EINST4INE Deliverable 2.1

(Best) Practices in the Integration of Social and Digital Decision-Making Approaches Across Industries

C. M. Leeb, L. Mortara, N. Felicini, R. Phaal, B. A. Moncur

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Executive summary

Humans need to take decisions in a variety of contexts: some relate to personal lives, whilst others concern companies, institutions, and society. Some decisions are taken individually, and others as a group. In all contexts, taking decisions can be critical and challenging tasks for humans, who have dedicated much attention and effort to develop decision-making support tools and approaches. An increasing number of digital technologies are becoming available to support the act of taking decisions, from digital meeting platforms to augmented and virtual reality technology, from simulations to robotics and artificial intelligence.

The application contexts for decision-making vary enormously, and as the integration of these various digital technologies is becoming more common the question is: What have we learnt so far? What do we still need to learn?

How do humans decide WITH digital technology?

This report investigates current practice at the interface between the social (human) decision-making process and digital technology. We want to provide an overview of current learning across various practice contexts, through a unified lens which allows us to assimilate the learning and guide further research.

To position 13 cases of integration of human and digital technology in decision-making (Pages 18-88), we propose a three-dimensional space, defined by three axes associated with fundamental questions:

1. Who takes the decision? (p.13)
2. What type of decision? (p.14)
3. Where in the decision-making process does the integration of digital technologies happen? (p.16).

The cases have been collected from academics and managers who study and deploy cutting-edge digital technology for decision-making, on an international basis. Cases were selected to represent a broad range of applications of digital technologies in a variety of decision-making contexts. Each case study presents not just the learnings to date, but also the boundary of current knowledge and future research directions.

By cross analysing the cases, we identified themes that are relevant across the three-dimensional space. For each application of a digital technology in decision-making, questions emerge about how to promote the:

- **Adoption** of the integration of the digital technology in decision-making, in terms of enablers and barriers (p.90)
- **Assessment** of the integration of the digital technology in decision-making in terms of effectiveness and appropriateness (p.94)
- **Adaptation** of the human systems to integrate digital technologies in decision-making, including inward and outward adaptation (p.100)

Contents

Introduction

The phenomenon of Digital Transformation

Digital transformation (DT) is a process that is transforming the world, in particular businesses across all industries. It involves the codification of tasks, instructions, and decisions in digital codes (I.e., codes that uses digits, typically binary codes which use only 1 and 0) which are used to automatise tasks and decisions.

Although **this phenomenon started long time ago**, having its routes in the implementation of binary codes in physical devices used to control machines (e.g. punched cards which controlled looms (see the invention of the Jacquard machine in 1725 or music boxes and carillons in the 19th century), this phenomenon has really taken full shape since the invention and diffusion of computers in the mid 20th century and mainly after the diffusion of the internet in the first quarter of the 21st century. From a research perspective, digital transformation as an organizational phenomenon is still at an early stage, as indicated by the 25-fold growth of publications in recent years (period 2015-2019, Al-Ali, 2020). In general, over the past 5-10 years **there has been a significant shift** in digital transformation that has gathered increased attention from academia, consulting, and industry. While some of this attention may be exaggerated, it is indicative of a fundamental change in the landscape of digital technology, (including the maturation of technologies such as networks, cloud computing and big data analytics), representing **a tipping point in digital transformation**.

Currently, **digital transformation (DT) applies increasingly** to all the activities undertaken across society, from those of individuals, to those of business and governments and has been recognised as **one of the most important trends** of this century (Dabrowska et al., 2022). Society, and business in particular, are aiming to increase the ratio of tasks that are dealt within the digital world and to complete the transformation (digitalization). The aim is to achieve multiple goals. The majority of organizations are embracing new digital technologies and innovations to improve their business processes, enhance their customer experience and gain competitive advantages (Alt, 2019; Kane et al., 2017). **Key-player governing institutions**, like the European Commission, **have realized the importance of digital transformation**, as highlighted by recent works on identifying breakthrough innovations (Warnke et al., 2019), or initiatives to foster digitalization (European Commission, 2021, 2022) and digital literacy (Martin, 2005) under the broader EU's Digital Strategy.

Embracing digital technologies is widely recognized as crucial process for industry (Fitzgerald et al., 2014; Westerman et al., 2011) as well as an important **phenomenon to investigate** by academics. In fact, **several recent reviews** summarise the state of the art in DT and propose corresponding frameworks as a basis for continuous discussion and future research. See the box below for main examples.

Recent literature on Digital Transformation

Vial (2019) framed DT as a process, where technology disruptions trigger strategic responses and generate positive and negative impacts on the company. Adopting a different perspective, the review by Van Veldhoven & Vanthienen (2023) identifies DT key topics and provides corresponding implementation guidelines for both researchers and practitioners. Kraus et al. (2022) analysed the evolution of the DT research in the areas of business and management and summarised the findings in a framework highlighting the current research themes and where the knowledge has mainly developed so far. Appio et al. (2021) deconstructed the topic by proposing three level of analysis (i.e., macro, meso, and micro) along which current and future research can be organised. Nadkarni & Prügl (2020) analyse the existing research to develop a thematic map which identifies technology and actors as the two dominant dimensions of DT. Finally, Hanelt et al. (2021) discern two patterns from the literature: firm moving towards malleable organizational design to ensure adaptability, and digital business ecosystems, that enable such shift. This context of continuous change is viewed from four different perspectives: technology impact, compartmentalised adaptation, systemic shift, and holistic co-evolution. Interestingly they find that **DT is only partially covered by existing frameworks** on organizational change, projecting how they **need to be advanced** to cover the complexity of the phenomenon.

About the report

The purpose of this report is not merely to present another literature review of the various tools and approaches used to facilitate decision-making with digital technologies. Rather, it aims to create a **framework based on real-life applications** and case studies that goes beyond a simple review of the literature.

Our report fits the context of Digital Transformation (DT) since decision-making (DM) is probably the main managerial process affected by DT (see for example the reviews from Ahmed et al., 2021, and Dabrowska et al., 2022). As more decision-making is committed progressively to the digital environment, **the interface between digital and physical is shifting**. It is at this interface that digital technologies are integrated with the human decision-making capabilities and **the report concentrates on this interface** and integration.

Following the previously cited studies, **this report introduces a generic decision-making process**, which explains the nature of decision-making, which can apply to a variety of circumstances in digital transformation. Further, it **identifies key dimensions** along which the digital transformation of the decision-making can be analysed to evaluate where, when and how the integration of the digital and human DM happens. Finally, it **brings together a concise number of case studies** which illustrate the integration of human and digital DM along the various dimensions, **suggesting guidelines to researchers and practitioners**, respectively for investigation and implementation of digital technologies in decision-making.

Decision-making as a process

Decision-making has long been described as **an iterative process** across disciplines (Hastie 2001; Mintzberg and Theoret 1976; Maltugueva and Yurin 2015; Tverksy and Kahneman 1974; Simon 1955). At the most basic level, it can be broken down into a 4-stage iterative process:

Feedback loop

1. Identification of the decision to be taken,
2. Gathering and analysing information to support the decision,
3. Taking the decision, and
4. Acting on the decision.

Identification of the decision involves **recognising that a decision needs to be made** and understanding the form that it will take. **This is most challenging in unstructured situations** where it is difficult to pinpoint decision choices and estimate the possible outcomes resulting from decision (Fellows, 2004; Tverksy and Kahneman 1974). **Gathering and analysing information to support the decision** involves synthesising relevant information from multiple sources through the lens of past experiences and future goals. Taking the decision involves **a choice between identified options** based on the insights generated from the previous stage. This can be done intuitively or by using formal assessments of "goodness" like utility (Kahneman and Klein 2009; Calabretta et al., 2017). Finally, **acting on the decision** involves implementing the outcome of the decision process in an action. For some decisions, this could be simply to review or repeat the decision process, forming a feedback loop.

This view of decision-making as a process (Hastie 2001; Mintzberg and Theoret 1976; Maltugueva and Yurin 2015; Tverksy and Kahneman 1974; Simon 1955) highlights **multiple steps**. However, the 4-stage process described above is over-simplified - in reality, **most decisions involve a sequence of decisions** embedded within each stage of the basic decision-making process described above. For example, in the gathering and analysing information stage, a decision needs to be made about when sufficient information has been processed to generate enough insights to take the decision. Therefore, the decision-making process should instead be viewed as a sequence of embedded decisions, as illustrated in Figure 1.

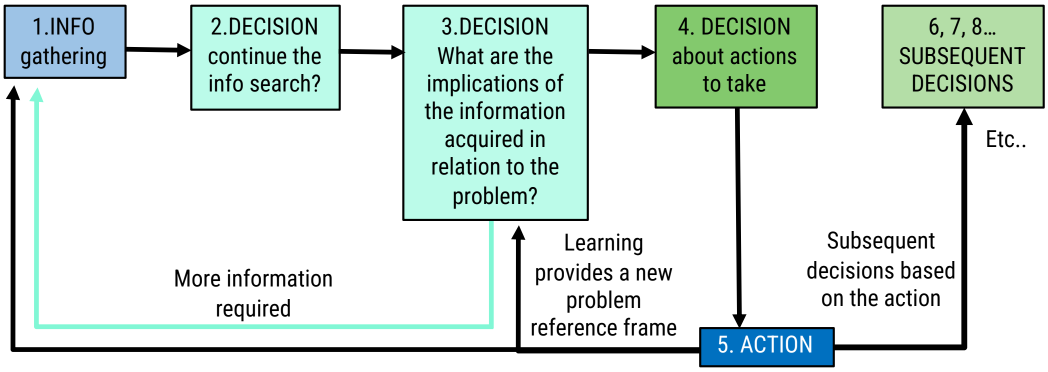


Figure 1: Sequence of embedded tasks in decision-making process.

The first decision – the process of information gathering about the problem - involves **deciding where to search for information**, **selecting the sources** from which to extract information, and **deciding how to filter** the information in terms of its relevance to the decision problem (Kerr et al., 2006). Subsequently, a decision must be made about **whether sufficient information has been gathered** to make an informed decision about the problem or whether more is required. These two decision stages iterate until enough information has been gathered. Once the information has been deemed sufficient, a decision must be made about **the implications of the gathered information**. This decision is more complex than the initial stage and requires transformation of the information into insights to be used in the next decision stage (North and Kumta 2018). A decision is then made about **how to use the insights to judge the 'best' action to take**. The resulting action may be to use what has been learned to loop back to an earlier decision in the process, for example to gather more information or extract more insights from the information with a new way of framing the problem. Alternatively, the action

> **Decision-making can be viewed as a nested sequence of embedded decisions.**

may result in subsequent decisions based on the action.

This view of decision-making as a sequence of embedded decisions represents the foundation of any type of decision, but **the complexity and interdependency of decisions can vary significantly**. Some complex decisions may require several iterations of the decision-making process, so it becomes a nested sequence of embedded decisions. For example, deciding the new strategic direction of an organisation is bound to require multiple iterations of the decision process due to the unstructured nature of the decision problem and vast array of information sources to combine and draw insights from (Mintzberg and Theoret 1976). This idea of decision-making as a nested sequence of interconnected embedded decisions highlights the complexity of decision-making and invites **the integration of digital technologies to ease the burden on decision makers**.

Integration of digital technologies

The integration of digital technologies into decision-making is not a novel concept. In the 1950s, researchers such as Herbert Simon and Marvin Minsky were producing early computer models of human cognition (e.g., Minsky, 1954; Simon, 1956). Digital decision support systems designed to assist people with decision-making started to appear in large companies in the 1960s (e.g., Corbato et al., 1962). Now, **digital technologies are prevalent in almost all aspects of human life** - in the home, at work, and on the go. As a result, today they are present in human decision-making in many forms, both actively in purpose-built decision support systems (Power, 2002) and passively as tools in the background that assist with decision-making activities. **Passive tools** include digital means of communication for people taking decisions and subtle guidance for route planning offered by mobile navigation apps. **Active tools** include the use of artificial intelligence (AI) agents to make decisions about the classification of patients in clinical settings (Giordano et al., 2021).

Therefore, key questions emerge about the role of digital technologies in decision-making and how they affect systems, humans, and societies. Traditional human-computer interaction research investigates the "fit" between people and technology with the aim of improving productivity. However, a human-centered perspective is needed that evaluates the integration of technologies with respect to the factors that shape the lives of humans (Bannon, 2011). In this perspective, **humans are used as the reference point for whether a technology is useful or not**. We adopt such a human-centered perspective in our aim to clarify the various dimensions along which to evaluate the integration of digital technologies with social actors (individuals or groups of humans) in decision-making.

We propose 3 axes on which to evaluate the integration:

1. **WHO makes the decision?**
2. **WHAT type of decision?**
3. **WHERE in the decision-making process does the integration of digital technologies happen?**

Axis 1 evaluates the extent to which the decision-making is done by a human(s). This can vary from one extreme of purely human decisions with no digital influence, to the other extreme of purely digital decisions with no human input. **Axis 2 evaluates the level of decision-making** that is required. **Decisions can be categorised** into three levels - **strategic, tactical, and operational** – based on their scope and time frames. **Axis 3** is a non-linear axis that **evaluates which parts of the decision-making process are being transformed by the presence of digital technologies**. The scope of this investigation excludes decisions about the design of the technology - we are interested in investigating the decisions that occur after the technology has been deployed. Combining the three axes generates a 3-dimensional space in which to evaluate the integration of digital technologies in decision-making, as shown in Figure 2.

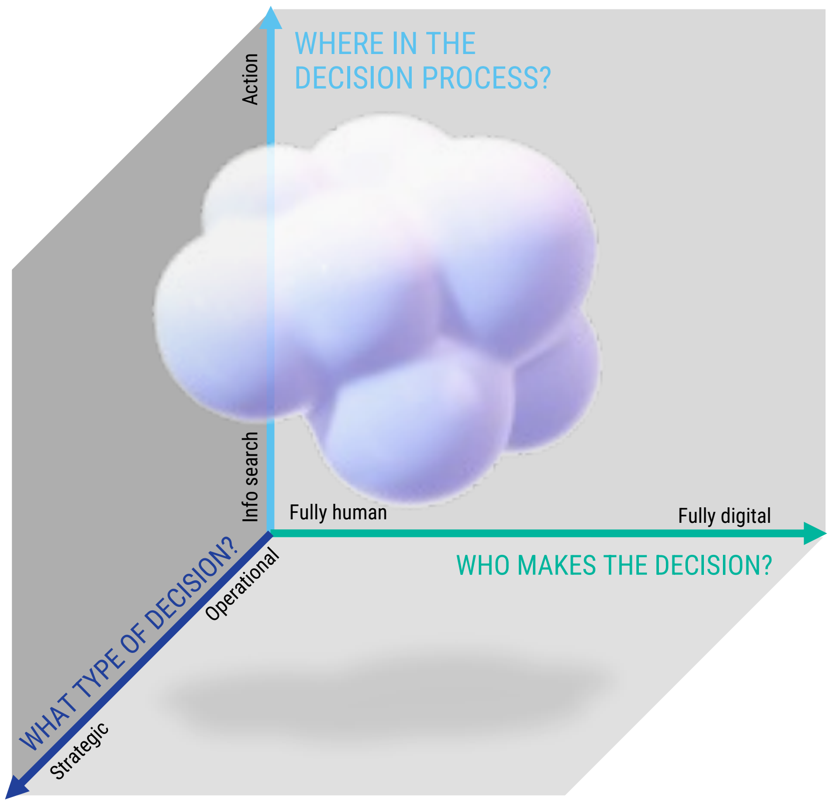


Figure 2: Three-dimensional space to evaluate the integration of digital technologies for/in decision-making

Axis 1: Who makes the decision?

The first axis on which to evaluate the integration of digital technologies in decision-making relates to **who is making the decision**. This can be viewed as a continuum, from one end where the human is fully in control of the decision, to the other where a digital agent has full control, as shown in Figure 2. The extreme case of digital agents having full control of the decision process is a full substitution of humans for digital technology. The other extreme is when humans do not involve digital technologies in their decisions. The space in between the two extremes shifts from **"substituting technology"** at the digital agent end of the spectrum, through to **"augmenting technology"** as you move towards the human end (Murray et al., 2021; Rouse and Spohrer, 2018).

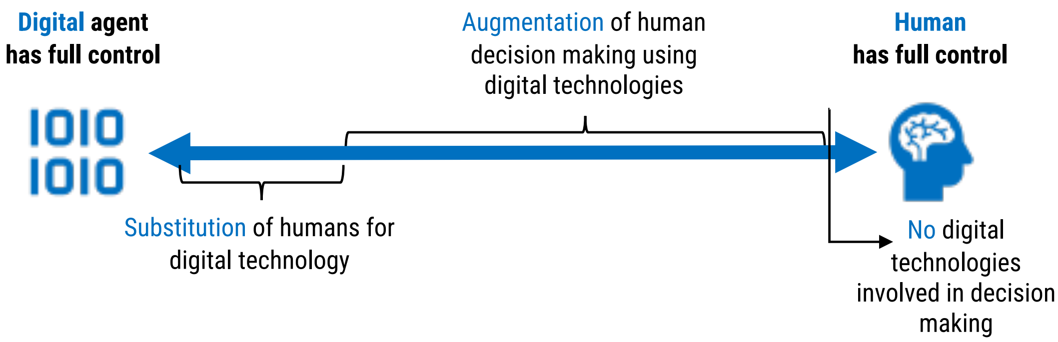


Figure 3: Who makes the decision? The axis varies from full digital control to full human control.

Returning to the model of decision-making as a nested sequence of embedded decisions, some embedded decisions may be fully substituted by digital technologies whereas others may just be augmented. For example, there are many nested decisions involved in keeping the floor of a house free of dust. Traditionally, all stages of the decision process are done by a human with a vacuum cleaner. However, robotic cleaners can be introduced to substitute or augment some of the embedded decisions in the decision-making process. In one scenario, the owner of a house might decide that the floor needs vacuuming. For instance, they could decide to sweep every 3 days, or on a specific day when it has gotten particularly messy, so they decide to program or activate the robot accordingly to automatically sweep the floor. At this point, it is the robot that decides where to go first, where to turn, how long to operate before the batteries run out, and when to return to the charging station. In an alternative scenario, the robot could be part of a more complex system which has sensors that realise when the floor needs to be vacuumed. The human decides upon a tolerable level of dirt, and the robot decides when and how often to vacuum. Further still, the robot might make its own decision about the required cleanliness standards based on what it learns from its environment, such as explicit or implicit feedback from the inhabitants of the house.

The **shifting of responsibility** of decisions from the human to the robot **represents a shift from augmenting technologies towards substituting technologies** (Murray et al., 2021).

Axis 2: What type of decision?

The second axis on which to evaluate the integration of digital technologies in decision-making relates to the **type of decision**. There are many ways to categorise decision problems – three are introduced here (Ackoff, 1990), as illustrated in Figure 3.

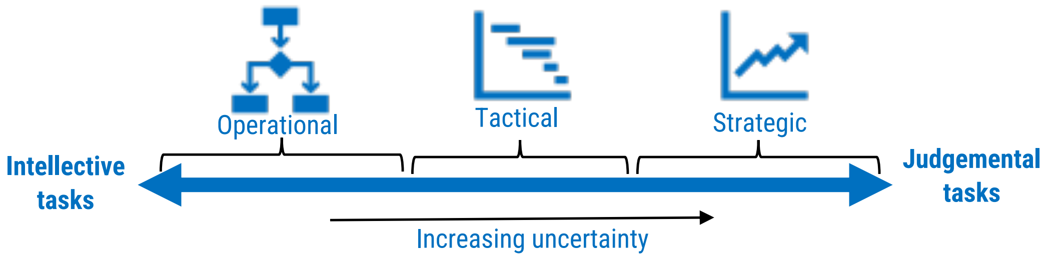


Figure 4: What type of decision? There are multiple ways to classify types of decision – here we integrate the distinction between operational/tactical/strategic decisions (Ackoff, 1990) with intellective versus judgemental tasks (Laughlin, 1980), and inherent uncertainty (Courtney et al., 1997).

Decisions are varied, and involve a spectrum of agents, from individuals to groups. Business decisions are commonly separated into three categories - **strategic, tactical, and operational**. Ackoff (1990) distinguishes between these types of decision based on time frame and scope. **Strategic decisions are focused on growth** – they set objectives for the organization as a whole and formulate principles to govern the means to pursue the objectives. They concern a period of time long enough to cover development of radically new products, development of new sources of products, or entry into a new business. **Tactical decisions are focused on how to enact the strategy**. They are concerned with the period of time for which the organization’s performance is evaluated by external evaluators (e.g., the fiscal year). **Operational decisions are focused on day-to-day existence**. They are concerned with completing tasks fundamental to the function of the organization, focused only on the immediate future.

Laughlin (1980) distinguishes also between intellective and judgemental decisions. **Intellective decisions have one objective demonstratable solution**, such as deciding how to pack items into a box with the aim of doing so in the most efficient way. In contrast, the criterion for evaluating **judgmental decisions** is the **subjective consensus of the decision makers or an external group**. One such example is the decision about the future strategy of an organisation.

Additionally, decisions can be categorized by the level of uncertainty about the future. Courtney et al., (1997) define four levels of uncertainty:

1. **A clear-enough future**, where a single forecast of the future can be developed. Any unknown information could be "knowable" if the right analysis were done.
2. **Alternate futures**, where the future can be described as one of a few alternate outcomes which are clear and discrete.
3. **A range of futures**, where the range is defined by a few key variables, but the outcomes are continuous rather than discrete.
4. **True ambiguity**, where the future is virtually impossible to predict due to multiple dimensions of uncertainty.

Intellective tasks and **operational decisions generally have lower levels of uncertainty** associated with them because they consider very short time scales and ambiguity is low. **Tactical decisions have higher levels of uncertainty** due to their wider scope, greater complexity, and longer time scales. The complexity, ambiguity and resulting uncertainty is further exaggerated for strategic decisions. The affordances of different digital technologies will dictate their application to different types of decisions. For example, AI is increasingly being deployed to perform highly structured decisions that are operational or tactical, based on large amounts of data (Brynjolfsson and McAfee, 2014; Gumusay et al., 2022).

Axis 3: Where in the decision-making process is the integration between social and digital happening?

The third axis on which to evaluate the integration of digital technologies in decision-making relates to **which parts of the decision-making process are being transformed by the presence of digital technologies**. As discussed, decision-making can be thought of as a nested sequence of embedded decisions. Therefore, the decision-making process can be depicted as a non-linear axis with feedback loops that circle back into each stage, as depicted in Figure 4.

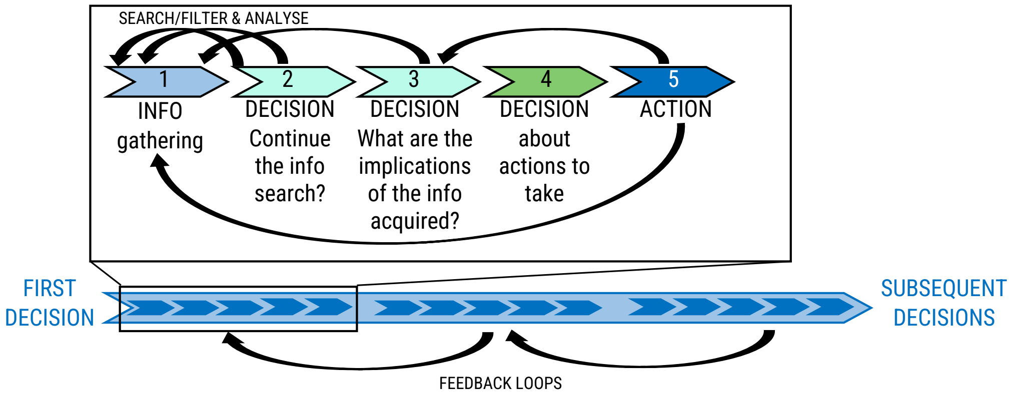


Figure 5: Where in the decision-making process is the integration between social and digital decision-making happening? This is a non-linear axis that evaluates which parts of the decision-making process are being transformed by the presence of digital technologies.

Digital technologies can be integrated into different stages of the decision-making process. For example, the technology could assist with searching and filtering information, or it could assist with the selection of decision actions. **The proportion of the decision-making process that is augmented with, or substituted by, digital technologies will vary case by case**. However, it is expected that some aspects of the decision-making process are more commonly integrated with digital technologies than others across all cases.

Using the axes

We now turn to using the three axes to investigate where current work is being done on the integration of digital technologies into decision-making. We have collated **13 case studies** and **evaluated them based on the type of decision, the involvement of the human** in the decision-making process, **and where in the decision-making process the integration is taking place**.

This analysis has generated a **3-dimensional representation of where current work is based**, with each dimension representing one of the axes, as shown in Figure 6. We then use the 3-dimensional plot to discuss the directions that future work can take, based on expanding the frontiers of current work along each of the axes.

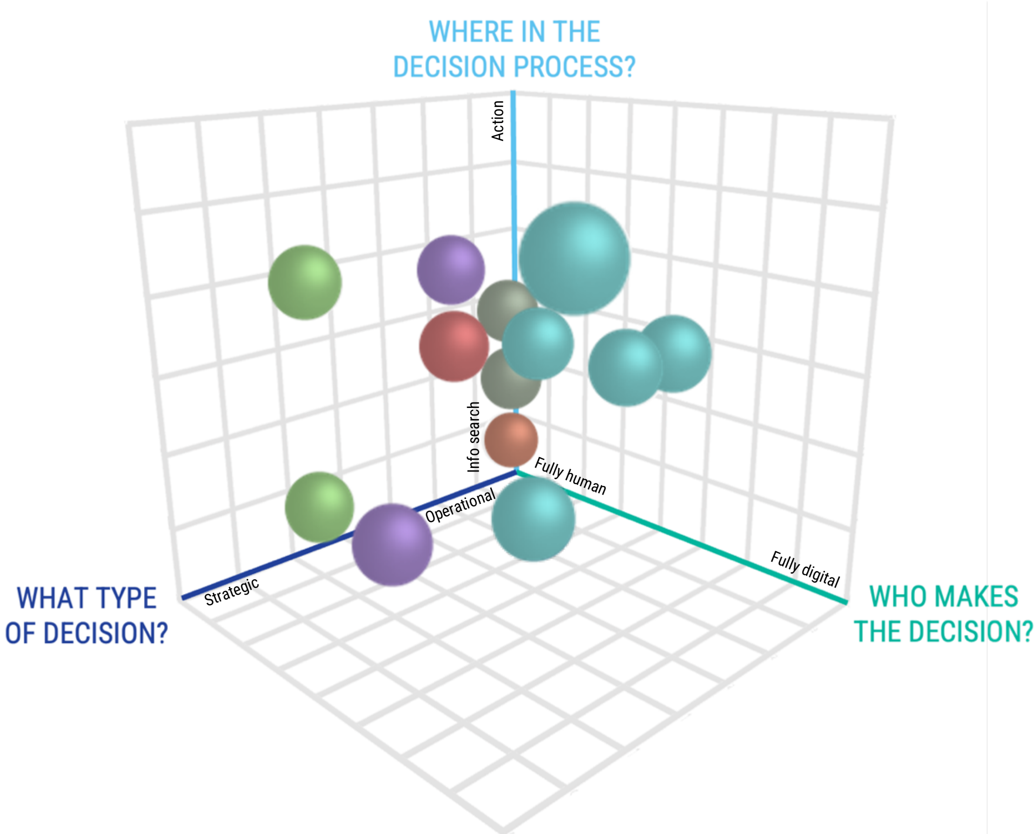


Figure 6: Case studies plotted on the 3 axes. Spheres' colour indicates the technology and tools used in the case study: **Telepresence Robots**, **AI**, **AR/VR**, **Digital whiteboard**, **Digital simulation**, **Digitalization framework**.

