AI in the Garbage Cans: How Data Scientists Contribute to Organizational Decision-Making

Mayur Joshi
Telfer School of Management, University of Ottawa
mayur.joshi@telfer.uottawa.ca

Saurav Chakraborty
College of Business, University of Louisville
saurav.chakraborty@louisville.edu

Abstract

Integrating artificial intelligence (AI) in organizations is often viewed as a way to enhance decision-making by extending human rationality. However, there is an interesting puzzle. While the theoretical accounts of AI conceptualize how contemporary AI technologies, like machine learning, may aid domain experts in making rational decisions, the empirical accounts highlight that despite the enthusiasm and willingness to explore, domain experts often fail to accept AI-based recommendations in making decisions. In this study, we address this puzzle by demonstrating the role of data scientists in shaping domain experts' decision-making processes. We do so by integrating insights from a qualitative study of three large banks with a computational model based on the tenets of the Garbage Can Model of organizational choice. Our findings highlight the complexities of organizational decision-making when the two groups, with their unique visions of rationality, are tasked to work together.

Keywords: Artificial intelligence, decision-making, garbage can model, rationality, data scientists

1. Introduction

What do we expect from artificial intelligence (AI)? It is hard to escape the contemporary enthusiasm for artificial intelligence (AI). Enthusiasts, advocates, and alarmists alike have noted a remarkable range of settings using AI applications: fast fashion, hedge funds creditworthiness, hiring and retention, medical diagnosis, traffic enforcement, internet prediction, and online retailing, among others. The current enthusiasm for AI follows the tantalizing possibilities that we are finally reaching the promise of AI as first defined by McCarthy et al. (1955, p. 11): "making a machine behave in ways that would be called intelligent if a human were so behaving." We have long hoped that the improved information processing of AI can be used to help people make better decisions (e.g., Davenport and Kirby 2016). Recent increases in computing power have made possible what are sometimes described as the "superhuman" accomplishments of AI (Brynjolfsson and McAfee 2017) in an ever-expanding range of activities.

These expectations for AI have long focused on the ways that AI can be used as a tool to overcome the limits on human decision-making (Anthony et al. 2023). Those possibilities follow from Herbert Simon's ideas of the Sciences of the Artificial (Simon 1969), his vision of procedural rationality (Simon 1978), and his foundational works on artificial intelligence (AI) (Langley and Simon 1995, Newell et al. 1958, Simon 1973, 1995). At the heart of these ideas are the assumptions that organizations pursue intelligence (March 2006), that domain experts making decisions in the organizations are intendedly rational but demonstrate anarchic behavior due to the bounds of their cognition—i.e., bounded rationality—(Simon 1972), and that their behavior can be aided by AI technologies. In this spirit, Simon and his colleagues designed AI artifacts (Langley and Simon 1995, Newell and Simon 1956, Newell et al. 1958) that could serve as tools in aiding "basic changes in man's equipment for making rational choices—in his computational capabilities" (Simon 1978, p. 14). While the earliest AI artifacts were conceptual, the subsequent artifacts that entered the material realm of organizations and aided the decision-making of domain experts include decision support and expert systems (Huber 1981, Turban and Watkins 1986, Leidner and Elam 1995, Huber 1990). The role of these AI artifacts was clear: To aid human information processing by bringing efficiency to their purposeful search. Accordingly, these early iterations of AI artifacts would fit well within the Garbage Can Model of decision-making by making the search more efficient without changing the basic fabric of the model.

The recent theoretical accounts on how AI influences organizational decision-making point to how contemporary AI applications are very different from their traditional counterparts. It has been argued that

URI: https://hdl.handle.net/10125/109545
978-0-9981331-8-8

these contemporary AI applications no longer serve as tools of rationality in the hands of domain experts but assume the role of counteractors in the system of work (Anthony et al. 2023). There is an agreement among scholars that the nature of data that are analyzed by AI algorithms and the nature of contemporary AI algorithms are very different from the traditional approaches. As March (1987) envisioned long back, due to the proliferation of digital technologies, organizations across industries have started collecting large volumes of novel, unstructured, and unpurposeful big data (e.g., Constantiou and Kallinikos 2015, Yoo 2015). Organizational scholars theorizing about contemporary AI have highlighted the capabilities of the machine and deep learning algorithms that can leverage these data to develop their own rules and protocols rather than following the rules provided by domain experts (Murray et al. 2021). These protocols can guide brute force search and facilitate data-driven learning, needing minimal input from human experts (Csaszar and Steinberger 2022). In other words, these algorithms have a unique ability to enact an unpurposeful search without a clear problem upfront (Agrawal et al. 2018; also see von Krogh 2018, Raisch and Fomina 2024). As such, these tools have the capabilities to become "supercarriers of rationality" because "they can improve themselves in performing their tasks; in this sense, algorithms can learn" and also "because of the unprecedented speed of processing vast volumes of "big" data to produce or calculate outcomes, although in ways that are often intractable and opaque, even to their programmers" (Lindebaum et al. 2020, p. 248-249). The thread that undercuts this scholarship theorizing AI is an assertion: With the improved search capabilities of AI, it is going to improve organizational decision-making, assuming that domain experts are going to accept and integrate AI in their work.

