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Giving Employees a Voice in Times of Digital Transformation: Modelling Employee Representation Voice in Algorithm-Based Decision-Making**

Abstract

Digital transformation goes hand in hand with profound changes to company structures. One aspect of digital transformation are algorithm-based decisions which strongly affect decision-making processes in general but also those between the company and employee representatives. This changes where employee representation can be introduced in decision-making, as well as how it is implemented and what competencies are required to do so. This conceptual article looks into how employee representation voice can be kept alive in organisational algorithm-based decision-making processes. To do this, employee (representation) voice will be derived from the German co-determination model. Analogue decision-making is then initially described as a social negotiation process, and modelling is used to show how it is linked to sensemaking in order to back up this claim. In contrast, it is highlighted how algorithm-based decision-making influences this analogue process. To face the resulting changes and challenges, the concept of "big judgement" is described. This concept proposes both structural problem-solving approaches as well as employee representative qualification requirements to provide scope for employee representation voice in algorithm-based decision-making and to avoid a culture of silence.

Keywords: employee representation voice; decision-making; sensemaking; algorithm-based decision-making; big judgement
(JEL: D79, J53, L20, O33)

Introduction

By using digital technologies, working environments are currently undergoing a dramatic change, and the field of human resources (HR) is experiencing a radical transformation. The software provider Precire Technologies, for instance, is creating personality profiles by using algorithm-based voice analysis. They promise their customers more objective and fair recruiting, employee communication and customer enquiry processes by adapting the analysis results (PRECIRE Technologies GmbH,

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n. d.; Tangens, 2019). The personal interview as a focal point of the exchange with the two-way expression of interests and ideals is coming under pressure as HR managers are increasingly dispensing with it (Peck, 2013) and replacing it with algorithm-based chat bots (Ryan, 2017). According to Microsoft, rational HR management could be established by using Workplace Analytics, a software service which is supposed to ensure comprehensive and objective involvement in the working and collaborative behaviour of employees (Microsoft, n. d.). What Microsoft hereby soberly describes as an efficiency gain, however, is, for Manokha (2020), nothing less than a "process of the transformation of human workers into things with objective indicators such as productivity levels, physical shape, cognitive characteristics and various aggregates of these measures that compute a comparative worth of each employee with respect to other." (p. 550) Within the scope of organisational network analysis (McDowell et al., 2016), the role of individual employees in complex social hierarchies is modelled, and their behaviour is predicted right through to breaches of the law (Skyrius et al., 2018). Here, we are talking about fully automated processes that do not provide for employee participation or representation.

The algorithm-based processing of mass data in the workplace increasingly reveals employee preferences and performance data (Couldry & Powell, 2014; Brennen & Kreiss, 2016). Employees are becoming more transparent and are fragmented into a string of individual data which can be analysed separately and optimised in the form of management processes, at least according to the technological optimists – the big data evangelists (Christin, 2017). Attracted by an increase in efficiency and new fields of business, companies are willing to invest highly in digital (HR) solutions (Sharma et al., 2017) – often even if the HR managers responsible have a critical personal view of them (KPMG, 2015).

However, the introduction of new technology not only leads to increased efficiency but, at the same time – often unintentionally – reorganises working conditions and relationships between employers and employees (Haipeter, 2020). A reduction in the quality of interpersonal relationships (Briône, 2017) through to a new interpretation of the employer-employee social contract (Obushenkova et al., 2018) are conceivable consequences of an arrangement that channels communication between individuals using technology and increasingly organises decision-making processes by including big data and these developing algorithms.

For this reason, this paper aims to research the question, "How can employee representation voice be modelled in organisational algorithm-based decision-making processes?" Within the scope of this article, the challenges for co-determination itself rather than for the employees (such as possible loss of jobs, changes in the quality of tasks, etc.) will be focused on, similar to the distinction made by Spindler and Schank (2020). The research question will be explored and answered by doing the following: (1) describing an integrated understanding of the employee (representation) voice, based on the German co-determination model; (2) describing decision-making, with the assistance of sensemaking and sensegiving, as a social negotiation process and working out what challenges might arise alongside this process from algorithm-based decisions; (3) furthermore, problem-solving approaches will be outlined which aim to avoid a potential moral muteness or culture of silence (Verhezen, 2010) and to support and enable employee representation and voice.

Employee Representation and Voice in the Age of Digital Transformation

Employee Representation and Employee Voice

From the literature, it is clear that a vast array of research proposals can be taken into account under the concept of employee representation. These range from formal types of co-determination, such as board-level employee representation in Germany (Fauver & Fuerst, 2006; Rosenbohm & Haipeter, 2019), through to less formal, unelected forms of employee representation (Charlwood & Terry, 2007). In this article, the definition of "employee representation" is based on the more formal understanding (Müller-Jentsch, 2014; Page, 2018) that becomes apparent in the context of co-determination in Germany. Foreign interest in the concept of co-determination in Germany appears to be growing, whilst in Germany, it is occasionally called into question (Berger & Vaccarino, 2016; Oberfichtner & Schnabel, 2019; The Economist, 2020). And yet the forms of co-determination in Germany and Austria have a much stronger legal basis compared to the rest of Europe (Fauver & Fuerst, 2006; Frege, 2002; Rosenbohm & Haipeter, 2019). Thanks to the strong connection with employees and their operational practice, co-determination in Germany can contribute within their right to have a say – their voice – towards better decision-making in companies (Bartölke et al., 2006; Fauver & Fuerst, 2006).

The German concept differentiates between (1) external co-determination, which includes the work of trade unions or political influence on employee representation (Althammer & Lampert, 2014; Müller-Jentsch, 2014); (2) corporate co-determination, which includes the co-determination of employee representatives on the supervisory board under company law (Althammer & Lampert, 2014; Deutscher Bundestag, 2014); and (3) operational co-determination which is firmly established in the German Works Constitution Act (BetrVG) and describes co-determination in terms of collective agreements and labour laws in companies (BMAS, 2018; Deutscher Bundestag, 2014). In this article, employee representation refers to operational co-determination. It plays a key role in the implementation of legal protection for employees as it enables the organisational details and great diversity of company structures to be taken into account (Althammer & Lampert, 2014). In the case of the concept of operational co-determination, employee representation within the company is provided by a works council that is elected by the staff (cf. §§ 1, 7 BetrVG; Bartölke et al., 2006).

The size of the company has a considerable influence on the co-determination structures (cf., e.g., §§ 9, 38 BetrVG[1]; Charlwood & Terry, 2007; Marsden, 2015). This work focuses on large concerns in which so-called qualified co-determination (Baum-Ceisig & Osterloh, 2011), also referred to as co-management (Müller-Jentsch & Seitz, 1998), is particularly common (Frege, 2002; Hocke, 2012). This qualified co-determination stands out for its relatively high degree of professionalism when collaborating with company representatives, for example, through particularly well-established and assertive co-determination structures, highly qualified employee representatives, and conceptional and strategic cooperation, e.g., in the case of proposed changes (Dombois & Holtrup, 2015; Minssen & Riese, 2006; Minssen, 2019).

The composition of the works council must adequately reflect the heterogeneity of the staff (cf. §§ 13, 15 BetrVG; Bartölke et al., 2006). This implies that the available professional (digital) competencies within the works council, according to the department and level of training in the company and the degree of digitalisation in the firm, are highly varied. More than three-quarters of German works councils recognise an increased need for qualification, instruction and advice in order to be able to keep pace with digitalisation and digital transformation (Haipeter, 2020). In addition, this increasing need for qualifications appears to be crucial to maintain the voice of the qualified co-determination at the same level.