Research method

We looked for cases which dealt with **examples of interaction between humans and digital tools in decision-making** in industry. As our model indicates, decision-making in digitalization happens at different levels and in different contexts. Hence our collection of cases did not aim to be exhaustive, but rather to provide practical evidence with regards to the dimensions highlighted in the model. Between June and October 2022, using a snowballing sampling technique, we called for submissions on relevant cases, starting by calling on the EINST4INE consortium https://www.einst4ine.eu/. This comprises 38 global researchers in the field of digitalization, in 7 universities, and 20 industrial partners involved in digitalisation.

Initially, researchers and industry partners from the EINST4INE project were approached to (1) provide short case studies from their research and industry exposure, (2) to invite colleagues and industry outside the EINST4INE circle to submit case studies. The request was to describe practices related to "interactions between humans and digital (including tools, environments, intelligence) in taking decisions". The authors were invited upon submission to indicate the approximate placement of their case study on the three axes described in this report.

After screening for overall quality, cases which clearly addressed the human-digital integration, were selected. The selection approach aimed to provide a good spread along three proposed axes.

Four independent coders used thematic coding (Mayring, 2000) to extract common trends. The first-order codes that emerged were discussed and evaluated as a group, leading to the identification of merged second-order codes. These reflected **common themes across all case studies**, and emerging future research questions for these themes were discussed.

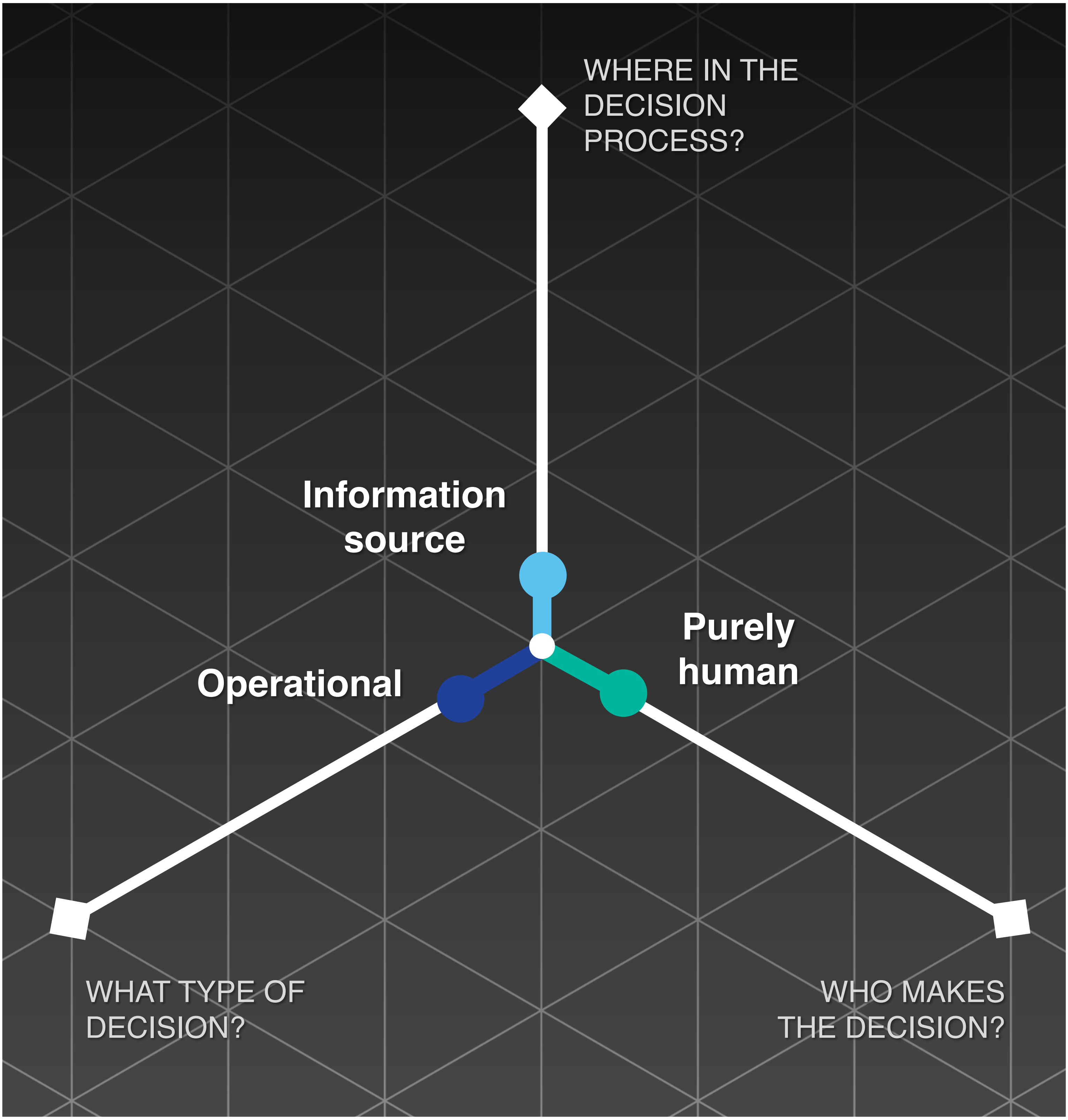
Two of the four coders then aggregated the themes into categories, resulting in the identification of **three emerging aspects**: Adoption, Assessment, and Adaptation of the digital technology. Extensive extracts of the coding are showed at the end of the respective sections in the Future Directions chapter (Figures 7, 8 and 9).

Case Study 1:

Medical Assessments Through Mobile Telepresence Robots

Alejandra Rojas[1]

[1]Department of Business and Technology Development, Aarhus University *[rojas@btech.au.uk]*



Introduction

This study discusses robots made for social uses with direct interaction with human beings, unlike industrial robots that are secluded from humans for safety reasons (Olaronke et al., 2017). Social robots can provide multiple benefits by being immersed in a social environment. For the healthcare sector, such technology can improve the efficiency or quality of caregiving tasks e.g., by facilitating access and speed (Sætra, 2020). In this case study, the type of social robot that is immersed in healthcare settings is a mobile telepresence robot (MTR). Such robots are remote-controlled, wheeled devices connected to wireless internet that enables a remote user to move the robot in the local setting to interact from a remote location.

> **Mobile Telepresence Robots (MTR): remote-controlled, wheeled devices that enable a remote user to move robot in physical space.**

In a healthcare context, these robotic systems are being used to improve interactions between clinicians, patients, and family members by supporting physical presence and enabling telemedicine (Koceski & Koceska, 2016; Laigaard et al., 2022; Li, 2015). Thus, MTRs are naturally non-autonomous (Olaronke et al., 2017) given that the clinician is remotely controlling the robot to communicate with the patient through this device.

Main description of the issue

Telemedicine through MTRs is a very promising but still unfamiliar option for healthcare practitioners. Some empirical studies have investigated their use in healthcare settings and found that MTRs may change work organization and that some medical assessments can be done remotely in an effective way (Beane & Orlikowski, 2015; Laigaard et al., 2022). However, can it be claimed as good practice? Most healthcare workers are hesitant (Haluza et al., 2016). Studies have identified issues with the acceptance of telemedicine technology among physicians, which are mostly related to its

Figure 1: GoBe (Source: Blue Ocean Robotics).

perceived usefulness (Garavand et al., 2022). Therefore, it may be good practice but is not widely adopted even when some patients seem to be satisfied with it (Laigaard et al., 2022). The utility and conditions that will allow MTRs to be beneficial in healthcare settings remain unclear. Thus, this study aims to qualitatively explore the perspective of clinicians in different healthcare settings to understand the affordances and constraints of MTRs when used for medical assessments.

Study

The empirical settings for this study are two different hospitals located in Seville, Spain, where the 'GoBe' MTR is being tested. GoBe (Figure 1) is an MTR with a touch display, multiple cameras, speakers, and a microphone, developed by Blue Ocean Robotics. The researcher visited both hospitals 3-4 times a week to participate and observe videocall tests with GoBe which typically lasted one hour and to conduct semi-structured interviews on-site with healthcare workers from different medical specialties. Additionally, the study included interviews with independent professionals working in different private physiotherapy clinics in Seville, Spain. These interviews were held online and a video recording of GoBe was shown to them. Likewise, the study used an in-depth interview with a clinician located in Aarhus, Denmark who used an MTR for medical assessments. From a total of 19 interviews, nine were conducted in the two hospitals, eight with independent professionals and one with an MTR user. Interviews typically lasted 20-30 minutes and were recorded and transcribed.

> **It is important to understand the affordances and constraints of MTRs in medical assessments.**

After transcribing interviews and field notes, a coding approach followed (first-order concepts, second-order themes leading to aggregated dimensions) with NVivo to identify patterns, determine categories, analyze them, and interpret them in-depth (Gioia et al., 2013).

Learnings

For an urgent first diagnosis, but not for a complete treatment

Results show that MTRs may be useful when clinicians have to see a patient for the first time in an emergency. The emergency department can benefit from MTRs more than other departments because the situation requires collaboration from different healthcare professionals that might not be present physically.

> **Helps to digitally connect clinicians, who cannot be there, to the physical space of patients and colleagues.**

The emergency team may need various medical specialties to respond to all cases, thus normally clinicians have to travel to the hospital at all times and days of the week. However, with the MTR they can access a patient easily, and in situ clinicians may feel supported by this specialist. On the other hand, some participants mentioned that MTRs might not be the best option for consultations of a routine type. In this case, in-person consultation is preferred because face-to-face interactions involve physical touch, which creates a feeling of alliance and ultimately trust. Some participants agreed that having follow-up video calls via MTR in the last part of the treatment might be a good option because the patient might need no intervention.

Useful even when being in the same hospital facilities as patients

Some participants recognized the value in communicating with patients via MTR even when physically present in the same building because moving between floors or putting on personal protective equipment involves time and energy.

> **Saves time and effort (e.g., putting on protective equipment).**

As two nurses illustrate, "to have the robot in the [patients'] room with a connection with the infirmary [...] instead of us having to go there, [...] it would benefit our work timing" (P7); "for isolation situations, it takes a lot of time to put on the PPE [Personal Protective Equipment] just to go in and do something, so with the robot's camera, one can assess how it is currently [...] it's essential to see their faces" (P17). Thus, introducing MTRs in a hospital may optimize nurses' movement and improve productivity.

The clinician's visual field is enhanced

Some participants mentioned that MTR's visual field may be better compared to other devices such as mobile phones or tablets. This type of MTR can display a more complete view of the patient while having online consultation, which is normally a problem they face when patients hold the devices in unusual ways while video calling with the clinician, not allowing a full view of their face which worsens when the image quality of their cameras is low. With an MTR, the vision that both patient and clinician have is steady and there is no need to hold the mobile device while participating in the video call.

Depends on the medical specialty and the type of patient

Findings revealed that MTRs can be beneficial for healthcare use depending on the medical specialty of the user. Participants that have a specialty in physiotherapy mentioned that using MTRs is problematic because they are not able to touch the patients, which is necessary for the techniques they use in therapies and also to build trust. As put by one physiotherapist, "they don't trust you if you don't touch them, if I have a session and I don't touch, that patient sees me strangely" (P18). However, some physiotherapists mentioned that MTRs could be used for educating patients i.e., showing patients a series of exercises they can do on their own and monitoring their programme. MTRs seem to be beneficial for other participants such as psychologists and psychiatrists because they do not use physical techniques.

However, in this case, MTRs or any other robot might distress patients, so they may be used only if the patient has no major mental illness.

> **Need to consider for what practices MTRs are useful (e.g., sometimes physical touch is important for trust).**

According to some participants, GoBe seems adequate for psychiatric patients because, compared to humanoid robots, it has a neutral appearance and some participants described it as 'just a screen'. The screen was identified as a positive feature for elderly patients who might present with visual impairment.

Possible Future Research Directions

How can medical assessments through MTRs be good practice? Empirical studies need to be done to understand more about the use of MTRs in specific conditions because, as this study illustrated, multiple scenarios and variables need to be considered when using MTRs in healthcare. What is needed for MTRs to be a tool that enhances medical assessments? Future research might investigate the implications for the design and development of MTRs to enhance medical decision-making. Some participants talked about a future in which MTRs have an integrated AI system that can help them measure vital signs, integrate it into the hospital's database, and send reports. Thus, technical developments are on the research agenda. How to decrease medical malpractice fears when using MTRs? Clinicians want to be safe and avoid risks related to medical malpractice, thus, there is a need to explore and develop legal frameworks that regulate this practice. Finally, how can we make sure healthcare is not dehumanized when using MTRs? Research is needed to understand how human values and healthcare workers' skills are not compromised.

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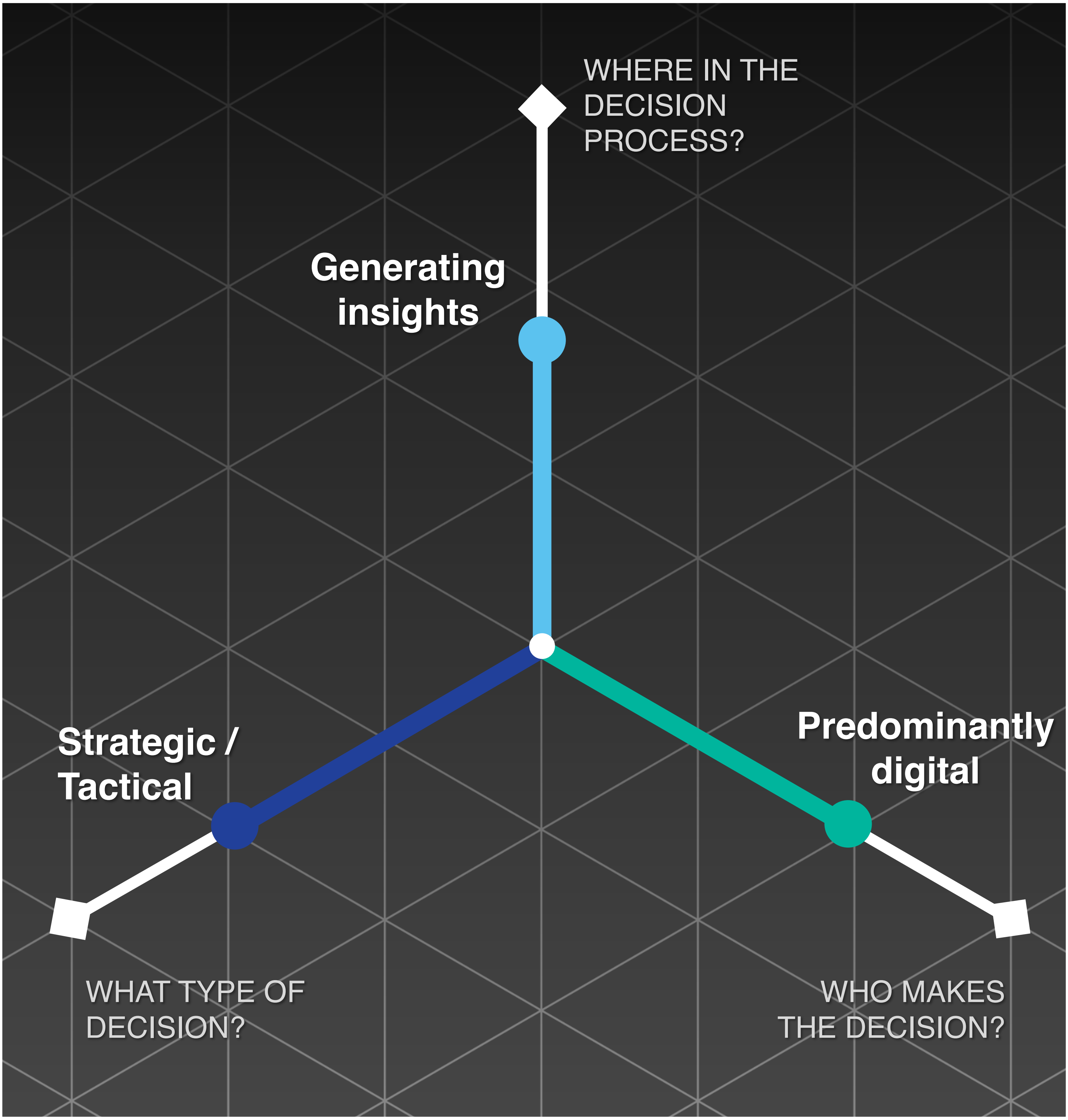
Case Study 2:

Crystal's Augmented Analytics: the Vision of Sustainable Business Intelligence

Giulio Ferrigno[1], Valentina Cucino[2]

[1]Catholic University of the Sacred Heart, Milan *[giulio.ferrigno@unicatt.it]*,
[2]Sant'Anna School of Advanced Studies, Pisa



Introduction

The concept of Augmented Analytics is closely linked to the idea of transforming Big Data into smaller, more usable, insights. These platforms do not replace data scientists and data teams. Rather, as the broader Business Intelligence (BI) landscape continues to evolve, Augmented Analytics provide many benefits. First, they enable companies' individuals and teams to interpret and realize the full potential of the data they are already collecting. Augmented Analytics offer enhanced support and assistance in bringing data to life by accelerating processing times, automating trend monitoring and producing accelerated business insights.

Second, Augmented Analytics tools empower businesses beyond their current data and analytics capabilities. Automated data cleaning and compilation, identifying patterns and trends in key metrics, tracking actions and strategies to identify effective approaches are just few examples of how Augmented Analytics platforms assist businesses in processing and analyzing their data. These examples demonstrate how Augmented Analytics is different from traditional BI tools, providing businesses a competitive advantage through faster, easier data driven decision-making.

Lastly, Augmented Analytics are commonly deployed within many organizations to manage and derive actionable insights from numerous and complex data sources (Joyoti, 2020). Through the use of Machine Learning (ML) and Artificial Intelligence (AI), they indeed provide technical and non-technical users digestible textual and visual insights that assist and augment companies' decision-making processes.

> **Augmented Analytics: assist in processing and analysing data for Business Intelligence.**

In this short case study, we discuss "Crystal", a virtual advisor for data intelligence that enables company managers to make smarter, faster decisions through the use of applied AI. This Augmented Analytics platform is developed by iGenius[1].

Main description of Crystal

Crystal is an AI business intelligence advisor which can interact with data sources in real time to interpret the information contained in the data. As a conversational AI technology, Crystal is capable of classifying commercial requests automatically and in real time, on the

[1] iGenius is an augmented intelligence company that is based in Milan, with offices in Losanna, New York City, and London. Born in 2016, nowadays the company employs 200 people. iGenius currently has thousands of active users across multiple countries and is engaged in strategic partnerships with Facebook, Google, and Twitter.

basis of known information, in order to know the needs of users.

> **"Applied AI […] simplifies the relationship between data and people, thus revolutionizing the very concept of BI."**

Its user-centered interface is easy to understand even for people who do not have specific digital skills. According to Uljan Sharka, CEO of iGenius, the company "deals with applied AI, which simplifies the relationship between data and people, thus revolutionizing the very concept of BI."

Crystal is made up of three main proprietary components: fast data retrieval, deep machine learning, and natural language processing. Thus, with a microservices-based approach, many programming languages are used to ensure that Crystal is fully integrated and independent from the cloud. Moreover, this platform can be defined as an innovative sustainable AI precisely because of the ability to halve the computing power required. The technology is available in six languages and is used by approximately 30,000 brands and dozens of companies, particularly in the financial services, insurance, health, energy, and utilities sectors.

Learnings

Compared to similar products on the market (Domo, Google Looker, IBM Cogns, MS Power BI, QilkSense, Tableau, YellowFin BI), Crystal changes the managers' experience as one tool which connects many data sources, allowing managers to ask the questions they need in a natural language environment as if talking to a colleague. Moreover, this Augmented Analytics platform reduces the time managers spend on exploring data, while giving them more time to act on the most relevant insights. The AI software, which is currently in its second version, has made this technology lighter, faster, and smarter than ever, as well as easily connectable to any open channel. What once needed three to six months to be integrated into a company's data set, today only takes a few minutes.

The platform increases managers' autonomy, enriches data exploration, and augments how they make decisions at every level of the organization, impacting both the operational efficiency and revenue growth. Sharka's goal in creating Crystal was to "make the use of data simpler, more effective and efficient and make it possible for everyone working in an organization to access [data] in a way that is not the case today."

Democratization - Everybody can use the tool without training.

As mentioned above, Crystal is an innovative sustainable AI. First, since it was created to democratize BI from any device (e.g., mobile phones or PCs), anyone within a company can converse with the AI, asking for data on turnover and much more. In other words, unlike a voice assistant, the advisor guides managers to explore data and offers ideas on how to use them to make the best decisions. Crystal classifies the data automatically, skipping the "training" step of traditional AI technologies.

Second, Crystal is capable of working with half of the computational resources compared to competitors, thereby making everything much more efficient.

Possible future research directions

Although Crystal is helpful as it supports managers' decision-making, the platform is far from being conclusive. Few questions still must be answered. First, further research is needed to determine whether platforms like Crystal can interact with or accompany other BI platforms that may be deployed concurrently. In the case of Augmented Analytics platforms (such as Crystal), users require minimal training, compared to the training and certification commonly needed to use BI platforms. Therefore, whether Crystal and similar Augmented Analytics platforms can interact with or accompany other BI platforms to reduce costs and learning time requires investigation.

Second, the language support of these platforms needs to be explored, as to whether these platforms might be used in countries such as Israel, India, and Asia. Indeed, many scholars from Israel and India indicate an opportunity abroad and many US/European companies outsource/offshore data analytics which may indicate a cross-regional opportunity. The scale of the opportunity is significant, with the Asia Pacific market for business intelligence platforms "expected to exhibit the highest growth rate" during 2021-2028.

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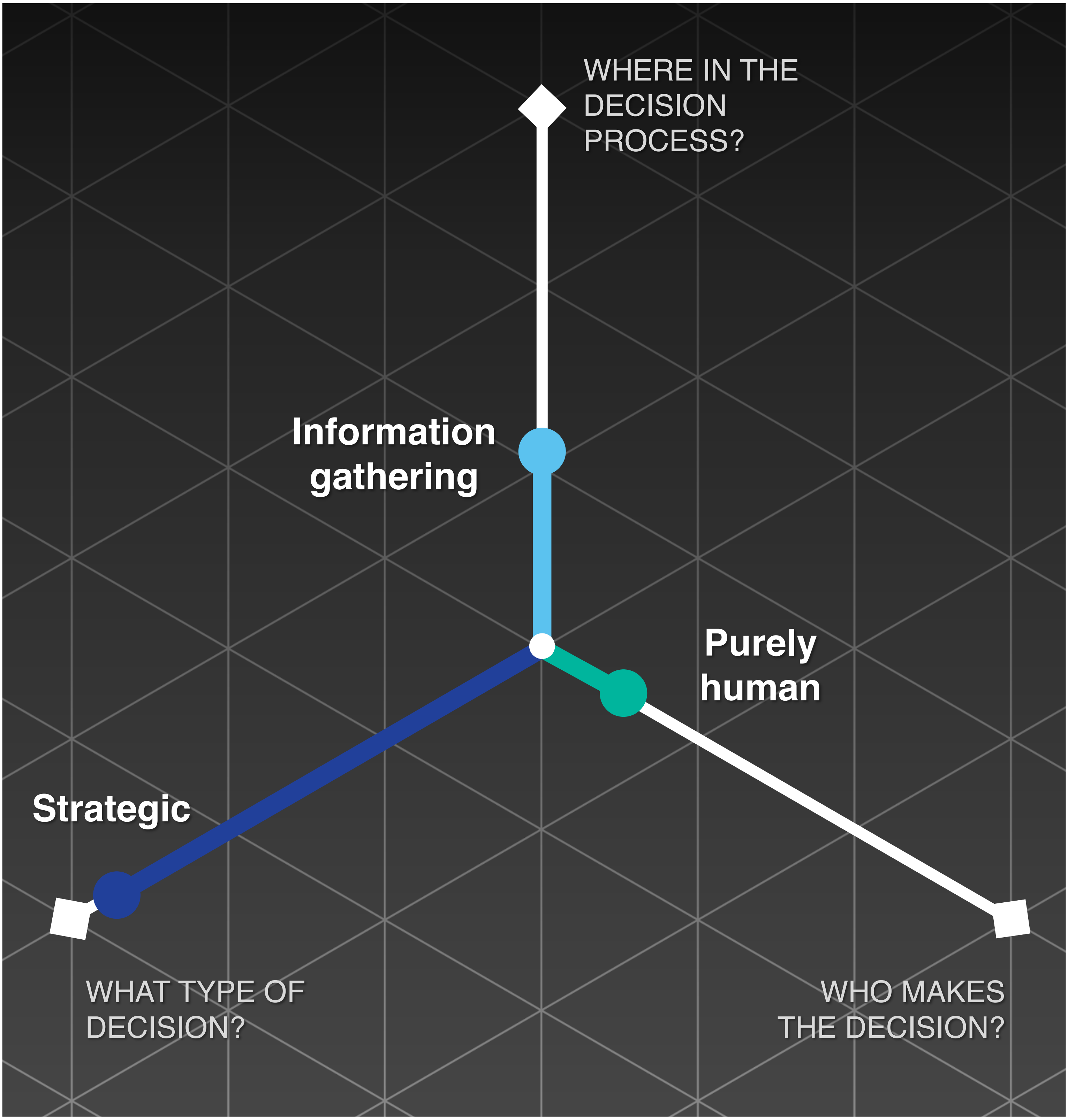
Source: Will H McMahan

Case Study 3:

Hybrid Roadmapping at Ambev

Maicon G. Oliveira[1], Solon Y.S. Meira[2], Bruna Ladeira de Souza[3], André W. P. Manhas[3], Rodrigo Furriel Inocentes[3]

[1]Dept. of production Engineering, EESC, University of São Paulo, Brazil *[maicongdo@usp.br]*
[2]Onovolag, São Carlos, SP, Brazil
[3]Ambev, Brewery of the Future, SP, Brazil



Introduction

Roadmapping processes have been primarily based on physical tools and co-located workshops (Phaal et al., 2004). However, digital transformation of organizations has opened several opportunities to consider the digitalization of roadmapping. Before the Covid-19 pandemic, between 2018 and 2019, we explored the application of digital tools (interactive displays and digital whiteboards) to roadmapping in a co-located format, corroborating the opportunities to support roadmapping with digital tools (Oliveira et al., 2022a).

> **Roadmapping: multi-layered chart with timeline that visually connects future aspirations with the current state of the company, created through workshops.**

With the pandemic, companies adopted digital tools and remote sessions for roadmapping since it was the only solution to maintain activities during social restrictions. At that time, learnings gathered before the pandemic were relevant to understand critical aspects to be considered for remote and digital roadmapping. As a result, based on industrial case studies between 2020 and 2021, learnings and best practices for digital roadmapping were collected and analyzed, revealing directions to explore hybrid roadmapping (Oliveira et al., 2022b).