On the contrary to these theoretical accounts of AI, the empirical studies show contradictory findings. Especially the ethnographies on AI highlight that despite the enthusiasm and willingness to explore, domain experts often fail to accept AI-based recommendations in making decisions (e.g., Lebovitz et al. 2022, Van den Broek et al. 2021, Valentine and Hinds 2021). These ethnographies on AI open up a dimension of decision-making that neither the traditional decision-making theories as well as foundational works on AI (e.g., Simon 1956, March and Simon 1958, Newell and Simon 1956) nor the contemporary conceptualization of AI's role in decision making (e.g., Murray et al. 2021, Raisch and Fomina 2024) pay attention to. That is the role of data scientists (as well as other technical experts like AI developers) in organizational decision-making. Since contemporary AI technologies cannot be easily plugged and played into existing organizational structures (Kellogg et al. 2019), "most of AI today is powered by humans" (Anthony et al. 2023, p. 1683). These are typically the AI developers or data scientists who work with the domain experts to build in-house AI models. Data scientists differ from the other support staff. They are trained in the discipline of data science at programs offered by premier institutions (Cao 2016, 2017). They spend most of their time independently working with data (Parmiggiani et al. 2022) and follow data-driven approaches in training, developing, and deploying AI-based models. In recent times, they have gained much higher status as they have been regarded as one of the most prestigious professionals consistently for over a decade (Davenport and Patil 2012, 2022). While recent theoretical accounts on AI have started focusing on the characteristics of AI in aiding unpurposeful search (Csaszar and Steinberger 2022, Raisch and Fomina 2024, Balasubramanian et al. 2022, Murray et al. 2021), we lack a theoretical understanding of how data scientists influence organizational decision-making.

In this study, we set out to theorize about decision-making in the era of AI by conceptualizing the dynamics between data scientists and domain experts as they collaborate in making decisions using a computational approach. We draw on the qualitative data we collected from three large banks in observing and interviewing data scientists and bank managers working together in order to make rational decisions with the help of AI. Based on the insights from the qualitative study, we construct a computational model that highlights the emergent dynamics between the two occupational groups. In this computational model, we follow the tenets of the Garbage Can Model of organizational choice (Cohen et al. 1972) and extend it further to the realities of contemporary AI applications.

2. Related literature on AI and rationality

2.1. Traditional AI Algorithms as Domain Experts' Tools of Rationality

The earliest conceptualizations of AI in modern history go hand-in-hand with the rational choice theories and can be traced to the foundational work of Herbert Simon and colleagues (e.g., Newell and Simon 1959, Simon 1969). Simon developed the early AI artifacts as tools to understand human behavior, which he also used to aid rational choice (e.g., Newell and Simon 1956). This has been the reason behind the consistent expectations of AI in aiding rational choice since the 1950s.

Simon believed that domain experts and managers are intendedly rational, and they actively guide, adapt, and enact rational choices in organizations. He acknowledged that despite the intentions, in practice, the domain experts could only be boundedly rational as they tend to engage in "a style of behavior that is appropriate to the achievement of given goals, within the limits imposed by given conditions and constraints" (Simon 1972, p. 161). The bounds to rationality were mainly the limitations of information processing due to constraints of incomplete information and a limited set of alternatives considered demonstrating a satisficing behavior (Simon 1955).

To improve human rationality amid these constraints, Simon offered a vision of procedural rationality (Simon 1978). In this vision, he simplified rational choice by focusing on the elements (i.e., search and evaluation) that can be augmented using structural and technological solutions by putting aside other elements (i.e., agenda setting and problem definition). In particular, he constructed a means-ends hierarchy of purposeful search, where the structure helped decide the ends, while the technology served as the means. First, he envisioned the values of domain experts as "exogenously given for the duration of decision making" (Cohen 2007, p. 504). This was possible by setting up a structure that helped determine the ends. These ends are automatically dictated by a problemistic search that is triggered when the organizational structure channels managerial attention on a performance shortfall (Cyert and March 1963, March and Simon 1958, Simon 1947). Organizations and managers are thus conceived as simple-minded who would solve problems when they appear on their radar (Posen et al. 2018). This pragmatic choice allowed Simon to put aside the disputes among domain experts over the ends and instead focus on how to help them in "selecting the most appropriate means for achieving currently preferred ends" (Cohen 2007, p. 504). Attentional structures thus helped solve the issues related to the ends that triggered the search, but humans could still engage in satisficing in choosing the easily accessible alternatives.

To make the search more efficient, Simon offered a technological solution in the form of AI artifacts that made the information processing of domain experts more efficient. In this spirit, Simon and his colleagues designed AI artifacts (Langley and Simon 1995, Newell and Simon 1956, Newell et al. 1958, Simon 1973, 1995) that could serve as tools in aiding "basic changes in man's equipment for making rational choices—in his computational capabilities" (Simon 1978, p. 14). While the earliest AI artifacts were conceptual, the subsequent artifacts that entered the material realm of organizations and aided the decision-making of domain experts include decision support and expert systems (Huber 1981, Turban and Watkins 1986, Leidner and Elam 1995, Huber 1990). The role of these AI artifacts was clear: To aid human information processing by bringing efficiency to their purposeful search.

This stylized image of procedural rationality became a dominant paradigm of rational choice in organizational research. It is a common thread that runs through the studies that directly (e.g., Cabantous et al. 2010, Langley 1989) or implicitly examine rational choice (e.g., Glaser 2017), as well as the ones that examine the purposeful search by drawing on Carnegie School (e.g., Siggelkow and Rivkin 2006) reflecting the assumptions of organizational scholars. For instance, in a study of a law enforcement organization, the enforcement officials identified a problem of scheduling patrolling routines, which they then set out to solve (Glaser 2017). The study is about their purposeful search in unpacking how they solve the problem by integrating a game-theoretic algorithm into their existing routines. Similarly, Cabantous et al. (2010) identify contextualization—"turning a big and messy situation into a decision-analyzable problem" (p. 1542)––by decision-makers as the first step in making a rational choice, and the focus is on the enactment of the solution (Cabantous and Gond 2011). More interestingly, this image of procedural rationality also explains the expectations of domain experts for AI in serving as a tool for purposeful search, as documented in recent ethnographies on AI (e.g., Lebovitz et al. 2022, Valentine and Hinds 2021).