The concept of the employee voice is highlighted from the professional perspectives of industrial relations (IR), organisational behaviour (OB) and human resource management (Wilkinson et al., 2020). However, employee voice is described differently from each of the three perspectives (Nechanska et al., 2020; Wilkinson et al., 2020), as is very clearly elaborated by Wilkinson et al. (2020). From this, we can see that the understanding of the employee voice from the point of view of IR is of a collective and confrontational nature and opposes managerial positions. Blue collar workers are specially protected and represented. On the contrary, in research into OB, the individual is in the spotlight, management too becomes a target group, and where the employee voice can be included, it is considered to be an advantage for the company (Wilkinson et al., 2020). However, to apply the IR and OB understandings of employee voice to employee representation, at least in the sense of the underlying qualified co-determination here, both perspectives – independent from each other – fall short. Although employee representation advocates collective interests, it also takes into account the interests of middle

1 § 38 BetrVG sets out, for example, that in the case of 200–500 employees, the release of a works council member is required. Further individual tiers follow up to 9,001–10,000 employees, in which case 12 released works council board members are provided for. For each additional fraction of 2,000 employees in a company, a further member shall be released.

management and white-collar workers (Bartölke et al., 2006; Marsden, 2015) and therefore addresses both target groups suggested by IR and OB. Furthermore, it not only presents itself in formal contexts but also interacts in informal contexts (Dombois & Holtrup, 2015). As elected representation and with the scope of influence outlined here, it appears obvious that the antithesis of employee representation voice is not an exit (leaving the company – as suggested by IR (Wilkinson et al., 2020)), but silence (failure to comment in decision-making processes – as suggested by OB (Wilkinson et al., 2020)). Hence an integrated understanding of IR and OB employee voice is necessary (Nechanska et al., 2020; Wilkinson et al., 2020) to meet the requirements suggested by qualified co-determination.

A further distinction that can be made is that the voice of employee representatives can be generally understood as an indirect form of employee voice (Kim et al., 2010). As has already been mentioned, qualified co-determination operates on a level playing field with company representatives. It has sufficient resources to design and monitor strategic projects (Minssen & Riese, 2006; Müller-Jentsch & Seitz, 1998), which in turn are associated with problem-solving approaches, innovations and improvements for the company (Bartölke et al., 2006; Luhmann, 2018). This is an understanding that is relevant to decision-making between the employee representation and the company representatives. In the following, employee representation voice is, therefore, an element of indirect employee voice and to be understood as the scopes of action and options of the qualified co-determination to be included in the company decision-making processes.

Digital Transformation, Algorithms and Big Data

Based on the approaches of Spindler (2020) and Wolf and Strohschen (2018), a distinction is made between the concepts of *digitalisation* and *digital transformation*.

On the one hand, digitalisation pursues a technological approach, which involves the transfer of analogue information and processes into digital data and processes (Brennen & Kreiss, 2016; IBM Institute for Business Value [Eds.], 2016). On the other hand, it takes an efficiency-driven perspective, which recognises computerised data, algorithms and programmes above all as an important part of process optimisation (Gobble, 2018; Schallmo & Williams, 2018). So, first and foremost, digitalisation signifies a shift within known business areas towards more technology-based and supposedly more rational actions (Spindler, 2020; Spindler & Schank, 2020).

Digital transformation, on the other hand, characterises the fundamental change from added value, organisational structures and collaboration (Carlsson, 2018; Reis et al., 2018; Schallmo & Williams, 2018) and is described as the new industrial revolution (Bogner et al., 2016). So, whereas digitalisation is to be subordinated to a demand for efficiency, digital transformation sets new benchmarks and is no longer to be seen as an efficiency tool but as an elementary and (alongside analogue components) equal part of the added value of a company (Spindler, 2020). These profound changes will have an influence on the organisational structure of employee representation (Bialeck & Hanau, 2018; Minssen & Riese, 2006), although, in the past, the latter was able to gain experience in industrial turnarounds (Marsden, 2015).

The new levels of connectivity associated with the expansion of spatial limits and acceleration in many areas of work and life (Klotz, 2018; Kuusisto, 2017) are characteristic of digital transformation. For example, Kuusisto (2017) states, "The major impact of digitalization on organizations is that information is more accessible and transparent" (p. 347). Whereas previously only limited information and knowledge were available to a limited group of people, digitalisation and digital transformation enable wider access on both fronts (Kuusisto, 2017). This is because the current technological means enable large amounts of digital data to be automatically gathered, processed and edited (Berry, 2011; Bhimani & Willcocks, 2014; Boellstorff, 2013; Galič et al., 2017; Huber, 2005).

This automated editing of data is frequently linked to the concept of big data. In academic discourse, different approaches can be found with regard to definition, which range from considering the quantity of data handled to the effectiveness of analysis (Ekbia et al., 2015). Big Data is widely characterised by the 5 Vs – Volume, Velocity, Variety, Veracity and Value (Ishwarappa & Anuradha, 2015), underscoring the complexity of the phenomenon. Thanks to the large amounts of data, it is possible "to identify patterns in order to make economic, social and legal claims" (Boyd & Crawford, 2012, p. 663).

Data is automatically edited by algorithms, which enable computers to work out step-by-step solutions to specific problems (Cormen et al., 2009; Hill, 2016; Huber, 2005; Skiena, 2020). The rules for problemsolving are either defined by humans or generated by machines from existing data, using systems that are capable of learning (Heise, 2016; Yatsko & Suslow, 2016). Alongside simple, clear deterministic algorithms, there are also those that can solve complex problems dynamically (Introna & Wood, 2004; Yatsko & Suslow, 2016). Machine learning in this context is supervised, unsupervised, or semi-supervised by humans. In unsupervised learning, the algorithm independently searches for previously unknown patterns and relationships. Supervised learning, while suggesting human control, rather refers to efforts to train and channel the algorithm at an early stage with respect to a target variable (Alloghani, 2019). Consequently, it is algorithms that analyse large amounts of data and, depending on the intensity and autonomy of the algorithm, decide on their weighting (Beer, 2017; Leicht-Deobald et al., 2019). This has led algorithms to become a "source of political concern, with the data being operationalised through those algorithmic decisions." (Beer, 2017, p. 3) Depending on the scope of the algorithm, this also includes the areas of action of (qualified) employee representation, whose forms of cooperation can be influenced by it (Pärli, 2022).

This brings with it the dilemma of responsibility, accountability and personal integrity in decision-making systems (Mittelstadt et al., 2016). This is because algorithmic and data-based analyses are often seen as more neutral and objective than they actually are (Boyd & Crawford, 2012; Gitelman & Jackson, 2013; van Dijck, 2014). Supervised algorithms also, and perhaps especially, trace discrimination, as issues often arise during training. Pre-existing discriminatory structures can be inadvertently transferred to the algorithm (Kim, 2016), and it is not uncommon for the training set and the data being evaluated to already include inherent discrimination in the first place, which the algorithm then merely mirrors (Haljan et al., 2016). Thus, an algorithm is only as good as its training.