After 2021, with people returning to their business offices, merging the physical, co-located, digital and remote activities appeared as an excellent opportunity to improve roadmapping. Simply returning to traditional approaches based on pure physical and co-located activities is not the best way forward.

In this context, this case presents an action research study that explores the development of a hybrid roadmapping approach at Ambev, the largest beverage manufacturer in Brazil. The roadmapping application focused on developing strategies for the development of new products and manufacturing processes. The roadmapping was successful, being presented to other Ambev's business units as a reference case.

Description of the roadmapping application

The core roadmapping team who conducted the project was formed by three employees (coordinator, technical expert, and innovation analyst) and two researchers (senior researcher and assistant researcher). The senior researcher coordinated the roadmapping process and facilitated the workshops.

The roadmapping process comprised a preparatory stage, execution of interviews and workshops, and consolidation of results.

Figure 1: Hybrid Collocated Roadmapping Workshop (Source: Maicon Oliveira).

Initially, the team designed the roadmapping to be fully remote and digital. However, due to the opportunity to conduct a full-day co-located workshop, the roadmapping team decided on a hybrid approach to meet the company's needs.

The preparatory stage involved: establishment of expected roadmapping results, analysis of the strategic context, development of the roadmap structure, development of a preliminary roadmap, and workshop planning. At this stage, the team used Zoom for remote meetings and Miro for digital whiteboarding.

Once the roadmap structure was established, the team interviewed an external technical expert and four senior managers related to the roadmap unit of analysis to identify business, market, product, and technology drivers. These interviews used the roadmap structure in Miro as a guide to collect information and used Zoom for communication. Then, the roadmapping team organized the information collected and populated the preliminary roadmap.

The next activity in this stage would have been to organize a digital roadmapping workshop involving experts from different functional areas. However, the team realized that organizing longer workshops (> 3 hours) in a remote format could discourage participants. In addition, finding several time spots to conduct small remote workshops with the group of twelve desired participants could lead to different groups over the process. Thus, the team decided to conduct a co-located workshop supported by Miro, bringing together the participants to spend the day developing the roadmap.

The full-day co-located workshop was organized following the S-Plan process for roadmapping (Phaal et al., 2007), lasting 8 hours. In the morning, the participants were introduced to the preliminary roadmap, brainstormed across the unit of analysis, and prioritized the most critical topics. In the afternoon, they were separated into four groups to tackle the top four innovation topics by developing specific roadmaps. All the activities were conducted using projectors to present information on the digital whiteboard. Each group was self-organized around a person assigned to type in the information using a laptop. At the end, the groups presented their results to the others. The facilitator recorded the person presenting and the screen used during the presentation, capturing the message and its explanation in the strategic narratives on the roadmap.

Learnings

This roadmapping application merged remote, digital, co-located, and physical activities to follow the company's needs for this specific project. The hybrid approach described can be considered an initial step for hybrid roadmapping, but there are relevant learnings to consider.

First, companies are much more favourable regarding using digital tools and remote collaboration after the pandemic, and it is evident that there are benefits. However, some activities that require intensive group communication and cognitive engagement, like brainstorming, may still face barriers when using digital conference tools that provide limited information access, views, and communication.

We observe that conference tools deliver a 'flat' rather than a multidimensional interaction experience, compared to traditional co-located workshops. When the activity intends to create results based on collaboration through multiple participants, they seem inadequate. The value of conference tools seems to be information exchange, not creation. In addition, people tend to stay productive for shorter times in activities conducted in remote meetings when compared to collocated meetings. This fact leads to the division of a roadmapping process into several small meetings and workshops, changing the speed and interaction approach, as explained in Oliveira et al. (2022b). Therefore, in a company context where participants are geographically close and can be united more easily, the development of co-located workshops seems the best option.

> **Limited cognitive resources and attention span in online activities.**

In contrast, adopting digital tools like digital whiteboards to substitute physical boards and sticky notes was productive and well accepted by everyone involved. They enable much more agile and flexible data processing and information sharing.

> **Democratization - everybody can see the data.**

Moreover, participants from different positions, even far from the displays or projections, or with their views blocked, can access and view the information from their personal computers. We think this positive experience is related to the progress achieved in the last years by digital whiteboards, which currently provide user-friendly interfaces with easy access from any device.

The ease of digital whiteboards to handle information creates an issue regarding information visualization. Digital whiteboards lack the size constraints of physical boards, and virtually unlimited data can be inserted into them. As a result, participants can lose visual access to all the information presented in a digital roadmap and need to continuously zoom in and out over the interaction, which can lead to dissatisfaction, interest loss, and reduced cognitive performance. This issue can be reduced using large displays to some extent, but needs further exploration.

Finally, this roadmapping project used videos to save the groups' speech when describing their topic roadmaps. These files were edited and delivered as part of the final report, adding a more live and complete view of the core strategic results. The group explaining its message regarding the topic is more precise and more motivating than the text in the report and can help communicate the main insights.

Future research

We recommend future research, based on the findings of this study, to investigate:

• Peoples' cognitive load and productivity when working remotely or co-located using digital tools in roadmapping.

• The dynamic visual structures and templates optimized to support roadmapping in devices with different screen sizes, such as smartphones, tablets, laptops, and interactive displays.

• Other diital tools that can provide a digital experience closer to co-located workshops for people in different locations. For example, the application of virtual reality to roadmapping workshops.

• Practices supported by digital tools that can enhance the roadmapping value and the implementation of results, such as recording groups' final speeches.

• Approaches for each roadmapping activity, using digital tools or not, and looking for an improved hybrid process.

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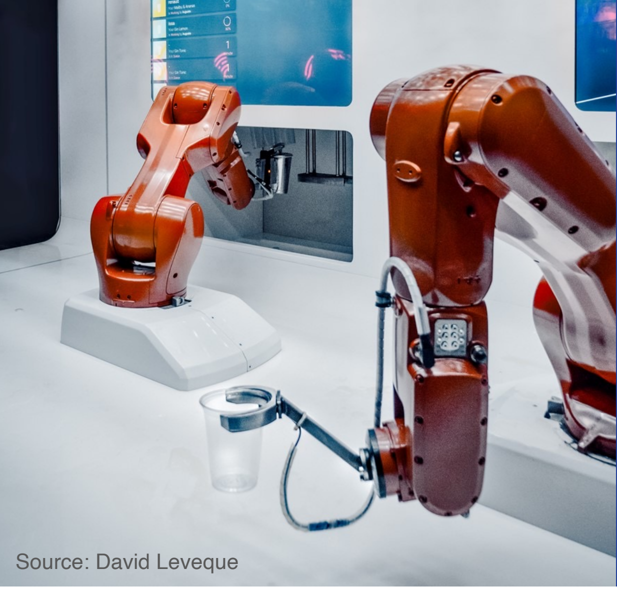


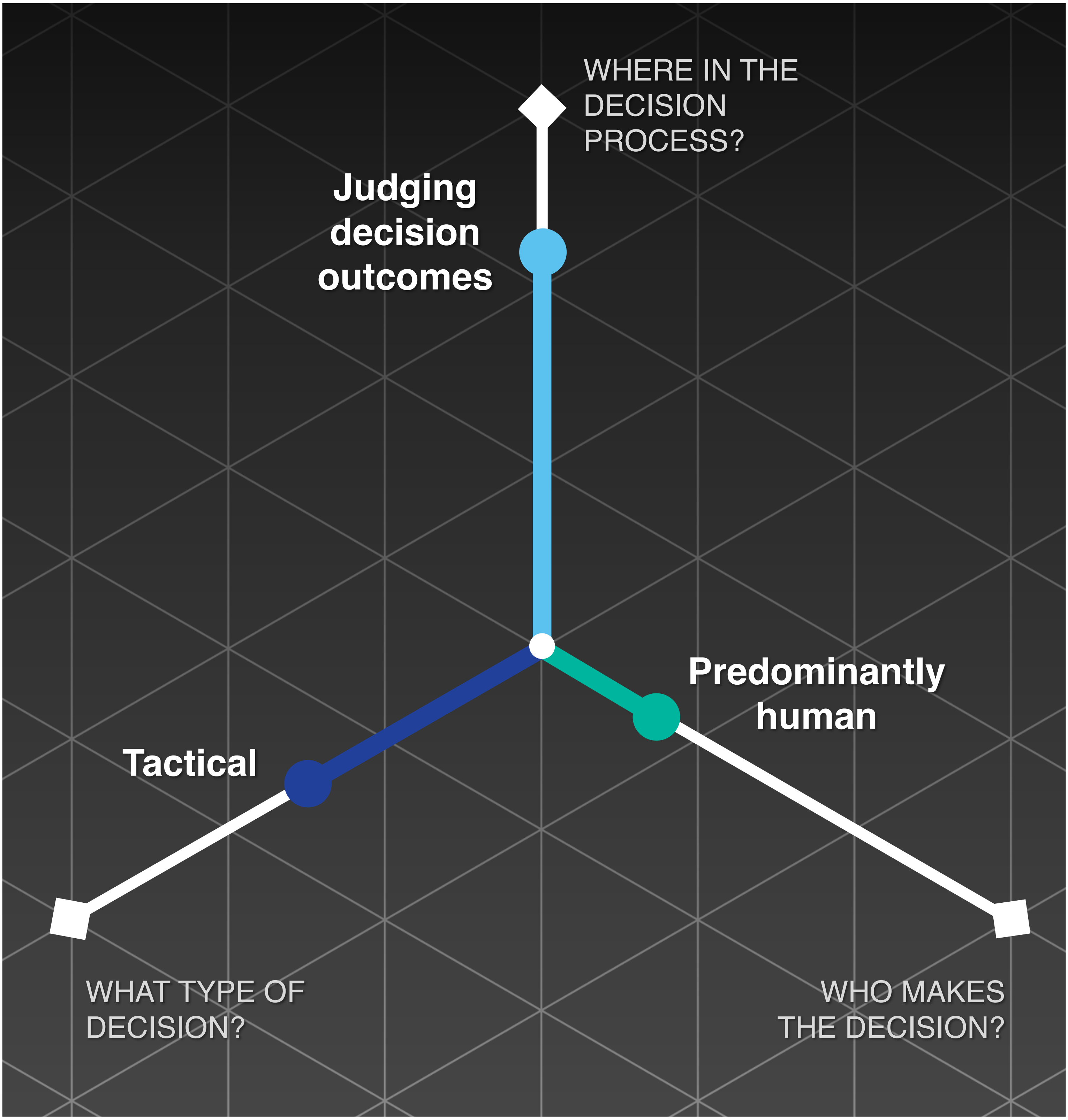
Source: David Leveque

Case Study 4:

Using Simulations to Improve Decision-Making Through Cobot Implementation

Philipp Jennes[1], Alberto Di Minin[1]

[1]Institute of Management, Sant'Anna School of Advanced Studies, Pisa
[p.jennes@santannapisa.it]



Introduction

Collaborative robots (cobots) are innovative cyber-physical systems that facilitate efficient, safe and ergonomically beneficial interactions with operators (Cardoso et al., 2021). This technology is considered to be a novel feature in the industry 4.0 movement and is currently disrupting the manufacturing sector. In contrast to traditional industrial robots, cobots are designed to interact with humans in a shared workspace and thus provide an uncontested potential by combining machine strength and inimitable human skills. Despite the potential, many organizations are facing challenges in integrating the technology (Matheson et al., 2019). To facilitate industry uptake, it is crucial to understand how to support an effective cobot integration into a production line.

> **Collaborative robots (cobots): cyber-physical system that facilitates efficient, safe and ergonomically beneficial interactions with operators.**

Existing literature shows that digital tools such as digital twins, virtual reality devices and simulations are success factors for a sustainable cobot implementation (Douthwaite et al., 2021). This article illustrates an example of how computer simulations and modelling can influence and eventually support the decision-making process related to the integration of cobots in a production line.The presented case study, performed by Raza et al. (2021), is therefore highlighting a positive side of digital technology utilization.

Main description of the practice

A Danish SME in the glass manufacturing sector has integrated a cobot to execute grinding operations to replace tedious and repetitive manual grinding operations along the production line. This cobot integration process was carried out by an external system integrator, who designed and deployed the cobot cell. After the deployment process, however, the company is facing a typical barrier of underutilization, as the cobot is only used for five hours a day. The present case study emphasizes, that these challenges can be mitigated by proactively applying a computer simulation to design the cobot workcell before the implementation phase. The study also gives insights of how simulations influence workers on the individual level and support the company to gain productivity.

The choice of the software used to create 3D animations is the Tecnomatix Process Simulate, which is normally used to digitalize and verify manufacturing processes in a simulation environment.

Initial work cell setup

Figure 1 shows the components of the initial workcell design. It consists of two steel tables (4 and 1), a vertical grinder (2), a water tub (3) and a robotic arm (5), equipped with a vacuum gripper (6). The initial process flow of the operation has a cycle time of 28 seconds and consists of the following steps:

1. Picking the part from the feeding tray.

2. The robotic arm executes the grinding operation on the vertical grinder.

3. Washing the part in the tub.

4. Placing the part in the part tray.

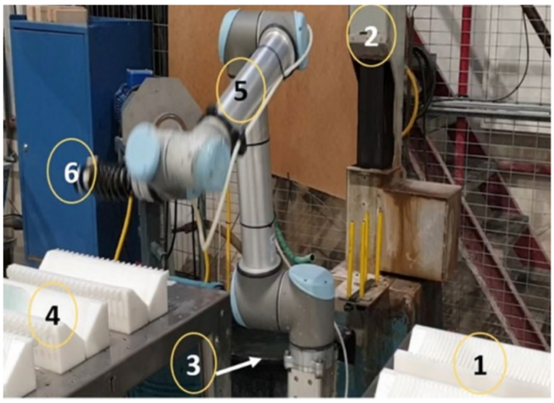


Figure 1: Initial setup of the workcell (Raza et al., 2021).

Optimized workcell set-up and cobot utilization

To improve cobot utilization and optimize the layout of the workcell, a virtual design was drafted with the production manager and shopfloor employees. Different simulations of the design were generated by using the so called PDCA (plan, do, check, act) approach, which is a social, team-based management method to discuss improvements for processes and products.

One of the biggest advantages of simulating process flows is the possibility to change many components in the workcell layout without interrupting the real workcell. Hence, a great variety of setups can be tested in a flexible way. One of the propsed designs is shown in Figure 2.

The main idea of the simulated workcell is to add an additional CNC grinding machine. This machine is also underutilized in the production line, being used only eight hours a day, as human operator is needed to feed the machine with materials.

In the proposed setup of the workcell, the robotic arm will continue to execute the grinding operation with the vertical grinder. The major difference in the process flow is the feeding of the CNC machine. Every 30 minutes, it will change the gripper without human effort and feed the CNC machine. In this way, the modelled cycle time of the vertical grinding process is reduced and the robotic arm will be fully utilized.

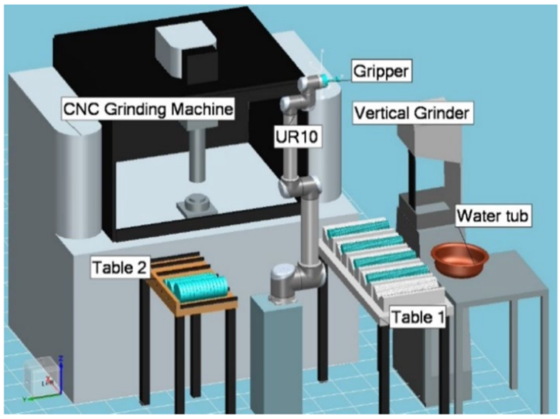


Figure 2: One proposed workcell scenario (Raza et al., 2021).

Learnings

Improved cycle time and productivity

The chosen scenario as new layout for the workcell not only improves the cycle time of the vertical grinder from 28 to 24 seconds, it also increases the productivity of the CNC machine from 8 hours to 24 hours a day and eliminates the working hours for the workforce. This has a huge impact not only on cobot utilization, but also on the overall productivity of the SME.

> **Simulations can help to choose a set-up that increases productivity without doing lots of tests.**

Optimizing by involving employees, doing simulations and modelling

The simulation study has shown that decision makers can gain important insights before and during the implementation of cobots. These insights do not only provide clarity about process information (i.e., cycle time) but also about required components and optimized layouts for the future workcell. The study emphasizes that simulations and modelling are suitable methods to investigate technological and economic feasibility in advance.

> **Involvement of all stakeholders increases acceptability.**

Finally, the study shows a solution which has the potential to accelerate industry uptake by addressing how a fundamental challenge in effective cobot implementation can be overcome.

In addition, it is worth mentioning that in combination with the PDCA approach, the involvement of all stakeholders during the brainstorming session increased process understanding and acceptability of the simulation, which are usually considered as challenges during simulation studies.

Future research directions

One of the challenges of generating simulations, are high costs of simulation software. It is therefore interesting to investigate when it is economically feasible for SMEs to invest in such a solution. Further, it would be interesting to assess whether there are significant differences between setups that are purely based on simulations and dynamic tools that require interactive employee involvement for the decision-making process. In this context, Augmented Reality (AR) is an advanced visualization tool based on real time reports for decision-making, training and maintenance and thus represents a more human-centered technology. This investigation would be a step towards understanding the role of human knowledge during the interaction with simulation tools. Finally, an empirical investigation of a broad spectrum of SMEs will reflect the impact simulations have on technology acceptance and innovation diffusion.

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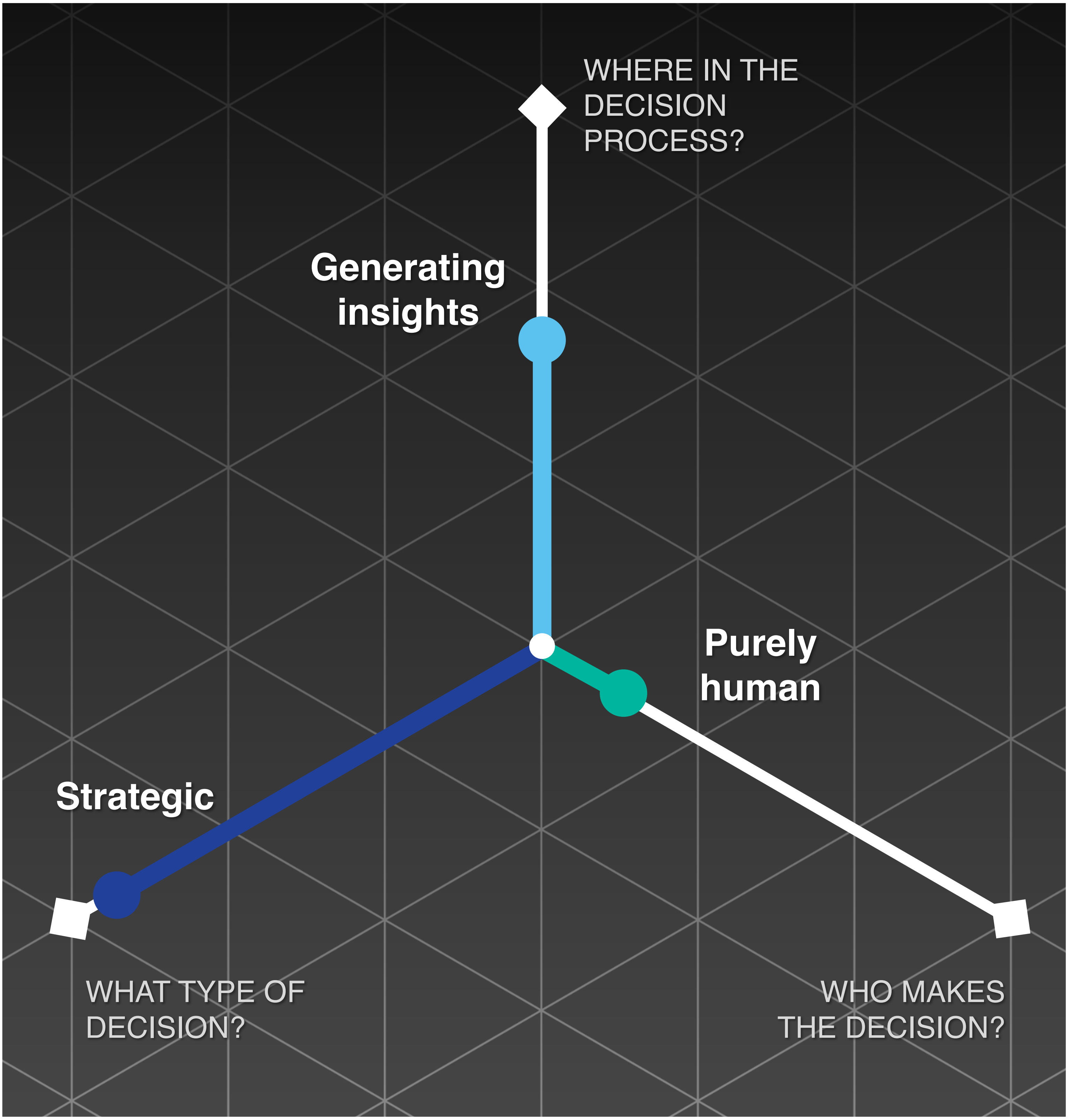
Source: airfocus

Case Study 5:

Digital Affordances for Group Prioritization

Michèle Routley[1]

[1]Emerson *[michele.Routley@emerson.com]*



Introduction

A key aspect of technology strategizing workshops is the prioritization of ideas or options. As part of a wider programme of research into the potential to use digital support for technology strategizing (Routley, 2022), this case describes group prioritization using digital tools to support decision-making in a single qualitative case study (Yin, 2018). The concept of digital affordances (Bygstad, Munkvold and Volkoff, 2016) - the possibilities offered by the digital technology - was found to be particularly relevant.

> **Digital affordances: the possibilities offered by digital technology.**

In this case study virtual strategy workshops were carried out as part of a broader activity to raise awareness of sustainability, particularly decarbonization, and engage participants in creating and evaluating ideas for a resilient future. Using a strategy-as-practice perspective (Jarzabkowski, Balogun, and Seidl, 2007), the workshops were serialised using WebEx and Mural. They were undertaken as a part of a larger programme, applying learning from an initial activity held in another world region and academic study of praxis. There were 16 participants, across multiple locations in the US, representing different functions, and they were not used to working together on a daily basis. During the activity, in 2020, most people were working from home due to Covid-19 pandemic restrictions. Techniques such as scenario analysis, SWOT analysis, and roadmapping were used, aligned with the process outlined by Ilevbare, Probert and Phaal (2010). The author was the lead facilitator of the workshops and undertook individual interviews with participants, asking them to reflect on the efficiency and effectiveness of the virtual workshops compared with the face-to-face activities. This case describes the reflections on the use of digital support used to support decision-making through prioritization.

Description of the practice

Within the scenario planning process, there were two group prioritization activities - the first to select scenario axes from key driving forces and the second to prioritise brainstormed SWOT ideas.

Key driving forces had been submitted individually, using an Excel template where participants selected categories for their suggestions, in advance of a synchronous workshop session. These suggestions were clustered under 12 broad themes in advance of the session, based on the categories selected and review by the facilitators. In the workshop session these 12 driving force clusters were reviewed in plenary to ensure everyone had a chance to review all 79 suggestions submitted and to move any items which they felt were in an incorrect cluster. The participants decided as a group whether anything needed to be added and consensually determined the cluster headings. As illustrated in Figure 1, the cluster headings were then duplicated randomly onto a matrix of importance and uncertainty. The participants were then asked to move the items onto the most appropriate part of the matrix. They did this primarily individually from their own computers moving items around the central digital whiteboard. Once most of the movement had stopped, the group then reviewed and verified the positioning of items, ensuring there was good understanding and agreement about the placement through discussion. The scenario axes were then selected from items in the top right of the matrix – highly important and highly uncertain.

Later in the scenario planning process, the plenary group of 16 split into 4 groups - one per scenario. Each group performed a SWOT analysis within their scenario – strengths, weaknesses, opportunities, and threats. Many factors were brainstormed, and to prioritise these to take through to a TOWS matrix, the groups made use of simple voting to identify ideas which were most significant in each quadrant, given the context of their scenario and the focal issue of decarbonization. Each group had added ideas asynchronously to the digital whiteboard, and then discussed these, clustering similar items as a group. The Mural voting function was used - allowing individuals to place votes on digital sticky notes anonymously - those voting could not see where other votes were being cast. This provided both instant results and a digital record of the votes placed at the time, as shown in Figure 2 for one of the groups.

Interviewees thought that the outputs were very good, with participants appreciating the reflection time not available in a collocated workshop, which they felt led to a better quality of output. Digital support meant that results were available immediately and participants were able to see all the details - using the digital whiteboard to adjust their

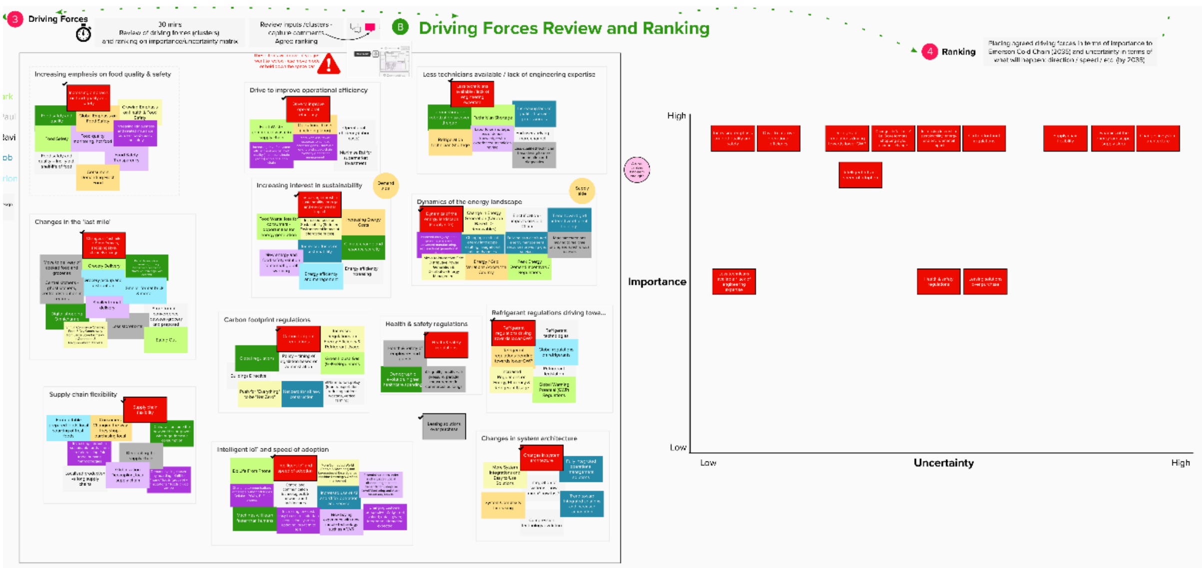


Figure 1: Driving forces clusters and importance-uncertainty ranking – image from Mural (Source: Michèle Routley).

own zoom level and review information at their own pace.