2.2. Contemporary AI algorithms and decision-making

The contemporary AI algorithms rejuvenate the hopes for aiding domain experts to do their work more effectively due to efficient information processing (Anthony et al. 2023, Brynjolfsson and McAfee 2014, Frank et al. 2017, Hess and Ludwig 2017, Koebler 2017, McAfee and Brynjolfsson 2017). AI signifies a frontier of technologies that provide three components to aid in decision-making: models as abstractions that identify relevant variables, causal structures, and action alternatives; collections of data to support those models; and decision rules to evaluate alternatives and predict consequences (March 2006). Past efforts at AI have focused on the predictive benefits of decision support and expert systems (Huber 1981, 1990, Leidner and Elam 1995, Turban and Watkins 1986). Contemporary versions of AI extend these prediction benefits to collaborative tools serving as a complement to the domain expert (Anthony et al. 2023).

Of particular interest are the generative search capabilities of machine and deep learning algorithms. With the proliferation of digital technologies, organizations are increasingly able to collect large volumes of novel, unstructured, and unpurposeful big data (e.g., Constantiou and Kallinikos 2015, Yoo 2015). The machine and deep learning algorithms allow for the development of their own rules and protocols to mine this data and ignore the rules provided by domain experts (Murray et al. 2021). These protocols can guide brute force search data-driven learning with only minimal inputs from human experts (Csaszar and Steinberger 2022). Unlike the purposeful search that the domain experts follow, these developments have opened up the possibilities of unpurposeful search. Problem definition and solution search can now occur with or without humans (Raisch and Fomina 2024). Rather than simply using tools to schedule law enforcement patrolling by metropolitan police (Glaser 2017), AI can now learn autonomously and generate predictions about where crime is most likely to happen without even involving the patrol officers (Waardenburg et al. 2022). Some hope for improved formal rationality through the more efficient and effective information processing of machine learning and AI algorithms, but Lindebaum et al. (2020) caution that AI systems can embed substantive rationality in the algorithmic models and become "supercarriers of formal rationality" that strip human actors of their agency.

2.3. Data scientists as emerging agents in decision-making

Although these latest theoretical accounts of AI offer illuminating insights, what is surprisingly absent from this discourse is the role of data scientists. In line with Anthony et al.'s (2023) arguments, scholars theorizing about AI have started conceiving AI as a counteractor alongside the domain experts in terms of how AI influences the domain experts' existing routines, learning, problem-solving and how it affords competitive advantage (e.g., Murray et al. 2021, Raisch and Krakowski 2021, Raisch and Fomina 2024, Tschang and Almirall 2021, Balasubramanian et al. 2021, Kepm 2023). However, this discourse still misses an important group of counteractors (Anthony et al. 2023) who are often hired by large organizations to build AI-based models in-house, i.e., data scientists.

Since contemporary AI technologies cannot be easily plugged and played into existing organizational structures (Kellogg et al. 2019), "most of AI today is powered by humans" (Anthony et al. 2023, p. 1683). These are typically the AI developers or data scientists––an emerging occupational group (Bechky 2020)—who work with the domain experts to build in-house AI models. Data scientists differ from the other support staff. They are trained in the discipline of data science at programs offered by premier institutions (Cao 2016, 2017). They spend most of their time independently working with data (Parmiggiani et al. 2022) and follow data-driven approaches in training, developing, and deploying AI-based models. In recent times, they have gained much higher status as they have been regarded as one of the most prestigious professionals consistently for over a decade (Davenport and Patil 2012, 2022). While the recent ethnographies on AI recognize the presence of data scientists in organizations (e.g., Lebovitz et al. 2022, Van den Broek et al. 2021, Waardenburg et al. 2022), in most cases, they are not in focus. Instead, the focus has been on the domain experts and how well they adopt or reject AI solutions with the support of data scientists. And, the data scientists are altogether absent from the discourse in the theoretical accounts of AI. In this study, we set out to offer a theoretical account of how data scientists and domain experts work together in order to employ AI in rational decision-making in organizations.

3. Computational model inspired by qualitative data

3.1. Analytical approach

We take the Garbage Can Model of organizational choice (Cohen et al. 1972) as the base model and adapt it to the era of contemporary AI, where data scientists play an important role. Traditionally, decision-makers within the Garbage Can Model were primarily managers who relied on their experience, intuition, and organizational hierarchy to make decisions. These managers operated within a framework where decision-making processes were often ambiguous, reflecting the complexities and uncertainties inherent in organizational environments. In recent years, there has been a significant shift in the decision-making landscape within organizations, characterized by the increasing involvement of data scientists and individuals with a data-induced mentality. Several key factors drive this transformation. The advent of big data and advanced analytics has revolutionized how organizations approach decision-making. With vast amounts of data available, there is a growing need for experts who can interpret and analyze this data to derive actionable insights. Technological advancements in machine learning, artificial intelligence, and data mining have empowered data scientists to develop sophisticated models to predict outcomes, identify trends, and optimize processes. These capabilities are beyond managers' traditional skill set, necessitating data scientists' inclusion in decision-making processes. Organizations are increasingly adopting a data-driven approach to decision-making, where decisions are based on empirical evidence rather than intuition or experience alone. Data scientists play a crucial role in this paradigm by providing the analytical rigor and quantitative analysis required to support data-driven decisions. The complexity of modern business problems often requires interdisciplinary approaches that combine domain expertise with advanced analytical skills. With their ability to handle complex datasets and uncover patterns, data scientists are essential in addressing these multifaceted challenges.

