Creating meaningful intelligence for decision-making by modelling complexities of human influence: review and position

Paulo Pina[1], Rui Neves-Silva [2]

[1] inknow solutions, Rua Adriano Correia de Oliveira, 4 A, 1600 – 312 Lisboa and UNINOVA CTS, NOVA University of Lisbon, 2829-516 Monte Caparica, Portugal, pina@inknow.pt

[2] Faculty of Sciences and Technology and UNINOVA CTS, NOVA University of Lisbon, 2829-516 Monte Caparica, Portugal

Abstract. Strategic decision-making still struggles to cope with the interference of people in its proposed plans, creating a gap between idealised and real-world versions. Even when the existence of humans is considered, models and abstractions tend to be simplistic and lacking in complex human traits (e. g. creativity, sentiment). We analyse the current scientific landscape in the dimensions that overlap in the field of strategic decision making and posit that to provide means to a more informed and robust decision-making, humans should not only be seen as elements that need to accept and adopt decisions, but also as actors that affect their outcomes. Humans should be understood as central pieces and the strategic decision-making process should thus consider their importance both in techniques that foster co-creation, and also in developing dynamic models that demonstrate their influence and impact. In this article, we describe this problem-space and outline an approach integrating Decision Intelligence, Enterprise Architecture, Design Thinking, and architectural principles to achieve a human-centric, adaptive strategic design. We also discuss the influence of information presentation and visuals for meaningful participation in strategic decision-making processes.

Keywords: strategic decision-making, decision intelligence, human-in-the-loop, enterprise architecture, digital twins, design thinking

1 Introduction

The nature of enterprises has evolved, and so has our understanding of it. Whereas at some point enterprises were seen just as a vehicle for benefiting shareholders (by means of profits), nowadays they are understood as more complex organisations with an ethical and social role [1], [2]. The centrepieces of these complex organisations are the people that work in them, interact or consume their produce [3]. Consequently, companies evolved from being product-centric, to being customer-centric and are now seen as being human- or stakeholder-centric. These last two concepts are complementary among themselves: a ‘stakeholder-centric organisation’ focuses its activities on being beneficial to all its stakeholders [1], i.e., “those with whom the business interacts in pursuit of achieving its goals" [4], following an increasing concern with corporate social responsibility, corporate reputation, and responsible governance [5], while a 'human-centric organisation' is one that is designed in face of an understanding of human traits and preferences [6], [7].

This shift is in part the result of changes to the nature of work. In recent history, links between workers and companies have loosened and even physical connections are less obvious, as the emergence of temporary contracts, offshoring, co-working spaces, and remote work [8], among other characteristics, have shown [9]. In consequence, the assumption of workers as stable resources with static links to the companies was replaced by concerns about knowledge retention [10] and competition for the most sought-after expertise in the market at a given moment [11]. Companies themselves have also become geographically distributed [12], automated [13], and cater to wider areas in result of globalisation [14], [15], adding to the dispersion and challenging the fabric of organisational culture [16], [17], [18]. Even if at first sight seemingly paradoxical, these changes result in a different nature of work, that, in its efforts to retain knowledge and expertise, emphasises knowledge [19], innovation [20], team-based work [21], [22], and even project-based [23] work as a paradigm for operation, thus centring itself on human workers and on their relationship with the other blocks in the organisation [24]. A growing trend in the last decade is to extend interactions to stakeholders and experts outside of the organisation, e.g., for innovation purposes [24], [25]. Project-orientation is one of the latest iterations in stakeholder-centric organisations, basing activities on coordinated and time-limited projects (mostly for innovation) and fluid teams of collaborating elements for specific objectives [23], [26].

The study of enterprises reflected this evolution, emphasising human elements in strategy, and in strategic decision-making (SDM) in particular. Scientific studies in collaboration and aspects related to team-based decisions, digital support of worker decisions to alleviate stress or managing communication in distributed teams are emerging, with trust being an important facet of decision-making. In collaborative teams, multiple levels of trust emerge – interpersonal, at team level, and outwards trust, affecting the effectiveness of knowledge sharing and cooperation [27].

In another perspective, technology is also shaping strategy. In [24], the impact of digital technologies is classified in three-orders: *convergent change*, or change that does not alter the main processes of the company; *transforming work*, where processes and perspectives suffer significant change, but still within the existing business operating model; and *transforming the organisation*, where the structure, business and values of the company are changed, typically in reaction to second-order changes.

The common denominator in all these research lines is the need to have a clearer understanding of how humans impact and are impacted by organisations' operations and strategies, and by the decision-making process, in particular.

In the next section of this document a brief description of SDM is provided and the concepts of enterprise architecture (EA), decision intelligence (DI) and design thinking (DT) in the context of SDM are introduced. In the third section, approaches to address human elements in SDM are analysed and conclusions are drawn.

This paper lays out the problem-space of the influence of humans in SDM by providing a broad review of the current landscape and approaches to the various domains that intersect in the area of strategic decision-making, while laying down the foundations to further research on the subject. A research question is thus drawn from here. The presented position is that, to make better strategic decisions, a more comprehensive model of human actors, both as stakeholders involved in the decision process and as affected parties of the decisions, is required.

2 Background

Strategic decision is typically a high-level, long-term management decision that is infrequent, may result in significant change, and may need to be translated in applicable processes inside the organisation [28]. It is unstructured and complex, requiring significant resources, affecting activities, long-term, involving different functions and elements, which can be both internal or external [29]. Strategic decisions comprise a goal, obstacles and constraints, and estimated path [30]. On a general level, the process that culminates in the strategic decision starts with gathering of information and evidence, which is analysed and processed into inputs for the decision process. These steps are in fact preceded by the identification of a need, complexity or environmental change [31], [32]. James March, in his foundational work "*The technology of foolishness*" [33] argues for the frequent pre-existence of decisions before goals (also referred in [34]). More than that, goals are many times achieved indirectly and evidence is an *ex-post* rational construct to support a vision. Strategic decision can be seen as a mediation between competing views or weighing capabilities and potentials [35].