This could become troublesome for personal integrity – both for company representatives and employee representatives. Personal integrity is understood to be consistency in personal convictions, intentions and acts (Palanski & Yammarino, 2007; Schank, 2019). If this consistency is broken, both the authenticity and credibility as a representative (Calhoun, 1995) are damaged, as is the individual's mental constitution (Korsgaard, 2009). Because of this single-sided emphasis on rule-based systems in terms of compliance (Paine, 1994), the individual human scope for interpretations is reduced. However, such a one-sided command-and-control culture makes it difficult to negotiate – especially when it comes to normative issues (Goodstein, 2000). A resulting culture of silence (Verhezen, 2010) or moral muteness (Heineman 2007) would threaten to replace a dualistic interaction of dialogue and conflict resolution between management and employee representation with another dualism, namely between an error-prone human being and a seemingly superior algorithm due to its supposed objectivity.

A concrete example is sketched out by Peck (2013) and the practical case of the company Xerox. After successfully introducing and implementing a new recruiting software within the company, it became apparent that the recruiters working for Xerox did not want to do job interviews themselves but would rather rely on the software. Against this background, Leicht-Deobald et al. (2019) consider the personal integrity of managers and decision-makers to be at risk. They bring to mind that it is more difficult to decide against an algorithmic recommendation than to advocate it (Leicht-Deobald et al., 2019). They support their argument by reminding their readers that such decisions usually need to be made in complex, high-risk and unpredictable environments. Since no obviously ideal decisions are able to be made in such environments, algorithmic decision recommendations do offer a certain degree of security and protection for the decision makers: if there is a need to justify their actions, they can refer to sophisticated algorithms. "In order to not be held accountable for human error, humans might thus willingly subject themselves to the monolatry and automation bias imposed by algorithmic decision-making" (Leicht-Deobald et al., 2019, p. 384).

Parry et al. (2016) suggest maintaining the accountability and allocation of responsibility in such algorithm-supported decision-making systems in that the (human) decision makers maintain the right to veto and speak out against the decision proposed by the algorithm. However, it remains unexplained how, depending on the algorithm used, sufficient basic information and transparency can be generated to enable an elaborate analysis of such a proposal (Heise, 2016; Mittelstadt et al., 2016). The overall incluence that algorithm-based decision-making systems and big data analyses can and will have over to classic management tools, structures, decision-making processes and benchmarks becomes clear (Carlsson, 2018; Couldry & Powell, 2014). Big data analyses and algorithms will themselves then become sociotechnical influencing factors and places of negotiation that interfere with the existing social interaction patterns, hierarchical structures and ideals, for example, between the company and employee representation (Beer, 2009, 2017).

Struggles of Algorithm-Based Decision-Making Processes

In the German co-determination model, the participation of employee representation in company decision-making is the most intensive way to represent the interests of employees (Bartölke et al., 2006; Luhmann, 2018). These ultimate co-determination rights are granted to employee representation in Germany, particularly in the case of social issues. Furthermore, Section 87 of the German Works Constitution Act (BetrVG) states that operational co-determination holds a right of veto where technical devices are used to monitor employee performance. In view of the previously outlined possibilities opened up by algorithmic big data analyses, there are two plausible conclusions: firstly, those algorithmic applications that work with mass data or personal data are in a position to draw conclusions about the performance and preferences of individual employees (Brennen & Kreiss, 2016; Couldry & Powell, 2014). Secondly, those algorithm-based decisions find their way into co-determined processes. For this reason, the next step is to outline an analogue decision-making process that links decision-making and sensemaking. Following that, where and how algorithm-based decision-making intervenes in the existing processes will be examined.

Decision-Making

The range of issues surrounding decision-making is examined from different perspectives and is a subject of controversial debate (Klöti, 2010). The smallest common denominator appears to be the understanding that a decision depicts the weighing up and selection of different courses of action (Boland, 2008; Sharma et al., 2017; Wolf, 2019). At the same time, however, the purpose of a decision can vary widely: from an ethical perspective, for example, the preservation of personal integrity as an inalienable value that must be safeguarded takes priority when making a decision (Koehn, 2005). According to business rationale, however, decision-making is based on the long-term maximisation of benefits and profit (Friedman, 1970).

Therefore, it is relevant to examine decision-making because strategic decisions, in particular, map out the sustainability of an organisation (Marchau et al., 2019; Rüegg-Stürm & Grand, 2015). Tactical and strategic decisions are especially important for forming the future of an organisation and compared to operational decisions, they hold the highest degree of uncertainty in decision-making processes (Marchau et al., 2019; Rüegg-Stürm & Grand, 2015).

Although Wolf (2019) emphasises that the more relevant the issues, the more rational and less intuitive decision-making processes are, Choo (2002) points out that "in practice, organizational decision-making departs from the rational ideal in important ways depending on the convergencies of the decision context." (p. 84) Because formal decision-making processes are often closely linked to informal and not always obvious decision-making structures (Balogun et al., 2008; Helmke & Levitsky, 2004), interests in companies are heterogenous (Boland, 2008), and decision-making processes are always accompanied by uncertainties (Marchau et al., 2019), this article will follow a descriptive understanding of decisions.

Decision-making between the company and employee representation is understood to be a multi-stage, iterative, social communication and negotiation process (Frege, 2002; Rüegg-Stürm & Grand, 2015; van der Brempt et al., 2017) between at least two independent stakeholders (Jaegher & Di Paolo, 2007). Against the backdrop of organisational and individual experience (Caughron et al., 2011; Choo, 2002), in this process, information is discursively processed and interpreted in order to deal with the uncertainty of the decision-making context and to develop collectively acceptable courses of action (Frege, 2002; Klöti, 2010; Marchau et al., 2019). At the same time, the assumption applies that the possible consequences and mechanisms of action of the selected courses of action are not fully known, and therefore the onset of the intended effect is open-ended (Marchau et al., 2019; Sharma et al., 2017). This understanding implies that a suboptimal outcome is not necessarily to be seen as negative but rather as a compromise that has been reached collectively.

Although the quality of complex decision-making can benefit from the involvement of the employee representation (Fauver & Fuerst, 2006; Marsden, 2015), in the research area of co-determination, significant theoretical studies of decision-making are few and far between. However, Budäus (1975) developed a theoretical approach toward behaviour in order to represent non-routine decision-making processes schematically. Although this approach takes iterations and interdependence with the company environment into account in decision-making processes (Budäus, 1975), it neither addresses sensemaking nor sensegiving. The influence of algorithmic decision-making processes is not taken into consideration either, which is not surprising given the year in which the approach was devised.

Sensemaking and Sensegiving

Since the 1960s, sensemaking in the organisational context has become an extensive area of research (Maitlis & Christianson, 2014). However, very few studies have been conducted (such as Appelt, 2016) in the context of employee representation that take sensemaking into account. In the area of organisational studies, the debate about sensemaking was essentially initiated and influenced by the work of Karl E. Weick (Boland, 2008; Brown et al., 2014). In 2008, Weick described sensemaking as "the ongoing retrospective development of plausible images that rationalize what people are doing" (p. 1404). So sensemaking primarily takes place retrospectively and makes events plausible (Boland, 2008; Weick, 2008) and is not concerned with the truth but with the corresponding context or historical origins (Weick, 2008).