In a larger project, we qualitatively examined the role that data scientists play in organizational decision-making in the context of three large banks. We collected data through on-site observations and in-situ informal interviews (600 hours), semi-structured formal interviews (67), as well as numerous documents, including the computational codes, model outputs, slide decks, and process manuals. These data were collected and analyzed by following grounded theory methods (Strauss and Corbin 1990) from 2018 to 2020. During this period, we observed the work of data scientists and domain experts (bank managers) as they collaborated on several projects of data extraction and model building with the aim of making rational decisions. While the key qualitative insights from this project are included in a separate manuscript, our aim in this study is to use these insights to build a theoretical intuition about how data scientists work with domain experts that guided our key assumptions in the computational model that we built. The key assumption that we draw from our qualitative data is that when data scientists and domain experts work together, each of the groups views rationality from the perspective of their own occupational values. Hence, while the domain experts conceive rationality as procedural—starting with problem formulation and searching for efficient solutions for a given problem, the data scientists conceive rationality as data-induced—modeling trends visible in data and the insights thus drawn serve as solutions for potential business problems. More details about the qualitative study are included in Appendix A (see supplementary files).

We argue that the shift towards data-driven decision-making and the inclusion of data scientists align well with Complex Adaptive Systems (CAS) principles (Holland 1992, Nan 2011). CAS theory views organizations as dynamic systems composed of interacting agents who adapt and evolve in response to changing environments. This perspective offers several advantages for studying contemporary decision-making dynamics. CAS emphasizes the adaptive nature of agents within a system. This means recognizing how data scientists and managers continuously adjust their strategies based on new data and feedback, leading to more resilient and flexible decision-making processes. CAS highlights the importance of interactions among agents and the emergent behaviors that arise from these interactions. By studying how data scientists and managers collaborate, share information, and influence each other, we can gain insights into the collective decision-making process and the emergent outcomes that shape organizational performance. CAS's non-linear and uncertain nature of decision-making environments is a core aspect. This perspective helps us understand how small changes in data or decision-making strategies can lead to significant impacts and how organizations can manage uncertainty through adaptive strategies.

Agent-based models (ABMs) provide an ideal methodological approach to exploring decision-making dynamics in this new context. ABMs simulate the interactions of individual agents within a system, allowing researchers to study complex behaviors and emergent phenomena (e.g., Haki et al. 2020, Ross et al. 2019). The use of ABMs offers several benefits. ABMs can model the diverse characteristics and behaviors of managers and data scientists, capturing the unique contributions of each to the decision-making process. This includes differences in expertise, decision-making styles, and access to information. ABMs facilitate the examination of interactions between agents, enabling researchers to understand how collaboration, competition, and information sharing influence outcomes. This is particularly relevant for studying the dynamic interplay between data-driven and experience-based decision-making approaches. By simulating various scenarios, ABMs can reveal emergent patterns and behaviors that arise from the collective actions of agents. This helps identify optimal decision-making strategies and understand the conditions under which specific outcomes will likely occur. ABMs can be used to test the impact of different policies and strategies on organizational decision-making. By experimenting with various configurations of data usage and decision-making structures, organizations can identify best practices and potential areas for improvement.

The evolution of decision-makers in the Garbage Can Model, from primary managers to a significant inclusion of data scientists, reflects the broader shift towards data-driven decision-making in organizations. CAS theory provides a valuable lens for studying this new dynamic, emphasizing the adaptability, interactions, and emergent behaviors that characterize modern decision-making processes. ABMs offer a robust methodology for exploring these complexities, enabling researchers and practitioners to gain deeper insights into the mechanisms and outcomes of decision-making in today's data-rich environments. Through this integrated approach, organizations can better navigate the challenges of contemporary decision-making and leverage the strengths of both managerial experience and data-driven insights.

3.2. Model building

Our ABM draws heavily from the Garbage Can Model and CAS theory principles combined with the insights from our qualitative study mentioned above to explore decision-making dynamics within an organization. In our model, decision makers (DMs) are represented as agents with distinct roles—Business Managers or Data Scientists. This reflects the evolving landscape of organizational decision-making where data scientists, with their data-induced mentality, play a significant role alongside traditional managers. The data-induced rationality focuses more on the data to extract relationships that can be developed into solutions. Business rationality, on the other hand, focuses more on the proper problem formulation first before searching for any solutions. Each DM has a job role that influences their rationality: 'business-induced' for Business Managers and 'data-induced' for Data Scientists. We allow a probabilistic chance for a DM to exhibit the opposite rationality to introduce variability and realism, for example, a business manager who wants to understand the data first before developing the problem statement.

Each DM is assigned ‘n’ energy units and a rationality dominance value, representing the degree to which their decision-making is dominated by their rationality (business or data). Energy in our model is a tracker that captures the decision maker’s effective utilization of any resource, for example, time. These parameters influence how much energy business managers contribute to solving problems and how effectively they do so, considering potential conflicts arising from different rationalities. Problems in the model are characterized by their complexity, represented by how much energy they need to be solved (for example, 900 and 3000; these values are randomly generated, and the wide range is provided to capture whether a problem is relatively simple or complex).