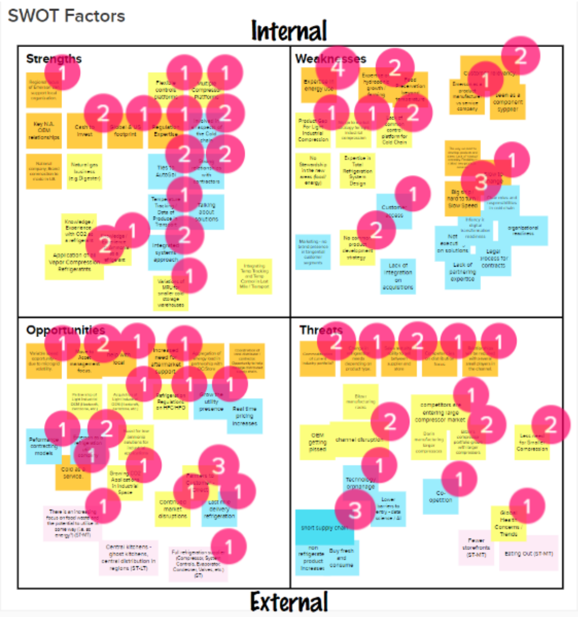


Figure 2: SWOT analysis example showing voting summary – image from Mural (Source: Michèle Routley).

Learnings

Although a primary driver for using digital technology to support these workshops was the global pandemic, the digital tools were found to afford certain possibilities in the prioritization activities to support group decision-making.

Individual access to and visibility of detail

For ranking on the importance and uncertainty matrix, undertaking the activity synchronously, while individuals had full visibility and the ability to relocate items, enabled transfer of individual knowledge and understanding to the group. Being able to move items on the screen gave participants buy-in to the location on the importance-uncertainty matrix. Everyone being able to read details simultaneously enabled the group to consensually build their understanding. This level of detail is not always visible to participants in a paper-based collocated workshop.

> **Digital affordances: the possibilities offered by digital technology.**

Particularly in contexts such as strategic technology management where there are multiple functions represented, participants need a good understanding of clustered information. In this case each participant was able to read the details of the different ideas within a cluster, read the cluster heading, and even move items in or out of a cluster. Participants had control of where on the Mural board they were looking, to take more time, if needed, to process certain information.

Workshop serialization – asynchronous/synchronous options

Serialization of the workshop activity affords the possibility of individual access outside the synchronous workshop time. With complex or large amounts of information, participants value time for individual processing of details. Digitized inputs and a common whiteboard accessed individually affords the possibility of the time for this activity.

> **Digital gives opportunity of asynchronous and synchronous workshop elements.**

Unbiased voting

Individual participants had unobstructed, anonymous access to items for voting which provided a democratic and instant prioritization. It was a quick and easy means to prioritize brainstormed ideas without bias from other opinions and instantly recorded results.

Comparison with other cases

This case has described one case, which built upon learning from a pilot case and published literature praxis. In this case initially the participants were asked to engage with and revise, if required, the clustering. For the second clustering activity, the participants undertook the clustering themselves. Challenges have been observed elsewhere when clustering was carried out by facilitators independently of the group and this was not well understood by individual participants when asked to carry out prioritization by voting asynchronously. This emphasises the need for clear cross-functional communication to underpin any prioritization of clustered elements, or individual visibility of the clusters and their headings for clarification.

The asynchronous prioritization in other cases experienced challenges in terms of technology issues when participants were not able to follow the instructions as to how to add their votes. Hence there is a need for clear instructions when using digital tools, particularly when working asynchronously when the facilitator is not readily available to help. When voting asynchronously, many participants appreciated the ability to take their time to review the options available, or research further details if necessary.

Other workshops have used digital tools, such as Mentimeter, to have anonymous voting within the group, but enabling the facilitator to see who has contributed different votes. This facility was not available in Mural, and it was not necessary in the voting session as no weighting was given to the different votes placed, but in certain contexts there may be subject matter experts whose view would carry more weight and should be recorded.

Possible future research directions

In terms of future research, there are many avenues still to investigate. For example, there is a need to gain a better understanding of the contexts in which it is important to promote the use of the affordances digital technology offers. This case has described virtual workshops, necessary during the pandemic, but as collocated events are possible again, there is also a need to understand how digital tools can support technology strategizing in face-to-face events.

> **To reduce technology issues clear instructions how to use the digital tool are needed.**

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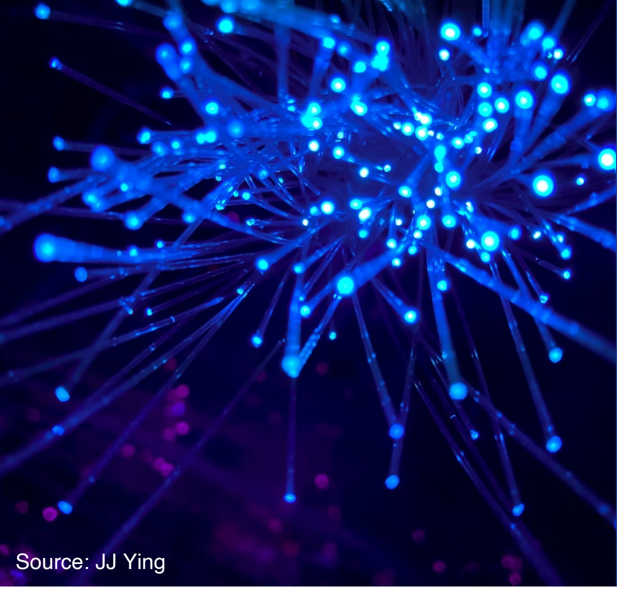
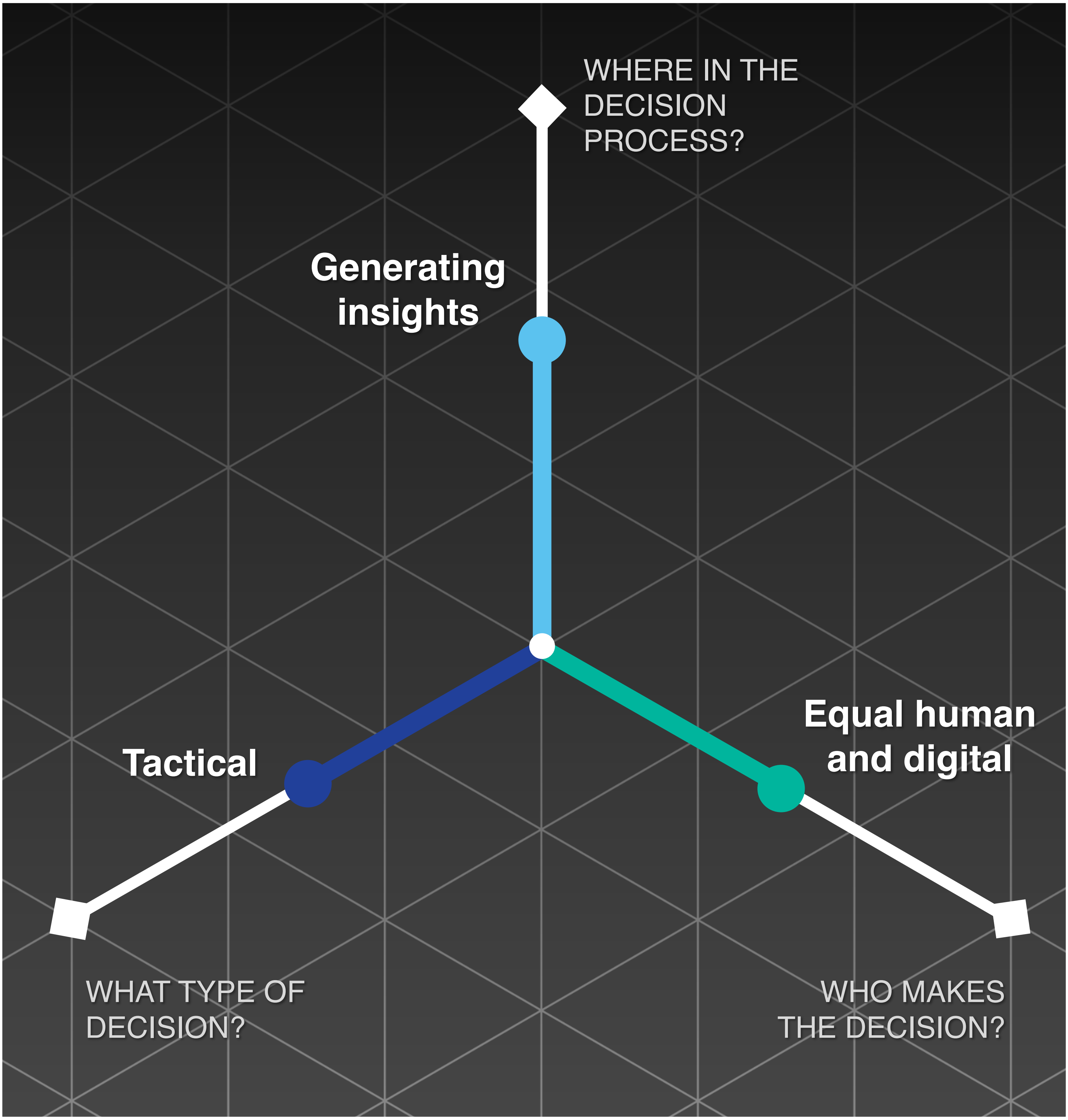

Source: JJ Ying

Case Study 6:

A Case for Adopting Knowledge Graphs in Agricultural Decision-Making Processes

Jack Foster[1], Alexandra Brintrup[1]

[1]Institute for Manufacturing (IfM), University of Cambridge
[jwf40@cam.ac.uk]



Introduction

Data is fast becoming the lifeblood of many industries, and understanding their data is no longer a luxury but a necessity for organizations hoping to compete in an industry 4.0 world. Leveraging data for decision-making can help optimize processes and improve the efficiency of organizations. This is of vital importance in agriculture, as the global food chain is under pressure from population growth, climate change and geopolitical strife (Duckett et al., 2018). To overcome these challenges, automation is needed to streamline the agrifood industry. Data is the backbone of precision agriculture, which aims to optimize processes to better handle spatiotemporal variance and ultimately improve yield through understanding at a granular level crop and environmental data (Pierce & Nowak, 1999). In practice, this is realized through the deployment of sensing technologies and automation (Duckett et al., 2018).

While the need for data-driven processes is now widely accepted, data siloing is a major issue that leads to information existing in isolated subsystems that are unable to communicate with each other. This is a major limitation as information that may be pertinent to decision-making may not be accessible. As machine learning technologies become increasingly ubiquitous in decision-making processes, access to clean, complete and large-scale data becomes imperative; data siloing can be a barrier to this. Another key issue in current data storage approaches are that the tabular techniques typically employed do not leverage structural information within data, which again imposes certain limits on the machine learning and data science techniques that may be utilized with the available data. In addition, tabular methods may have varying degrees of readability and interpretability for human decision makers. An emerging and increasingly popular approach to knowledge representation is knowledge graphs, which attempt to store data in a representation that is structured and useful for machine learning techniques, but also human readable and explainable. In addition, recent studies show that one of the major applications of knowledge graphs in industry is for data integration and discovery (Atking et al., 2021).

> **Knowledge graphs (KG): a graph that is a structured representation of facts, consisting of entities, relationships, and semantic descriptions.**

That is to say, knowledge graphs are very good at overcoming siloing problems and at helping organizations better understand their data. In the coming sections, we will discuss agricultural knowledge graphs in greater detail, outlining the merits of their application, before discussing limitations and barriers to their adoption, finally concluding with future research directions in this area.

Knowledge graphs

Many real-world structures and phenomena can be elegantly represented as a graph; where objects or entities are represented as points, which are in turn connected by lines that represent some relation (Bondy et al., 1976). For example, a set of people may be the points, and they may be connected if they are friends. Formally, a graph is comprized of nodes or vertices (i.e. the points or entities) V(G), and links or edges (i.e. the lines) E(G). Both nodes and links can have features, which define some properties about them. For example, a graph of food products may have nodes with features being the set of ingredients the product is comprized of.

A knowledge graph is a special kind of graph that is a structured representation of facts, consisting of entities, relationships, and semantic descriptions (Ji et al., 2021). Within knowledge graphs, triplets represent key pieces of knowledge, and take the form (h, r, t), where h,t ∈ V(G) and r ∈ E(G); these triplets define individual relationships between nodes. For example (Biden,isPresidentOf,USA), is a triplet. Knowledge graphs are a useful tool to facilitate human decision-making as they not only facilitate the integration of data from multiple sources, but also serve as an intermediary between humans and machine learning systems. Knowledge graphs can be used to generate human readable explanations but also contain rich structural representations of knowledge that may be leveraged by machine learning systems. As such, knowledge graphs are at the centre of many human-facing technologies, such as being used to augment Google's search queries (Fensel et al., 2020), in financial systems such as market return prediction (Fu et al, 2018), quantitative investment guidance (Cheng et al., 2020) or financial report querying (Zehra et al., 2021), supply chain risk analysis (Zhang et al., 2019) as well as a wide range of biomedical applications such as drug discovery (Koscielny et al., 2017; Nguyen et al., 2017).

Knowledge graphs store data in useful ways for Machine Learning techniques and human readable and explainable.

In agriculture, knowledge graphs have a wide range of applications, from representing gene-to-trait associations in plants (Mawkhiew et al., 2021), to crop pest and disease knowledge (Xiaoxue et al., 2019) to general agricultural process knowledge (Chen et al., 2019). These works highlight how knowledge graphs can be leveraged for several problems in agriculture to improve yield. We propose that by integrating these industry-wide knowledge graphs with farm-specific knowledge, such as environmental data or crop growth state data, rich knowledge graphs could be constructed that could guide decision-making on how to maximize crop yield at a granular level, facilitating the adoption of automation technologies that the agrifood industry needs, while remaining transparent and explainable to human farmers, experts, policy makers and other stakeholders.

Despite their evident efficacy and applicability, adoption of knowledge graphs remains limited. Next, we outline the current limitations that preclude the widespread adoption of knowledge graphs.

Limitations and future directions

Recent studies suggest that the lack of adoption of knowledge graphs is a cultural challenge, rather than a technology challenge (Atking et al., 2021). A key component of this problem is "organizational inertia", whereby organizations are change-resistant and not inclined to adopt new technologies unless they are absolutely necessary. Therefore, steps need to be taken to reframe the advantages of knowledge graphs from technical advantages, to very clear and irrefutable business benefits.

Another key limitation is that there exists a large gap in skill sets. Adopting new technologies requires industry professionals to be capable and skilled in the new technologies. Upskilling employees is expensive, and attracting highly skilled data and computer scientists is not traditionally a strength of the agricultural industry. Special attention needs to be paid to how the industry can rebrand itself as a desirable location for highly skilled technical staff.

> **Lack of adoption is a cultural challenge, rather than a technology challenge.**

In addition to continued technical research, future directions in knowledge graphs should prioritize making the technologies easier to access, understand and implement, to further encourage their adoption.

Conclusions

The agrifood sector is set to come under increasing pressure, which may be alleviated through automation technologies. Automation requires data, and current data processes are ineffective and rife with problems such as data silos. Knowledge graphs are a powerful tool that offer a structured approach to data storage that can be leveraged by machine learning technologies yet remains explainable and human understandable, all while avoiding the data siloing problem. Despite these advantages, cultural problems continue to inhibit the adoption of knowledge graph technologies. We are excited by the opportunities knowledge graphs promise for optimizing agricultural processes and improve the efficiency of the global food supply-chain.

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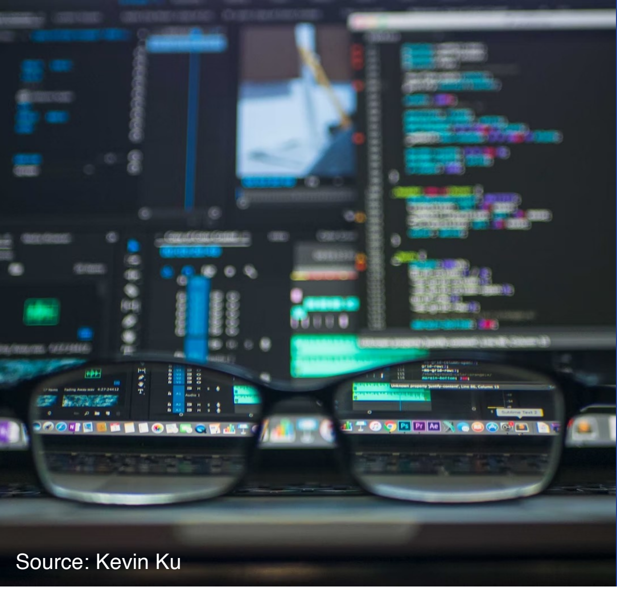


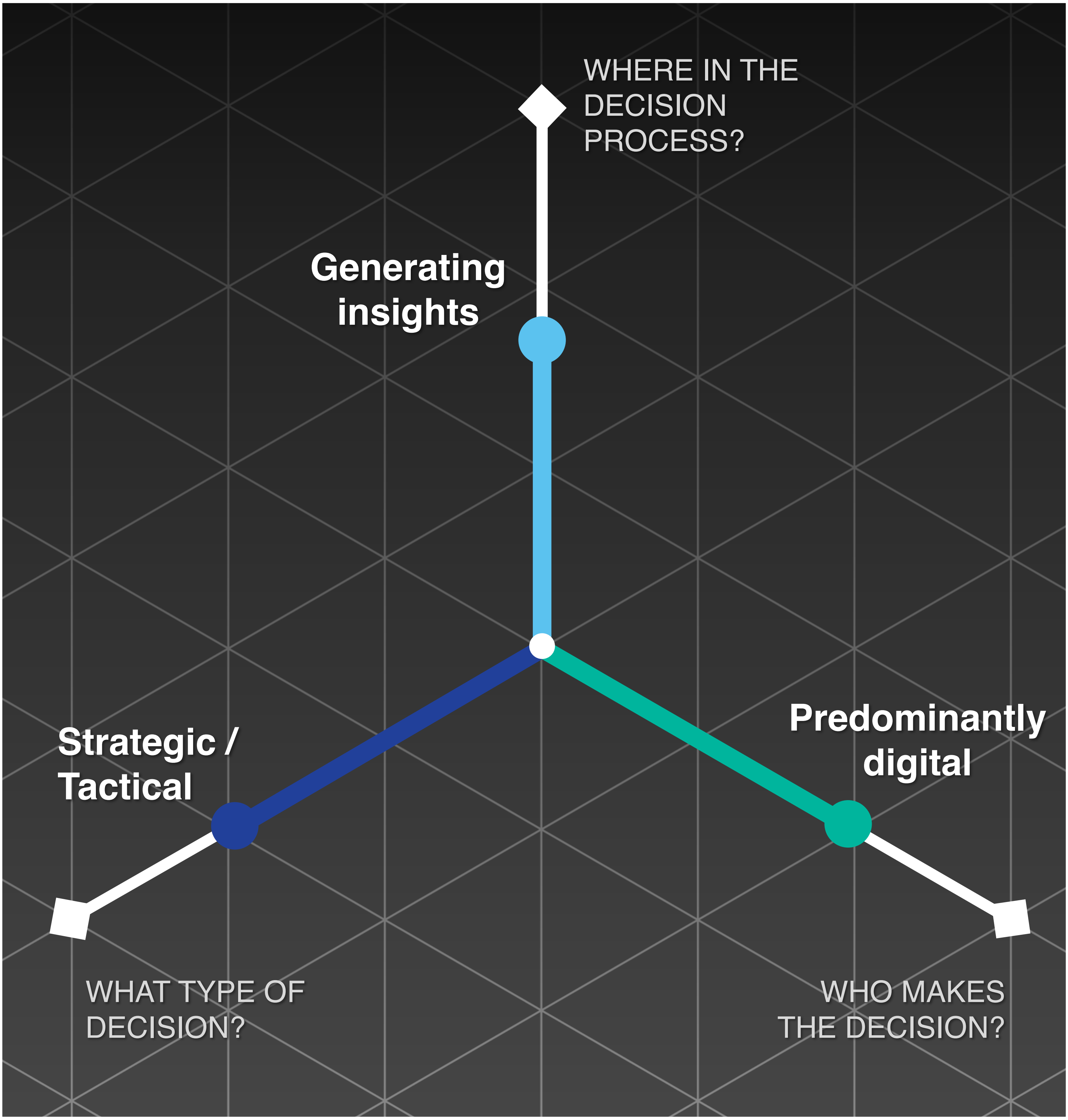
Source: Kevin Ku

Case Study 7:

'Power Users' at Work: AI-Driven Technologies in Intelligence Work

Constanze M. Leeb[1]

[1]Institute for Manufacturing (IfM), University of Cambridge
[cl876@cam.ac.uk]



Introduction

Knowing about the company's environment and particularly about any changes that might occur, such as the performance of competitors or emerging technologies that could pose a threat or might be an opportunity, is crucial to be able to adjust and to stay competitive (Teece, 2007). In our fast-changing world there is (too) much information to keep track of. This makes life difficult for the people responsible for intelligence work, who need to provide decision-makers with timely insights (Mortara, 2015). A particular challenge for intelligence officers is tracking of information in unfamiliar topics. New artificial intelligence (AI) tools are emerging to facilitate and improve performance of the process of developing insight, as these tools can process large amounts of information fast (Brynjolfsson & McAfee, 2017). The practice of expert users of AI tools in intelligence work is analyzed in this case study.

Main description of the practice

Qualitative field work was performed at a company, which provides AI-driven technologies for intelligence work and offers small contract research projects with a fast turn-around, which utilize their AI tools. The field work consisted of observations and interviews.

In this case study intelligence workers use an AI-driven technology to investigate an unfamiliar topic to answer a research question posed by a customer.

The AI tools

The tool typically takes the content of a few thousand sources as an input. It reads the documents and performs different analyses on them. These are then graphically presented to the user (e.g., bar charts, timelines, etc.). The user can choose among several visualizations and can filter the data by date, keywords, organizations, geography, and other options.

The users

The users studied are expert users, who use the AI tool every day. These users are referred to as "power users" by their colleagues. They consider themselves to be researchers and analysts. Their task is to answer a research question for a customer as part of a small contract research project. This can be about a certain technology, geographical region or market space. The output they need to produce is typically in the form of a presentation or report for the customer.

> **Power users: expert users that use AI-driven technologies on a daily basis.**

Learnings

Becoming a 'power user'

To make the most of the AI-driven technology, the user needs the right mindset.

First, expert users make it a habit to use the tool. For them, the AI tool is the default option to do their research. Only initial or superficial understanding of terms are gained by googling the words, and some visualizations are done via Excel.

Second, while experience with the tool or algorithms can help, more important is to have a "mindset about the imperfection of the software" (I03). This means that the user is aware that the machine is not perfect and can make mistakes. Knowing this enables the user to double check the results and not to lose faith in the AI tool altogether when it does make a mistake (e.g., it misunderstands BP as the company name, when the term is used as an abbreviation for blood pressure).

Important aspects for "power users" in their work

Quality of input data

When using AI-driven technologies in intelligence work the quality of the input data is crucial. The users make sure that the input data is filtered properly and consists of the right sources. They iterate back and forth until they are satisfied with the quality and amount of the documents that are fed into the AI-driven technology. Here, their experience helps them to judge the quality and quantity.

They use the most common key words extracted by the AI tool to check whether they are in the correct space of investigation and if the key words make sense.

> **Need to have a "mindset of imperfection of the software" to become a power user.**

Further, the users manually filter out any noise left, as outliers can drive the whole analysis of the AI tool in a misleading direction.

Struggling to gain insights

The AI tool empowers the reading skills of humans, as it can read thousands of documents in little time. It then provides visualizations of the analysis. However, the users of these tools still need to actively gain insights from the outputs. This is one of the hardest parts of doing intelligence work with AI, not just for average users but also for expert users.

> **Gaining insights is one of the most important and hardest parts of working with AI-driven technologies in intelligence work.**

The users explore the data for a long time and go back and forth in the data. They adjust timelines, filter by regions, companies or keywords. They often gain insights by playing around with the data and not through the visualizations themselves. The AI tool provides them with the necessary data, but they need to manually gain this insight. This shows that the choice, judgement and decision-making stays with the human.

Tell a story – the client wants opinions and interpretations

The expert users see themselves as analysts, they like to gain their insights just from the data provided by the AI tool. However, in order to be able to make their insights accessible for others, they need to build a story from the data that answers the question: "so what?". Their presentations and reports utilize lots of visualizations to tell this story to the customer. Depending on what story they want to tell, they use different visualizations.

> **Visualizations help to tell a story with the data.**

Interestingly, customers often want more than the story based on data – they want opinions. This is often difficult for the power users, as they see themselves as analysts and researchers and feel uncomfortable to consult. Therefore, they state trends that they can extract from the data, but do not provide predictions. Further, they include clearly labelled opinion comments in their outputs.

Possible future research directions

While this small case study gave first insights into the practice of expert users, the practice of average users' needs to be studied as well. Their struggles and experiences will differ, as they do not have the same amount of experience of working with the tool. Also important to investigate is how the interaction and use of an AI-driven technology changes the agency individuals feel about their tasks and the outputs they produce. Lastly, a future direction of research could investigate how people receive outputs that were generated using AI-driven technologies compared to ones that were only generated by humans in regard to trust and credibility.

