VIII ENCONTRO DE ADMINISTRAÇÃO DA INFORMAÇÃO - EnADI 2023
São Paulo - 16 - 18 de mai de 2023
2177-2487 - versão online

Towards Automated Framing: A New Look at an Old Problem

Autoria
Victor Ogeda - victor.ogeda@gmail.com
Prog de Pós-Grad em Admin/Faculdade de Economia, Admin e Contab – PPGA/FEA / USP - Universidade de São Paulo

Cesar Alexandre de Souza - calesou@usp.br
Prog de Pós-Grad em Admin/Faculdade de Economia, Admin e Contab – PPGA/FEA / USP - Universidade de São Paulo

Abraham Sin Oih Yu - abraham_sinoih_yu@hotmail.com
Prog de Pós-Grad em Admin/Faculdade de Economia, Admin e Contab – PPGA/FEA / USP - Universidade de São Paulo

Resumo

Organizational decision-making requires effective framing of problems, which is traditionally done manually and may result in inconsistent or incomplete framing. With the advancement of Artificial Intelligence (AI), we propose that it is possible to automate the framing process, providing a more consistent and efficient way of framing decision-making problems. This essay explores the challenges and opportunities of developing an automated framing system for organizational decision-making, which involves applying various AI techniques, including natural language processing and machine learning. To achieve this goal, we explain the steps necessary to collect diverse and representative data, preprocess it, and train unsupervised learning models. These models can be evaluated and fine-tuned to improve their accuracy and effectiveness in identifying and framing decision-making problems. However, this approach poses several challenges, such as ensuring data quality, considering linked decisions, and evaluating the system's effectiveness. Future research should address these challenges and test the proposed automated framing system's engineering, effectiveness, and accuracy.

TOWARDS AUTOMATED FRAMING: A NEW LOOK AT AN OLD PROBLEM

ABSTRACT

Organizational decision-making requires effective framing of problems, which is traditionally done manually and may result in inconsistent or incomplete framing. With the advancement of Artificial Intelligence (AI), we propose that it is possible to automate the framing process, providing a more consistent and efficient way of framing decision-making problems. This essay explores the challenges and opportunities of developing an automated framing system for organizational decision-making, which involves applying various AI techniques, including natural language processing and machine learning. To achieve this goal, we explain the steps necessary to collect diverse and representative data, preprocess it, and train unsupervised learning models. These models can be evaluated and fine-tuned to improve their accuracy and effectiveness in identifying and framing decision-making problems. However, this approach poses several challenges, such as ensuring data quality, considering linked decisions, and evaluating the system's effectiveness. Future research should address these challenges and test the proposed automated framing system's engineering, effectiveness, and accuracy.

Keywords: automated framing, decision-making, artificial intelligence, natural language processing, machine learning.

1. INTRODUCTION

The ability to make effective decisions and solve problems is critical for the success of management and organizations. However, before managers can make an informed decision, they must identify, define, and clearly structure the problem. These steps can have a significant effect on the future decisions made, especially when the framing of the problem is poorly defined.

A poor frame of the problem can have significant consequences for decision-making processes. It can lead to a lack of clarity, ambiguity, and confusion, making it challenging to identify the relevant information or options. Decision-makers may overlook critical factors, focus on the wrong aspects of the problem, or select suboptimal solutions. Poor framing can also delay decision-making as decision-makers attempt to clarify the problem or gather additional information (McNamee & Celona, 2007).

The framing process involves emphasizing some aspects of perceived reality in written or verbal communication to encourage a particular interpretation of a problem and identification of its causes (Entman, 1999). Within the field of decision-making, this concept can be applied as a formal representation of a problem and the definition of its boundaries, providing an adequate understanding of what will be considered by the decision-maker and what is outside the responsibility or expertise of the decision-makers, encompassing the relevant aspects solely while excluding unnecessary details, while still preserving essential opportunities (Tversky & Kahneman, 1981; Smith, 1989). Therefore, effective problem framing can help decision-makers identify the relevant information and options and avoid potential biases or pitfalls that may arise from poor framing.