Choice opportunities involve a selection of decision-makers working together to address a problem. The energy requirement (ER) of the problem is set based on its complexity, and DMs contribute their energy towards solving it. The effectiveness of their energy contribution is influenced by conflict intensity, which is determined by the average rationality dominance among the selected DMs. For example, if the set of decision makers have business managers with very high business-induced rationality values and data scientists with very high data-induced rationality values, then there will be a greater amount of conflict, leading to a waste of energy. The model incorporates mechanisms to calculate various types of waste, reflecting inefficiencies in the decision-making process. Problematization conflict waste arises from variability in rationality dominance among DMs with similar rationalities (business or data). Solution space waste occurs due to differences between business-induced and data-induced rationalities. These waste calculations are crucial for understanding how conflicts and diverse rationalities impact decision-making effectiveness. We have added a description of these constructs and other key details of their operationalization in Table 1 below.

3.3. Operationalization of key constructs

In addition to the above, the ABM model evaluates various wastes from decision-making processes. Problematization conflict waste measures the variance in rationality dominance among DMs with similar rationalities, while solution space waste assesses differences between business and data-induced rationalities. Other waste, introduced to simulate real-world inefficiencies, is calculated as a random fraction of the total energy. These variables are crucial for understanding how conflicts and diverse rationalities impact decision-making effectiveness.

This ABM leverages the principles of the Garbage Can Model and CAS to simulate complex interactions and adaptive behaviors in organizational decision-making. The model captures the evolving dynamics of decision-making processes by incorporating traditional managers and data scientists. ABMs allow for a detailed exploration of these interactions, revealing how different rationalities and conflict levels impact decision effectiveness and organizational outcomes. This approach provides valuable insights for optimizing decision-making strategies in modern, data-driven organizations.

4. Simulation results

The results from the baseline computational model reveal interesting findings related to decision-making dynamics involving decision-makers with different rationalities and job roles. Incorporating business managers and data scientists in the decision-making process provides insights into the complexities and challenges of modern organizational environments.

Effective energy, which accounts for conflict and efficiency losses, varies significantly among decision-makers and, hence, across problems. This variation underscores the impact of rationality and conflict on decision-making effectiveness. Conflict waste, which includes problematization and solution space waste, fluctuates across different problems. The variability in conflict waste highlights the role of rationality dominance and the interactions between decision-makers with different rationalities. For instance, the higher the variance in rationality dominance among business-induced decision-makers, the higher the conflict waste within the occupational group. The higher the conflict waste, the lower the effective energy.

Table 1. Constructs and operationalization

Coonstruct	Definition	Range of Values	Considerations
DM ID	Unique identifier for each decision-maker	Integer	Ensures traceability of each DM
Job Role	Role of the decision maker (Business Manager or Data Scientist)	'Business Manager', 'Data Scientist'	Defines primary rationality and influences decision style
Rationality	Primary decision-making approach (business-induced or data-induced)	'business-induced', 'data-induced'	Introduces variability based on job role
Rationality Dominance	Degree of adherence to the primary rationality	0.5 to 1.0	Impacts conflict intensity and decision effectiveness
Energy	Available energy units for each decision-maker	10	Standardized initial energy allocation
Problem Load	Complexity of the problem to be solved	M	Represents problem difficulty
Energy Requirement (ER)	The energy needed to solve the problem	M	Derived from problem load
Total Energy	The sum of energy contributed by all decision-makers	0 to N (variable)	Varies with the number of DMs and their contributions
Cumulative Effective Energy (EE)	Effective energy after accounting for conflict	0 to N (variable)	Measures the actual effective energy used
Conflict Intensity	Degree of conflict reducing energy effectiveness	K	Calculated based on rationality dominance
Other Waste	Random waste not attributable to conflicts	Fn(Total Energy)	Introduces randomness to simulate real-world inefficiencies

The random component of waste, representing inefficiencies not directly tied to rationality conflicts, also shows considerable variation. This suggests that even in well-structured decision-making processes, inherent inefficiencies need to be managed. The presence of both business-induced and data-induced rationalities within the same team participating in the decision arena introduces a layer of complexity. While diverse perspectives can lead to innovative solutions, they also increase conflict waste if not managed properly. Effective decision-making in such environments requires careful management of these conflicts to harness the strengths of both approaches while minimizing the associated waste. This is a non-trivial trade-off that organizations will need to address in order to successfully leverage data scientists' expertise in decision-making. Table 2 summarizes the results from the computational model.

Overall, the results from the ABM simulation provide valuable insights into the complexities of decision-making processes involving diverse rationalities and job roles. The findings emphasize the importance of managing conflicts effectively to harness the strengths of both business-induced and data-induced decision-makers. By balancing the contributions of business managers and data scientists, organizations can maneuver decision-making effectiveness while minimizing conflict-related waste. This study highlights the need for adaptive strategies and integrated approaches to address the dynamic challenges of modern organizational decision-making.