In fact, the process of decision-making itself is not as straightforward or sequential as classical approaches suggest [36]. Over the years, two conflicting lines of thought were developed: a *rational* (or formal or rational) approach, indicating a well-defined process with clear phases and an *incremental* (or informal, or unstructured) approach, with an adaptive nature comprising emerging, instead of planned steps [37], [38]. Organisations employ both approaches, sometimes in the same process [36], [37], [39].

Considering human stakeholders in the SDM process does not imply that strategic decision should not be supported by facts and evidence, but only that the complexity of strategic decision is not yet completely matched by current algorithms and technologies and there is an interesting topic for research on how to improve utility. In fact, the utility of artificial intelligence (AI) can be maximised through the combination of human intelligence and AI in a team that combines human stakeholders and machines [40].

The early stages of industry 4.0 that we are now witnessing, with Cyber-Physical & Human Systems (CPHS) where humans and and robots work together, highlight the importance of addressing the questions related to human actors in the context of production. Ethical issues, in particular, are of key importance, since automation and autonomy rely on machines capabilities to operate within realms that until now were exclusive to humans (e.g. production planning, operative safety) [41]. Technologies used to achieve the goals of Industry 4.0 can be distributed in three main group: *cognition-enhancing technologies* (cognitive computing, computer vision, AI, Big Data, cloud computing); *interaction technologies* (physical human-machine interfaces, exoskeletons, augmented reality); and *sensorial technologies* (Internet of Things, activity trackers, wearables). Decision-making in this context needs to take into consideration the acceptance of human actors towards this work environment and the defined objectives [42]. From these characteristics, four core design principles can be drawn: Interconnection, Information transparency, Assisted technical support; and Decentralised decisions [43].

2.1 Supporting methods for Strategic Decision-Making

Enterprise Architecture (EA) "*provides a long-term view of a company's processes, systems, and technologies so that individual projects can build capabilities- not just fulfil immediate needs*" [44]. It aims to manage complexity and promote alignment of strategy with processes and resources [45]. Although earlier incarnations were focused on the perspective of information technologies (IT) to realize the strategy, posterior developments in research and practice consider it from a wider viewpoint, covering the enterprise as a whole [46], [47], [48]. It can thus be said that EA is a tool for strategic decision, providing meaningful information and advice through models and roadmaps regarding current and future states of the organisation [49], [50], [48].

Decision Intelligence (DI) results from the realisation that decision-making and context-filtering techniques have not been brought up to the level of the latest developments in information technologies, big data, machine learning or AI in general. It also comes from the understanding that in the current context, purpose and value system are still provided by humans. The aim of DI is to integrate existing technologies by unifying them on a single framework. DI sees technology as tool that must be used according to the intended objectives of the decision-making process under penalty of being a distraction instead of an enabler [51]. Technology by itself has much less value then when used in collaboration with humans on a problem-focused environment, to understand how the building blocks of the problem work together [51], [52].

In face of the current societal environment characterised by *volatility*, *uncertainty*, *complexity* and *ambiguity* (VUCA), organisations are bombarded with fast-paced demands and at the same time are gathering copious amounts of information that goes largely unused [52], [53] or counterproductively result in increased decision bias, costs or delays. To combat this, decision proficiency is required to be able to filter the insights that matter and discard those that do not. Having the adequate level of information for a decision does not mean having all the information available: market requirements and VUCA mean that there may be a limited time for information acquisition and processing and the amount of uncertainty therefore increases. To minimise this, information processing capabilities should be tuned to fit intelligence requirements, including time-to-decision. For this, it is paramount that decision-makers are able to identify context of the decision (intelligence requirements in light of the problem frame), while having adequate processing power (by developing decision-making models that provide relevant answers to the problem) and accessing the necessary information to provide answers to the raised questions [52] These must then be translated in decisions, according not only to the input data, but also to the proficiency of the decision-maker. It is important to note that strategic decision and innovation, while relying on intelligence, are also change agents and implicate risk and uncertainty in results. Repeating exactly the same approach as always will hardly result in change or innovation. This is one of the main challenges of following formulaic methods for SDM or using a similar approach to the rest of the ecosystem (e.g., the same algorithm for information gathering or decision-making across a whole sector). And this is the crucial point for the need for Human-AI collaboration in DI.

As previously seen, strategizing involves a great deal of uncertainty, particularly in contexts of innovation where there are knowledge gaps in both technologies and markets [54]. Tapping into copious amounts of data or resort to managers' intuition poses challenges to the effectiveness of the decision-making and its outcomes. **Design Thinking** (DT) to support SDM was abundantly researched as a tool to overcome those challenges [54], [55], [56], [57]. DT has been shown to minimises cognitive bias [31], [55], [54] in the decision-making process, such as confirmation bias, over optimism or oversight of barriers, by using co-creation, building empathy and challenging assumptions [57], [54], [56]. It is also a practice that enables to reduce the existing divide between top management and operations and provides valuable insights into the market while filtering the required information volume and cognitive load, by introducing visual and material representations. The main procedural benefit from DT in this context is the combinations of analytical and intuitive thinking, surfacing tacit knowledge through the means of images and materialisation.