However, pursuing effective framing is a complex, challenging task. Various factors can influence the process. A growing body of research has documented influences of external environmental factors (Mårtensson, 2004), organizational structure, politics and, past experiences of stakeholders (Rosenhead, 2006; Champion, 2010), moral and ethical constraints (Bastons, 2008), time availability (Choo, 2014), evocative frames as shapers of approach to data (Marshak & Heracleous, 2023) and, cognitive biases (Hodgkinson et al., 1999, 2002; Wright & Goodwin, 2002; Kühberger, 1995).

These multifactorial influences build a complex and challenging process for decision-makers to control, who must navigate and balance these factors while understanding and addressing these complexities to ensure desirable decision-making outcomes.

Being an essential issue in the decision-making field, many academic studies have explored fundamental aspects of problem formulation in theoretical (Kotiadis & Mingers, 2006; Baer et al., 2013) and empirical (Lyles & Mitroff, 1980; Howard, 2000; Mingers & Rosenhead, 2004) manner, as well as analyzed and proposed methods and processes (Schwenk & Thomas, 1983; Bowen, 2001).

The central object identified in these study branches has been the agents (i.e., individuals involved), developing tools, guidelines, and strategies to assist them in executing the framing process. While this body of knowledge is vital for deepening our understanding of framing, studies incorporating new technologies into this topic are still scarce.

We believe that by leveraging AI technologies (such as machine learning and natural language processing), it is possible to automate the framing process, allowing decision-makers to focus on evaluating the outputs and inputs of the models rather than the framing process itself. Technologies of AI nature can aid in the analysis and interpretation of vast amounts of data, facilitating the identification of patterns and relationships that may be imperceptible to humans. AI algorithms can learn from past decisions and recommendations, improving the accuracy of future decision-making while providing insightful guidance for framing future decisions. Furthermore, AI can help mitigate decision-making biases by providing an objective analysis and unbiased recommendations based on available data. However, while there are many potential benefits to automating the framing process with AI, there are also challenges and limitations to consider.

This essay will discuss organizational decision-making from a complex adaptive system (CAS) perspective, with the framing process as a cybernetic detector subsystem. Viewing decision-making as a CAS provides a useful framework for understanding its complexity, dynamics, and emergent behavior. By recognizing the system's complexity and adaptability, it is possible to anticipate better and manage potential challenges and uncertainties.

Furthermore, we will explore the potential benefits and limitations of using AI, especially machine learning and natural language processing, to automate the framing process and the feasibility and challenges of such an approach. Finally, we will offer conclusions and recommendations for future studies on engineering systems for framing in management and organizational context.

2. DECISION-MAKING AS A COMPLEX ADAPTIVE SYSTEM

Complex Adaptive Systems (CAS) is a theory that focuses on the behavior of interconnected components in complex systems. It examines how these systems change and adapt over time and how new properties emerge from their interactions. CAS is associated with recursive interactions between system layers through control rules and feedback mechanisms, which guide systems toward achieving their objectives (Ellis & Herbert, 2011).

Figure 1 presents a general model of a complex adaptive system. It is possible to identify that, in the system's environment, different variables (information, matter, and energy) are captured as input by the system through a detector. This detector is responsible for initiating the rule system, processing the captured information, and generating an output in the effector, allowing the environment to access the output. Finally, the feedback mechanism allows the system to learn and adapt itself, thus generating new outputs based on new inputs to be processed in an infinite cycle as long as the system exists.

