuasive message displayed through data visualization in which they lack ownership, heightened by individual trait dominance, may make such powerful individuals feel less powerful, less credible and useless.

Theoretical perspectives on decision-makers' resistance to effective data visualization

Effective implementation of workforce analytics requires building trust and buy-in from relevant decision-makers, which involves embracing and overcoming managers' resistance to change and heavy reliance on intuition in decision-making (Coco et al., 2011). Marler & Boudreau (2017) emphasize the need for HR professionals involved in the process of workforce analytics to build credibility among the key decision-makers by involving them in the process from the very beginning and building a network of supportive stakeholders across and up the company hierarchy. However, the literature does not provide an adequate theoretical explanation for decision-makers' resistance and distrust of data-driven visualization.

Senior managers tend to reject data that threatens their existing beliefs (Rasmussen & Ulrich, 2015). Cognitive dissonance theory (Festinger, 1957) provides one explanation as to why some data visualization techniques may be rejected by key decision-makers or why they may avoid implementation of workforce analytics altogether. In his theory of cognitive dissonance, Leon Festinger (1957) essentially argued that two pairs of cognitions relevant to one another are dissonant if the opposite of one cognition follows from the other. Since the experience of cognitive dissonance is psychologically uncomfortable, it motivates an individual to minimize the degree of dissonance, which is usually achieved by avoidance of information that is likely to increase dissonance (Mills & Harmon-Jones, 1999). In this sense, the theory of cognitive dissonance helps us understand why some senior executives, when presented with effective data visualization reports that are inconsistent with their beliefs, intuition or past decisions related to the business case, may resist the course of action communicated by data visualization in the process of workforce analytics. However, this theory does not help us understand why these decision-makers may scrutinize and distrust data visualization of workforce analytics even when data visualization is in agreement, or at least not in conflict, with their beliefs, intuition, and past decision.

To address this shortcoming, I take a power perspective to explain why effective data visualization may be treated with suspicion and scrutiny by people in power. Power is defined as assymetrical control over another person's outcomes (Fiske, 1993). In essence, what makes individuals feel powerful is having control over outcomes. In the context of workforce analytics, the outcomes would be the strategic decisions developed as a result of accurate problematization, data collection, analysis, visualization and communication. Hence, power would imply being in control of data and information visualization displays that suggest these decisions. Building on this perspective, I elaborate on a set of hypotheses below.

Effective visualization is a powerful tool to convey multi-dimensional data and information. Workforce analytics scholars recognize the benefits of advanced data visualization techniques (i.e. interactive, dynamic, transparent about uncertainty, visually appealing) beyond traditional forms of data presentation (i.e. statistical summaries) for managerial decision-making (Al-Kassab et al., 2014; Oswald et al., 2020). Due to its persuasive capability to instill a particular message in the mind of the perceiver in a matter of seconds and influence the decision-makers' perceptions of the situation, advanced data visualization displays may appear as a source of threat to the decision-makers in power. This is because they may perceive that they are no longer the person who makes the decision – the decision is already suggested by the effective visualization. In other words, powerful people may feel loss of ownership in the decision-making process, when confronted with a powerful data visualization and if they were not involved in co-creation of the story.

H1: Decision-makers will distrust an advanced information/data visualization (i.e. inferential) more than a traditional information/data visualization (i.e. descriptive).

Information and data visualization displays serve as the messengers of critical information and suggested course of action in the workforce analytics process. Managers may perceive the decision-suggesting message of data visualization as a power threat unless they have been meaningfully involved in the workforce analytics process from the beginning. This power threat stems from a sense of lack of ownership in the decision-making process and feeling deprived of autonomy to arrive at their own decision. Consequently, to avoid the risk of losing influence and credit for successful solution, people in power may distrust powerful data visualization and stumble progress in the workforce analytics process.

H2: Decision-makers will distrust an advanced information/data visualization less, if they have participated in its creation.