Sensemaking is enabled when the events of a situation deviate from the expectations, so when there is some kind of irritation within the existing thought pattern (Caughron et al., 2011; Maitlis & Christianson, 2014; Strike & Rerup, 2016; Weick et al., 2005). This is usually the case when events are ambiguous or are accompanied by uncertainty (Weick et al., 2005; Appelt, 2016). This irritation is worked off by communicating and interacting and is meaningfully integrated into the existing thought pattern or mental model (Bagdasarov et al., 2016; Weick et al., 2005). This implies that mental models are continually being further developed (Bagdasarov et al., 2016; Rüegg-Stürm & Grand, 2015). In times of transformative changes – such as digital transformation, this appears to be necessary in order to be able to recognise impulses with long-term relevance in a changing environment (Brown et al., 2014; Dörner & Schaub, 1994; Sharma et al., 2017). Therefore, mental models are the basis and outcome of sensemaking (Bagdasarov et al., 2016).

If irritations are conscientiously placed in organisations, their interpretation and processing can be guided in the form of sensegiving. This term was coined by Gioia and Chittipeddi (1991) and defined as "the process of attempting to influence the sensemaking and meaning construction of others toward a preferred redefinition of organizational reality" (p. 442). Ideally, it leads to a common understanding of the undertaking and is a stimulus to action (Appelt, 2016).

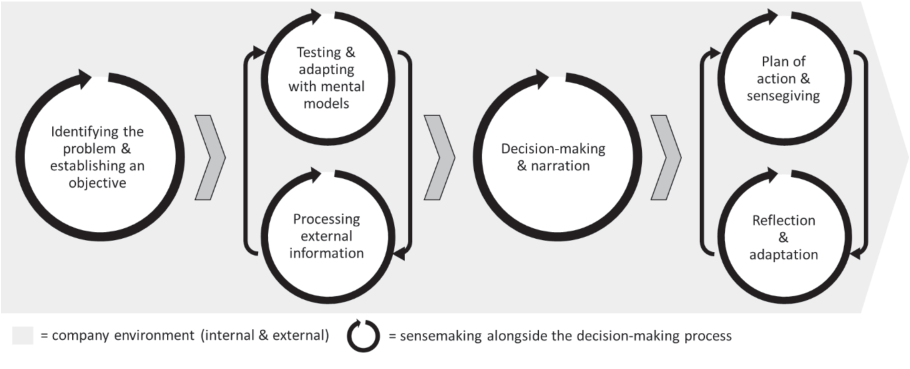
As established by Maitlis (2005), sensegiving is, above all, understood to be a management task and is analysed both at the leadership level (among others, Bartunek et al., 1999; Gioia & Chittipeddi, 1991) and the middle management level (among others, Dutton & Ashford, 1993; Rouleau & Balogun, 2011). On the other hand, sensegiving is not a classic management tool, but even in the ideal situation, it is only capable of accompanying and guiding the interpretations and sensemaking of others (Balogun et al., 2008). Alongside resource allocation and process design – as more formal frameworks, Balogun et al. (2008) identify opinion leadership as a possible basis for sensegiving and sensemaking. In organisational practice, it is not normally possible to clearly separate the three dimensions (Balogun et al., 2008). However, it is apparent that the first two dimensions are more closely linked to hierarchy and duties, and the third dimension is accessible to all employees (Balogun et al., 2008). Thus, sensegiving and the (ideally) resulting sensemaking occur in not only formal contexts but also informal ones. Furthermore, Appelt (2016) emphasises that managerial staff often have no access to these informal contexts.

This is where the management focus of sensegiving reaches its boundaries. This also becomes apparent in the research of Maitlis (2005), which focuses on sensegiving and sensemaking by stakeholders. She addresses staff as a significant stakeholder group, employee representation, however, is not explicitly addressed. Elsewhere too, the role of works councils in ensuring successful sensemaking and sensegiving in organisations has barely been researched to date. Although Appelt (2016) does refer to employee representatives as possible sensegiving actors, they occupy a subordinate role. Especially in the case of informal sensemaking and sensegiving by opinion leaders (Appelt, 2016; Balogun et al., 2008), it seems relevant to examine employee representation because due to their role, their relationship with the staff might allow them to participate even in informal sensemaking.

Theoretical Modelling

Weick (2008) states that sensemaking precedes decision-making, and both are closely linked: "Once they have some story/direction in hand, people then usually move on to decide, forecast, plan, strategize, and budget. But those successor activities unfold within frames fashioned by earlier sensemaking." (p. 1406) Against this backdrop, an approach linking decision-making, sensemaking and sensegiving is modelled below. The interpretation applied here is depicted in four process steps, which are based on Budäus (1975) (see Figure 1).

Figure 1. Social Negotiation Process of Sensemaking and Decision-Making (Source: Own Diagram)



The *first step* involves the identification of a problem and the formulation of an initial decision or objective by the stakeholders in communication with their environment (Budäus, 1975; Dörner & Schaub, 1994; Marchau et al., 2019). The parallels to sensemaking are obvious, as both start with some kind of irritation and look into processing it (Caughron et al., 2011; Weick, 2008). In order to identify a problem, the information on the organisational environment must be classified as relevant within the organisation (Rüegg-Stürm & Grand, 2015; Sharma et al., 2017). This is why mental models are given a leading role; thanks to their organisational function, they reduce the perceived complexity, support the identification of patterns (Pomerol & Adam, 2008; Strike & Rerup, 2016; Weick et al., 2005) and provide sufficient structure and certainty to be able to make a decision in the first place (Choo, 2002). On this matter, Bagdasarov et al. (2016) state that "Mental models are used to make sense out of complex issues and, thus, trigger sensemaking, which then facilitate the decision-making process." (p. 135). Even though representatives of qualified co-determination do have a basic knowledge of economics and business administration (Müller-Jentsch, 2008) the mental models of company representatives and employee representatives differ (van der Brempt et al., 2017; Spindler, 2020). While company representatives are supposed to act upon economic normativity, such as utility and profit maximisation, employee representatives are meant to aim for social normativity, such as securing jobs and representing employees' interests (Denis et al., 2007; Spindler, 2020). These different mental models are apparent in the choice of words or problem-solving strategies (van der Brempt et al., 2017) and can make dialogue difficult as they indicate a pluralistic decision-making context (Denis et al., 2007).

In the *second step* of the decision-making system, a preliminary decision is developed. This is achieved by iteratively and continually gathering and processing information from the environment and subsequently testing and modifying the decision (Budäus, 1975). Mental models are a central resource of organisational knowledge and experience, based on which decisions, actions and communication can be continually legitimised, and the environment can be interpreted (Choo, 2002; Bagdasarov et al., 2016; Rüegg-Stürm & Grand, 2015). For a start, this means that the creativity and selection of decisions are closely linked to the organisational and cognitive limitations of organisations and their stakeholders, which accounts for suboptimum decisions (Boland, 2008; Drucker, 1967; Sharma et al., 2017). Secondly, the robustness and sustainability of mental model against conflicts increases with every irritation that is classified (Weick et al., 2005) and is reflected in the higher quality and creativity of the proposed solutions (Bagdasarov et al., 2016). Thirdly, it means that the continual reflection on and adaptation of the decision with the help of the sense of entitlement and expectations of the environment require the mental model itself to be reflected upon and adapted (Bagdasarov et al., 2016; Sharma et al., 2017).