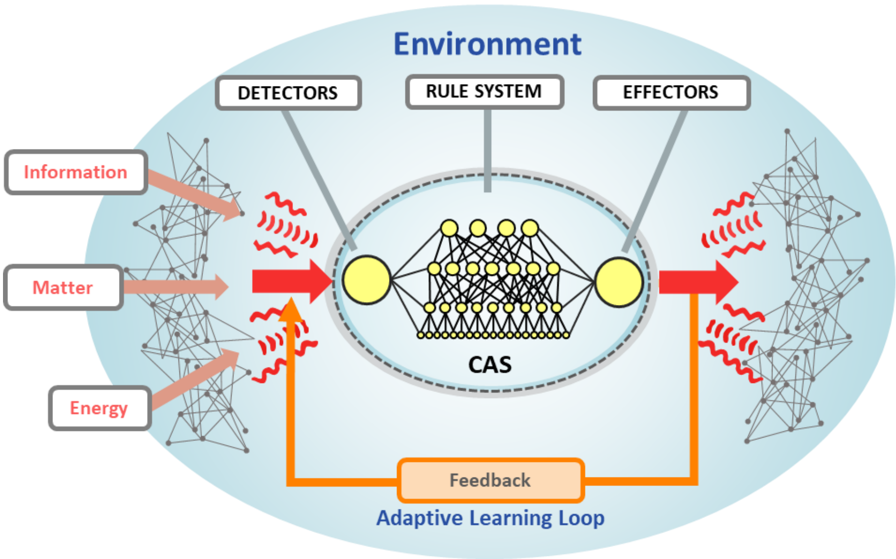

Fig. 1 – General Model for a Complex Adaptive System. Adapted from Clemens (2017).

Similarly, the Decision-Making Process can be viewed as a CAS since it is a dynamic and evolving process that involves multiple actors, inputs, and outputs, all of which are interdependent. In a CAS, the system's behavior emerges from the interactions between the individual components rather than being determined solely by a set of predetermined rules or objectives (Ellis & Herbert, 2011; Kuziemsky, 2016). The same is true for decision-making, where the behavior of the decision-making process emerges from the interactions between the decision-makers, the information available, and the problem at hand. Figure 2 illustrates the decision-making process as a complex adaptive system.

One key characteristic of CAS is its ability to self-organize and adapt to changing circumstances (Ellis & Herbert, 2011; Kuziemsky, 2016). In the context of decision-making, this means that the decision-making process can adapt to new information, changing goals or objectives, and other factors that may affect the decision. This adaptation can occur through feedback loops, where information about the outcomes of previous decisions is used to inform future decisions.

Another characteristic of CAS is its ability to exhibit non-linear behavior, where small changes in one part of the system can have significant and unpredictable effects on other parts of the system (Ellis & Herbert, 2011; Kuziemsky, 2016). This characteristic is also true for decision-making, where small changes in the framing or available information can significantly affect the final decision (Kühberger, 1995; Mojzisch & Schulz-Hardt, 2010).