Four distinct activities can be identified in DT as a practice for SDM: *reviewing* – an individual analysis of materials and design contents, to support subsequent discussions; *simulating* – a group interaction with different materials to produce better insights into users; *conversing* – an open discussion on the subject of decision to create alignments and shared understandings about the strategic issues; and *collaborating* - to organise and create materials, generating complex solutions and shared understandings [54]. But design practices go beyond simple ideation for decision-making. They can contribute and improve strategy development in different steps of the strategy: *human-centred design* for a new perspective on opportunities; *prototype* and test models and required capabilities for future practices; identify and *deal with uncertainties and dynamics* in managing the portfolio of existing and future offerings; *storytelling and engagement* when increasing scale from prototype to market; and apply *design practices to support the whole strategical development* of organisations and create incremental or disruptive innovation. [57]

3 Looking for the human in the loop

There is no doubt that AI is a very valuable tool for decision-making. It provides a plethora of tools and capabilities to gain insights into existing data to understand current contexts and future trends. But processing copious amounts of information without criteria is not an efficient way to operate on a strategic level. More than that, resorting to AI without reviewing capacities raises questions of transparency and accountability [58]. Finally, humans are still the agents and receptors of the activities and strategies of organisations. If their influence on the process and the impact that decisions have on their lives and actions are not accounted for, the decision-making process will always be impaired. This means that human stakeholders must be modelled as more than just units of work, comparable to other physical resources in the organisation. Cognitive aspects, creativity, sentiment, interplay, all of them come into play in this context.

In the field of SDM, a significant trend is to analyse and steer the use of AI in decision-making, either complementing, expanding, or emulating human intelligence. Studies also address human biases as cautionary constraints to develop better AI [59], [58]. On the other hand, explainability, transparency and unpredictability present obstacles to the autonomous use AI in critical subjects. Yet, there is nowadays a prevailing feeling that technology provides better decisions than humans (called 'automation bias') [58]. Ultimately, the use of the same tools and techniques for SDM, which is an eminently creative process, may lead to a lack of diversity that impairs innovation and loss of the richness of human and social heterogeneities in favour of a monolithic, uniformised society managed by algorithms and scripted procedures [1].

3.1 Towards Industry 5.0 – the ethics of the new human-centricity

This centrality of the human aspect is emphasised by the emergence of a new wave of industrial development, sometimes coined as Industry 5.0, centred on intelligent manufacturing, with a focus on human intelligence in collaboration with robotics and artificial features that complement and extend human capabilities. The main differentiating characteristic is that technologies (e.g. big data, AI, etc.) adapt to the need of human actors instead of the contrary [60]. In this context, robots and humans collaborate or work in synergy, being aware, and able to understand and anticipate each other's actions [61]. For this, new sensorial skills and techniques will be required (eye motion detection, near infrared spectroscopy). Industry will also strive on mass-customisation, requiring a new perspective into productions, integrating elements of industrial production and artisanship [61], [62], [63]. The concept of Industry 5.0 goes beyond manufacturing, tapping into cultural, moral and lifestyle issues, integrating elements from Social Sciences and Humanities with a systemic approach to accurately model humans and machines in interplay [64]. This approach to industry and work presents some technological and scientific challenges, both regarding design. Machines and AI will not follow explicit rules but autonomously maximise compliance to goals, raising key ethical issues that must be addressed from the design stages [41]. Use of detailed data and sensorial inputs is also a serious issue – to which point is ethically acceptable to acquire private data and act upon it to minimise failures and hazards?

Machine ethics can be considered from a deontological (rule-, or principle-based according to established social values; or from a consequential perspective (especially utilitarian, where ethical decisions are considered according to their consequences or outcomes). Ethical issues should also be seen in two different scopes: the ethical design of digital systems (which guides the behaviour and actions of authors, researchers and developers designing the system); and the design of ethical digital systems (focused on the behaviour and actions of the systems themselves) [65].

But there is a marked shift in the current approach to ethical issues. These are designed *a priori* as a requirement, as an additional value, instead of being seen as a cost or a constraint to value-adding requirements [42]. When defining or evaluating the performance of future industrial systems, and in order to address the issues raised by the enabling future digital systems, ethical issues should be considered an indicator, together with efficiency, effectiveness and relevance [66]. SDM in the context of this new work environment, where machines and humans work as symbiotic systems also requires consideration for potential ethical risks that arise in these environments (e.g. lack of programmed common sense and bad conscience, decisional ambiguity, limits to mutual interaction, master-slave dependency; emotional dependency) [67].

3.2 Modelling of cognitive and behavioural aspects

To increase the accuracy of decision-making, better models of humans and their interactions in this context are needed, including models for human behaviour. Methods for considering humans in models can be classified according to the degree of detail in which they consider human behaviour:

- *simplify* – bypassing human behaviour through simplification, either by omitting, aggregating or substituting it in the model;
- *externalise* – in which behavioural aspects are obtained outside of the model via user input, expert systems or datasets;
- *flow* – by considering group behaviour as flow, using continuous simulation or system dynamics;
- *entity* – where humans are elements equivalent to other resources and have statuses, eventually interact with the model in specific steps of the process;
- *task* – using Discrete-Event Simulation, individual performance attributes are included in the interaction within the model, affecting general rules;
- *individual* – using cognitive architectures (e.g. Visual, Cognitive, Auditory, Psychomotor – VCAP; Physis, Emotion, Cognition and Status – PECS; Adaptive Control of Thought-Rational – ACT-R [68]) to model human behaviour [69].