Table 2. Summary of results

Problem	IDs	Job Roles	Rationalities	Business-induced rationality dominance (average)	Data-induced rationality dominance (average)	Effective energy	Conflict waste	Other waste
1	0, 2, 8, 1, 9	BM, BM, DS, BM, DS	business-induced, data-induced	0.66	0.92	762.715	7.23	2.57
2	1, 4, 7, 0, 7	BM, BM, DS, BM, DS	business-induced, data-induced	0.69	0.63	787.072	6.3	16.46
3	3, 2, 8, 5, 1	BM, BM, DS, DS, BM	business-induced, data-induced	0.81	0.87	748.188	3.89	25.8
4	4, 3, 6, 5, 7	BM, BM, DS, DS, DS	business-induced, data-induced	0.92	0.74	735.08	8.52	32.67
5	4, 1, 7, 1, 7	BM, BM, DS, BM, DS	business-induced, data-induced	0.7	0.63	774.604	3.67	27.14

5. Discussion and implications

The findings from this study have several important implications for organizational decision-making and management practices. Integrating business managers and data scientists in decision-making processes highlights the need for a balanced approach that leverages the strengths of both roles. The challenge is how organizations make sure to leverage the best and not the worst of both worlds. Business managers bring experience-based insights and strategic oversight, while data scientists contribute data-driven analysis and technical expertise. However, organizational decision-making is often fraught with conflicts. While the literature has already recognized the conflicts among business managers and the role of routines as truces (e.g., Zbaracki and Bergen 2010), our study demonstrates the need to understand the conflict between the domain experts (e.g., business managers) and technical experts (e.g., data scientists). The situation becomes tricky, especially in conditions where there is no evident difference in terms of status and authority of the two groups, which are usual factors in inter-functional conflict resolution (e.g., Anthony 2018, Huising 2014). If the team composition is always dominated by business managers with stronger business-induced rationality, the data scientists are less likely to leverage their full potential and may engage in legitimizing practices that they themselves consider illegitimate (e.g., Stice-Lusvardi et al. 2023), while on the other hand, if a team is dominated by data scientists, they may chase novel solutions to problems that may not be relevant to business teams. Both scenarios may lead to under-optimal outcomes. The trick for organizations is to find a sweet spot that maintains healthy conflict and, therefore, improves the effectiveness of decisions.

Organizations may invest in training programs that enhance collaboration and communication between these diverse roles. Organizations can reduce conflict waste by fostering an environment where business managers and data scientists can effectively share their perspectives and work towards common goals. Additionally, implementing adaptive decision-making frameworks that accommodate varying rationalities can help manage modern business challenges' dynamic and complex nature. However, the challenge is to ascertain the training needs and goals. If organizations train the data scientists extensively in the business domains, the data scientists may start thinking like business managers (and hence may lean toward business-induced rationality). The question is whether organizations want data scientists who think like business managers, and if they do, will they be able to solve novel problems? Similar arguments can be made on training business managers to work with data.

The second is the challenge of goals. Organizations structure the attention of the business managers (Ocasio 1997) to focus on a set of goals and establish mechanisms (e.g., Problemistic search, Cyert and March 1963) that make sure that whenever the performance deviates from the goals, the managers move the machinery in an attempt to bring it back on target. These governance mechanisms work well so far as we assume that the goals ascertained by the senior managers are actually the right goals for the organization. What if there are better goals that organizations can pursue? One way to discover and engage with newer goals is to let the data scientists extensively pursue their data-induced rationality, and in the process, organizations may be able to discover and pursue newer goals that they did not conceive before. Yet, there is no guarantee that the novel goals are the right ones. In other words, the presence of data scientists may help organizations make decisions effectively in some ways, but it will also open up newer challenges of organizing and governance. In such situations, the problem of rationality will be less about how to solve a particular problem more efficiently but more about figuring out which problem to solve in the first place.

Additionally, the study's insights into the non-linear effects of rationality dominance and conflict waste suggest that organizations may need to regularly assess and adjust their decision-making processes. This involves monitoring the levels of internal and inter-group conflicts and making necessary adjustments to ensure a harmonious decision-making environment. The implications extend to designing and implementing decision support systems that can facilitate better integration of diverse decision-making styles. Such systems should incorporate features that promote transparency, real-time feedback, and collaborative problem-solving, thus enhancing the overall effectiveness of organizational decision-making.

There are some natural extensions of this study that we are already pursuing. In this study, we took the Garbage Can model of decision-making, and added one complexity to the model. We introduced data scientists as a new set of agents, with their specific role and their unique vision of rationality to the decision space. In the next iteration, we plan to introduce AI to the model. There are at least two scenarios. In one, AI can serve as a tool for performing a better search. In this case, where AI searches is dictated by the respective agents (i.e., data scientists or business managers), but wherever they search, AI may offer efficient means (to shorten the time to search and/or search in a broader landscape). This scenario is similar to what Raisch and Fomina (2024) theorized verbally, but their theory does not consider the role of data scientists as agents and they do not formalize their theory using a computational model. In the other scenario, AI can serve as a counteractor (Anthony et al. 2023) working alongside the data scientists and the business managers. In this scenario, each of the agents is able to decide where to search (AI, data scientists, and business managers) and what problems to solve. Hence, it will show much more complex dynamics of how the three agents negotiate and learn to work together.

In conclusion, the study provides valuable insights into optimizing decision-making processes by balancing the contributions of business managers and data scientists. By addressing the challenges of conflict and leveraging the strengths of diverse rationalities, organizations can improve decision-making efficiency, drive innovation, and achieve better outcomes in an increasingly data-driven business landscape.

6. References

Agrawal, A., Gans, J., & Goldfarb, A. (2018). Prediction Machines: The Simple Economics of Artificial Intelligence. Harvard Business Review Press.

Anthony, C. (2018). To Question or Accept? How Status Differences Influence Responses to New Epistemic Technologies in Knowledge Work. Academy of Management Review, 43(4), 661–679.