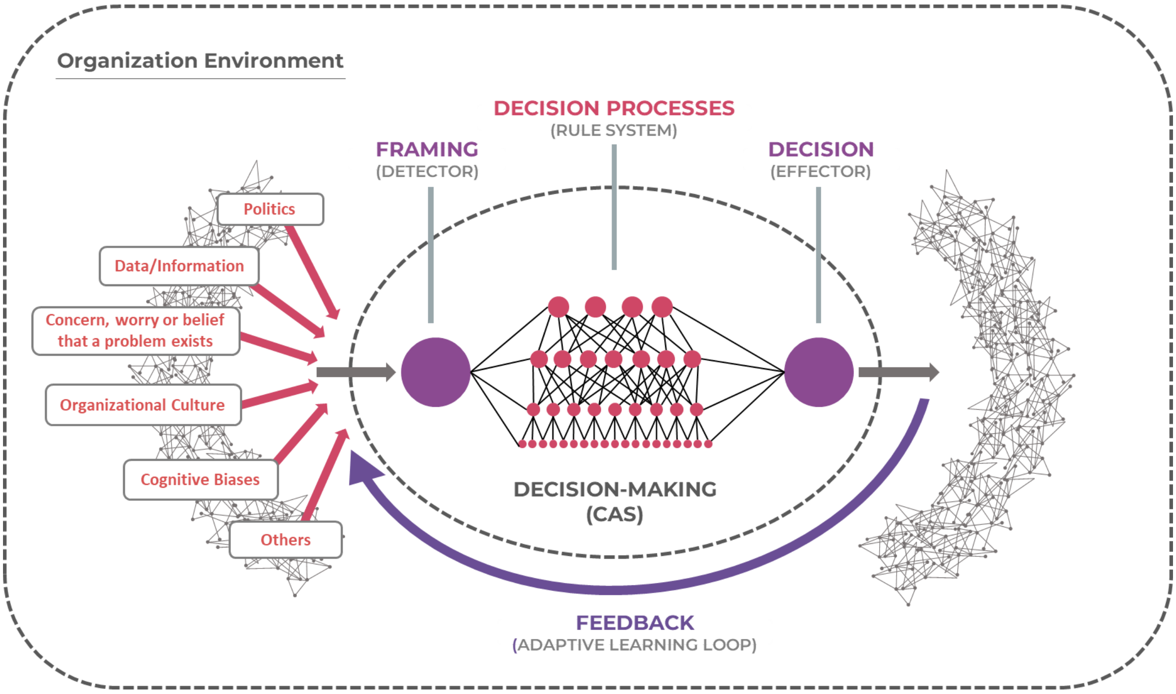

Fig. 2 – Decision-Making as a Complex Adaptive System. Elaborated by the authors.

3. FRAMING PROCESS AS A CYBERNETIC DETECTOR SYSTEM

The framing process is responsible for identifying and defining the boundaries and parameters of the problem or decision at hand, which acts as the input to the decision-making system. In a CAS view of decision-making, framing can be seen as the system's cybernetic detector system, as it is analogous to the detector of a CAS, which senses and collects data from the environment, converting it into a signal that can be interpreted by the system.

A cybernetic system (CS) is similar to a CAS in structure. Nevertheless, these systems have a predetermined set of rules and goals that they follow to achieve a specific outcome. The system's behavior is determined by the interactions between the input and output and the feedback loops that regulate the system, rather than emerging like in a CAS. For instance, a thermostat is a CS. It uses feedback to maintain a stable temperature in a room or building by sending signals to the heating system to turn on/off and adjust the temperature until it reaches the desired level.

Just as the detector in a CAS plays a crucial role in the system's ability to adapt and respond to environmental changes, the framing process in decision-making is essential for ensuring that decision-makers have a clear understanding of the problem and can make informed decisions. A well-defined and accurate framing of the problem can help decision-makers identify the relevant information, options, and potential outcomes, facilitating a more effective decision-making process.

To describe the framing as a cybernetic system, we must consider a CS's central axioms: input, throughput, output, and feedback loops. The system's input includes various types of information, such as data, context, and stakeholder interests, which are fed into the system. The system's throughput involves the process of interpreting and organizing the input information, which includes identifying key variables and relationships and constructing problem definitions and causal interpretations. The system's output is the framed problem, which is presented to decision-makers and stakeholders. Lastly, the feedback loops of the framing system involve evaluating and refining the framed problem based on stakeholder feedback, new information, and changing contexts. Figure 3 illustrates the framing process as a cybernetic detector system for the decision-making CAS.