Another approach regards modelling emotions. Most used emotional models are Ekman and Friesen, who consider six plus one main categories: *anger, disgust, fear, happiness, sadness,* and *surprise,* plus *neutral*; and Russell's theory, who states that emotions can be distributed along two axes: the valence-arousal model. Twelve emotions distributed along four quadrants: *Pleased, Happy, Excited, Annoying, Angry, Nervous, Sad, Bored, Sleepy, Calm, Peaceful*, and *Relaxed*. Research on mood modelling and lower frequency emotion changes is still scarce [68]. Models of personality can be achieved through types of modelling, like the Big Five Personality factors (*openness; conscientiousness; extroversion; pleasantness;* and *neuroticism*) and applying text mining tools for linguistics analysis (e.g. Linguistic Inquiry and Word Count – LIWC or Structured Programming for Linguistic Cue Extraction - SPLICE) [70]. *Irrationality* is also a subject of research [71], [72] as are *persuasiveness*, or *superstition* in heuristics [73]. Modelling and simulating knowledge characteristics is also essential for representing humans in SDM. Character models are created for individuals, including context-based perceptible attributes, character saliences (like notable physical attributes); potential belief mutations. Evidence is considered the base to acquire knowledge, like (self-)*reflection*, *observation*, *transference*, *confabulation* or lie (an additional type, called *implant*, is also included for the single purpose of setting base simulation information). This knowledge can be reinforced or deteriorated. [74]. Propagation of knowledge and mediation is an adjacent subject of research [75], [76], [77]. Other lines of research focus on modelling creativity, by employing natural language processing and ontologies [78]. Domain ontologies are indeed useful to generate better user representations [79]. Most of these models are used in different operational decision-making activities (task-related decisions), gaming (character definition) or in robotics (e.g. to detect or induce human reactions), but human cognitive models for SDM still require further research.

Digital twins started out as real-time simulators running in parallel with industrial processes to estimate and observe internal states and variables, and to predict future outcomes. Over the years, their use widened, and they began being used in various areas beyond manufacturing, like health, security, safety, transport, energy, mobility and communications. **Human Digital Twins** (HDT) are psychophysiological virtualisations of human beings, usually applied to specific scenarios [70]. HDT can represent cognitive characteristics, including how humans react, what they do, found obstacles and user feelings. These are translated to an ontology [80]. HDT have a set of characteristics that should include identification, sensors to receive data from the human twin or the environment (they eventually may have actuators, depending on the purpose, information processing capabilities that may include an ontology and machine learning techniques, and they should also have real-time communication capabilities to provide and receive and process critical data [81]. HDT can be used for decision-making purposes like agile planning in manufacturing [82] or co-creation for decision-making [83], albeit with limited strategic focus or concern for humanist modelling

In the context o Industry 4.0, digital twins are required to model the represented world adequately and accurately, assessing the circumstances and consequences, managing the complexity of infrastructure, process, and interactions, including human individual and collective behaviour, many of them not yest devised in setup or training, which still present significant challenges [41].

3.3 The human factor in supporting methods for strategic decision-making

Early approaches to EA were mainly static and structure based. Newer approaches and iterations consider the importance of the elements that provide dynamics to EA artifacts and tools now provide dynamic modelling and simulation features. But the human factor still requires more analysis in these frameworks. TOGAF, FEA and others generically consider the relevance of modelling humans but provide no frameworks for that. Zachman and UAF explicitly identify stakeholders, but their links and dynamics to other models in the framework are not detailed. Recent research identifies the gap in human modelling [84] and suggests ways of addressing it, highlighting the importance of trust [27] and sociological, psychological, and emotional issues that, at micro-level, shape the culture of organisations [85]. However, most of the approaches address the same limited number of stakeholders [86]. Additionally, no significant research was found regarding models for emotional and implicit characteristics. Humans are still modelled as simplistic resources, at the same level of equipment and processes.

Decision Intelligence addresses this issue. The underlying theory is that the acritical use of machine learning and AI for prediction and SDM poses an unnecessary burden in companies' resources and wastes strong assets in decision-making and impact analysis, today only available in human beings. The objective of DI is to look to these technologies as tools to provide meaningful support to informed decisions by expert and seasoned decision-makers in the organisation. But work is still required to stabilise this discipline and systematise its integration with other methods and tools for SDM.

Impact of humans in the decision process

Strategic decision does not end in the moment when decisions are made. When considering humans in decision-making, science mostly observes them as stakeholders of the decision process, but there is also a different extent to which they should also be considered as key actors. SDM impacts people working in companies and people consuming the results of that work (be it services or products). And their acceptance rejection or aptitude to adopt the outcomes of decisions constitutes a second-link consequence of the decision-making process that requires further analysis and observation [33]. Thus, the implementation and observation of the effectiveness of change, including multiple-link effects, are essential stages [51]. And it is once more essential to consider the influence of human stakeholders in purveying, enabling, or adopting change. Factors like influence and trust are crucial also here [27], [87]. The excessive focus on rationality not only does omit important repercussions of decisions, but it is also undesirable, as it can become an obstacle to strategy implementation [88]. Capturing tacit knowledge is a possible way to feed future decision-models with meaningful information [89].

The importance of visualisation

In this interaction between humans and other elements in the SDM process, a burden in information processing arises. Visualisation is critical here. Presenting information visually has benefits in enabling a faster processing by decision-makers, but also in minimising biases and extracting patterns from complex or unstructured data [51], [57]. Visual analytics are an emergent field centred in extracting meaningful information from large volumes of data, in providing new perspectives on existent data [90] or even in ethical approaches to decision-making [91], [92]. Typically, decision outcomes are first visualised inside the decision-makers' heads and then put into practice. Graphical visualisation allows decision-makers to envisage second-link effects of decisions better than by using words alone [51]. Charts and graphics can be systematised according to the purpose. 3D and augmented reality are potential tools for this [93]. More than that, diagrams may elicit convergence, highlight commonalities and identify boundaries in heterogenous groups of decision-makers [94] But studies show there is also potential for visualisation bias [95] Additional research in this subject is thus required.