Here too, sensemaking is a key element of decision-making as, although sensemaking primarily attempts to come up with a plausible story for past events (Weick et al., 2005), future-oriented decision-making situations are based on the experience of the mental models, which can enable alternative solutions to be worked out (Bagdasarov et al., 2016). Thus, the retrospective story appears to be the basis for a common narrative throughout the decision-making process. This means that a common narrative/storytelling is an important part both of sensemaking and sensegiving, as well as decision-making (Appelt, 2016; Brown et al., 2014). As different perspectives compete against each other, the joint development of such a narrative implies a complex negotiation process (Balogun et al., 2008).

Here, the sociopolitical dimension of sensemaking and decision-making manifests itself (Balogun et al., 2008; Brown et al., 2014). To develop a joint narrative, it is necessary "to be able to understand the social order in one's particular sphere of operation, and to use it to good effect. In this way, some people who may not be nominally as powerful as others may still exercise significant influence" (Balogun et al., 2008, p. 242). Such blurring of formal imbalances of power is evident, for example, in the case of qualified co-determination (Bosch, 1997; Frege, 2002).

Alongside structural and procedural design options (Brown et al., 2014; Weber & Glynn, 2016), relevant soft skills become apparent that can considerably influence sensemaking and decision-making. For example, the ability to empathise with others and convince them or the sustainability of the relationships with the other stakeholders (Frege, 2002; Balogun et al., 2008). In line with this, the control of the narrative of the participating stakeholders is continually evolving and becoming more dynamic (Balogun et al., 2008), and so the essential role of sensemaking is to moderate the decision-making process so that a collectively sustainable decision can be reached (Appelt, 2016). As the mental models of the company representation and the employee representation differ greatly, the complexity of reaching such a solution is increased because the way of speaking, the problem-solving strategies and the objectives are extremely different (van der Brempt et al., 2017). From the perspective of the employee representation, one advantage could be that they are used to working in numerous contexts and moderating different interests (Müller-Jentsch, 2014).

There is a smooth transition into the *third process step*, in which a final decision is established and so a decision is made (Budäus, 1975). Whilst negotiating a problem-solving approach can take place in informal contexts, as described above, it appears – in view of the (legal) legitimisation of the decision – to make sense to locate the act of decision-making in the formal structures (Czada, 2010; Grunden, 2014). The narrative, which gives direction to the decision-making in the preliminary stages, is often used as an argument later to legitimise the selected problem-solving approach (Weick, 2008).

As explained by Gioia and Chittipeddi (1991), sensegiving is linked accordingly to the communication and derivation of a decision. This brings us to our *fourth and final process step*, the plan of action. According to Budäus (1975), after this step, the decision-making process is complete. Whereas Drucker (1967) highlights how important aiding the implementation of the decision is, Gioia and Chittipeddi (1991) outline the continual iteration between sensemaking and sensegiving, and Weick points out in numerous places that talking can be understood as negotiation and, therefore, an initiator for sensemaking (e.g. Weick, 2008; Weick et al., 2005), it appears to be questionable whether a decision-making process ends after the plan of action has been initially communicated. Instead, it is more plausible that the final decision should be slightly adapted during implementation by means of sensemaking and sensegiving, wherever necessary. For instance, the symmetry of information and responsibility between decision makers and those affected by the decision (Langley & Denis, 2006) could be cause for such adaptation. Based on the depiction that mental models become more resistant to crises thanks to discussions and increasing reflection throughout the sensemaking process (Weick et al., 2005), the assumption applies that the necessary amount of reflection during the implementation phase continually decreases.

Algorithm-Based Decision-Making and Sensemaking

Challenges and Limitations of Algorithm-Based Decision-Making

Lycett (2013) explains that "top-performing organisations made decisions based on rigorous analysis at more than double the rate of lower-performing organisations" (p. 381). Likewise, Kuusisto (2017) and Sharma et al. (2017) explain that problem-solving and decision-making by managerial staff can be accelerated with the help of algorithms. However, Sharma et al. (2017) outline two aspects that stand in the way of the acceptance of algorithm-based evaluations:

(1) Algorithm-based, strategically relevant insights and information are sometimes not recognised as such in organisations. This leads to those insights not being considered to an appropriate extent (Lycett, 2013; Sharma et al., 2017). As internal and external impulses are not always clear-cut, in organisations, they are processed with the help of data-processing methods in order to reduce uncertainty and analyse the data (Choo, 2002). With reference to Joshi et al. (2010), Kuusisto (2017) explains: "Usually the information needs to be transformed to fit the context of each company." (p. 350). Thanks to digitalisation (e.g., based on search algorithms which help to filter data), organisations can process impulses streaming in from the outside more effectively (Joshi et al., 2010; Kuusisto, 2017). However, it is yet to be clarified how or through whom these external, digitally processed impulses take effect and thus bring their added value to the organisation. This is because this processing does not imply that the outcomes are classified as relevant from human decision-makers and taken into account accordingly in the decision-making process and implementation (Sharma et al., 2017). Therefore, acknowledging data generated by algorithms as relevant and incorporating them meaningfully into the self-image of the organisation has become one of the biggest challenges for the

company and employee representatives who are involved in such algorithm-based decision-making.

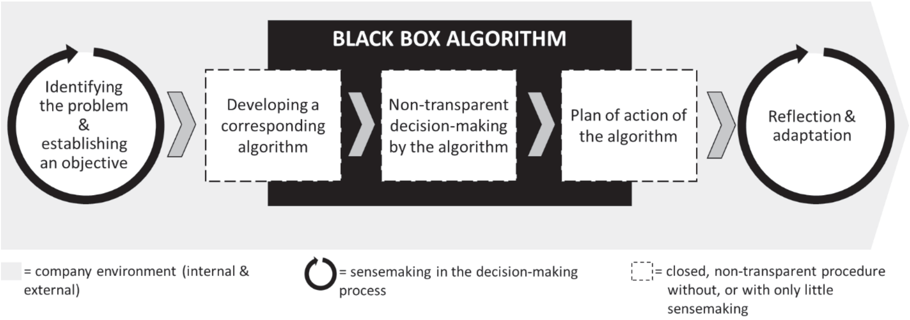
(2) The lack of involvement of stakeholders who are in key functions in the implementation of decisions needs to be considered (Sharma et al., 2017). "[W]e suggested that algorithm-based HR decision-making may harm employees' personal integrity because it can evoke blind trust in processes and rules, which may ultimately marginalize human sense-making as part of their own decision-making process", stated Leicht-Deobald et al. (2019, p. 388). Furthermore, they do not consider algorithm-based decision-making to be capable of competing against human decision-makers in the case of motivation and involvement of employees in the implementation of decisions (Leicht-Deobald et al., 2019) because the narratives, authenticity and commitment that human managerial staff can bring are far superior to algorithm-based decisions (Leicht-Deobald et al., 2019). Moreover, as algorithm aversion implies (Dietvorst et al., 2015), people lose faith in algorithms more quickly than in human decision-makers when they are associated with a flawed decision.