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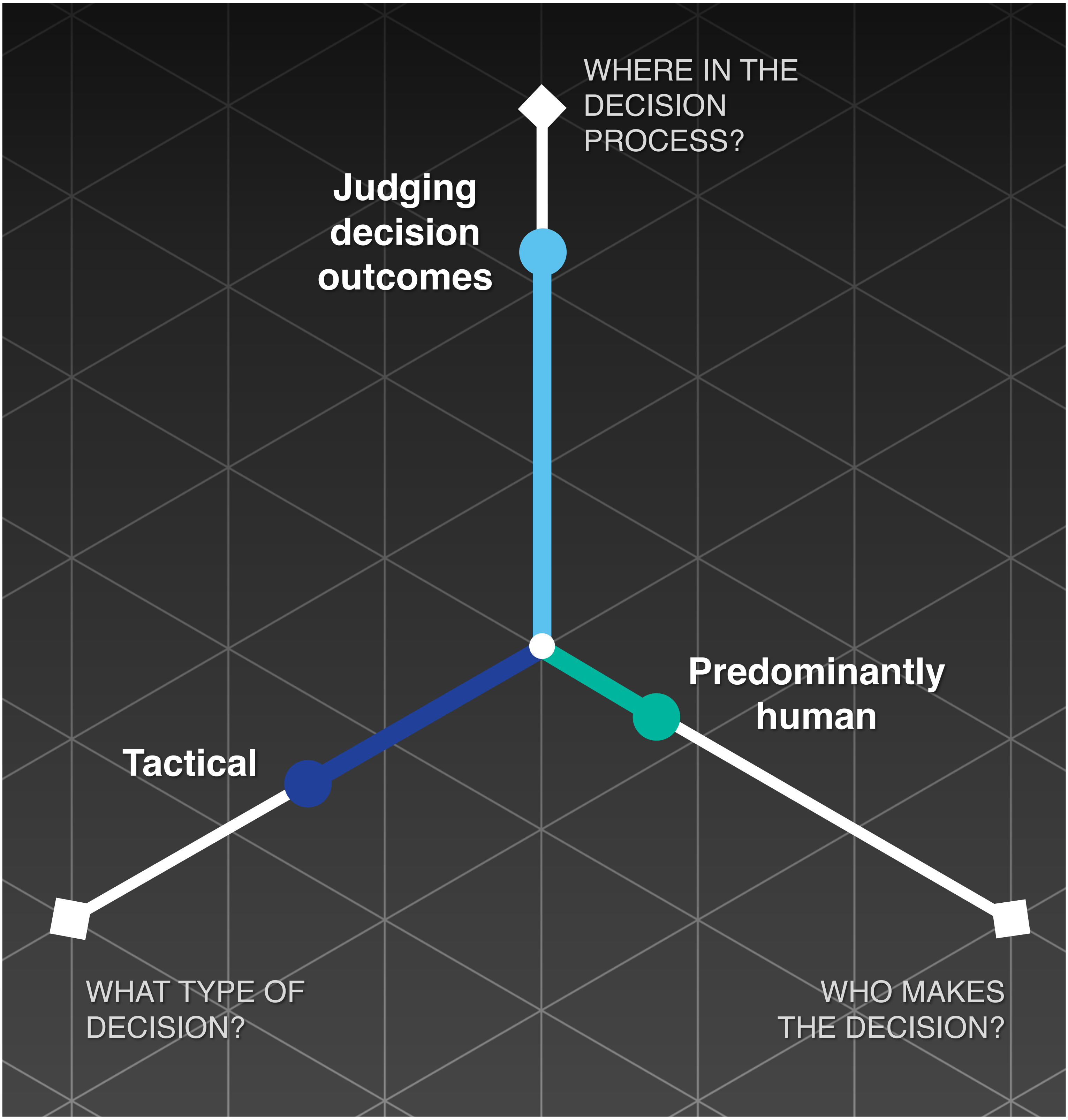
Source: Minh Pham

Case Study 8:

Virtual Reconstruction for Orientation and Decision Studies Inside Complex Spaces

Nicola Felicini[1]

[1]Institute for Manufacturing (IfM), University of Cambridge
[nf382@cam.ac.uk]



Introduction

The abilities to represent and simulate have always given humankind terrific support for taking decisions. The representation of space, for instance, has been one of the most important inventions of human history. Maps still allow humans to explain and navigate the world they live in.

Architecture is one of the fields that has gained a lot from these abilities, given the complexity and costs involved and the related critical decisions. The capacity to represent space has evolved along with technological advances. The dawn of computer graphics replaced handmade scale models and graphical representations with digital tools that allow a more accurate, fast, and flexible representation and simulation. Rapidly growing technologies like augmented reality (AR) and virtual reality (VR) have huge potential in the representation of spaces and on informing the decisions related to them.

Virtual Reality (VR): showing a simulated environment through glasses, creating an immersive experience.

Figure 1: Architect Norman Foster checking out a project in VR (Instagram: @officialnormanfoster).

Main description of the practice

A case study conducted by Bianconi et al. (2019) explored the potential of VR technology for decision-making in construction from the dual perspective of designers and occupants of the space. In the study, an office building was reproduced in a virtual space and made explorable using VR headsets (Figure 2). A series of experiments involved several participants which were asked to perform orientation tasks in the virtual building. The tasks required users to find and reach specific rooms and to estimate their position within the facility. Collected data included the orientation success rates but also tracking of the movements of participants in the building (Figure 3) and their gaze point (where the user was looking). This information was used to understand where the occupants got lost and where they were looking for orientation cues to reach the objectives. The data allowed identification of critical design issues and failures in the wayfinding system.

A renovation proposal has been developed and modelled in virtual space addressing the weak points, which emerged from the first

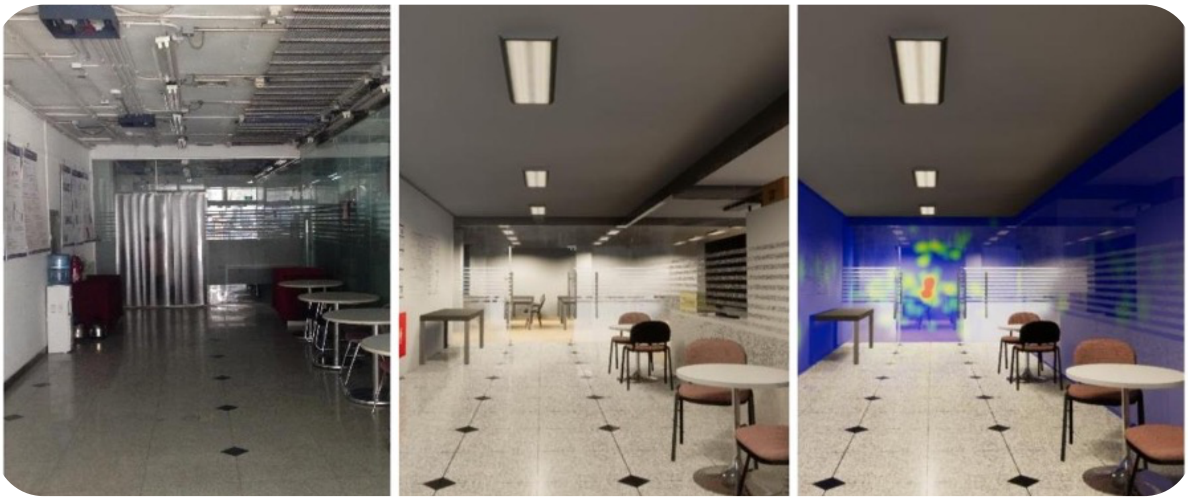


Figure 2: From the left: (1) the real building's atrium, (2) its virtual reconstruction and (3) the heatmap representing the eye-tracking data (Source: Nicola Felicini).

round of experiments. The refurbished virtual facility has then been tested in VR using the same protocol and collecting the same type of data (Figure 4). Results revealed an increase in success rate of orientation tasks and less bewilderment for the participants.

Learnings

Representation and simulation capabilities proved to be efficient tools in informing and taking decisions. The advantages of representation, enhanced by the digital nature of this one, allowed data collection in a controlled and controllable environment. Considering the inconveniences of testing inside an operating building or the costs of building a mock-up of a proposed renovation, the amount of work appeared negligible compared to 'real' test options. Virtual reality was confirmed to be a cost-effective way of running complex spatial simulations.

VR can help reduce costs of testing new solutions in architecture.

Another relevant aspect of the case study was the interaction between the human and the digital environment. The value of the case was not in the representation and simulation of the building, but in the interaction of it and the occupants. Wearable digital tools like VR allowed a close look at what decisions

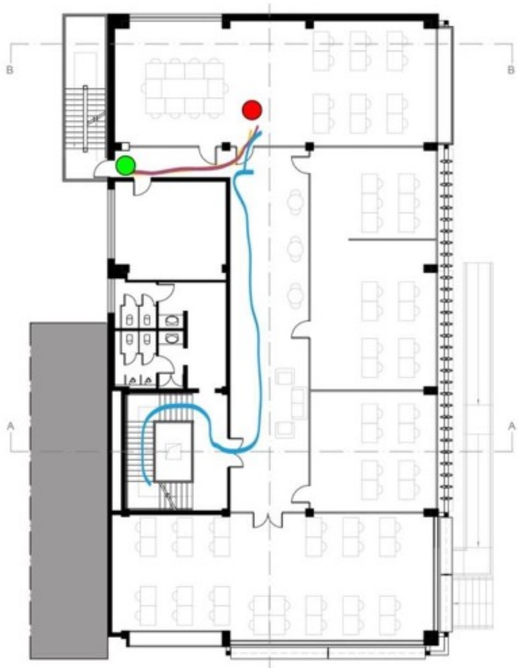


Figure 3: Tracking of participants' movements in the reconstructed building (Source: Nicola Felicini).

occupants took (movement tracking), which information they needed and where they looked for them (eye-tracking). As this case exemplifies, wearable technologies can constitute a means of access for humans to the digital realm (and vice-versa), enabling new ways of interaction between ecosphere and infosphere.

> **Wearable technologies can constitute means of access for humans to the digital realm and vice-versa.**

Possible future research directions

With the diffusion of digital tools, we are assisting a progressive 'democratization' of them. At the time of the study, the simulation required intense modelling work and knowledge of specific software and techniques. Current trends in building design tools allow real-time immersive simulation as the building gets 'drawn'. In opposition to the simplification and diffusion of digital tools, we need to clarify their actual potential and when they are worth the investment. In the presented case, which design decisions have been taken following the architect's experience and which derived from the simulation in the digital environment? A comparative study with analogic design techniques could elucidate these aspects.

The other question emerging from the study, is how much reality there is in digital reality? In other words, how applicable are the results obtained in a virtual environment to the real world? Would those occupants take the same decisions in the real building? How much does the level of immersivity affect behaviour? Again, a comparative study could help identify the weight of these factors.

Investigating the potential of digital simulations and their relationship with the real world are promising research directions that will acquire importance as digital tools and virtual experiences progressively gain ground in our daily lives.

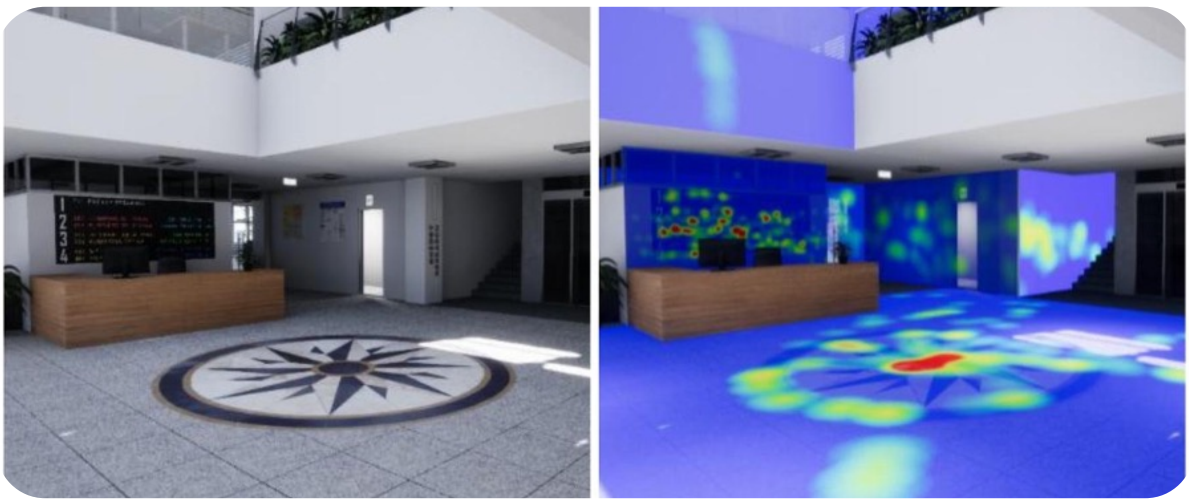


Figure 4: The atrium of the renovation proposal and the eye-tracking heatmap obtained in the second round of tests (Source: Nicola Felicini).

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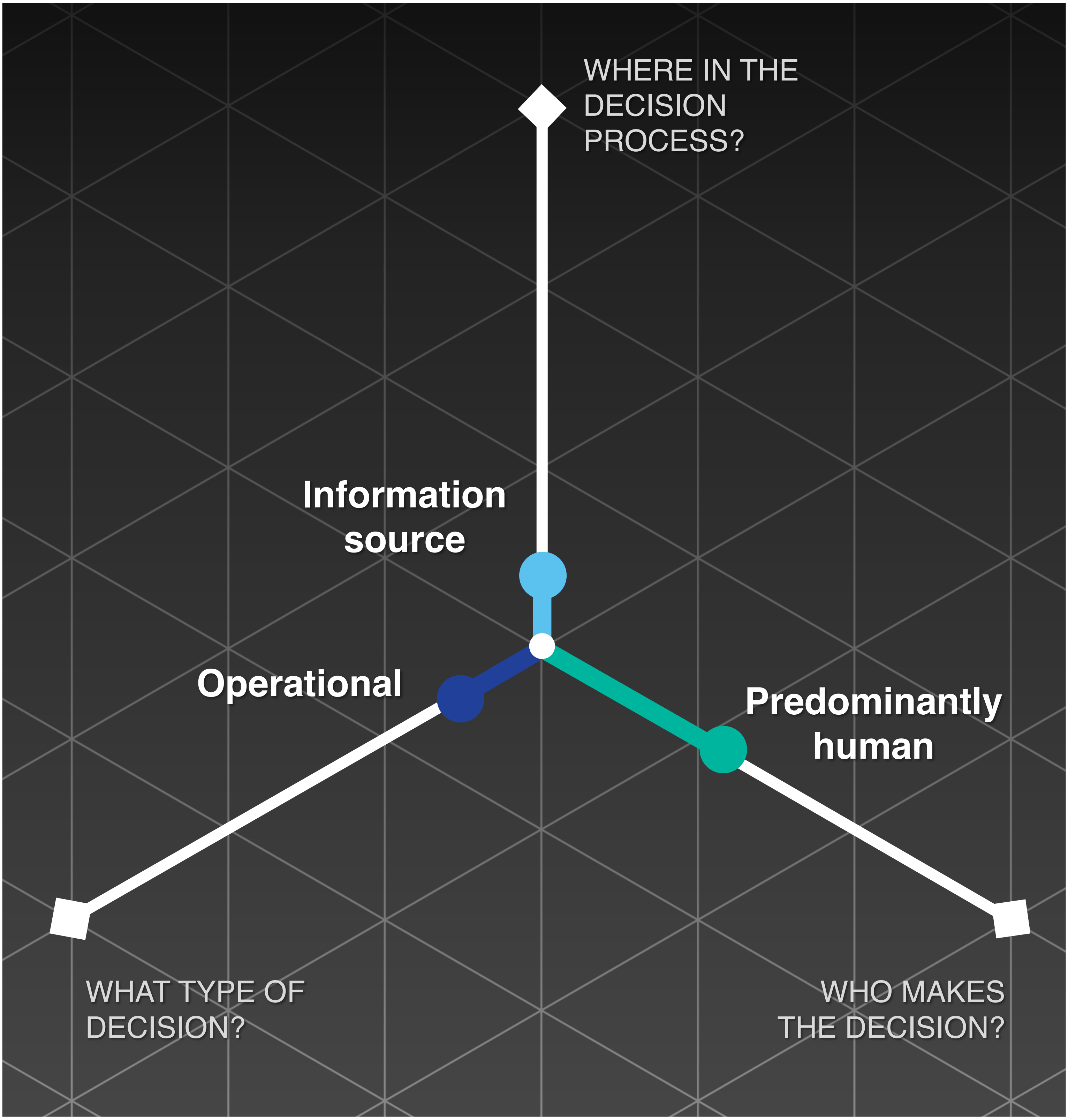
Case Study 9:

Using Augmented Reality to Help Humans Solve a Bin Packing Problem

Bethan A. Moncur[1,2], Maria Galvez-Trigo[2]

[1]Institute for Manufacturing (IfM), University of Cambridge
[bam49@cam.ac.uk]
[2]School of Computer Science, University of Lincoln



Introduction

Bin packing problems consist of a set of items which need to be packed into bins whilst minimizing the number of bins, cost, or excess capacity. These problems appear throughout manufacturing operations, such as minimizing waste in stock-cutting, or minimizing makespan in machine scheduling (Eliiyi and Eliiyi, 2009). Humans are intuitively good at solving such problems, however, complex problems involving multiple factors to consider can lead to miscalculations, resulting in excess waste and costs.

> **Augmented Reality Decision Support System (AR DSS): a digital system to assist the decision-making process by providing relevant and appropriate information to the decision maker through augmented reality.**

One such problem is the decision of how to pack items of different weights into different vehicle types, which may have different weight limits and costs associated with them (Correia, Gouveia and Saldanha-da-Gama, 2008). This problem can be modelled using the one-dimensional variable-sized bin packing problem. A set of items of different heights needs to be packed into bins, where each bin type has a fixed height capacity and cost associated with it. The decision maker must try to minimise the cost of the bins used to pack all the items.

Digital tools known as decision support systems (DSS) can be used to assist the decision-making process by providing relevant and appropriate information to the decision maker (Sauter, 2010). One way to provide the decision support information is through the use of augmented reality (AR), a human-machine interaction tool that overlays digital information onto the real world (Martins et al., 2021). It is thought that AR can serve as an effective DSS by reducing the cognitive load of mental reasoning for decision makers by making solutions readily perceivable (Zhang, 1997).

This case study discusses the format of an augmented reality decision support system (AR DSS) designed to help humans solve a one-dimensional variable-sized bin packing problem and subsequently explores the interactions that occurred between humans and the AR DSS.

Description of the AR Decision Support System

In typical bin packing problems, the decision maker solely needs to focus on minimizing the number of bins used. However, in this setup the bin packing problem was designed so that the capacities and costs of the various bin

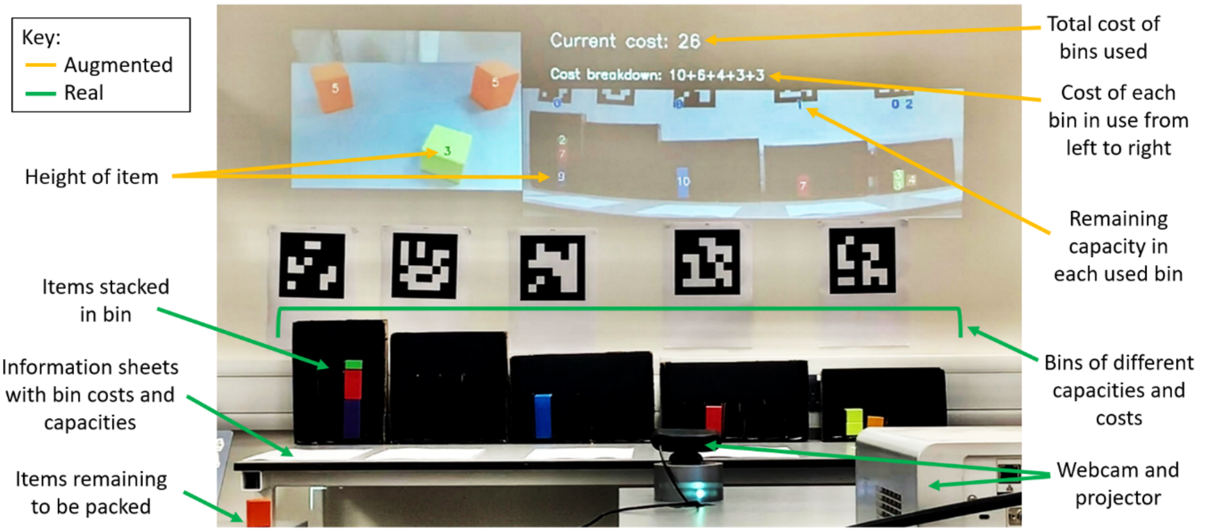


Figure 1: Annotated image of the AR DSS in action. The left-hand projection is of remaining blocks to be packed and the right-hand projection shows the bins with the blocks already packed into them (Source: Bethan A. Moncur).

types were not directly proportional, thus forcing the decision maker to consider both cost and capacity in their decisions.

The DSS was designed to explore the interaction of humans with the digital tool when taking decisions. Therefore, the DSS did not provide the users with the solution to the bin packing problem. Rather, it supplemented the scene with additional information that could be used by the decision maker whilst completing the task. This decision support information included the heights of the items being packed, the remaining capacity of each bin in use, and the cost calculation of the bins used in their current solution. The information was overlaid onto an image of the scene, and the resulting augmented reality decision support system (AR DSS) was projected directly above the bin packing task area, as shown in Figure 1.

Visualisations of information can operate as external memory.

Learnings

The application of the AR DSS to the bin packing problem blended the digital world into the physical world. This approach can be considered an initial step for the introduction of digital tools into human decision-making - it supplemented the real world with additional information relevant to the decision problem but left the human with full autonomy over the decision. The learnings from this approach focus on how humans used the information presented by the decision tool, however, they may also be relevant for situations where the digital tool has a greater influence over the decision.

Although there was an information sheet indicating the height of each item based on colour, users found that the augmentation of the heights onto the items sped up their decision-making. This aligns well with the literature concerning visualization for decision support, which suggests that visualizations can operate as an 'external memory', thus saving space in the working memory of the decision maker (Zhu and Chen, 2008). The learning from this observation is that seemingly simple support mechanisms from digital tools can have meaningful impacts on the mental processes of decision makers.

Choosing information that is relevant for objectives of the problem.

The users also seemed to 'outsource' the mental maths calculations for the remaining capacity of each bin to the AR DSS. This indicates that decision makers used the AR DSS as a tool to reduce their cognitive load, thus enabling them to focus on other aspects of the decision-making problem. However, the presence of the remaining capacity information did cause some users to focus on minimizing the excess capacity of the bins in use rather than focusing on minimizing the cost of their solution (the defined objective of the problem). The learning from this observation is that any information provided by digital tools must align with the objective(s) of the decision problem to avoid 'distracting' decision makers away from the primary focus.

AR DSS created new way of approaching the decision – a trial and error approach.

Finally, the augmentation of the cost breakdown to the scene encouraged trial and error from the users. They were allowed to re-pack items, so the augmentation indicated how the cost changed with different packing configurations – the only constraint on the decision maker was a time limit.

The AR DSS enabled users to quickly trial different solutions to the problem without having to perform mental calculations, and this changed the way that some users approached the task. The learning from this observation is that although digital tools can be used to complement existing ways of solving problems, they can also be used to encourage new approaches to decision-making.

Future research

Other formats for the AR DSS were explored, including handheld devices, desktop-based augmented reality, and head-mounted displays (primarily the Microsoft HoloLens 2). However, the AR DSS was designed to be an initial exploration of the integration of augmented reality to support decision-making. As a result, it made use of straightforward projection-based augmented reality, developed using an open source software library for computer vision applications (OpenCV). Therefore, future work could investigate the use of more immersive augmented reality formats, such as head-mounted displays, to explore other areas of the human-digital decision-making spectrum.

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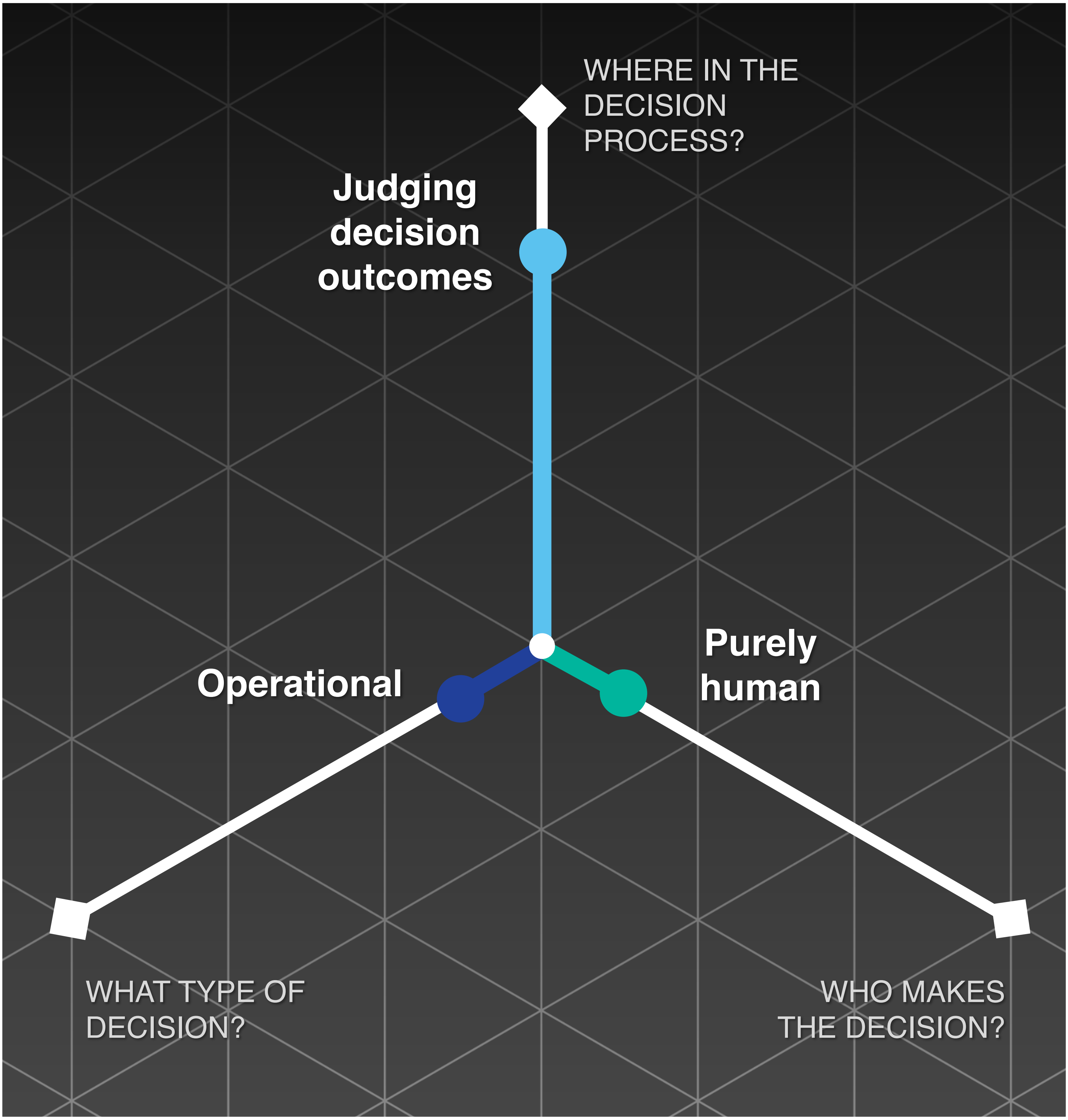
Source: Maximalfocus

Case Study 10:

Robots in Job Interviews: Insights from Experimental Studies

Sladjana Nørskov[1]

[1]Department of Business and Technology Development, Aarhus University *[norskov@btech.au.dk]*



Introduction

Job interviews are typically conducted in ways that allow for the job candidate to be visible to the interviewer, thus most often taking place face-to-face, via a videoconference, or, since recently, as a digital interview in which interviewees record their answers to prespecified questions (Langer et al., 2017). Such interview methods entail seeing the interviewee either on a screen or face-to-face. However, when we are able to see a person, visual cues related to, e.g., physical attractiveness, race, body size, or gender, have been found to trigger implicit biases (Hinton, 2017). Implicit biases are unconscious and based on rapid and automatic processing of information (ibid.), which makes them very difficult to control and change (Dobbin and Kalev, 2016). In job interviews, such biases have been found to unintentionally influence the way job candidates are perceived and evaluated (e.g., Grant and Mizzy, 2014; Ruffle and Shtudiner, 2015). In the context of job interviews, a key area of concern is thus related to the fairness of selection methods (Robertson and Smith, 2001). This is because the job interview is an inherently interpersonal process (Rivera, 2012) and a situation in which subjective impressions (e.g., similarities between the interviewer and the candidate) and affective reactions (e.g., liking) to job candidates have been found to prevail over applicants' qualifications and skills (Graves and Powell, 1996; García et al., 2008; Huffcutt, 2011; Rivera, 2015).