4 Summary and future discussion

The relevance and the importance given in current research to humans integrated in today's companies, namely as stakeholders in strategic decisions, was analysed in this document. Evidence suggests that while humans are becoming a centrepiece of SDM, they are still modelled in a simplistic way, without emphasis on elements that distinguish them from machines and provide unique features when making and adopting decisions. The adoption of decisions is a field where modelling and simulation could provide further support, to understand potential outcomes. This requires work in modelling but also understanding human traits and their role in social interaction (both with other humans and other elements in the organisation). Simulation of mechanisms of individual decision-making, such as character traits, behaviour, creativity or emotions, and emergence of negotiated decisions and factors that concur to this, like trust, knowledge transfer, power balance, or communication, provide space for better regulation and traceability of the decision-making process.

On another level, modelling influence of human factors in cause-effect chains of decision-making and impact of decisions on stakeholders can provide a better understanding of decision failures and successes in medium- and long-term. These can be anticipated by means of digital twins and simulation. These, combined with AI are potential tools for devising mechanisms of redundancy and alternative paths in SDM.

From this work, a research question arises:

RQ: What is a suitable way to model complex human traits and relations and the way to increase the effectiveness and acceptance rates of SDM in organisations?

From the research in this paper, we can conclude that humans influence and are impacted by SDM, but critical elements of their characterisation are not being addressed in a way that allows their accurate simulating and consequently the effective evaluation of (i) how the decision-making process effectively occurs; and (ii) how the decision-making outcomes influence and are impacted by stakeholders involved or affected by them. The objective is to provide insight into new approaches on how to predict and react to influence or resistance of human actors to strategic change.

This work has multiple limitations and challenges. Complex human traits (e.g. creativity, emotions) are not easy to model or translate into clear and accurate dynamic models. DT and DI have a strong procedural approach but not much is specified regarding how individual and collective complex human characteristics should be transformed into archetypes and artifacts. The knowledge areas presented here are diverse and an exhaustive analysis of all of them by a single research line would not be feasible.

In the end, it is important to highlight that, with all the technological and scientific developments that occurred in the last decades, and in spite of many previsions in contrary, human beings are still the key element in work and production, in the sense that complex decisions, strategies, or responsibilities still rely on them. More than that, proposed new approaches to industry, work and society show a clear understanding of how crucial it is to re-adjust the perspective and centre it on the human aspects. Work represents one of the largest amounts of time spent in life by humans. Tools that support a better understanding of how humans are influenced and influence their work environment, and a contemporary approach to the issues and concerns that arise from emerging business landscapes are needed.

References

[1] E. A. Kassa and J. C. Mentz, "Towards a Human Capabilities Conscious Enterprise Architecture," *Information,* vol. 12, no. 8, p. 327, 2021.

[2] T. Tran, *Corporate Social Responsibility and Profits: A Tradeoff or a Balance?,* Stanford University, 2015.

[3] A. Yang, N. Uysal and M. Taylor, "Unleashing the Power of Networks: Shareholder Activism, Sustainable Development and Corporate Environmental Policy," *Bus. Strat. & the Environ.,* no. 27, p. 712–727, 2017.

[4] K. F. Latif, "The Development and Validation of Stakeholder-Based Scale for Measuring University Social Responsibility (USR)," *Social Indicators Research,* no. 140, p. 511–547, 2018.

[5] M. Javed, M. W. Akhtar, M. Husnain, R. Lodhi and S. Emaan, "A stakeholder-centric paradigm bids well for the "business case" - An investigation through moderated-mediation model," *Corporate Soc. Responsibility & Environ. Mgmt.,* vol. 27, no. 6, pp. 2563-2577, 2020.

[6] J. Narayanan, P. Puranam and M. V. Vugt, "Human Centric Organization Design: A Perspective from Evolutionary Psychology," *INSEAD Working Paper No. 2021/63/STR,* 2021.

[7] I. Shaikha and K. Randhawa, "Managing the risks and motivations of technology managers in open innovation: Bringing stakeholder-centric corporate governance into focus," *Technovation,* vol. 114, 2022.

[8] L. Yang, D. Holtz, S. Jaffe, S. Suri, S. Sinha, J. Weston, C. Joyce, N. Shah, K. Sherman, B. Hecht and J. Teevan, "The effects of remote work on collaboration among information workers," *Nature Human Behav.,* no. 6, p. 43–54, 2021.

[9] J. Aroles, N. Mitev and F.-X. d. Vaujany, "Mapping themes in the study of new work practices," *New tech., Work & Employm.,* vol. 34, no. 3, pp. 285-299, 2019.

[10] D. Singh, "Literature Review on Employee Retention with Focus on Recent Trends," *Intl. Journal of Scientific Research in Science & Tech.,* vol. 6, no. 1, pp. 425-431., 2019.

[11] I. Tarique, "Contemporary Talent Management," *Routledge Research Companions in Bus. & Economics,* 2022.

[12] M. S. Henry, D. B. l. Roux and D. A. Parry, "Working in a post Covid-19 world: Towards a conceptual framework for distributed work," *South African Journal of Bus. Mgmt.,* vol. 52, no. 1, 2021.

[13] C. Coombs, D. Hislop, S. K. Taneva and S. Barnard, "The strategic impacts of Intelligent Automation for knowledge and service work: An interdisciplinary review," *Journal of Strat. Info. Sys.,* vol. 29, no. 4, 2020.

[14] M. Gorynia, "Competition and globalisation in economic sciences. Selected aspects," *Economics and Business Review,* vol. 5, no. 3, pp. 118-133, 2019.

[15] R. Teer-Tomaselli, K. Tomaselli and M. Dludla, "Peripheral capital goes global: Naspers, globalisation and global media contraflow," *Media, Culture & Society,* vol. 41, no. 8, pp. 1142-1159, 2019.