It is precisely this development of such narratives that is a cause of concern for Couldry and Powell (2014). They argue that the development and communication of narratives is an important component in the continual interpretation of oneself and one's environment and enables retrospect, reflection and rationalisation. However, this "is not immediately compatible with a world saturated with the automated aggregation of analytic mechanisms that are not, even in principle, open to any continuous human interpretation or review" (Couldry & Powell, 2014, p. 4). The inherent problem seems to be that through automated interpretations and data analyses, the ability to form narratives and, therefore, to engage in sensemaking and independent decision-making could be lost. In the case of the formulation of narratives, a paradox of digital transformation is apparent. As has already been outlined, on the one hand, the ability to develop a narrative is strongly affected by algorithm-based systems and the way in which they process and edit data. On the other hand, Brennen and Kreiss (2016) indicate that due to flatter hierarchies and decentralisation, it is expected that more people can make their narratives heard in organisations.

In the course of the discussion so far, it seems as if algorithm-based decision-making systems contribute to the fact that decisions can no longer be understood as a socio-political negotiation process but rather as a black box (Beer, 2017; Pasquale, 2016). This black box prevents the second and third decision-making process steps and even partially extends to the fourth step, as described during the theoretical modelling, and therefore the development of narratives. Instead of discussing and adapting external information and mental models, the decision-making algorithm is developed, applied and concluded with an action plan with only a little involvement of key stakeholders in the implementation of those decisions (see Figure 2).

The idea seems plausible that this black box does not leave the preservation and integration of co-determination rights untouched throughout an algorithm-based decision-making process. Especially when it comes to the quality of decision-making, Balogun et al. (2008) clearly oppose this and point out that the key to better decision-making lies in a better understanding of the socio-political processes of organisations rather than in a better more objective and up-to-date information situation. This does not mean that decisions calculated by algorithms cannot possibly have a higher degree of objectivity (Dahm & Walther, 2019), but it is necessary to consider the acceptance and understanding of such decisions in the organisation. Nevertheless, algorithms themselves can be understood to be the outcome of social negotiation processes (Heise, 2016; UNI Global Union, 2017).

Figure 2. Black Box Algorithms in the Decision-Making Process (Source: Own Diagram)



Algorithm-Based Decision-Making as a Social Negotiation Process Through Sensemaking

Subsequently, several existing approaches will be outlined for better integration of social negotiation processes in algorithm-based decision-making. Couldry and Powell (2014), Sharma et al. (2017) and Lycett (2013) introduce the integration and strengthening of sensemaking as a possible solution. As was explained earlier, added value is not acquired from the automated analysis process alone but can only exist if the relevance of the analysis is understood and is integrated into the decision-making process. Lycett (2013) urges that “densities do not emerge from data alone” (p. 384). Instead, added value and new insights within the context of consolidation would only come about if the algorithm-based analyses are complemented by human interactions, and an IT-supported sensemaking process can take place (Lycett, 2013). As Sharma et al. (2017) explain, “insights emerge out of an active process of engagement between analysts and business managers” (p. 435). The interpretation and analysis of the phenomena inherent to the data reside with human stakeholders (Lycett, 2013; Sharma et al., 2017). Their ideas on how to implement sensemaking will be described briefly. Following their lines of argumentation, the integration of sensemaking is believed to be plausible in three ways:

(1) If algorithms themselves are understood to be the result of social negotiation processes (Balogun et al., 2008; Heise, 2016), then sensemaking could be dealt with more consciously alongside these negotiation processes. (2) As long as it is not a matter of automated decision-making systems, sensemaking could also be initiated by discursively interpreting the algorithmic analysis results (Lycett, 2013; Sharma et al., 2017) and developing a common narrative (Couldry & Powell, 2014). Involving sensemaking in algorithm-based decision-making processes could contribute toward the resulting decisions (or outcomes) being more widely accepted and implemented in organisations. (3) Finally, Parry et al. (2016) suggest that humans should evaluate the algorithmic feasibility of a problem first. It would then be necessary to check the results of the algorithm-based analysis and assess the viability at a later point. If no practicable algorithm-based decision can be found, it should be possible to establish a problem-solving approach developed by humans (Parry et al., 2016).

All three approaches outlined above allow better integration of sensemaking in algorithm-based decision-making. In addition, they all train the reflexivity of those involved, which could counteract both blind conformity and the marginalisation of forming one's own opinion (Leicht-Deobald et al., 2019). Another positive aspect is that all three approaches presumably allow a more diverse group of people to engage in algorithm-based decision-making. This is important for two reasons:

(1) Boyd and Crawford (2012) intensely discuss structural inequalities and hierarchical shifts as a result of changing competence requirements due to digital transformation, big data and algorithm-based decision-making. They denounce that IT expertise is overrated compared to other skills (Boyd & Crawford, 2012). But still, the need for IT skills is increasing (Leybert & Khalikov, 2019; Schwarzmüller et al., 2018), a skills gap that certainly cannot be neglected in the area of employee representation. Therefore, it is important to be aware of the shifts in hierarchical power and the information asymmetries that are arising and have arisen to be able to act upon them. So, qualification is not only a fundamental part of a successful digital transformation (Sousa & Rocha, 2019; Spindler, 2020) but is essential to be able to maintain a comprehensive employee representation voice and qualified co-determination.

(2) This could contribute to a better levelling of individual, discriminatory impacts and power distribution in algorithms. Boyd and Crawford (2012) point to the disproportion between the number of actors that can participate in data collection, analysis and processing and the actors that produce these data. They state, "Who is asking the questions determines which questions are asked." (Boyd & Crawford, 2012, p. 674). The fact that only few people are involved in the algorithmic collection and processing of data must be examined critically. On the one hand,

with regard to the relative homogeneity of this group of people, since the cultural bias[2] of the developers is constantly infused into their work (Crawford, 2016; Lowrie, 2017; Mittelstadt et al., 2016; Striphas, 2015). On the other hand, the people involved are not necessarily elected employee representatives and do not have the power to make decisions nominally.

However, neither the first nor the third approach helps to maintain and further train the ability to develop problem-solving strategies and solution approaches in situations of high uncertainty. It becomes apparent that the training of these skills has an influence on the flexibility of mental models and thus on the quality of decisions and problem-solving (this means quality, originality and elegance of problem-solving) (Bagdasarov et al., 2016; Bossaerts & Murawski, 2017). At the same time, errors will be paramount in the future for the further sustainable development of organisational integrity and knowledge so that out-of-the-box decisions and problem-solving approaches have a chance (Leicht-Deobald et al., 2019).

Big Judgement

Challenges and Qualification Requirements of Algorithm-Based Decision-Making

A further challenge of algorithm-based decision-making is its complexity and the lack of transparency of its analyses, regardless of whether they are descriptive, predictive or prescriptive algorithms (Davenport, 2013; Huber, 2005). As previously mentioned in this work, in any case, organisations and decision-makers are currently faced with an excess of data rather than a scarcity, and sorting and prioritising data has become a challenge (Bhimani & Willcocks, 2014). Berry (2011) argues that technological options change the way that companies handle knowledge and data and maintains that "digital technologies are transforming our ability to use and understand information outside of these traditional knowledge structures" (p. 5). Boyd and Crawford (2012) coincide with this tenor, stating that "Big Data has emerged a system of knowledge that is already changing the objects of knowledge" (p. 665).

Furthermore, data from algorithm-based or big data analyses are often used indiscriminately in organisations (Couldry & Powell, 2014; Lazer et al., 2014). In uncertain contexts, in particular, algorithm-based decisions are often seen to be more reliable than human appraisals (Heise, 2016). Along the same lines, Boyd and Crawford (2012) outline that these technological options are often accompanied by the myth that only this form of technological intelligence reveals new knowledge

2 However, bias in algorithms is not exclusively due to programming, but in the case of machine learning significantly depends on the data quality of the training material (Buolamwini & Gebru, 2018).

and insights and, at the same time, is accompanied by an "aura of truth, objectivity, and accuracy" (Boyd & Crawford, 2012, p. 663).