Anthony, C., Bechky, B.A., & Fayard, A.-L. (2023). “Collaborating” with AI: Taking a system view to

explore the future of work. Organization Science, 34(5):1672–1694.
Balasubramanian, N., Ye, Y., & Xu, M. (2022). Substituting Human Decision-Making with Machine Learning: Implications for Organizational Learning. Academy of Management Review, 47(3), 448–465.
Bechky, B. A. (2020). Evaluative Spillovers from Technological Change: The Effects of “DNA Envy” on Occupational Practices in Forensic Science. Administrative Science Quarterly, 65(3), 606–643.
Brynjolfsson E, McAfee A (2014) The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies (Norton, New York).
Brynjolfsson E, Mcafee A (2017) The business of artificial intelligence. *Harvard Business Review https://hbr.org/ 2017/07/the-business-of-artificial-intelligence (July 18).*
Cabantous, L., & Gond, J.-P. (2011). Rational Decision Making as Performative Praxis: Explaining Rationality’s Éternel Retour. Organization Science, 22(3), 573–586.
Cabantous L, Gond JP, Johnson-Cramer M (2010) Decision theory as practice: Crafting rationality in organizations. Organization Studies, 31(11):1531–1566.
Cao, L. (2016). Data Science: Nature and Pitfalls. IEEE Intelligent Systems, 31(5), 66–75.
Cao, L. (2017). Data Science: A Comprehensive Overview. ACM Computing Surveys, 50(3), 43:1-43:42.
Cohen, M. D. (2007). Perspective—Administrative Behavior: Laying the Foundations for Cyert and March. Organization Science, 18(3), 503–506.
Cohen, M. D., March, J. G., & Olsen, J. P. (1972). A Garbage Can Model of Organizational Choice. Administrative Science Quarterly, 17(1), 1–25.
Constantiou, I.D., & Kallinikos, J. (2015). New games, new rules: Big data and the changing context of strategy. Journal of Information Technology, 30(1): 44–57.
Csaszar, F.A., & Steinberger, T. (2022). Organizations as artificial intelligences: The use of artificial intelligence analogies in organization theory. Academy of Management Annals, 16(1): 1–37.
Cyert, R. M., & March, J. G. (1963). Behavioral Theory of the Firm (2 edition). Wiley-Blackwell.
Davenport TH, Kirby J (2016) *Only Humans Need Apply: Winners and Losers in the Age of Smart Machines* (Harper Business, New York).
Davenport, T.H., & Patil, D.J. (2012). Data scientist: The sexiest job of the 21st century. Harvard Business Review, 90(10): 70–76.
Davenport, T.H., & Patil, D.J. (2022, July 15). Is data scientist still the sexiest job of the 21st century? Harvard Business Review, https://hbr.org/2022/07/is-data-scientist-still-the-sexiest-job-of-the-21stcentury
Frank, M., Roehrig, P., & Pring, B. (2017). What to Do When Machines Do Everything: How to Get Ahead in a World of AI, Algorithms, Bots, and Big Data (John Wiley & Sons, Hoboken, NJ).
Glaser, V. L. (2017). Design Performances: How Organizations Inscribe Artifacts to Change Routines. Academy of Management Journal, 60(6), 2126–2154.
Haki, K., Beese, J., Aier, S., & Winter, R. (2020). The Evolution of Information Systems Architecture: An Agent-Based Simulation Model. MIS Quarterly, 44(1).
Hess, E.D., & Ludwig, K. (2017). Humility is the New Smart: Rethinking Human Excellence in the Smart Machine Age (Berrett-Koehler Publishers, Oakland, CA).
Holland, J. H. (1992). Complex adaptive systems. Daedalus, 121(1), 17-30.
Huber, G.P. (1981). The nature of organizational decision making and the design of decision support systems. MIS Quarterly, 5(2): 1–10.
Huber, G.P. (1990). A theory of the effects of advanced information technologies on organizational design, intelligence, and decision making. Academy of Management Reveview, 15(1): 47–71.
Huising, R. (2014). The Erosion of Expert Control Through Censure Episodes. Organization Science, 25(6), 1633–1661.
Kellogg, K. C., Valentine, M. A., & Christin, A. (2019). Algorithms at Work: The New Contested Terrain of Control. Academy of Management Annals, 14(1), 366–410.
Kemp, A. (2023). Competitive Advantage Through Artificial Intelligence: Toward a Theory of Situated AI. Academy of Management Review, https://doi.org/10.5465/amr.2020.0205
Koebler, J. (2017). The rise of the robolawyers. Accessed January 10, 2024, https://www.theatlantic.com/magazine/archive/2017/ 04/rise-of-the-robolawyers/517794/.
Langley, A. (1989). In Search of Rationality: The Purposes Behind the Use of Formal Analysis in Organizations. Administrative Science Quarterly, 34(4), 598–631.
Langley, P., & Simon, H. A. (1995). Applications of machine learning and rule induction. Communications of the ACM, 38(11), 54-6.
Lebovitz, S., Lifshitz-Assaf, H., & Levina, N. (2022). To engage or not to engage with AI for critical judgments: How professionals deal with opacity when using AI for medical diagnosis. Organization Science, 33(1): 126-148.
Leidner, D.E., & Elam, J.J. (1995). The impact of executive information systems on organizational design, intelligence, and decision making. Organization Science, 6(6): 645-664.
Lindebaum, D., Vesa, M., & den Hond, F. (2020). Insights from “The Machine Stops” to better understand rational assumptions in algorithmic decision making and its implications for organizations. Academy of Management Review, 45(1): 247–263.
March, J. G. (1987). Ambiguity and accounting: The elusive link between information and decision making. Accounting, Organizations and Society, 12(2), 153–168.
March, J. G. (2006). Rationality, foolishness, and adaptive intelligence. Strategic Management Journal, 27(3), 201–214.
March, J.G., & Simon, H.A. (1958). Organizations (Wiley-Blackwell, 2 edition).
McCarthy, J.L., Minsky, M.L., Rochester, N., & Shannon, C.E. (1955). A Proposal for the Dartmouth Summer