Individual differences play an important role in shaping trust perceptions (Mayr et al., 2019). For example, individuals with a higher need for cognition (Cacioppo & Petty, 1982) are more influenced by a quality of arguments and less by emotional aspects of information. It is only fair to assume that individuals traits also play a role in developing perceptions of distrust. For example, powerful people with dominant personalities may be even more likely to experience a sense of threat and distrust to information and data visualization in the workforce analytics process. Trait dominance is associated with self-confidence, assertiveness, task-orientation, ambition, and desire for status in interpersonal relations (Gough, 1987). Individuals with dominant personalities seek power and leadership attainment (Dyson et al., 1972; Mudrack, 1993). They pursue social roles and environments where they can enact their desire to be in charge of situations and people, and have personal status recognized by others (Operario & Fiske, 2001). Empirical research suggests that individuals with dominant personalities exercise negative judgmental biases and react negatively to those who appear threatening and challenge their status, yet positively to those who appear non-threatening (Operario & Fiske, 2001).

H3: Compared to decision-makers with non-dominant personalities, decision-makers with dominant personalities will experience:
(a) higher levels of distrust in advanced information/data visualization, if they have not participated in its creation;
(b) higher levels of trust in advanced information/data visualization, if they have participated in its creation.

Method

This study is conducted through an experiment. The experiment consists of a 3-hour role-play game with a group of MBA students. 60 students are randomly assigned to four experimental conditions: 1) traditional visualization + no participation; 2) advanced visualization + no participation; 3) traditional visualization + participation; 4) advanced visualization + participation. Each group consists of 15 randomly assigned students and is provided with the same business case scenario: “Your organization has problems with employee engagement. Your group has been set up by the CEOs as a workforce analytics task force to collect relevant employee data, analyze it, and visualize a solution to this problem.”

In each group: 5 students are randomly assigned the role of line managers (decision-makers) who are responsible for reporting the final solution to the CEOs, 5 students are randomly assigned to the role of HR professionals that conduct workforce analytics, and 5 students are randomly assigned to the role of employees. The employees are each given a pre-written scenario that describes their tenure with organization, work attitude and problems to meaningful engagement. The script of employee scenarios is the same across all four experimental conditions. The line managers in each group are primed to feel in power and responsible for resolving the problem of employee disengagement by emphasizing the number of complaints received from the customers on poor quality of service provided by employees, the decreasing sales figures, and the need to reporting a solution to the CEOs.

Before the start of the game, all participants fill out a survey to assess their demographic information, level of experience with data visualization techniques and individual trait dominance. Each experimental condition is given a frame to approach the task:

In group 1 (traditional visualization + no participation), the HR professionals are encouraged to survey/interview the employees to collect relevant information, analyze it and present it in the form of descriptive table to the line managers. The line managers are discouraged from participation in the workforce analytics process and instead are loaded with alternative assignment. At the end of the 3-hour session, HR professionals report to the line managers the results of workforce analytics in a table format with the focus on descriptive statistics.

In group 2 (advanced visualization + no participation), the HR professionals are encouraged to survey/interview the employees to collect relevant information, analyze it and present it in the form of advanced graphical design (inferential focus) to the line managers. A statistician is involved to help the HR team develop an appealing-looking, predictive graphical design. The line managers are discouraged from participation in the workforce analytics process and instead are loaded with alternative assignment. At the end of the 3-hour session, HR professionals report to the line managers the results of workforce analytics in advanced visualization format with the focus on inferential statistics.

In group 3 (traditional visualization + participation), the HR professionals are encouraged to survey/interview the employees to collect relevant information, analyze it and present it in the form of descriptive table to the line managers. The line managers are encouraged to participate in the workforce analytics process. At the end of the 3-hour session, HR professionals report to the line managers the results of workforce analytics in a table format with the focus on descriptive statistics.

In group 4 (advanced visualization + participation), the HR professionals are encouraged to survey/interview the employees to collect relevant information, analyze it and present it in the form of advanced graphical design (inferential focus) to the line managers. A statistician is involved to help the HR team develop an appealing-looking, predictive graphical design. The line managers are encouraged to participate in the workforce analytics process. At the end of the 3-hour session, HR professionals report to the line managers the results of workforce analytics in advanced visualization format with the focus on inferential statistics.

After the game ends, all participants fill out another survey to assess their power motives, level of threat experienced by the data visualization display and degree of distrust or trust in the decision suggested by the visualization display. For all variables surveyed, validated measures will be used if available, or question items developed if validated measures not available. Results will be analyzed across the four conditions to test the three hypotheses.

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