Moreover, the handling of private data in the workplace is determined by formal and informal contextual information norms, which require different patterns of interpretation and can only be computerised to a limited extent (Nissenbaum, 2010). Similar to the accounts of Bhimani and Willcocks (2014) and Abubakar et al. (2019), Kuusisto (2017), referring to Johannessen et al. (2001), warns that "investing in information technologies easily leads to focus on explicit knowledge and demotion of tacit knowledge, as tacit knowledge is not easily transferred to digital form." (p. 349) Accordingly, data and its processing are always based on a modelling of reality (Królikowski et al., 2017) and, as Korzybski (1995) illustrates: "A map is not the territory" (pp. 58–59). The data basis and indicators of algorithm-based decisions should be analysed by the employee representation when introducing and applying such systems.

Especially when it comes to data quality – which is difficult to evaluate – poor insights into survey practices and a lack of information about the context of data collection occur (Boyd & Crawford, 2012; Couldry & Powell, 2014). This is because data cannot be equated with facts and even large amounts of data are not automatically representative or complete (Boyd & Crawford, 2012; Bozdag, 2013; Gitelman & Jackson, 2013; Mittelstadt et al., 2016). Instead, machine-generated data too are always subjectively influenced in some way by elements such as the underlying user interface, the underlying algorithm or the context in which they are gathered (Beer, 2017; Bhimani & Willcocks, 2014; Boellstorff, 2013). As Couldry and Powell (2014) point out, the aim of data analysis can be to reinforce existing structures and procedures, as well as to fundamentally question them and establish new objectives. Therefore, it seems more important to fathom against what backdrop (purpose and objective) a specific pattern is looked for and identified in the corresponding amounts of data (Boyd & Crawford, 2012; van Dijck, 2014).

In the context of data, it is no longer just content, e.g., from messages, that is processed but also background information, e.g., origin and time of a sent message – the so-called metadata (Angrave et al., 2016; Brennen & Kreiss, 2016; Couldry & Powell, 2014). This metadata can be collected and analysed in such ways that, for example, conclusions about a person's private life, health or work commitment can be drawn (Angrave et al., 2016; Beer, 2017; Healy, 2013; Schwarzmüller et al., 2018). This opens up new means of employee surveillance in the workplace (Galič et al., 2017; Leicht-Deobald et al., 2019) and places demands on the employee representation in terms of security issues and privacy (Barton et al., 2018; Ekbia et al., 2015). These claims are becoming even more pressing, as users are not always aware of when and which kind of metadata is collected (Boellstorff, 2013; Mittelstadt et al., 2016), and user privacy and anonymity can no longer be guaranteed when different data collections are combined (Boyd & Crawford, 2012).

Alongside this background information, qualitative supervision seems to be a useful option for creating reference points for valid reflection and interpretation. Price and Shanks (2008) critically discuss that evaluations which are only algorithm-based often go hand in hand with a loss of quality and objectivity of results. For example, people do spend most of their time with their colleagues, but this does not necessarily say anything about the quality, relevance or scope of the relationship (Boyd & Crawford, 2012). Thus, a qualitative reflection of the quantitative results appears reasonable and appears to be a possible way of enforcing the employee representation voice. With regard to practical implementation in organisations, Królikowski et al. (2017) are sceptical about whether ethics or reflection are compulsory elements in IT and data analytics training and whether such competencies are usually taken into account in organisations (with a view to promotions or salary increases). This would be inevitable in order to give the issues the necessary relevance.

This does not imply a demand for absolute transparency. This is because such transparency could, on the one hand, contribute to the conscious manipulation of algorithms (Martin, 2019). On the other hand, the information flows and connections within an algorithm-based system might be observed but not necessarily understood by the users (Ananny & Crawford, 2017). This is how absolute transparency of the data basis and programming in algorithm-based decision-making could lead to excessive demands in terms of analysis (Diakopoulos, 2016). The type and scope of the transparency should depend closely on the reach and criticality of an algorithm-based decision-making system and, above all, focus on the core elements, significant indicators and location within the organisation (Diakopoulos, 2016; Martin, 2019). However, what is clearly established by Ananny and Crawford (2017) is that here too, transparency is not suitable as an easy solution when allocating responsibility because an across-the-board demand for more transparency is not helpful. For instance, in terms of personal data, this would instead be counterproductive, and a lack of transparency would be preferable (Ananny & Crawford, 2017). With our critical objection to absolute transparency, we are moving within a traditional understanding that sees the employee as an actor in particular need of protection. Such comprehensive transparency distributes information asymmetrically to their disadvantage. With the concept of inverse transparency, Gierlich-Joas et al. (2020) make a novel case for employee engagement and digital leadership innovation as a new form of process transparency that empowers both leaders and the led. However, such a form of transparency has rarely been the goal in organisations.

In the next section, we will take a more in-depth look into how the employee representation voice can be maintained alongside algorithm-based decisions. With regard to electing employee representation, those elements that merely suggest increasing IT expertise should be left out. The proposals developed to design algorithm-based decisions via sensemaking as a social negotiation process should be complemented by the following models but not replaced by them.

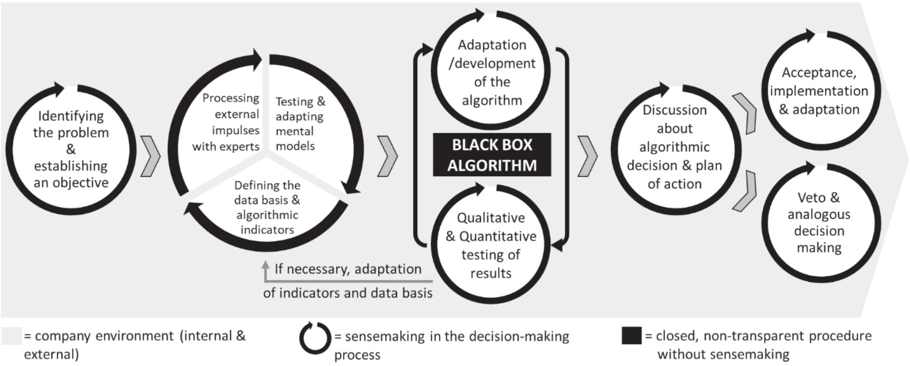
Modelling: Big Judgement, Sensemaking and Empowering of Employee Representation Voice

As previously mentioned, an active exchange between IT specialists and management is required to generate insights and, in turn, add value from digital data or algorithm-based decision-making (Sharma et al., 2017). As this work focuses on such decision-making processes, which include the co-determination rights of the employee representation, the latter must also be included when acquiring insights. With reference to a critical examination of data collections, algorithms, and their results, Shah et al. (2012) argue, "To overcome the insight deficit, Big Data – no matter how comprehensive or well analyzed – needs to be completed by Big Judgment." Based on the previous discussion, it is clear that the employee representation requires the following aspects for such big judgement and to maintain the employee representation voice alongside algorithm-based decision-making:

- sufficient information about the context of origin (when, where, for what purpose, with or without consent) of underlying data collections (Bhimani & Willcocks, 2014; Couldry & Powell, 2014; Shah et al., 2012; van Dijck, 2014)
- qualitative as well as quantitative methodological knowledge in order to weigh up the choice of the method for the object of investigation as well as the strengths and weaknesses of the methods used and, if necessary, to qualitatively test quantitative results (Boyd & Crawford, 2012; Couldry & Powell, 2014)
- knowledge and understanding of which explicit information and knowledge are disproportionately included in the data set and which strategic, tacit, or cultural information and experience values are not processed or are underrepresented (Johannessen et al., 2001; Królikowski et al., 2017; Kuusisto, 2017)
- all human actors should have a final veto right for any kind of algorithm-based decisions or, better yet, a self-determined decision (opt-in) on whether to consent to the collection and analysis of their data at all. This could, at the same time, leave the allocation accountability of those decisions to humans (Parry et al., 2016).