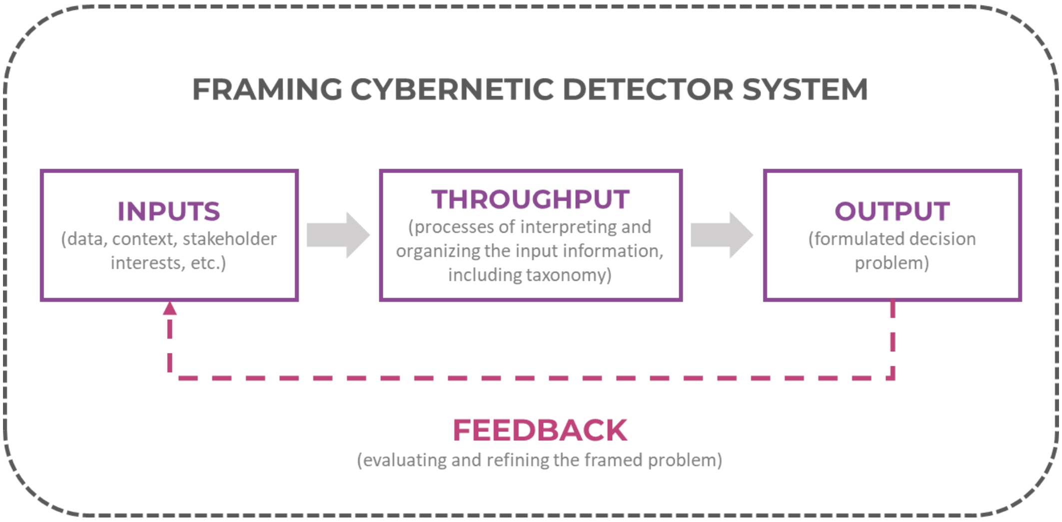

Fig. 3 - Framing Process as a Cybernetic Detector System for the Decision-Making CAS. Elaborated by the authors.

4. AUTOMATED FRAMING: FROM CONVENTIONAL TO AUTOMATIC

The conventional way of executing this system involves decision-makers manually identifying and defining the problem, often based on their own biases and assumptions. This process can be time-consuming and may result in inconsistent or incomplete framing, leading to suboptimal decisions or resolving the wrong problem (Smith, 1989; McNamee & Celona, 2007).

The framing of decisions was traditionally seen as a process that was not programmable or generalizable, varying from the case (Dyson et al., 2021; Reisman & Oral, 2005). And this may have been true for many years. Brooks et al. (1996) defined framing automation as one of the challenges for AI at the time and that there was a long way to go. The last decades of data science and AI advances show that this long way has been traveled.

Since the 1990s, AI has undergone a remarkable resurgence owing to the advancement in computing power and the development of the internet. Subsequently, the field has progressed significantly, particularly with the adoption of machine learning techniques such as deep learning and neural networks in the 2000s. These approaches have led to remarkable breakthroughs in speech and image recognition. In recent years, AI has been widely integrated into people's lives, with the rise of personal assistants like Alexa, self-driving cars, and intelligent robots like Roomba. The field is advancing rapidly, with ongoing research in reinforcement learning, explainable AI, and quantum computing (Gruetzemacher et al., 2021; Bahoo et al., 2023).

The advancement of AI in recent decades has impacted the field and various other areas, including organizational decision-making. The increasing ability of AI to perform complex tasks and make decisions that were previously done by humans allows discussions in facilitating and automating the framing system in organizational decision-making.

To develop an automated approach to FCS, advances are required in three necessarily linked topics: description, structuring, and prescription. The description refers to mapping and analyzing how decision-makers in management areas formulate problems. Structuring refers to reducing problems into smaller and analyzable parts at a taxonomic and reductionist level. Prescription refers to recommending a framing to the decision-making group (Smith, 1989).

To address the topics from an automation point of view, many AI techniques can be posed and combined. Machine learning can be applied to develop algorithms to learn from data and provide recommendations for framing decision-making problems based on past data. Specifically, using Deep Learning (a machine learning subfield), it is possible to create models that can analyze and interpret large amounts of unstructured data to identify patterns and relationships that can help frame decision-making problems. Another AI technique that can be used is neural language processing (NLP). NLP models can process and understand human language, which can help analyze and structure problem statements and recommend appropriate framing. Combining these techniques can provide a powerful toolset for developing an automated approach to framing in organizational decision-making.

This powerful combination has recently gained popularity with OpenAI's ChatGPT. ChatGPT was built based on GPT-3 model, using advanced machine learning algorithms and natural language processing techniques. The creators used neural networks with transformer architecture on a massive dataset of human language data, including text from books, websites, human conversations, and other sources. Transformer architecture allows the processing of sequences of words, also known as sequences of tokens, more efficiently than earlier models. (Vaswani, 2017). The training process involved letting the model learn the patterns, structures, and relationships within language data, allowing it to generate human-like responses to new inputs, exposing the model to vast amounts of text, and rewarding it for generating contextually appropriate and grammatically correct responses. The training process was iterative, with the model constantly adjusting its weights and parameters to improve performance (Brown et al., 2020).