In trying to resolve this problem, social robots are being tested for their applicability in mediating job interviews to ensure objectivity and increase applicants' fairness perceptions (Nørskov et al., 2020; Nørskov et al., 2022). The following sections briefly present the idea behind the robot-mediated job interview and provide some insights and learnings stemming from recent experimental studies.

Proposed practical application of robots in job interviews

Robots and fair proxy communication

To reduce discriminative biases associated with the employment interview, the use of robots as a fair proxy communication (FPC) technology has been proposed (Seibt and Vestergaard, 2018). FPC is defined as: "a specific communicational setting in which a teleoperated robot is used to remove perceptual cues of implicit biases in order to increase the perceived fairness of decision-related communications" (ibid., p. 1).

> **Fair Proxy Communication (FPC): specific communicational setting in which a teleoperated robot is used to remove perceptual cues for implicit biases.**

The concept of FPC aims to improve the communication situation for the party that is typically exposed to biases. Consequently, in the job interview, the applicant would be represented by a teleoperated robot while being able to see the interviewer via a computer screen, as shown in Figure 1. The experiments that have so far tested the concept of FPC in job interviews utilized the Telenoid, a teleoperated robot based on a minimal design approach (Ishiguro, 2016). The Telenoid's design is intended to reflect minimal human embodiment and to appear "as both male and female, as both old and young" (Seibt and Vestergaard, 2018, p. 9). Previous research showed that this reduction in visual cues enabled a greater focus on the conversation (ibid.).

Figure 1: The photo shows an interviewer communicating via the robot with a job candidate, who is seated in another room, as shown in Fig. 2).

Figure 2: The candidate operates her robotic proxy while she communicates with the interviewer (Fig. 1). Her head movements, lip movements and speech are transmitted via the robot.

Setting up the robot-mediated job interview

The original idea behind using a robotic fair proxy in job interviews involved a setup in which the applicant is visually anonymous, while the interviewer is not (illustrated in Figure 1). This setup can be described as the "asymmetrical fair proxy" situation, or a single-blind interview, in quadrant II in Figure 3. However, this original conceptualization of FPC may be extended. In practice, one could imagine that quadrant III, namely the "symmetrical fair proxy" setup, could also be considered relevant. This setup could be described as a double-blind interview in which both parties are represented by a robot (Figure 3). Such a setup reduces the risk of

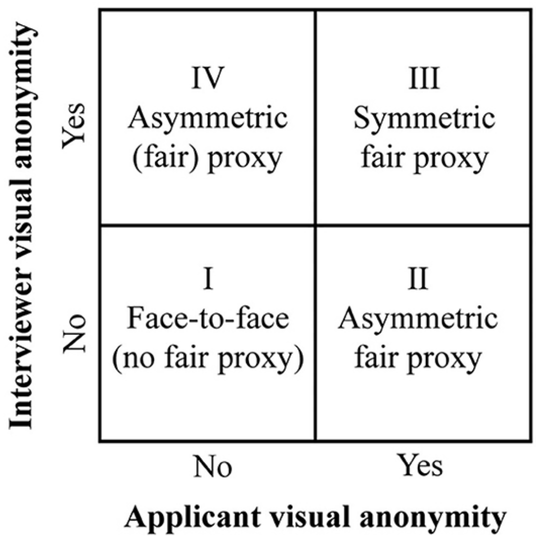


Figure 3. The four types of job interview setups with and without a fair proxy (Nørskov et al., 2020).

applicants' impression management tactics, because the applicant is unable to see the interviewer and the interviewer's non-verbal reactions, and thus unable to adjust the tactics used to create, uphold, or change the image of the applicant as a response to the interviewer's non-verbal reactions. This double-blind interview may therefore be able to place more emphasis on the applicant's knowledge, abilities and skills as the objective criteria for applicant selection (Nørskov et al., 2020).

Selected learnings

The two fair proxy setups, the symmetrical and the asymmetrical, have been tested in two different studies with respect to perceived fairness. The first study investigated the symmetrical fair proxy setup from the applicant perspective (Quadrant III in Figure 2) (Nørskov et al., 2020). Here, the main finding was that such robot-mediated interview was perceived as less fair than the traditional face-to-face job interview. However, since the study was based on bachelor students as respondents (n=235), it did not reflect a representative sample of job applicants, as bachelor students' experience with job interviews and the related discrimination is likely to be low.

Applicants perceive interview with robot as fairer.

The second study investigated the asymmetrical job interview setup (Quadrant II) from the perspective of applicants and employers. One part of this study was experimental and conducted at an unemployment center (n=250), i.e., with individuals who have more experience with job search and job interviews (Nørskov et al.,

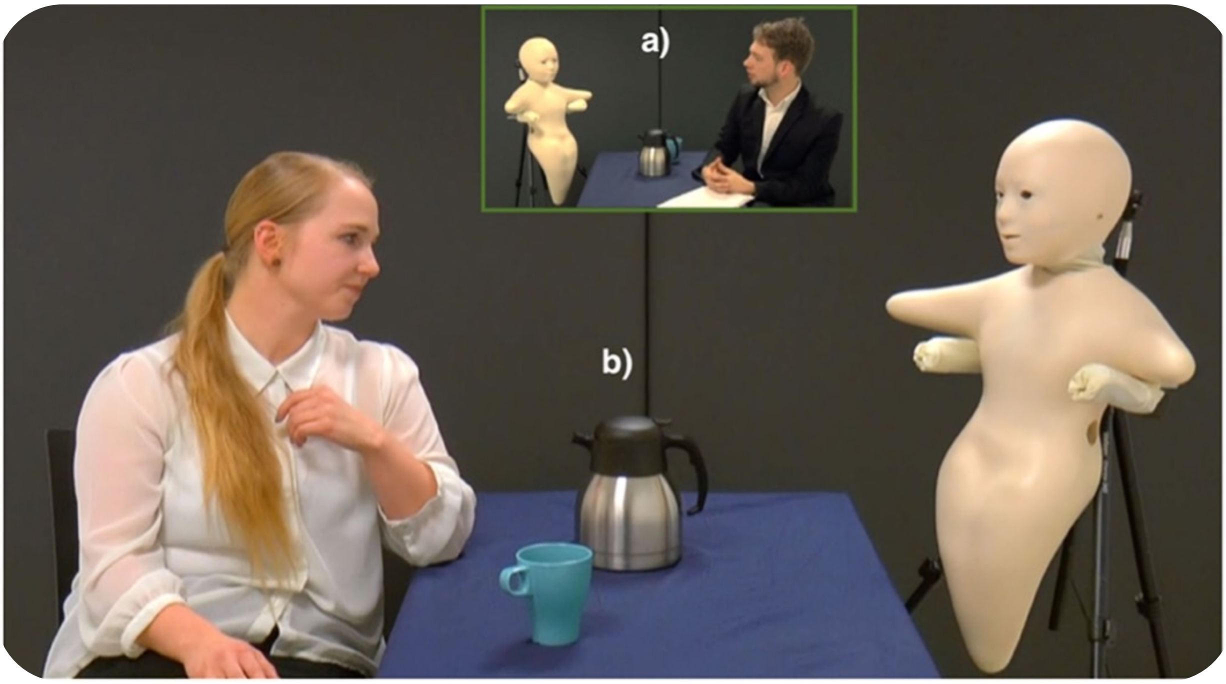


Figure 4. The "symmetrical" robot-mediated job interview. The interviewer (a) and the job candidate (b) are seated in two different rooms, and each is represented by a teleoperated robot (Nørskov et al., 2020).

2022). The study found the opposite effect, namely that the robot-mediated interview was perceived as fairer. The second part of the study was based on a mini-public methodology. It primarily uncovered employer perspective on robot mediation and found that Human Resource (HR) professionals (recruiters, consultants, HR partners, etc.) had mixed but mainly negative fairness perceptions of the robot-mediated job interview. One reason for this was that the HR professionals viewed an interview procedure as fair only if it made room for intuition and subjectivity. Relatedly, HR professionals also perceived the robot-mediated interview as dehumanizing as it removed personality, intuition and emotions from the interview. Furthermore, the HR professionals believed that biases are permissible because companies should have the right to choose according to their own needs and preferences. Indeed, moral pragmatism was a prominent reason behind negative fairness perceptions of robot mediation in interviews. HR professionals upheld their preference for the traditional interview methods due to: a) their role morality, which compels them to meet their clients' needs and requirements even if those involve biases and b) their strong focus on the business rationale behind a novel selection method (e.g., cost and time effectiveness), which undermines the social rationale (i.e., reducing discrimination), even if the two rationales could be achieved in parallel.

> **HR professionals perceive interview only as fair if there is room for intuition and subjectivity – which is being cut out with robots.**

Hence, employers and applicants seem to hold diverging fairness perceptions of the robot-mediated interview.

Our research also indicated that the HR professionals may be more likely to adopt autonomous rather than teleoperated robots, as autonomous robots could free up HR personnel's time for other tasks. Autonomous robots could thus be a way of resolving some of the identified moral pragmatism issues. On the other hand, using a telepresence robot means that candidates still get to speak with a human interviewer through a robot rather than with "merely" a robot. The quality and dynamics of interview communication as well as applicant reactions may differ depending on which robot technology is used. More importantly, as it has been argued that the use of Artificial Intelligence (AI) in hiring fails to resolve racial and gender biases (Drage and Mackereth, 2022), teleoperation may hold more promise for job interviews.

Future research

It is too early to make general conclusions based on the above studies, because they used two different populations, and investigated robot-mediation in two different interview setups, the symmetrical and the asymmetrical. Nonetheless, these studies provide important insights into the use of robot mediation in job interviews and open up new questions to be answered.

Typically, the teleoperated robot-based job interview is intended for the first round of interviews during the early screening rather than as a replacement for the face-to-face job interview. While such a method of interviewing may improve the focus on competences and skills, and give applicants a better chance to perform, we still need more insight into the extent to which the robot-mediated interviews actually reduce or eliminate biases compared with face-to-face interviews. As human interviewers keep their presence in the robot-mediated interview, biases are likely to remain present to a certain degree. Relatedly, socially desirable responses and other common impression management tactics may still be at play during the robot-mediated interview, and it is relevant to consider to what extent this interview method can limit or disregard such tactics and achieve an objective assessment.

Additionally, more knowledge is needed about how different design elements of robotic agents are able to facilitate job interviews in ways that increase applicant fairness perceptions, while being able to identify the best candidate for the recruiting organization (Nørskov and Ulhøi, 2020). The quality of the communication that a teleoperated robot facilitates is equally under the influence of the robot design. Moreover, in the role of an interview mediator, the robot may be perceived as an organizational representative, and thus affect organizational attraction and reputation (Turban and Dougherty, 1992). Future research could investigate whether and how the perceptions related to the robot, the interview method, the communication quality as well as the hiring organization may be enhanced by adjusting the kinematic, functional and physical parameters of the robot design.

Finally, the use of robots in personnel selection is likely to alter HR employees' roles and work procedures as well as re-design Human Resource Management (HRM) activities and processes. How robotics gives rise to novel practices and processes in HRM, how it affects the norms and values of organizations, and how it shapes HR as profession are some of the pending questions.

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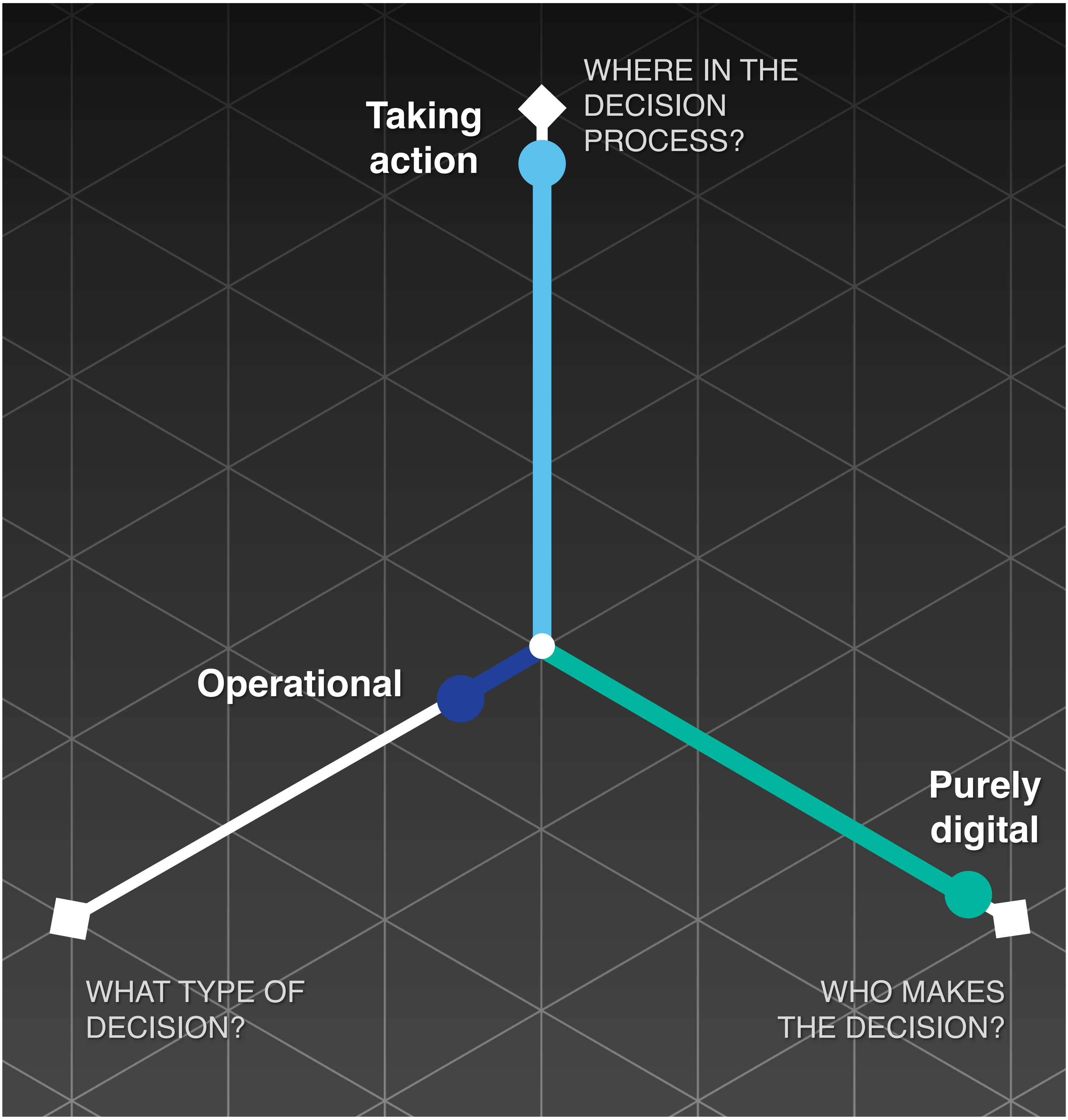
Case Study 11:

The Role of Participatory Design in Responsible AI Development

Emma Kallina[1]

[1]Institute for Manufacturing (IfM), University of Cambridge
[emk45@cam.ac.uk]



Introduction

Artificial Intelligence (AI) use is increasing across industries: 56% of companies in a global survey report AI adoption in at least one function. 'AI' has become a buzzword, forcing companies to adopt it if they wish to be perceived as innovative. However, introducing AI at the workplace is non-trivial. Responsible AI guidelines point out the risks involved when introducing AI-based systems into environments and their existing workflows, power structures and communities (Fjeld et al., 2020). The guidelines aim at guiding the development and use of AI technologies in a way that is 'ethical', i.e. aligned with human rights and the values present in the application context. To this end, they state principles such as 'Fairness', 'Transparency' or 'Human Control' (Fjeld et al., 2020). Unfortunately, an enormous divide exists between these theoretical guidelines and the practice of developing AI systems (Jobin et al., 2019; Morley et al., 2021). McNamara et al. (2018) showed that the mere presentation of such guidelines did not influence the decisions of professional software engineers, as well as Computer Science students. Remarkably, this gap is even recognized by practitioners themselves (Ibánez and Olmeda, 2021). The following quote from an interview study provides a glimpse into the current situation: "I think we read them all because they are coming out. There are many in the 'stratosphere'. That is when you read the principles and say, how do I translate them in practice? It gets more complicated." (Ibánez and Olmeda, 2021, p. 9). A main reason that renders it challenging to implement the principles listed in the guidelines in practice is their high level of abstraction. Ensuring 'Fairness', 'Human Control' or 'Respect for Human Values' when building an AI system is not a trivial question and cannot be answered independently of its domain. It is likely impossible to translate these philosophical concepts to a specific use case without a thorough understanding of its context.

> **Responsible AI: development and use of AI technologies ina. Way that is aligned with human rights and the values present in the application context.**

A study that harnessed participatory design techniques to gather detailed insights into the application context and the preferences of the affected communities is presented below. These insights were successfully used to inform the design of the system, leading to a high level of trust and perceived fairness by all parties involved. Only if we understand and include the values, needs, and perceptions of all impacted parties can we ensure a system design that truly respects the environment in which it is implemented.

Main description of the practice

Lee et al. (2019) created a framework for the design of AI systems. It aims at including and balancing the interests of all parties affected by the system. This is achieved through enabling them not only to participate in the design process, but to provide them with the main decision power.

The resulting framework was tested in a case study of an on-demand food donation transportation service. Donors (e.g. grocery stores or restaurants) with superfluous food call the food rescue service who matches these donations with one of several non-profit recipients. After the match has been made, volunteers collect the donation from the donor and deliver it to the receiving organization. Unsurprisingly, the allocation decisions are crucial in ensuring a fair distribution of the goods. To increase equity and decrease the workload of their employees, the food rescue service seeked to automate these allocation decisions through an AI tool.

> **Perception of what is "fair" various not just by case but also by role/person.**

This proved challenging since the preferences of the different parties resulted in different distribution decisions: Volunteers and organizations would prefer shorter routes to save resources and make volunteering more attractive (easier to recruit volunteers for short distances). However, the recipients in the greatest need are often the furthest away from the donors (often located in wealthier areas). Thus, distributing based on recipient needs contradicts efficiency. To strike the correct balance between these two preferences, all affected parties - food donors, volunteers, recipient organizations, and nonprofit employees - were questioned regarding their allocation preferences, as well as involved in the design of the system. Their preferences were collected through focus groups, interviews, exercises in which they explicitly allocated weights to the different decision factors, experiments in which participants had to repeatedly select between two alternative donation allocations, as well as evaluative post-interviews.

These insights resulted in a decision model for each participant that they could adjust until they felt that it correctly reflected their preferences. Then, a workshop was conducted to agree on the correct weighting of the preferences of the different parties. This weighting was used to aggregate the individual models to an overall model that recommended donation allocation decisions. Through understanding and including the preferences of all parties, the resulting AI model was trusted by all participants to reflect the beliefs of everyone involved. Furthermore, the participatory design process improved both procedural fairness and the distributive outcomes of the distribution choices, partly through identifying inconsistencies in the human decision-making in the governing organization.

Learnings

The work of Lee et al. (2029) demonstrates the feasibility and potential of community involvement in the creation of AI systems. In this case study, the values, beliefs and preferences of all affected parties were included to arrive at a case specific understanding of what 'fairness' means for this application context. Thus, the gap between the abstract principle and the specific use case has been closed through harnessing participatory design. This promising approach should be further developed and become an integral part of the design of AI technologies.

> **Community involvement of all stakeholders in the creation of an AI system increase "Fairness" of tool.**

Possible future research directions

Despite the vast amount of AI systems, only very few examples demonstrate a consistently participatory design approach. This is due to the investments in time and resources required to involve the affected communities in a meaningful way, paired with the lack of perceived urgency. Especially the narrative of an 'AI Race', as well as the mindset of 'move fast and break things' are extremely counterproductive since they frame the careful assessment of potential needs and risks not only as unnecessarily cautious, but also as an economic disadvantage (Cave & ÓhÉigeartaigh, 2018). Thus, future research could focus on questions such as: How could participatory design be integrated in industry practice? How can we create internal advocacy / a sense of urgency for stakeholder involvement? What are effective methods to gain insights into the values present in an application context? Only if we enable all parts of society to participate in the design of AI systems, can we avoid that the abstract principles stated in the responsible AI guidelines are interpreted by a subgroup of society to speak for us all.

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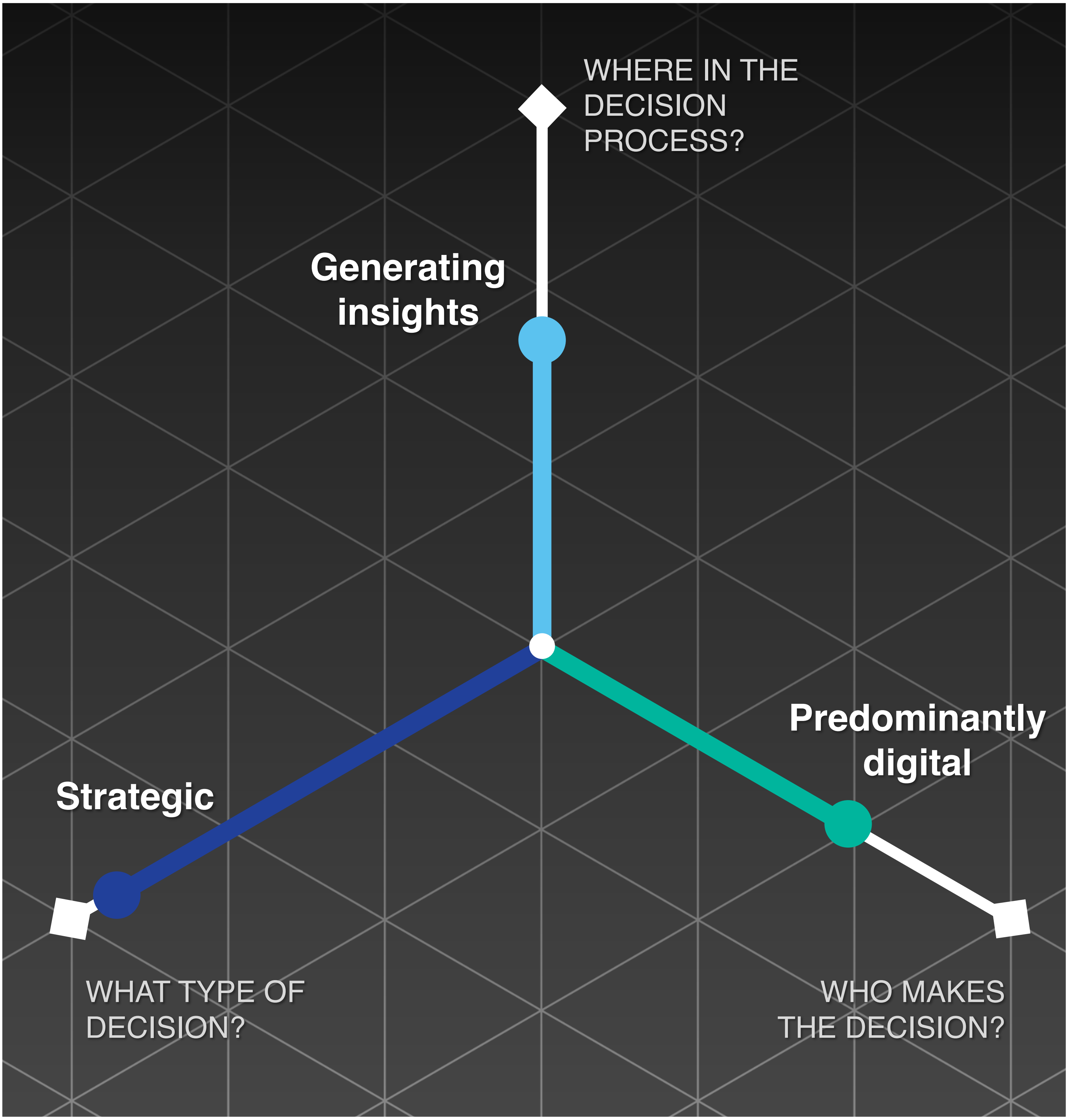
Source: Carlos Muza

Case Study 12:

Challenges in Using Machine-Driven Analysis to Inform Strategic Decision-Making

Ian Jones[1]

[1]AMPLYFI *[ian.jones@amplyfigroup.com]*



Introduction

Since the early 1990's, Business Intelligence (BI) has been shaped by a series of computer and digitally enabled developments with advances in Artificial Intelligence (AI) and Machine Learning (ML) ushering in the latest wave of technological progress. In each instance, organisations that moved early and adapted quickest benefited the most. Key to maximising value was not only seamlessly integrating the latest technologies into the existing business processes (or rapidly transitioning to new ones), but also understanding the impact on skills, capabilities, and working practices. This case study considers the challenges for integrating machine-driven analysis into strategic decision-making processes. It draws upon the experiences of AMPLYFI, a company founded in 2015 to develop AI-based platforms that perform machine analysis of vast quantities of textual content and automatically generate results that lead to better informed and faster decision-making.

The digitalisation of business intelligence

When computers first began to digitalise the office in the mid-1990s, solutions centred around on-premise, client-server models in which reports were produced by dedicated Information Technology (IT) teams in response to specific business requirements. From a data infrastructure standpoint, relational databases were prominent. This generation of BI Platforms was dominated by incumbents like Microsoft Reporting Services, IBM Cognos (pre-IBM Watson) or SAP Business Objects. The emergence of cloud computing and evolution of Not-Only Structured Query Language (NOSQL) database models were the catalyst for the next wave of digital transformation to BI in the early 2000s that featured the "Big Data" phenomenon. From around 2005, digital technologies began to shift BI away from IT-centric to business-centric solutions by enabling users to create their own dashboards and analysis under self-service models. It featured enterprise mobile solutions that allowed users to consume information on the move from mobile devices.

The latest wave of BI digital transformation to emerge from around 2015 is typified by platforms that are predictive, proactive, and cognitive. Led by the emergence of ML as well as real time data analytics, it is increasingly embracing trends like the Internet of Things (IOT) and Distributed Ledger Technologies (DLT). The focus is shifting to discovering unknown-unknown insights and predictive analytics.

The impact of artificial intelligence on business intelligence

Whilst the rise of AI in the context of BI is a relatively recent phenomenon, its potential to impact a business on multiple fronts, drive down costs through efficiency gains, improve accuracy, increase processing speeds, and generate value has seen a rapid growth in new data science teams and the emergence of prominent positions such as Chief Data Officer (CDO) and Chief Information Officer (CIO) with the new functions often represented at Board level. Initial deployment of AI focused on more operational business activities such as process automation and cyber-security; gradually expanding into low-level decision-making processes where choices are measurable and binary i.e., credit checks, loan approvals etc. The use of machine-driven analysis in informing key strategic decisions is nascent.

> **New prominent roles related to information and intelligence emerged as data became crucial for companies.**

The Rise of Unstructured Data

A key attribute of AI is its ability to unlock and create value from unstructured data. In 2006, British mathematician Prof. Clive Humby coined the phrase "data is the new oil" and went on to state that "Like oil, data is valuable, but if unrefined it cannot really be used. It has to be changed into gas, plastic, chemicals, etc. to create a valuable entity that drives profitable activity". The true value of data comes from the quality and speed at which it can be converted into information and insight. Typically, BI has been driven by analysis of structured datasets that are highly organised, formatted, predefined, and follow fixed schema – unusually in table and numerical formats. Examples include company accounts, commodity prices, exchange and interest rates, names, dates, addresses, credit card numbers etc.