[16] N. O'Donovan, "From Knowledge Economy to Automation Anxiety: A Growth Regime in Crisis?," *New Polit. Econ.,* vol. 25, no. 2, pp. 248-266, 2020.

[17] Y. Khmelevsky, X. Li and S. Madnick, "Software Development Using Agile and Scrum in Distributed Teams," in *IEEE Intl. Sys. Conf.*, 2017.

[18] V. Stray and N. B. Moe, “Understanding coordination in global software engineering: A mixed-methods study on the use of meetings and Slack,” *The Journal of Sys. & Sw.,* vol. 170, 2020.

[19] M. Azeem, M. Ahmed, S. Haider and M. Sajjad, “Expanding competitive advantage through organizational culture, knowledge sharing and organizational innovation,” *Technology in Society,* vol. 66, p. 101635, 2021.

[20] Y. K. Na, S. Kang and H. Y. Jeong, “The Effect of Market Orientation on Performance of Sharing Economy Business: Focusing on Marketing Innovation and Sustainable Competitive Advantage,” *Sustainability ,* vol. 11, no. 3, p. 729, 2019.

[21] A. K. L. Hernandez, A. Fernandez-Mesa and M. Edwards-Schachter, “Team collaboration capabilities as a factor in startup success,” *Journal of Tech. Mgmt. & Innov.,* vol. 13, no. 4, 2018.

[22] V. Prokop, J. Stejskal and O. Hudec, “Collaboration for innovation in small CEE countries,” 2019.

[23] H. G. Gemünden, P. Lehner and A. Kock, “The project-oriented organization and its contribution to innovation,” *Intl. Journal of Proj. Mgmt.,* vol. 36, no. 1, pp. 147-160, 2018.

[24] J. Baptista, Mari-KlaraStein, S. Klein, M. B. Watson-Manheim and J. Lee, “Digital work and organisational transformation: Emergent Digital/Human work configurations in modern organisations,” *The Journal of Strategic Info. Sys.,* vol. Volume 29, no. 2, 2020.

[25] K. Lee and J. Yoo, “How does open innovation lead competitive advantage? A dynamic capability view perspective,” *PLoS ONE ,* vol. 14, no. 11, 2019.

[26] B. Alla, B. Sergiy, O. Svitlana and H. Tanaka, “Entropy paradigm of project-oriented organizations management,” in *CEUR Works. Proceedings*, 2020.

[27] A. C. Costa, C. A. Fulmer and N. R. Anderson, “Trust in work teams: An integrative review, multilevel model, and future directions,” *Journal of Organizational Behavior,* vol. 39, no. 2, p. 169– 184, 2018.

[28] S. Verboven, J. Berrevoets, C. Wuytens, B. Baesens and W. Verbeke, “Autoencoders for strategic decision support,” *Decision Supp. Sys.,* vol. 150, 2021.

[29] M. Nooraie, “Factors Influencing Strategic Decision-Making Processes,” *Intl. Journal of Academic Research in Bus. & Social Sciences,* vol. 2, no. 7, pp. 405-429, 2012.

[30] X.-b. Yu, “What Is an Organizational Strategic Decision?,” in *The Fundamental Elements of Strategy*, Springer, 2021, pp. 45-59.

[31] C. Acciarini, F. Brunetta and P. Boccardelli, “Cognitive biases and decision-making strategies in times of change: a systematic review,” *Management Decision,* vol. 59, no. 3, 2020.

[32] P. Shrivastava and J. H. Grant, “Empirically Derived Models of Strategic Decision-Making Processes,” *Strategic Mgmt. Journal,* vol. 6, no. 2, pp. 97-113, 1985.

[33] J. March, "The Technology of Foolishness (original text from 1971)," in *Shaping Entrepreneurship Research*, Routledge, 2020.

[34] BøjeLarsen, "Whatever happened to "The Technology of Foolishness"? Does it have any potential today?," *Scandinavian Journal of Mgmt,* vol. 36, no. 1, 2020.

[35] J. Kay, "Obliquity," *Capitalism & Society,* vol. 7, no. 1, 2012.

[36] L. Aristodemou and F. Tietze, "Technology Strategic Decision Making (SDM): an overview of decision theories, processes and methods," *Centre for Tech. Mgmt. working paper series,* no. 5, 2019.

[37] K. M. Ismail and X. Zhao, "Comprehensiveness in strategic decision making: toward clarifying the construct," *American Journal of Mgmt.,* vol. 17, no. 4, pp. 133-142, 2017.

[38] H. M. Alhawamdeh and M. A. K. Alsmairat, "Strategic Decision Making and Organization Performance: A Literature Review," *Intl Review of Mgmt & Mktg,* vol. 9, no. 4, pp. 95-99, 2019.

[39] A. Intezari and S. Gressel, "Information and reformation in KM systems: big data and strategic decision-making," *Journal of Knowl. Mgmt.,* vol. 21, no. 1, pp. 71-91, 2017.

[40] K. Dear, "Artificial Intelligence and Decision-Making," *The RUSI Journal,* vol. 164, no. 5-6, pp. 18-25 , 2019.

[41] D. Trentesaux and S. Karnouskos, "Engineering ethical behaviors in autonomous industrial cyber-physical human systems," *Cogn Tech Work ,* no. 24, p. 113–126, 2022.

[42] F. Longo, A. Padovano and S. Umbrello, "Value-Oriented and Ethical Technology Engineering in Industry 5.0: A Human-Centric Perspective for the Design of the Factory of the Future," *Appl. Sci.,* no. 4182, p. 10, 2020.