Considering this approach, several steps must be taken to develop an automated way to frame decisions in organizational decision-making.

(1) Collection of data needed to train the model. This data can be obtained from various sources such as news articles, academic papers, social media posts, and other forms of text data. The data should be diverse and representative of the problem domain and the decision-making context (Ghosh & Gunning, 2019; Rao & McMahan, 2019; Vajjala et al., 2020).

(2) Second is to preprocess the data. This involves cleaning the text data, removing irrelevant information, and converting it into a format that can be used for training and

exploratory analysis. The preprocessing step may also involve tokenization, where the text is split into individual words or more subwords, and feature extraction, where the raw text data is transformed into numerical representations for the model (Ghosh & Gunning, 2019; Rao & McMahan, 2019; Vajjala et al., 2020).

(3) After preprocessing, the data is ready for model training. This involves selecting an appropriate machine learning algorithm, such as a deep neural network, and training the model on the preprocessed data. The model should be trained using an unsupervised learning approach, where the model learns to identify patterns and relationships within the data without any prior knowledge of the correct output. This approach is ideal for topic modeling, word embeddings, and sentiment analysis tasks (Ghosh & Gunning, 2019; Rao & McMahan, 2019; Vajjala et al., 2020).

Topic modeling is an unsupervised learning technique used in NLP to discover the underlying topics within a corpus of text data. It involves extracting a set of topics or themes from the data, where each topic is represented by a set of words that frequently co-occur within the text data. Topic modeling can help automate the framing system by identifying the key topics and themes that concern determined discussion. This can provide resources to refine the model and insights into framing the decision problem (Ghosh & Gunning, 2019; Rao & McMahan, 2019; Vajjala et al., 2020).

Another unsupervised learning approach that can be used in NLP is word embeddings. Word embeddings are a numerical representation that captures the meaning and context of words in a corpus of text data. Word embeddings can be incorporated using techniques such as Word2Vec and GloVe, which involve training a model on a large corpus of text data to predict the context in which a word appears. Once the word embeddings are learned, they can be used as input features for downstream NLP tasks such as text classification and sentiment analysis. Word embeddings are a powerful tool for automating the framing of decisions. They help capture the semantic relationships between words, such as synonyms, antonyms, and analogies, the context of words and phrases, and can help to improve the accuracy of NLP models. These embeddings can also be used as input features for downstream NLP tasks (Ghosh & Gunning, 2019; Rao & McMahan, 2019; Vajjala et al., 2020).

Unsupervised sentiment analysis enables the model to learn to identify the sentiment of text data without pre-defined labels. Unsupervised sentiment analysis typically involves using techniques such as lexicon-based analysis or machine learning algorithms that can identify the emotional tone of the text and classify it as positive, negative, or neutral (Ghosh & Gunning, 2019; Rao & McMahan, 2019; Vajjala et al., 2020). In the automated framing context, it could identify and equalize biases, for example.

(4) After training the model, evaluating its performance on a validation set or using performance metrics (e.g. accuracy, precision, coherence, perplexity) is essential. The evaluation step helps to ensure that the model is performing well on the specific task at hand and can help identify areas for improvement. Additionally, it is vital to ensure that the model is generalizable and can perform well on new data that it has not seen before (Chen et al., 2021).

(5) Once the model is trained and evaluated, it can be deployed to automate the framing system in organizational decision-making. For example, the model can analyze and structure problem statements, identify key topics and themes, and recommend appropriate framing based on past data. Using an automated approach to framing can reduce the time and effort required to frame decision-making problems, improve consistency, attenuate cognitive and political bias, and ultimately lead to better decision-making outcomes.

Building a model for automated framing in organizational decision-making involves several steps. Using unsupervised learning approaches such as topic modeling, word embeddings, and sentiment analysis can help automate the framing system and provide insights into how to approach framing the decision problem. Combining machine learning and NLP techniques, such as deep neural networks and transformer architectures, can provide a powerful toolset for developing an automated approach to framing in organizational decision-making.