Unstructured data exists in multiple formats including emails, books, scientific papers, pictures, videos, audio files, satellite images etc. Industry experts believe that 80%-90% of the world's data is unstructured in nature with 90% of it created since 2019. Of this, it is estimated that only 0.5% is analysed and used today. With the largest of human research and analytical teams struggling to cope with Big Data, transitioning from structured to unstructured data is next to impossible without AI.

> **Giving a structure to the increasing amount of data without using AI is nearly impossible.**

Advances in AI, particularly in Natural Language Processing (NLP) and Pattern Recognition, mean that machines are increasingly able to analyse textual content at speeds and scale far beyond a human analyst. The challenges of analysing unstructured data have driven developers to push boundaries, particularly in unsupervised machine learning and deep learning. Algorithms can now perform sentiment and tense analysis, identify topics and quantify their relationships with other topics, entities, people, and locations, identify risk or adverse events associated with organisations or persons of interest, work across multiple languages etc. and all within a matter of minutes or hours rather than the months or years that it would take humans to complete.

Barriers to acting on machine-driven insights

The development of AI is driving a paradigm shift in the skill requirements, not just of those that create the algorithms, but also of the analysts and researchers who provide the information that informs strategic decisions. Development wise, it is placing greater emphasis on mathematical, data science, and computational linguistic skills rather than pure software coding (though this remains important for developing optimised, robust and scalable platforms).

Working from structured (and primarily numerical) datasets, analysts today typically have strong numerical, rational analytical skills. They are used to working from data that they assume to be 100% accurate and very specific in scope. This is not the case with machine-driven analysis. Today, results from AI algorithms are expressed in probabilities and confidence scores with errors and false positives likely to be present.

> **Machine-learning analysis inevitably involves 'noise' that can undermine the analysts' confidence.**

This is especially so with unsupervised learning where a lot of "noise" can be generated alongside the insights. This can undermine analysts' confidence in the results and requires patience to distil the insights. In addition to accuracy and potentially noisy results, greater emphasis is also placed on interpreting results, particularly on topics that analysts may be unfamiliar with. For this, attributes such as the ability to make inferences, apply judgement, creative and original thinking, see patterns or stories in graphical outputs, strong communication, etc. become more important than the traditional quantitative, rational analytical skills of the typical analyst.

Enabling the transition

Whilst employers need to understand the skills implications from investing in AI and act to develop training and recruitment practices to ensure they have people with the right skills in their workforce, developers and suppliers of AI platforms have a role to play in helping to drive their adoption. At AMPLYFI, we work on a number of fronts to help users make the transition:

Transparency

AI models are often opaque or "black boxes" with even their creators unable to explain how the machine has gone from a set of inputs to a set of outputs. Building in transparency so that the user has line-of-sight to the original content and the machine's analysis wherever possible is crucial to building trust in the machine.

User experience (U/X)

Designing frontends that deliver a compelling user experience and mix familiar visuals with new, innovative outputs helps users become comfortable with working with results. In addition, everyone has different preferences for how they absorb and process information, so presenting results flexibly and in multiple formats helps cover all users' needs.

Onboarding and training

Comprehensive onboarding processes that combine traditional one-to-one classroom style teaching, user manuals and dedicated helpdesk support with multi-media assets such as "how to..." videos, "hints and tips" pop-up menus, automated chat-boxes, all backed-up by regular catch-up and review meetings, internal champions, and user forums to spread good practice help ensure that new users do not feel isolated.

Reinforce benefits

Regularly highlighting to users, either through the platform or direct interactions, the benefits of the machine in terms of time to insight, number and breadth of documents mined and analysed, user engagement statistics, savings on content subscriptions etc.

Flexible business model

Developing platforms that allow users to subscribe and engage at different levels so that they are not overwhelmed with features and functionality surplus to their needs. For deep analytical users, AMPLYFI's own in-house Research team comprising of expert users can be engaged in joint research as part of any familiarisation programme.

Possible future research directions

At present, the main challenge is getting analysts comfortable with adapting and embracing technological change (a feature of every wave of digital transformation in the BI space) and working with machine-driven analysis. However, bringing researchers and analysts to a level where they work effectively in harness with machine-driven analysis is only a first step in having AI inform key strategic decisions. These are invariably taken at the highest echelons of an organisation by senior management and executives with analysts and researchers working to deliver the insights and recommendations that underpin their thinking. The next challenge is then in communicating and explaining those insights in ways that ensure key decision makers feel comfortable acting on BI originated by a machine.

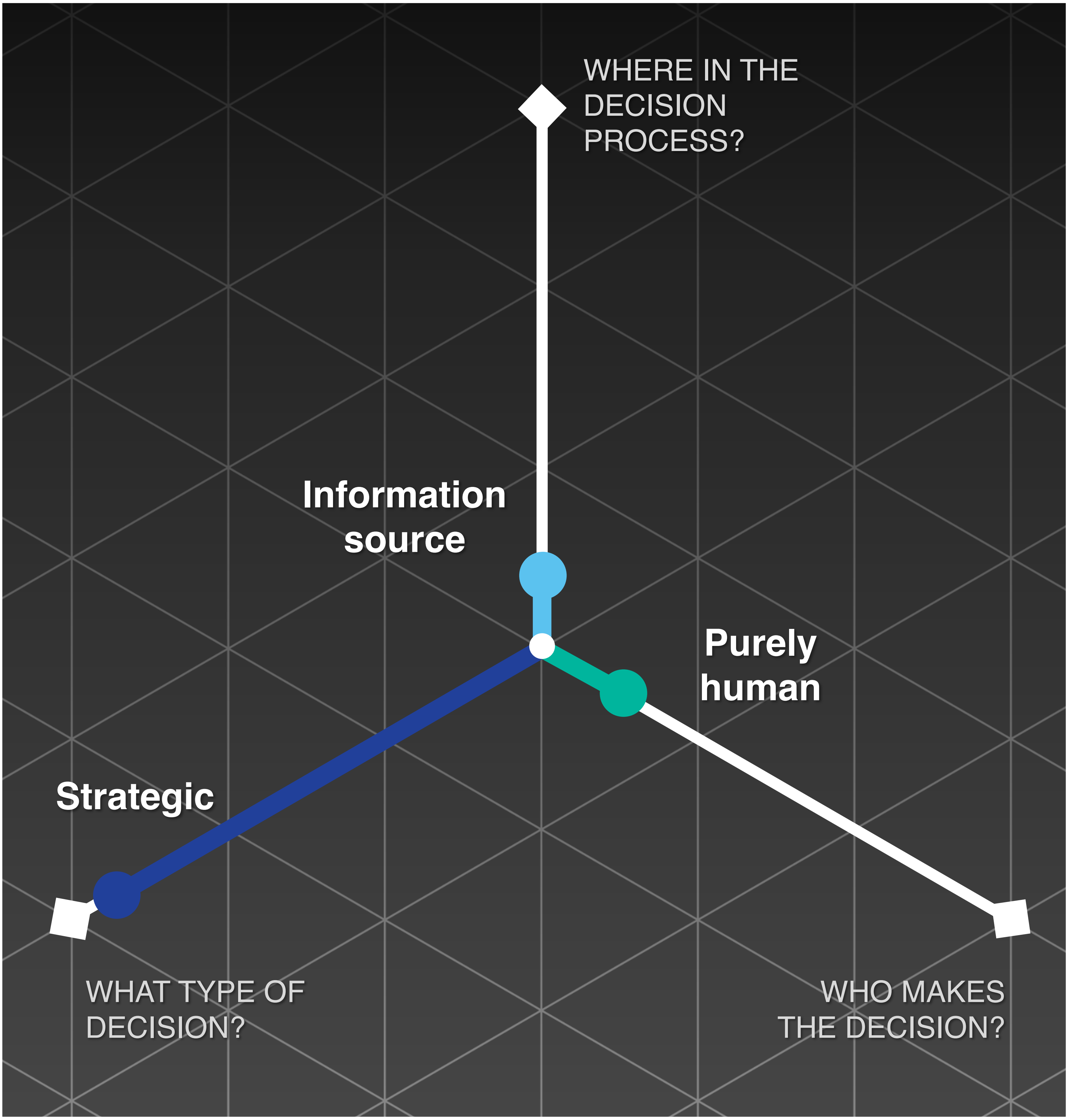
As we have seen, technological change comes in waves. For BI, the next step for machines will be for them to go beyond delivering analysis and on to generating recommendations. Looking further into the future, it is conceivable that they will one day go a step further and take strategic decisions themselves. However, significant technology development is required before then and a lot of trust will need to be built between humans and machines first. Currently, computers are a long way away from understanding the combined social, economic, political, and technological contexts within which such decisions are made. In the meantime, it is important to focus on the positive effects that the influx of these new technologies is having. It is the opinion of many that, despite all of the digital technological advances made in BI since the early 1990s, actual productivity gains have been limited with knowledge workers still spending significant portions of their time simply searching for information. This excludes the time then spend conducting analysis, deriving insights, and making recommendations. With technology reaching a point where it can seamlessly connect data held in siloes, intelligently find information at scale, analyse it, and present results, this is set to change. For users that can adjust and work with the machine, this will allow them to dedicate the majority of their time on the more interesting, value-add, and fulfilling aspects of their roles - extracting insights, communicating results, making recommendations, and supporting strategy rather than data gathering, reading, and number crunching.

Case Study 13:

Digital Kaizen™ and Decision-Making in Digital Transformation

Duy Dang[1], Karlheinz Kautz[2]

[1]RMIT University Vietnam, HCMC, Vietnam
[duy.dangphamthien@rmit.edu.vn]
[2]RMIT University Melbourne, Australia



Introduction

Digital technologies are being integrated into all areas of businesses, changing the way organisations operate and deliver values to their customers. However, businesses are generally unsure about what digital transformation is and how it can be implemented, which prevents them from making informed decisions and effectively executing such transformation (Wessel et al., 2021).

Digital transformation refers to the technology-induced changes that are necessary for digital businesses, in which businesses go through a fundamental and socio-technical transformation (Vial, 2019). Many organisations and practitioners have been struggling to grasp the digital transformation processes and seek advice and directions for how digital transformation programs, especially large and complex ones, can be executed in their firms.

> **Digital transformations are fundamental and socio-technical changes necessary for digital businesses.**

It is for this reason that having a stepwise approach is essential for businesses, as they are usually hesitant to commit resources to major digital transformation projects whose outcomes are uncertain. Lacking the understanding of digital transformation processes not only increases the risk of failing the transformation programs, resulting in high organisational and sometimes societal costs, but also limits knowledge of digital transformation strategies and how transformation efforts may differ across contexts e.g., large enterprises versus small and medium ones.

Description of the practice

We performed a study at FPT Software, a large software development and IT outsourcing company that turned into a digital transformation service provider in Vietnam. Our research team explored Digital Kaizen^{tm}, a systematic approach to conduct large-scale digital transformation. A total of five in-depth interviews were conducted with key informants at FPT Software, including the CEO, CD&TO (Chief Digital & Technology Officer) cum Executive Vice President, and Head of Digital Innovation.

The Digital Kaizen^{tm} approach integrates the Kaizen philosophy and Kaizen based decision-making, which has mainly been applied in manufacturing to optimise production lines, into digital transformation practices that lead to digital improvements and transformation. Kaizen is a Japanese business philosophy which involves the concepts of change (kai) and to become good (zen), and it emphasises a "continuous improvement" approach in organisations (Masaaki, 1986). Applying the

Kaizen philosophy means continuously identifying and developing new or improved processes to achieve outcomes that contribute to organisational goals. From our analysis, we found Kaizen and digital transformation to share similar characteristics.

First, Kaizen focuses on making continuous improvements, while digital transformation requires continual changes and innovative technology deployment. Second, Kaizen aims to influence organisations' productivity to achieve better customer satisfaction, and similarly, transformation enabled by digital technologies focuses on generating value-creation processes that benefit both organisational activities and the company's stakeholders. Third, both Kaizen and digital transformation draw on people and processes to capture the changes. These similarities and connections between Kaizen and digital transformation support the conceptualisation of the Digital Kaizen™ concept as an approach to digital transformation.

Learnings

Breaking it down in organisational activities

There is an alignment between Digital Kaizen™ and the dynamic capabilities framework, which suggests Digital Kaizen™ can shed light on the organisational activities that are required for organisations to achieve a competitive edge and sustainable growth. The concept of dynamic capabilities refers to the organisation's ability to integrate, build, and reconfigure internal and external competences to address the changing environments (Teece, 2007). According to the dynamic capabilities framework, there are three main capabilities, namely sensing, seizing, and transforming. By reflecting on the Digital Kaizen™ approach and comparing it against the dynamic capabilities framework, our research team was able to draw theoretically grounded and actionable guidelines for implementing large-scale digital transformation.

Capabilities organisations need for digital transformation

Sensing capabilities refer to the tools and techniques that organisations use to detect, identify, and filter opportunities for developing new products and services. On the other hand, seizing focuses on the decision-making capability of the business to invest in the identified opportunities and take action.

In terms of Digital Kaizen™, the management at FPT Software conducts regular workshops involving managers of different departments to identify cross-functional pain points, from which digital transformation initiatives can be proposed and ranked based on a set of metrics to determine their priority. These transformation initiatives must be aligned with the company's strategic objectives, and more importantly, their values must be realised within a few months. These activities of the Digital Kaizen™ approach can be considered as the specific microfoundations that contribute to developing the sensing and seizing capabilities for digital transformation of FPT Software.

Transforming capabilities maintain the profitability of a business in a turbulent and uncertain environment. Transforming entails the redeployment and reconfiguration of assets and routines, which require microfoundations such as achieving decentralised structures and managing complementary assets, as well as knowledge management and corporate governance capacities.

At FPT Software, most of the intended target outcomes are created and realised in the transforming stage. These outcomes include user uptake of the digital solutions, improved morale, change capability and digital maturity, which are attributed to the creation of small and quick wins, the fast realisation of transformation values, and the cross-functional collaboration and understanding that have been built up from the beginning to this stage.

Capabilities organisations need for digital transformation

It is important to note that the emergence or development of a new business model can take place as a result of the transformed work practices, as in the case of FPT Software transforming from a software development and IT outsourcing company into a digital solution provider. More specifically, the digital transformation initiatives, which were implemented successfully and resulted in positive organisational outcomes internally, were re-packaged and commercialised to be sold to external clients.

Possible future research directions

Digital transformation programs are often large and complex, consisting of multiple related projects which depend on each other. Consequently, it is useful to have an approach that separates such large programs into smaller and more manageable pieces of work. The case of FPT Software confirmed that successful digital transformation is strategically motivated and can be carried out in a stepwise manner that employs decision-making, change management and communication techniques to engage with the employees, especially by striving for and demonstrating quick wins during the transformation process to gain their buy-in. Moreover, the approach of Digital Kaizentm can contribute to a company's digital readiness for further transformation. Top management may consider adopting our proposed model for managing the implementation of large and complex digital transformation programmes.

Future studies are invited to continue identifying the microfoundations, practices, and enablers of successful digital transformation implementation, as well as examining the implementation in various contexts and conditions. Last but not least, it is critical important to investigate digital transformation implementation from the perspective of the employees as well, e.g., their acceptance of and resistance to the implementation.

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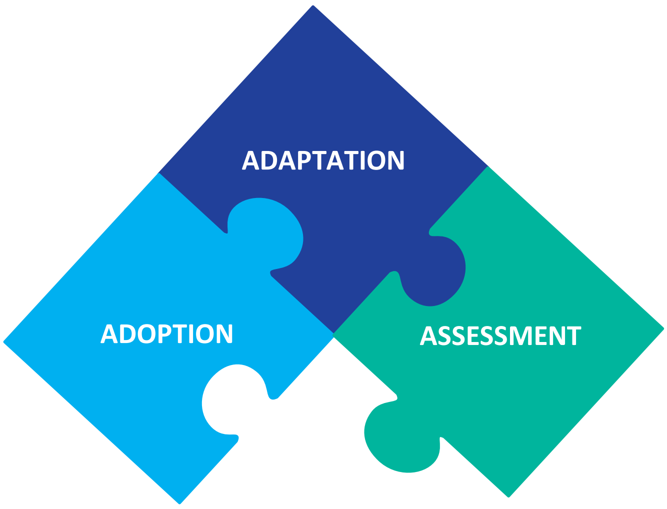
Future directions

Looking back at the rich landscape of collected case studies, three important aspects emerge that are pointing towards future research directions.

Adoption is an important issue that came up across case studies and technologies, in line with ongoing research in this field by many scholars (Berg et al., 2023; Davis et al., 1989; Lai 2017; Sohn and Kwon 2020). In addition, the theme **Assessment** is relevant in various configurations of integration of human/social and digital. This area of research has opened many interesting research questions to be tackled. Lastly, the aspects relevant for **Adaptation** are common issues raised in the case studies. In the following we present and discuss each of these themes in more detail.



It is important to highlight **the relevance of the application context. The same digital tools can be applied to several contexts**, using different configurations. Depending on the digital technology, the considerations in the following sections on adoption, assessment and adaptation differ greatly This is visible when trying to compare the case studies on robots (C1: Rojas, C10: Nørskov) and the ones discussing AI (C6: Foster, C7: Leeb, C11: Kallina, C12: Jones). Using a telepresence robot in a medical context (C1: Rojas) requires different assessment criteria, adoption considerations and adaption strategies than the use of these technologies in a shopfloor.

Every configuration where humans and digital technologies integrate present a different scenario. These configurations can be mapped on the three axes introduced.

Adoption of the digital technology

The integration of human (social) and digital in decision-making is contingent on the adoption of the digital technology. **Adoption is often linked to the acceptance of the technology** (Davis et al., 1989). Further, this is linked to (but not necessarily the same as) how effective and appropriate the use of the digital technology in the decision-making is. Effectiveness and appropriateness will be discussed in more detail in the next section.

For a successful adoption of a digital technology three aspects need to be investigated:

1) **What determines an adoption?**

2) **What are barriers to adoption?**

3) **How can decision-makers change towards successful adoption?**

Factors that influence adoption

Adoption of a digital technology in decision-making processes can be determined by factors at individual, organisational or societal levels. Some of the case studies point towards important questions to be answered:

- **What are personal factors influencing adoption?**
- **What organisational factors are influential?**
- **What is the cultural dimension of adoption of digital technologies?**

At the individual level, personal factors can influence the adoption. These influencers can be, but are not limited to, skills, personal experiences or personality traits (Allen and Choudhury 2022; Choudhury et al., 2020; Libert et al., 2020). It is established that personal factors influence the acceptance of technologies (Davis et al., 1989). Further, studies show that **the acceptance of digital technologies** (e.g., Artificial Intelligence) **can be influenced by personality traits**, such as conscientiousness (Tang et al., 2021), and level of expertise (van den Broek et al., 2021). The case studies discussing AI-driven technologies in particular demonstrate the importance of investigating the personal factors associated with adoption (C2: Ferrigno, C6: Foster, C7: Leeb, C12: Jones). Further, personal factors seem especially important whenever an individual interacts with a digital technology one-on-one, such as when using Telepresence Robots for communication with a relative (C1: Rojas) or using a robot for job interviews (C10: Nørskov). **Successful adoption of digital technologies** in companies **can depend on organisational and cultural factors**, as suggested by case studies C2 (Ferrigno), C6 (Foster) and C13 (Dang).

This is closely linked to establishing **appropriate infrastructure**. In addition, the **right mindset and data culture** needs to be in place. Many digital technologies are data driven, which requires people working with them to be able to deal with noisy and messy data inputs. In addition, they need to tolerate more uncertainty and probabilities in relation to data outputs, as discussed in case studies C7 (Leeb) and C12 (Jones). Future research should investigate what concrete factors at the personal, organisational, and cultural levels strongly influence the adoption process and how these can be addressed.

The nature of the task that needs to be performed and the type of decision that needs to be taken influences adoption as well. This is important, when **deciding for which task a digital technology should be used**. For example, the more difficult a task and the higher the degree of uncertainty of the outcome of a decision, the more humans tend to offload the choice to an AI-driven machine (Schneider and Leyer, 2019), which is also relevant for other digital technologies, leaving the question open:

- **How does the task at hand influence the adoption?**

Lastly, a common theme appearing across case studies is the question:

- **How does the humanization or dehumanization of digital technologies contribute to the adoption?**

Considerations need to be taken along this spectrum. For example, whether it is helpful for the adoption to create a tool with a human voice that discusses issues with employees as if it were a colleague (humanization), such as in case study C2 (Ferrigno). On the other end are the case studies discussing robots (C1: Rojas, C10: Nørskov), which report that it is mostly more beneficial to create robots that are not too human-like for a higher degree of adoption (dehumanization). The collection of case studies already shows that there is no one correct answer to the question, whether dehumanization or humanization of digital technologies is beneficial. For a successful adoption, future research should investigate this dimension for various digital technologies in more detail.

Barriers towards adoption

Closely linked to factors influencing the adoption, are barriers to it. These barriers can be linked to the humans interacting with the digital technology (e.g., not having the appropriate skills or mindset), as well as to the technology itself (e.g., having to wear heavy and uncomfortable VR glasses). Most commonly, **barriers include aspects linked to both humans and technologies**.

Barriers to adoption are particularly noticeable in case studies discussing digital technologies which show a higher degree of autonomy. On the dimension “who is taking the decision" these, therefore, tend to be located towards the end of "the machine is taking the decision" spectrum (C11: Kallina, C2: Ferrigno). Further, in many of these cases most of the decision-making process happens in the digital space (C7: Leeb, C11: Kallina, C12: Jones). The adoption of digital technologies in this space is often faced with the problem that **humans fear to be replaced** by these technologies. The fear of losing one's job and becoming redundant has been reported for various jobs (Agrawal et al., 2018; Blauner 1964; Brynjolfsson and McAfee 2014; Daugherty and Wilson, 2018). In most cases the machine does not replace the human in the task, nevertheless, the fear persists. For a successful adoption and to support people facing this fear, it is important to study the question of:

- **How could humans and organisation deal with the issue of feeling replaced by a digital technology?**

Another big barrier is **not having trust in the technology** and its outputs (Glikson and Woolley 2020). Especially, if it is not possible to track the steps the digital technology (i.e., AI) has taken, it becomes difficult for humans to trust the output (Lindebaum et al., 2020). Case study C11 (Kallina) reports how important it is to develop a trustworthy and ethical technology. This requires taking into account the opinions and expertise of the people creating the technology, as well as those working with them in the end (Lebovitz et al., 2022). Closely linked to this are the appearance and features of the technology. While it is sometimes desirable to create more trust, it also needs to be considered that humans tend to over rely on digital information (Zerilli et al. 2019), such as in C9 (Moncur). Future research should investigate the questions:

- **What is needed to increase trust in digital technologies?**
- **What appearances and features create the right level of trust in the provided information?**

Changing towards successful adoption

Any significant technological transformation changes the rules of the game. To handle the new tools and be competitive, new skills will be required throughout companies' hierarchies (Appio et al. 2021; Lanzolla and Schilling 2020).

- **What changes are needed in management?**

C13 (Dang) discusses a possible approach towards a successful digital transformation of a company. In addition, as mentioned above, **a cultural shift in an organisation is often required** for a successful adoption, which needs to be implemented by management and will affect the company vertically (Brynjolfsson and McAfee, 2017). To introduce such a culture shift managers will require new skill sets, generating the research questions:

- **What skills do future managers need?**
- **What skill sets are managers expecting of their future analysts?**

A change in skill-set requires changes in training for employees across the hierarchy, as **new capabilities are required** to tackle the issues arising with digital technologies (Brynjolfsson and Mitchell 2017).

That technical roles need to be trained in coding and data analysis is well established. Another aspect of skill-set for technical roles emerged from some case studies (see for example C7: Leeb): employees need to be able to extract insights from uncertain data outputs and make sense of them. There seems to be a shift towards augmented data-analytics supported by AI-driven technologies, which opens up the question:

- **What other new skills will be required to perform augmented data-analytics?**

Intermediary roles, which are tasked with reporting and communicating information, need new forms of skills as well.

- **How can insights be best translated and communicated?**

Employees need to be able to understand and interpret data in new forms, such as Knowledge Graphs (C6: Foster). This triggers the question:

- **What are the best outputs to foster data and information interpretation?**

Another important aspect for a successful adoption are changes in the technology itself. These should focus on improvements in the performance of the digital technology, always aiming towards supporting the humans.

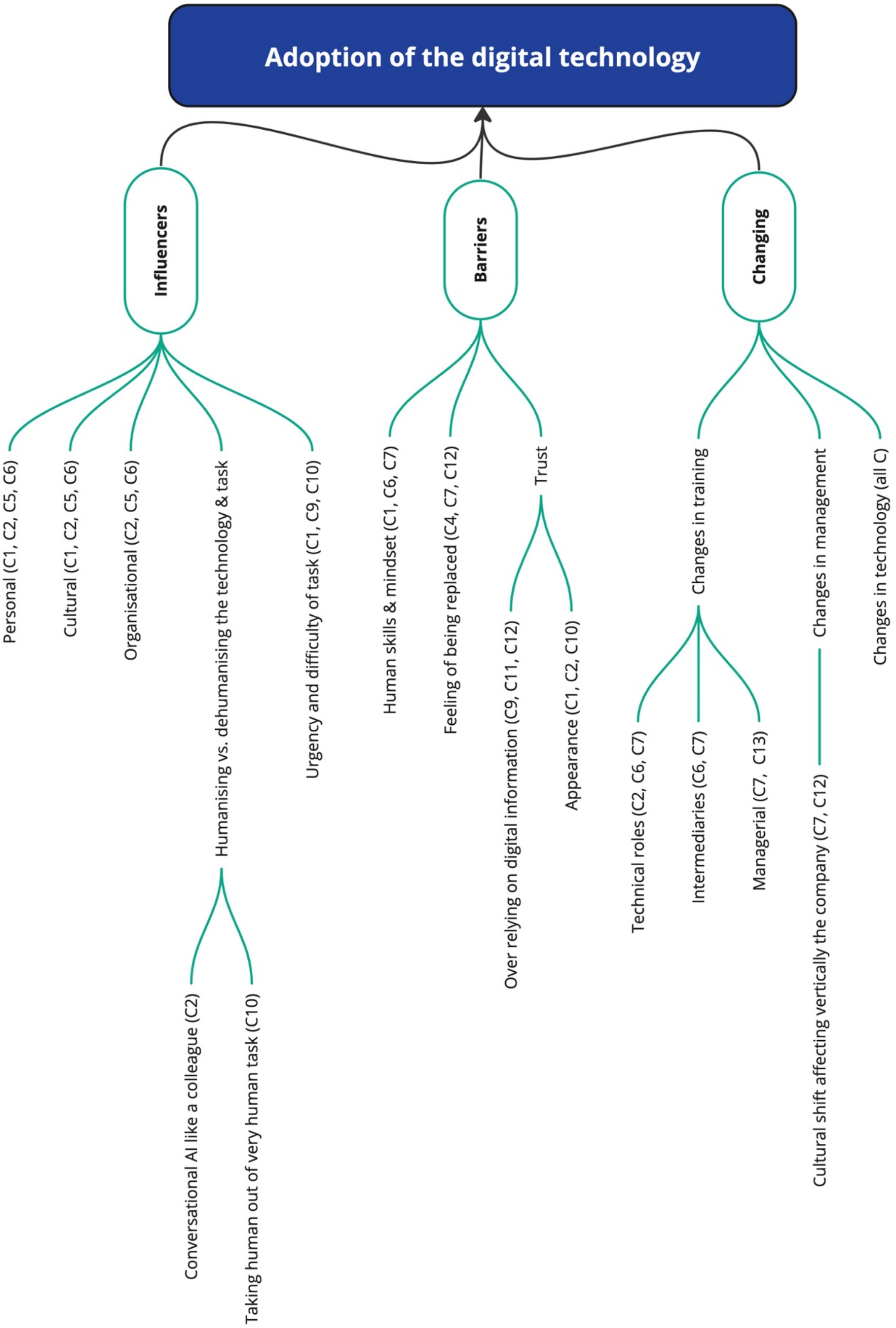


Figure 7: An extensive extract from the thematic coding process. Common themes are extrapolated across cases (indicated by numbers C1, C2, etc.). Themes are then aggregated into categories, which led to the individuation of emerging relevant aspects. In this case Adoption of digital technology.