[43] H. Rahanu, E. Georgiadou, K. Siakas, M. Ross and E. Berki, "Ethical Issues Invoked by Industry 4.0," *Sys, Sw and Serv Proc Improvement. EuroSPI Comm in Comp and Info Science,* vol. 1442, 2021.

[44] J. W. Ross, P. Weill and D. Robertson, Enterprise Architecture As Strategy: Creating a Foundation for Business Execution, Harvard Business Press, 2006.

[45] A. Wegmann, "On the systemic enterprise architecture methodology (SEAM)," in *Proc. of the 5th Intl. Conf. on Enterp. Info. Sys.*, 2003.

[46] M. S. &. J. V. Paola Lara, "OT Modeling: The Enterprise Beyond IT," *Bus. & Info. Sys. Eng. ,* no. 61, p. 399–411, 2019.

[47] J. Lapalme, A. Gerber, A. V. d. Merwe, J. Zachman and K. H. Marne De Vries, "Exploring the future of enterprise architecture: A Zachman perspective," *Computers in Industry,* vol. 79, pp. 103-113, 2016.

[48] G. Shanks, M. Gloet, I. Someh, K. Frampton and T. Tamm, "Achieving benefits with enterprise architecture," *The Journal of Strategic Info. Sys.,* vol. 27, no. 2, pp. 139-156, 2018.

[49] M. B. Jusuf and S. Kurnia, "Understanding the Benefits and Success Factors of Enterprise Architecture," in *Proc. of the 50th Hawaii Intl. Conf. on Sys. Sciences*, 2017.

[50] M. Jayakrishnan, A. K. Mohamad and A. Abdullah, “Digitalization Approach Through an Enterprise Architecture for Malaysia Transportation Industry,” *Intl. Journal of Civil Eng. & Tech.,* vol. 9, no. 13, p. 834–839, 2018.

[51] L. Pratt, Link: How Decision Intelligence Connects Data, Actions, and Outcomes for a Better World, Emerald Publishing Limited, 2019.

[52] R. Moser, S. Rengarajan and G. Narayanamurthy, “Decision Intelligence: Creating a Fit between Intelligence Requirements and Intelligence Processing Capacities,” *IM Kozhikode Society & Mgmt Review,* vol. 10, no. 2, pp. 160-177, 2021.

[53] Y. Duan, J. S. Edwards and Y. K. Dwivedi, “Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda,” *Intl Journal of Info. Mgmt.,* vol. 48, pp. 63-71, 2019.

[54] E. Knight, J. Daymond and S. Paroutis, “Design-Led Strategy: How To Bring Design Thinking Into The Art of Strategic Management,” *California Mgmt Review,* vol. 62, no. 2, pp. 30-52, 2020.

[55] E. Kotina, M. Koria and S. Prendeville, “Using design thinking to improve strategic decisions during collaborative sensemaking,” in *Design Mgmt Academy Conf.*, Hong-Kong, 2017.

[56] S. Graf, “Design Thinking for Strategizing? – A Critical Literature Review,” *Journal of Emerging Trends in Mktg & Mgmt,* vol. 1, no. 1, pp. 110-119, 2021.

[57] J. Liedtka and S. Kaplan, “How design thinking opens new frontiers for strategy development,” *Strategy & Leadership,* vol. 47, no. 2, 2019.

[58] J. Johnson, “Delegating strategic decision-making to machines: Dr. Strangelove Redux?,” *Journal of Strategic Studies,* pp. 1-39, 2020.

[59] J. E. Korteling, A.-M. Brouwer and A. Toet, “A Neural Network Framework for Cognitive Bias,” *Frontiers in Psychology,* vol. 9, 2018.

[60] E. Fonda and A. Meneghett, “The Human-Centric SMED,” *Sustainability,* vol. 14, no. 51, 2022.

[61] S. Nahavandi, “Industry 5.0—A Human-Centric Solution,” *Sustainability ,* vol. 11, no. 16, p. 4371, 2019.

[62] E. H. Østergaard, “Welcome to industry 5.0,” Universal Robots, 2018.

[63] P. K. R. Maddikunta, Q.-V. Pham, P. B, N. Deepa, K. Dev, T. R. Gadekallu, R. Ruby and M. Liyanage, “Industry 5.0: A survey on enabling technologies and potential applications,” *J. of Industrial Info. Integration,* vol. 26, 2022.

[64] P. Skobelev and S. Borovik, “On the way from Industry 4.0 to Industry 5.0: from Digital Manufacturing to Digital Society,” *Intl Scientific J. "Industry 4.0",* vol. II , no. 6, pp. 307-311, 2017.

[65] D. Trentesaux and S. Karnouskos, “Engineering ethical behaviors in autonomous industrial cyber-physical human systems,” *Cognition, Technology & Work ,* vol. 24, no. 1, pp. 113-126, 2022.

[66] L. Berrah, V. Cliville, D. Trentesaux and C. Chapel, “Industrial Performance: An Evolution Incorporating Ethics in the Context of Industry 4.0,” *Sustainability,* vol. 13, no. 9209, 2021.

[67] M.-P. Pacaux-Lemoine and Damien Trentesaux, "Ethical Risks of Human-Machine Symbiosis in Industry 4.0: Insights from the Human-Machine Cooperation Approach," *IFAC-PapersOnLine,* vol. 52, no. 19, pp. 19-24, 2019.

[68] F. Cavallo, F. Semeraro, L. Fiorini, G. Magyar, P. Sinčák and P. Dario, "Emotion Modelling for Social Robotics Applications: A Review," *Journal of Bionic Engineering,* vol. 15, no. 2, pp. 2543-2141, 2018.

[69] A. Greasley and C. Owen, "Representing Human Behavior," in *Behavioral Operational Research*, Palgrave Macmillan, London, 2016, pp. 47-63.