The elements of big judgement emphasise the previous statement that digital transformation is to be understood to be a huge qualification campaign (Sousa & Rocha, 2019). For organisations, this results mainly in two tasks: "training workers to increase their data literacy and more efficiently incorporate information into decision-making and giving those workers the right tools" (Shah et al., 2012). At the same time, big judgement goes beyond a classic qualification initiative and is to be understood as empowerment to assess algorithm-based decision-making processes and their outcomes. This requires both structural and procedural adaptations alongside the implementation and use of algorithm-based decision-making to open its black boxes. Incorporating possible approaches to sensemaking and sensegiving platforms as an integral part of these processes is not only shown in Figure 3 but also further explained below.

Figure 3. Algorithm-Based Decision-Making as a Social Negotiation Process (Source: Own Diagram)



The co-design of algorithms outlined by Balogun et al. (2008) and Heise (2016) seems to require elaborate expertise in programming. Therefore, it appears to be necessary to find negotiations that are less demanding. This could be achieved by a negotiation about indicators and the scope of underlying data collections, which serves as an exemplary basis for the evaluation of applicants. In this way, employee representatives could possibly benefit from their knowledge of HR processes, regardless of their ability to read and interpret programming languages and codes.

As proposed by Lycett (2013), Sharma et al. (2017), Parry et al. (2016) and Couldry and Powell (2014), it seems reasonable to discuss the results of an algorithm-based analysis. As this paper focuses on negotiations between management and elected employee representatives, such a discussion of results would always include at least two people, which is a prerequisite for sensemaking. Since this would lead to group responsibility rather than individual responsibility for the assessment and evaluation of the results, it could strengthen the preservation and consideration of personal integrity. This discursive processing of the results could, at the same time, contribute to the development of a collectively acceptable narrative and thus improve the acceptance and communication of the algorithm-based decision within an organisation. In this way, algorithm-based decision-making processes would no longer have a linear but rather an iterative character. This could strengthen employee representation and voice within algorithm-based decision-making processes.

In addition to that, appropriate support for employees – combined with better access to information – could help to shift some decisions to lower hierarchy levels, as then there is sufficient information to make an informed decision (Kuusisto, 2017). Shah et al. (2012) stress the relevance of transparently reflecting the elements of big judgements in the target agreements and remuneration systems of organisations to strengthen controversial dialogues and participatory decision-making approaches. Strengthening the competencies which are required to execute a big judgement within the employee representation appears to be a possible approach for maintaining and strengthening the employee representation voice.

Together with increased competence in the sense of big judgement, opportunities for dialogue and discourse can also be created in the future, which enable objectives, data sets and intentions, as well as the outcomes of algorithm-based decision-making, to be examined critically (see Figure 3). This should help to maintain the employee (representation) voice alongside such systems, not to exaggerate the power of judgement of data sets and algorithms, and to reinforce the creation of narratives in the future. Furthermore, it appears to be conceivable that, at the same time, such a discursive examination increases the reflection upon mental models and, therefore, the creativity and quality of decision-making by the participants (Maak & Ulrich, 2007; Bagdasarov et al., 2016). In addition, making mistakes will continue to be relevant as they support further development of both organisational integrity and knowledge in the long term and enable and promote unconventional, creative, and new problem-solving approaches (Leicht-Deobald et al., 2019).

Conclusion

Particularly with regard to decision-making and employee representation voice, a wide range of changes is involved in digitalisation and digital transformation. As far as digitalisation is concerned, for example, new opportunities arise to represent information and processes digitally and so speed up the communication and exchange processes. Digital transformation questions whether the existing hierarchies are useful, which decisions can be delegated to lower levels of the hierarchy, which new business models should be considered, and what new forms of collaboration, interaction and participation are necessary to sufficiently drive decision-making forward in the future.

Previous research clearly shows that striking a balance between the necessary changes and the stabilisation of existing decision-making systems will become a great challenge. Especially because the transition between digitalisation and digital transformation is understood to be a smooth one, the balancing act between current and future requirements and demands will be a challenge. Alongside the more general cultural and social implications, the existing research also showed that some incisive changes are to be expected alongside sensemaking and decision-making. Thus, the stakeholders involved and their influence will change, as will the speed, information basis and accountability linked to the decision-making. The use of algorithm-based data collection, assessment and analysis appear to come hand in hand with a particularly decisive turning point as this has a massive influence on previous sensemaking and decision-making processes. Depending on the degree of automation, it is to some extent so severe that individual elements are caused to become obsolete. However, the literature consulted shows that in such volatile contexts it is necessary, for example, to maintain sensemaking processes and enable managerial staff to continue to participate in decision-making.

The discussions in this article lead to the following conclusions regarding our research question, “How can employee representation voice be modelled in organisational algorithm-based decision-making processes?”: firstly, dealing with algorithm-based results by discussion and dialogue could contribute to strengthening the personal integrity of employees, managers and employee representatives by ensuring that controversial algorithmic proposals are not decided and taken responsibility for by an individual but by a group; secondly, a sensemaking platform is created in which different perspectives can be brought together, and a common narrative can be developed. This narration, in turn, supports consistent communication decisions between managers and employees; and thirdly, it is conceivable that this form of communication and critical debate could increase moral imagination and sensitivity in detecting ethical dilemma situations.

To develop the required level of discussions and dialogue on algorithm-based decisions, it is necessary to apply big judgement – especially in the context of employee representatives considered here. Big judgement includes methodical, technical and organisational qualification requirements, veto rights and a structural problem-solving approach to secure employee representation voice in algorithm-based decision-making. To increase the practical use of the concept for employee representatives, a checklist could potentially be used to give them a quick overview of the quality and scope of an algorithm-based decision-making system, as well as a clear understanding of their own value basis.

Even though the scale of big judgement is useful in algorithm-based decisions that involve employee representatives, it is not easy to use for all kinds of algorithmic decisions. From a more practical and general point of view, it is necessary to consider which types of algorithm-based decisions require such big judgement as their criticality differs widely.

Future research should focus on whether the interpretation of the output of algorithm-based decision-making described here (e.g., as a result, recommendation or information) influences the reflection of mental models and, therefore, the quality and creativity of decision-making. This could especially be of central importance when it comes to contributing tacit and cultural knowledge as well as creativity and originality within the problem-solving process. In addition, algorithm-based decisions proposed in the context of big judgement could be discussed not only against the background of personal integrity but also in light of a collective moral understanding.

Disclaimer

The results, opinions and conclusions expressed in this publication are not necessarily those of Volkswagen Aktiengesellschaft.

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