Assessment of the integration of social and digital decision-making

Strongly linked to the points highlighted in the previous section (Adoption) is **how the integration of human (social) and digital technologies in decision-making is evaluated**. According to the group of cases we collected, **this assessment currently mostly happens by taking a human-centred approach**, whereby it is the human who evaluates the quality of the integration rather than the technology evaluating how good the integration is.

The assessment is done mainly on how humans value the integration in terms of its 'effectiveness' and 'appropriateness'.

Effectiveness

Is judged based on how **'easier'** or **'better' it is to take a decision for humans**, thanks to the integration of digital technologies in the decision-making process (Choudhury et al., 2020; Metcalf et al.,2019). Several case studies reported on how the integration of digital technologies changes (or has the potential to change) human cognitive processes. For example:

- **How do human cognitive capabilities get extended (or augmented)?**
- **Is the integration accelerating decisions, reducing the effort to take decisions or slowing them down to obtain better decision outcomes?**

The addition of information overlayed on the natural environment helps reducing decision complexity, liberating human brains from laborious tasks (such as remembering information or taking in new information, spotting connections between pieces of information, inferring consequences etc.) (Hutchins, 1996; Hollan et al., 2000). This results in a lighter process of decision-making which uses less energy and time to arrive at a conclusion. Using an established (although sometimes contested) framework, this externalisation of information shifts the decisions from the very energy-consuming human decision mechanism known as "system 2", towards the lighter "system 1" (Tversky and Kahneman, 1983). This is not only a prerogative of digital technology integration. As an example, drivers automatically take in information encoded in road signals, accelerating and automatising their responses to the external environment while driving. Further, humans have historically developed visual content (e.g., marketing material) which provides cues and influences decision-making processes, for example with the intention of influencing voting or purchasing preferences (Krishna, 2012). An overall proposal from several of our cases studies is that **the principles demonstrated so far through analogue media could be enhanced by using digital technology** (e.g., virtual and augmented reality), as this is more adaptable and amenable to loading and transferring of a variety of information inputs (see for instance C3: Oliveira, C9: Moncur). Even the lack of cues masterfully administered helps to improve humans' decisions. **Reducing or eliminating automatisms** arising from externalised information **could be a powerful way to improve decision-making processes**, in that, although the effort is larger, the outcome are better decisions. For instance, driving at high velocity on a narrow road is dangerous, but drivers typically downplay the importance of slowing down, increasing their risk of crashing (i.e. they might take the wrong decision). Some studies have shown that eliminating road marks, has resulted in fewer accidents (Jenkins, 2016). Similarly, case study C05 (Routley) shows that processes ran at the interface between the digital and physical spaces, through online activities such as roadmapping, because of the efforts required at the interface between digital and humans slow down cognitive decision process. However, not necessarily for the worse! Examples of 'imperfect experiences' (e.g., C3: Oliveira, C4: Jennes, C5: Routley) caused by the integration of digital tools, in comparison to what humans are used to, show that a careful use of these, or experiments with addition of cues (like in C9: Moncur) might be administered across the axis 3 in Fig 5. "Where is the integration of digital technology happening?". Research in this direction will identify **how to mitigate human decision-making fallacies**. It will develop ways to carefully design the interface between humans and digital to leverage (and maybe easily test) principles that improve the effectiveness of decision-making processes. For instance, **the theory of nudging**, which **has shown positive results in affecting health decisions** (Vlaev et al., 2016), could be one of the candidates for being effectively administered by taking advantage of digital technologies.

Part of the process of improving human decision-making is **the possibility digital technologies offer to reduce human bias**. Human decision-making is far from being driven by logic alone (Kahneman et al., 1982). The result is that, for example, individuals skew their decisions to support what they are more familiar with, rather than towards the most rational, or even the most adventurous (Tversky and Kahneman, 1973), of the options available. This biased attitude, mostly unconscious, is particularly evident when decision-making affects society (e.g., recruitment, or granting prisoners parole), often resulting in unfairness. The use of digital technology to support human decisions is being investigated as an opportunity to reduce these biases, as in the case described by C10 (Nørskov). Here it was shown that robotic interfaces could increase the degree of objectivity in the selection of candidates during personnel selection interviews. This is a very promising area of research, which is being considered across a variety of digital technologies beyond robots (e.g., AI, Yarger et al., 2019; van den Broek et al., 2021). This has great potential to impact the integration of digital technologies in human decision-making, which however opens another question:

- **How would humans be able to work well with the outcomes of non-biased decisions?**

The evidence in our case studies shows this might be a challenge, as the outcome of a non-biased and well supported process for decision-making is sometimes rejected (e.g., "Interestingly, customers often want more than the story based on data – they want opinions!" – C7: Leeb). As explained at the start of this report, decision-making is a process which encompasses a sequence of decisions. Hence, this spurs the question of researching the successive decision steps of non-biased decisions. For instance:

- **How well would a person, recruited with a non-biased approach, integrate into the work environment once the filter provided by the digital technology is removed?**

Mistake reduction in decision-making is also an anticipated benefit of digital technologies (Kahneman, 2016). For instance, AI technology is being developed commercially as a way of reducing uncertainty in business decisions by providing powerful means to identify and predict trends in technology and markets (e.g., C2: Ferrigno, C12: Jones). These applications of digital technologies, however, pose a difficult judgment decision scenario where it is hard to evaluate whether AI is 'making a mistake' or is highlighting a very counter-intuitive scenario. This plausibility assessment is currently undertaken by trained analysts who utilise AI-driven data to support their insight developed (C7: Leeb). Many other applications of AI would instead be assessable for success (whether an AI-driven refuse sorter is capable of accurately detecting non-qualified items in a feedstock), as these applications are 'intellective' (Laughlin, 1980). It is hence possible to say that there are **two different types of decisions being tackled** with the integration of digital technologies in decision-making: **"assessable"** and **"un-assessable" problems**. Further, it would be interesting to understand whether humans demonstrate a different tolerance for 'mistakes' by humans and machines.

The **cost-effectiveness of integrating digital technologies** in decision-making is a dominant evaluation criterion for most.

- **Under which conditions investments in decision-making would provide economic and time benefits?** (e.g., C7: Leeb).

Access in and democratization of decision processes also appeared as criteria in our case studies. C1 (Rojas), C3 (Oliveira) and C5 (Routley) case studies clearly highlight the opportunity for increased access to decision-making to those who would otherwise be unable to participate. Doctors can interact with patients (Beane and Orlikowski, 2015) and managers can participate in strategic meeting thanks to the space-bridging power of digital technology. Digital technology, if ethically integrated (C11: Kallina), also gives access to resources to those who would not be otherwise able to obtain them (e.g., redistribution of food).

Appropriateness

- **How can we judge whether the integration of human and digital is appropriate?**
- **How to judge what human process needs digitalisation versus what needs to stay as it is? (i.e. what aspects/processes can and should we make digital?).**

Our case studies revealed different use cases, which substantially highlight that some consideration needs to be paid to the type of decision. As highlighted above, for some decisions it is possible to check whether the outcome is right-or wrong, for others it is not. Considering the uncertainty scale (Courtney et al., 1997), the more 'checkable' decisions are those for which uncertainly is limited. Further, and maybe more importantly, **if we consider the decisions in our collection of practices**, we can see **two types:**

1. Decisions (or problems) whereby whatever the quality of the decision, there will be **no effect on the system on which we are trying to decide** (i.e., for these decisions, the feedback loop illustrated in Figure 1 doesn't exist). For example, for decision: "is this integration helping the packing of items in bins?" (e.g., C9: Moncur), the options available for the optimization are limited, whether we decide to pack things in an optimized way or not. The same is for moving between two points in a building (e.g., C8: Felicini). Whether we take one route or another will not change the number of options available to move between two points A and B.

2. **Decisions which instead shift the decision system** altogether. For instance, if we consider traffic decisions (e.g., "where should traffic be re-directed to avoid a traffic spot?"), applications of AI which help drivers navigate around an accident, impact on the traffic itself, as AI diverge the traffic from busy, to less-busy roads. Other examples of decisions with feedback loops are algorithms which drive decisions in the financial markets, as they can push people to buy or sell, in turn skewing the trends in these markets. In our group of cases, decisions of this type include that of selecting whom to recruit at job interviews (e.g., C10: Nørskov), and whether trends in technology are important for a firm (C2: Ferrigno, C7: Leeb, C12: Jones). C11 (Kallina) demonstrated that the result of such decisions shifts the balance of those who benefit from the decisions. This second type of decisions present strong feedback loops in Fig 1.

As reported by Agarawal et al. (2018), **the decisions without a feedback loop present a good case for using digital approaches** such as AI. The reason is that **the algorithms can identify trends and 'predict' outcomes, without the risk of skewing the system**. For the second type of "judgment" decision, whereby uncertainty is high, where past trends do not (and we dare say, should not) influence future trends, **where the feedback loop could potentially impact on the decisions themselves**, and which are not "checkable", **the evaluation** of whether the digital integration is appropriate **should only be done via ethical principles** (i.e., subjective to current society). This need for ethical principles from our case studies is also starting to be addressed by governmental agencies (OECD, 2022; "Future of Work, Future of Society", 2019).

Further, as decisions are nested, often decisions of one type are linked with decisions which could be of the other type. For example: for the decision: "Is this type of skin lesion going to develop in a cancer?", the outcome (yes or no, or with 30% probability, etc.) will not impact on whether the lesion will in fact turn malignant or not (no feedback loop). However, the following decision in the chain is "What to do about the lesion (e.g., should we operate on it or not?)". This will instead have consequences on the problem itself, as if for instance we proceed to remove the lesion, we will not know for certain whether it will develop into a cancer or not. This latter decision has a feedback loop.

This distinction between types of decisions provides a good basis to evaluate the appropriateness of the integration of digital and social decision-making along the 'agency' axis (who takes the decision) in Fig 3. It reinforces Agarawal's suggestion of identifying when AI should be integrated in decision-making. As digital agents work (mostly) on prediction based on past data, the decisions which are taken by machines on the problems without decision feedback loops, where the AI decision is mostly in 'discovery mode' (Leventi-Peetz and Weber, 2023), are safer (i.e., an error will not compromise the system and what will happen in the future). Hence, we feel that at this time the integration of AI is more appropriate for decisions with no loop. Instead, decisions which will try to 'regulate' systems, based on judgment and impact on future outcomes, can lead to reinforcing loops and change the future based on what happened in the past. These applications of AI seem less appropriate as they risk skewing the world in which we live without appropriate controls in place (Završnik, 2020). In fact, the current ethical and regulatory paradigm is designed to protect humans from other humans (Gunkel, 2016), while **we do not yet have any framework to ensure accountability on decisions where agents are technologies**. Work in this direction is being done by setting up ethical frameworks for the adoption and integration of AI technologies in decision-making (e.g., C11: Kallina, Jobin et al., 2019; OECD, 2022; "Future of Work, Future of Society", 2019; Soler Garrido et al. 2023).

How humans perceive the experience of deciding: our cases highlighted that in some types of decision processes the worry when integrating digital and social elements is not to lose the human experience (e.g., when the decision-making happens around the health of a patient, C1: Rojas). In other cases, the integration of digital technology aims instead to 'dehumanise' processes/tasks/practices – i.e making them more rationale (e.g., Job interviews, C10: Nørskov). The questions emerging are then linked with the evaluation above:

- **When is rational decision-making better than heuristics-driven decision-making?**
- **How and when is it appropriate and possible to embed subjectivity in decisions taken by machines?**

The experience of humans in the decision-making process is also clearly affected by the locus of the boundary between human and digital: Each type of digital interface described above, i.e., **where the human input meets the digital input, affects the experience of humans**, making it easier (e.g., C8: Felicini, C9: Moncur) or less so (e.g., C3: Oliveira, C5: Routley, C12: Jones). One aspect affecting the process is for instance the degree of immersivity of humans in a digital environment where the decision process might occur (C3: Oliveira, C5: Routley) or whether it is the digital aspect that permeates the real world (e.g., AR technology overlayed with the physical world, C8: Felicini, C9: Moncur). The benefits of a standardised and detailed simulation might be less appreciated because of the challenges in experiencing a simulation (C4: Jennes). As discussed above, impairing cognition is not necessarily a negative thing, hence there is a requirement to define the boundaries for each type of digital interface, and to evaluate the benefits and limitations.

- **In the long chain of decision-making, when do humans lose touch with reality and when is reality transformed thanks to the digital interface?**
- **How is reality distorted?**

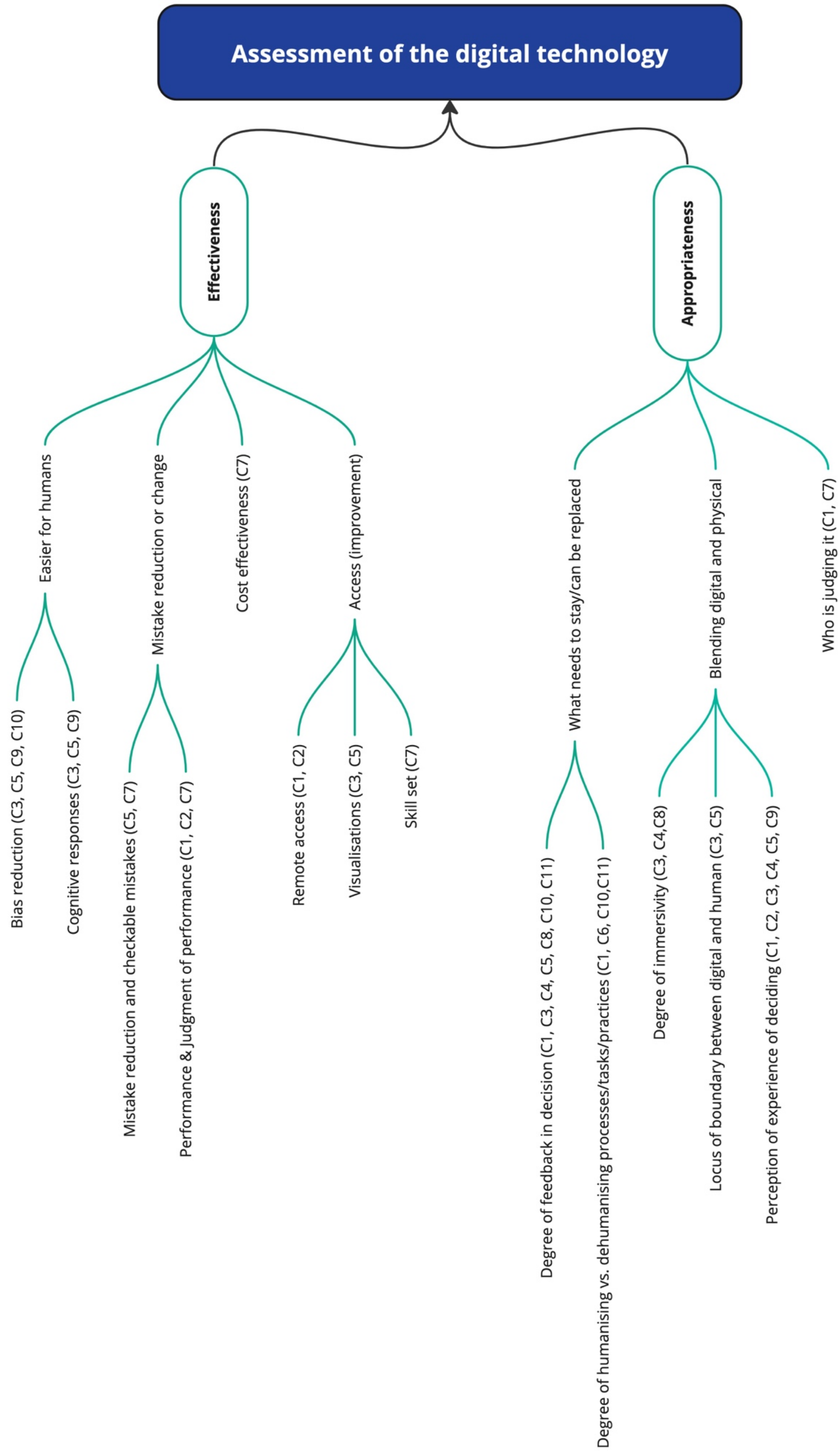


Figure 8: An extensive extract from the thematic coding process. Common themes are extrapolated across cases (indicated by numbers C1, C2, etc.). Themes are then aggregated into categories, which led to the individuation of emerging relevant aspects. In this case Assessment of digital technology.

Adaptation to digital transformation

Digital transformation is rapidly changing the industry landscape, and **companies will have to adapt** to seize the new possibilities (Teece et al., 1997; Berg et al., 2023). **Adaptation will impact both internal processes and practices, and external interactions and relationships**. New regulatory frameworks will be needed to ensure a successful and sustainable integration of digital and social aspects in the decision-making process:

Inward adaptation

Business models - Every emerging technology poses the question of what the best business model (BM) is, and how to exploit it.

- **What is the optimal BM for a particular digital technology?**
- **How does the value proposition change?**
- **Is the current BM adequate?**

Such questions are continually relevant, as also BMs deemed innovative and successful have also experienced downturns. For instance, the excessive push for servitization, enabled by digital technologies, from BMW (Vincent, 2022) and Amazon (Palmer, 2022) brought to a rejection from consumers not willing to accept a future full of microtransactions. Case study C2 (Ferrigno) about an AI analytics software proposes the interesting possibility to implement successful AI analytical tools in conjunction with others already deployed, rather than replacing them. The simplicity of the tool can make it an integrable platform as well as an integrator for different AI offerings, and not only a direct competitor.

HR Management - The introduction of new digital tools affects processes within organizations, and inevitably human resources (HR) as well (van den Broek et al.,2021; Tambe et al., 2019).

- **How does HR management change?**
- **Can digital technology introduce new models for HR management?**

The case study C10 (Nørskov) tested telerobots in recruitment interviews to overcome implicit biases. As this example shows, digital technologies can influence not only the activities of the human capital but also its management. Case studies C7 (Leeb) and C12 (Jones) as well exemplify how the skill sets of the people to employ is changing with the introduction of new digital tools.

Outward adaptation

Industry and Business - A changing landscape can lead to new and novel types of collaborations between organizations.

- **How can companies interact with other companies that offer new technologies?**
- **In which conditions is collaboration advisable as opposed to direct competition?**

The aforementioned case of AI platforms (C2: Ferrigno) poses questions about whether such platforms should interact with others to reduce costs and learning time. Moreover, providers of new technologies undertake a journey of legitimization.

- **How should digital technology providers operate to obtain legitimization?**

In one case study (C12: Jones) the AI intelligence company provides a set of approaches to enable the transition, which includes building on transparency and highlighting the benefits for the user.

Standards and regulations - While there have been guidelines for specific industries (De Baerdemaeker, 2023; EIOPA´s Consultative Expert Group on Digital Ethics in insurance 2021), universal standards are needed across industries and regions. This entails official aspects, as well as more informal frameworks and guidance. The design of products implementing new digital technologies must consider existing ones and ongoing practices.

- **How is it possible to integrate new tools with other systems?**
- **How can we test and experiment with them?**

Case studies C3 (Oliveira) and C5 (Routley) implement and test digital remote communication technology in long-standing practices such as roadmapping workshops. More rigid considerations will be required for health and safety. The remote communication technology implemented in C5 (Routley) proved to be effective in creating safe environments for collaboration during a pandemic crisis. However, the same technologies that bring new possibilities must ensure safe conditions for users.

- **Which safety standard are required?**
- **Can existing ones be adapted or do new ones needs to be conceived?**

Finally, similar questions arise for legal aspects. The example from C1 (Rojas) proposes adoption of emerging Telepresence Robots in the sensitive context of healthcare.

- **How does the introduction of digital tools change who is repsonsible for the outcomes?**

- **Who is accountable for decisions taken remotely or independently by autonomous agents (AI)?**
- **Is the current regulatory framework sufficient or outdated?**

Ethics and society - The non-written rules of ethics will have as strong an impact as the legislative ones on the diffusion of digital tools (e.g., Gunkel, 2018). Society must be progressively introduced to sensitive innovations. What is considered unethical today, might be more tolerated in the future.

- **What is the optimal pace to introduce potentially controversial innovations?**

The example of healthcare telerobots (C1: Rojas) introduces important ethical questions along with the advantages of the technology. To avoid rejection and controversies, the design must also consider what would be acceptable to users and society. An example of participatory practice is shown in case C11 (Kallina), where all the stakeholders took part in the design phase of an AI platform. Case study C13 (Dang) describes a systematic approach for large scale digital transformation that involves communication techniques to engage with the employees.

- **What are the best practices, methods and governance frameworks to ensure ethical and responsible digital innovation?**
- **How to create ethical recommendations for designers?**

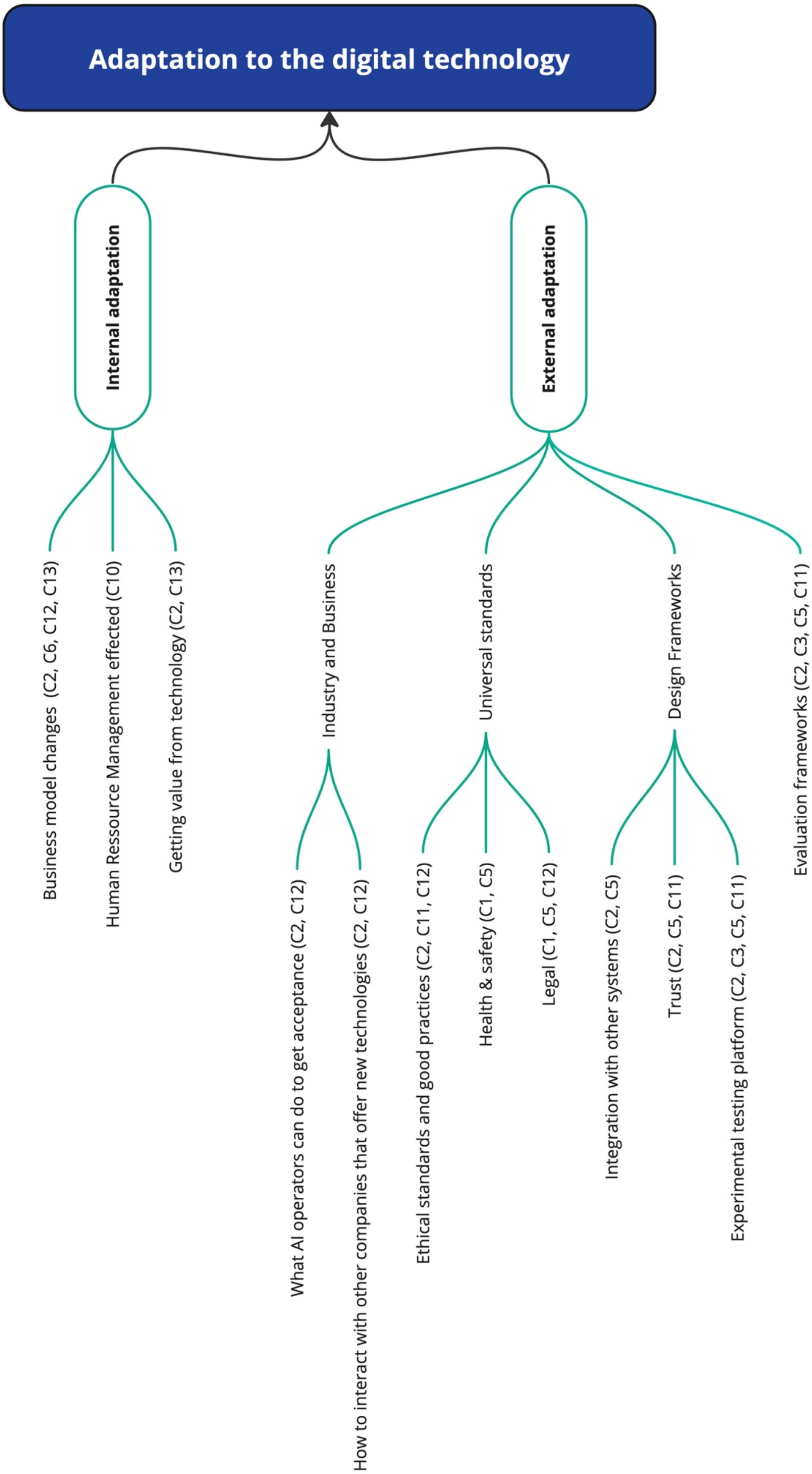


Figure 9: An extensive extract from the thematic coding process. Common themes are extrapolated across cases (indicated by numbers C1, C2, etc.). Themes are then aggregated into categories, which led to the individuation of emerging relevant aspects. In this case Adaptation to the digital technology.

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The authors

Constanze M. Leeb is an EINST4INE Early-Stage Researcher and doctoral student at the Centre for Technology Management, Institute for Manufacturing, University of Cambridge. She is researching how AI-driven technologies influence individuals working with them.

cl876@cam.ac.uk

Letizia Mortara is a Lecturer in Technology and Innovation Management at the University of Cambridge and a Senior Fellow at Newnham College, Cambridge. She is also an Associate Editor for the R&D Management journal. Letizia's focus is in strategic technology management and decision making for emerging technologies.

lm367@cam.ac.uk

Nicola Felicini is an EINST4INE Early-Stage Researcher and doctoral student at the Centre for Technology Management, Institute for Manufacturing, University of Cambridge. He is researching in the field of Augmented Cognition to enhance strategic decision-making.

nf382@cam.ac.uk

Rob Phaal is a Director of Research within the Department of Engineering at the University of Cambridge and conducts research in Strategic Technology and Innovation Management (STIM). Interests include the emergence dynamics of technology-based industries and the development of practical management tools and toolkits.

rp108@cam.ac.uk

Bethan A. Moncur is an AgriFoRwArdS doctoral student at the Centre for Technology Management, Institute for Manufacturing, University of Cambridge. She is researching the integration of digital technologies in deciding to implement emerging technologies, potentially involving augmented and virtual reality.

bam49@cam.ac.uk

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