Research Project on Artificial Intelligence. August 31 (http://jmc.stanford.edu/articles/dartmouth/dartmouth.pdf).
McAfee, A., & Brynjolfsson, E. (2017). Machine, Platform, Crowd: Harnessing Our Digital Future (Norton, New York).
Murray, A., Rhymer, J., & Sirmon, D.G. (2021). Humans and technology: Forms of conjoined agency in organizations. Academy of Management Review, 46(3): 552–571.
Nan, N. (2011). Capturing bottom-up information technology use processes: A complex adaptive systems model. MIS quarterly, 505-532.
Newell, A., & Simon, H. (1956). The logic theory machine--A complex information processing system. IRE Transactions on Information Theory, 2(3), 61-79.
Newell, A., & Simon, H. A. (1959). The Simulation of Human Thought (p. 1734). Santa Monica, CA, USA: Rand Corporation.
Newell, A., Shaw, J. C., & Simon, H. A. (1958). Elements of a theory of human problem solving. Psychological Review, 65(3), 151.
Ocasio, W. (1997). Towards an Attention-Based View of the Firm. Strategic Management Journal, 18, 187–206.
Olsen, J. P., Cohen, M. D., & March, J. G. (2012). A Garbage Can Model? At Forty: A Solution that Still Attracts Problems. In *The Garbage Can Model of Organizational Choice: Looking Forward at Forty* (Vol. 36, pp. 19–30). Emerald Group Publishing Limited.
Parmiggiani, E., Østerlie, T., & Almklov, P. (2022). In the Backrooms of Data Science. Journal of the Association for Information Systems, 23(1), 139–164.
Posen, H.E., Keil, T., Kim, S., & Meissner, F.D. (2018). Renewing research on problemistic search—A review and research agenda. Academy of Management Annals, 12(1): 208–251.
Raisch, S., & Krakowski, S. (2021). Artificial Intelligence and Management: The Automation-Augmentation Paradox. Academy of Management Review, 46(1), 192–210.
Raisch, S., & Fomina, K. (2024). Combining Human and Artificial Intelligence: Hybrid Problem-Solving in Organizations. Academy of Management Review, https://doi.org/10.5465/amr.2021.0421
Ross, B., Pilz, L., Cabrera, B., Brachten, F., Neubaum, G., & Stieglitz, S. (2019). Are social bots a real threat? An agent-based model of the spiral of silence to analyse the impact of manipulative actors in social networks. European Journal of Information Systems, 28(4), 394-412.
Siggelkow, N., & Rivkin, J. W. (2006). When Exploration Backfires: Unintended Consequences of Multilevel Organizational Search. Academy of Management Journal, 49(4), 779–795.
Simon, H.A. (1947). Administrative Behavior. A Study of Decision-making Processes in Administrative Organization (Chicago, IL: Macmillan).
Simon, H. A. (1955). A Behavioral Model of Rational Choice. The Quarterly Journal of Economics, 69(1), 99–118.
Simon, H. A. (1969). The Sciences of the Artificial (third edition edition). The MIT Press.
Simon, H.A. (1972). Theories of bounded rationality. In: McGuire CB, Radner R (eds) Decision and Organization. North-Holland, Amsterdam
Simon, H. A. (1973). The structure of ill structured problems. Artificial Intelligence, 4(3), 181–201.
Simon, H.A. (1978). Rationality as process and as product of thought. American Economic Review, 68(2): 1–16.
Simon, H. A. (1995). Artificial intelligence: An empirical science. Artificial Intelligence, 77(1), 95–127.
Stice-Lusvardi, R., Hinds, P. J., & Valentine, M. (2023). Legitimating Illegitimate Practices: How Data Analysts Compromised Their Standards to Promote Quantification. *Organization Science*.
Strauss, A.L., & Corbin, J.M. (1990). Basics of Qualitative Research (Sage Publications)
Tschang, F. T., & Almirall, E. (2021). Artificial Intelligence as Augmenting Automation: Implications for Employment. Academy of Management Perspectives, 35(4), 642–659.
Turban, E., & Watkins, P.R. (1986). Integrating expert systems and decision support systems, MIS Quarterly, 10(2): 121-136.
Vaast, E., & Pinsonneault, A. (2021). When Digital Technologies Enable and Threaten Occupational Identity: The Delicate Balancing Act of Data Scientists. MIS Quarterly, 45(3), 1087–1112.
Valentine, M.A., & Hinds, R. (2021) "Rolling up the leaf node" to new levels of analysis: How algorithmic decision-making changes roles, hierarchies, and org charts. Working paper, Stanford University, Stanford, CA.
van den Broek, E., Sergeeva, A., & Huysman, M. (2021). When the Machine Meets the Expert: An Ethnography of Developing AI for Hiring. MIS Quarterly, 45(3): 1557–1580.
von Krogh, G. (2018). Artificial Intelligence in Organizations: New Opportunities for Phenomenon-Based Theorizing. Academy of Management Discoveries, 4(4), 404–409.
Waardenburg, L., Huysman, M., & Sergeeva, A. V. (2022). In the land of the blind, the one-eyed man is king: Knowledge brokerage in the age of learning algorithms. Organization Science, 33(1): 59–82.
Yoo, Y. (2015). It is not about size: A further thought on big data. Journal of Information Technology, 30(1): 63–65.
Zbaracki, M. J., & Bergen, M. (2010). When Truces Collapse: A Longitudinal Study of Price-Adjustment Routines. *Organization Science*, 21(5), 955–972.