[70] J. Sun, Z. Tian, Y. Fu, J. Geng and C. Liu, "Digital twins in human understanding: a deep learning-based method to recognize personality traits," *Intl. Journal of Comp. Integrated Manuf.,* vol. 34, no. 7-8, 2021.

[71] T. Wängberg, M. Böörs, E. Catt, T. Everitt and M. Hutter, "A Game-Theoretic Analysis of the Off-Switch Game," in *Intl. Conf. on Artificial General Intel.*, Springer, 2017.

[72] D. Gatherer, "The spread of irrational behaviors by contagion: An agent micro-simulation," in *A Memetics Compendium*, 2008, p. 727.

[73] J. Liu, "The Superstitious Heuristic in Strategic Decision-making (Dissertation)," City Univ. of New York, 2019.

[74] J. Ryan and M. Mateas, "Simulating character knowledge phenomena in Talk of the Town," in *Game AI Pro 3*, AK Peters/CRC Press, 2017, pp. 433-448.

[75] N. Bakanova, A. Bakanov and T. Atanasova, "Modelling Human-Computer Interactions based on Cognitive Styles within Collective Decision-Making," *Advances in Science, Tech. & Eng. Sys. Journal,* vol. 6, no. 1, pp. 631-635, 2021.

[76] B. Xu, R. Liu and Z. He, "Individual irrationality, network structure, and collective intelligence: An agent-based simulation approach," *Complexity,* vol. 21, no. S1, pp. 44-54, 2016.

[77] D. Tomlin, "Consensus decision-making: performance of heuristics and mental models," *Evolution & Human Behavior,* vol. 42, no. 4, pp. 316-330, 2021.

[78] A. Jordanous and B. Kelle, "Modelling Creativity: Identifying Key Components through a Corpus-Based Approach," *PLoS ONE,* vol. 11, no. 10, 2016.

[79] J. Hale, J. Hastings, R. West, C. E. Lefevre1, A. Direito, L. C. Bohlen, C. Godinho, N. Anderson, S. Zink, H. Groarke and S. Michie, "An ontology-based modelling system (OBMS) for representing behaviour change theories applied to 76 theories," *Wellcome Open Research,* vol. 5, no. 177, 2020.

[80] P. Saariluoma, J. Cañas and A. Karvonen, "Human Digital Twins and Cognitive Mimetic," in *Intl. Conf. on Human Interaction & Emerging Tech.*, 2020.

[81] A. E. Saddik, "Digital Twins: The Convergence of Multimedia Technologies," *IEEE MultiMedia,* vol. 25, no. 2, pp. 87-92, 2018.

[82] C. H. d. Santos, R. D. C. Lima, F. Leal, J. A. d. Queiroz, P. P. Balestrassi and J. A. B. Montevechi, "A decision support tool for operational planning: a Digital Twin using simulation and forecasting methods," *Production,* vol. 30, 2020.

[83] S. West, O. Stoll, J. Meierhofer and S. Züst, "Digital Twin Providing New Opportunities for Value Co-Creation through Supporting Decision-Making," *Applied Sciences,* vol. 11, no. 3750, 2021.

[84] R. Oberhauser, P. Sousa and a. F. Michel, "VR-EAT: Visualization of Enterprise Architecture Tool Diagrams in Virtual Reality," in *Intl. Symposium on Bus. Modeling & Sw. Design*, 2020.

[85] E. Aromaa, "Emotion as soft power in organisations," *Journal of Org. Effectiveness: Ppl & Perf.,* vol. 7, no. 4, pp. 341-357, 2020.

[86] F. Gonzalez-Lopez and G. Bustos, "Integration of Business Process Architectures within Enterprise Architecture Approaches: A Literature Review," *Eng. Mgmt. Journal,* vol. 31, no. 2, pp. 127-140, 2019.

[87] J. Battilana and T. Casciaro, "Power, social influence and organizational change: The role of network position in change implementation," in *Academy of Mgmt Proceedings*, 2010.

[88] M. P. Healey and G. P. Hodgkinson, "Making Strategy Hot," *California Mgmt. Review,* vol. 59, no. 3, pp. 109-134, 2017.

[89] S. Y. Cho, J. Happa and S. Creese, "Capturing Tacit Knowledge in Security Operation Centers," *IEEE Access,* vol. 8, pp. 42021-42041, 2020.

[90] S. K. &. D. A. Kadi, "Strategic eco-design map of the complex products: toward visualisation of the design for environment," *Intl. Journal of Prod. Research,* vol. 65, no. 24, pp. 7296-731, 2018.

[91] A. Parkavi, A. Jawaid, S. Dev and M. S. Vinutha, "THE PATTERNS THAT DON'T EXIST: Study on the effects of psychological human biases in data analysis and decision making," in *3rd Intl Conf. on Comp. Sys. & Info. Tech. for Sustainable Sols., IEEE*, 2018.

[92] Y. Ahn and Y.-R. Lin, "FairSight: Visual Analytics for Fairness in Decision Making," *IEEE transact. on visualiz. & computer graphs.,* vol. 26, no. 1, pp. 1086-1095, 2019.

[93] A. Hollberg, B. Kiss, M. Röck, B. Soust-Verdaguer, A. H. Wiberg, S. Lasvaux, A. Galimshina and G. Habert, "Review of visualising LCA results in the design process of buildings," *Building & Environm.,* vol. 190, p. 107530, 2021.

[94] I. Pluchinotta, G. Salvia and N. Zimmermann, "The importance of eliciting stakeholders' system boundary perceptions for problem structuring and decision-making," *European Journal of Op. Research,* 2021.

[95] G. Ellis and A. Dix, "Decision Making Under Uncertainty in Visualisation?," in *IEEE VIS2015*, Chicago, 2015.