5. FEASIBILITY AND CHALLENGES

Automated framing using AI poses several challenges that must be addressed before it becomes a feasible and valuable tool for decision-making. One significant challenge is to ensure that the framing algorithms and models are trained on diverse and representative data, once the quality of the training data can significantly affect the performance and accuracy of the algorithm.

To overcome this barrier and undertake automated framing, it is necessary to consider transfer learning. Training an NLP model from scratch is a task that requires large amounts of data and significant computing capacity, often not accessible to organizations and researchers. In this situation, a pre-trained model can be used as a starting point for solving a new related task. In transfer learning, a model is first trained on a large and diverse dataset, typically unsupervised or self-supervised, to learn a general data representation. This pre-trained model can then be fine-tuned on a smaller dataset for a specific task – in this case, framing of decisions (Raffel et al., 2020).

The system should also consider fine-tuning the scope. This poses a challenge since if the scope is too narrow, then decision-makers might miss out on potential opportunities, at the same time, a scope that is too wide can make a project overly complex and fail to achieve its goals or communicate its results effectively (McNamee & Celona, 2007).

An automated framing system should be able to identify relationships between different framed decisions and determine which decisions are interdependent or linked. This requires an understanding of the decision-making context and the relationships between decisions, as well as the ability to analyze complex data sets. Decision exclusion is also important to reduce noise and improve the accuracy of the automated framing system. One approach uses network analysis techniques to visualize and analyze the relationships between decisions. This can help decision-makers identify which decisions are most critical and which can be excluded (Han & Lai, 2011).

Evaluating the quality of the framing is another challenging task. One approach is to use human evaluators, stakeholders, and agents involved in decision-making to judge the effectiveness of the framing based on factors such as clarity, completeness, and relevance. Alternatively, performance metrics such as accuracy, precision, and recall can be used to evaluate the model's effectiveness in identifying and framing decision-making problems. A composed approach can be an efficient feedback loop for assessing the quality of the automated framing system (White, 2006; Midgley, 2013).

Controlling the inputs of the automated framing system is vital to ensure that the system produces reliable and accurate results. Inputs that are biased, incomplete, or irrelevant can result in flawed framing that may not accurately reflect the decision-making problem.

However, it is important to balance control with the need for diversity and representativeness in the training data (Ghosh & Gunning, 2019; Rao & McMahan, 2019; Vajjala et al., 2020).

Another key challenge with an automated framing system is that the model may not always be sure about its recommendations. This can be due to uncertainty in the data, ambiguity in the decision-making context, or limitations in the model's capabilities. To address this challenge, models can be trained to express their uncertainty in words. Bayesian approaches and Monte Carlo methods can also be used to quantify and express uncertainty probabilistically. By teaching models to express their uncertainty, decision-makers can better understand the system's limitations and moderate their reliability on the system (Lin et al., 2022).

The automated framing system should be able to integrate seamlessly with existing decision-making processes and tools to ensure that it is used effectively and efficiently. This may involve developing APIs or plugins that can be easily incorporated into existing systems or a standalone system that can be used alongside existing tools. It is important to ensure that the model fits into the existing decision-making workflow and that decision-makers are comfortable using it. This can be achieved by involving stakeholders in the development process and providing training and support to ensure they understand how to use the system effectively.

The success of an automated framing system ultimately depends on user acceptance and adoption. It is important to involve end-users and stakeholders in the development process and incorporate their feedback into the system to ensure that it meets their needs and expectations. Additionally, transparency and explainability of the system's functions can help to build trust among users. Providing clear explanations of how the system works and what data is being used, can help to reduce user skepticism and increase confidence in the system.

6. CONCLUSIONS AND FUTURE RESEARCH

In this essay, we discussed organizational decision-making and framing process from a Complex adaptive system (CAS) perspective, with framing as a cybernetic detector of such a system. This theoretical background posed a better understanding of the decision-making and framing systems' dynamics and allowed us to advance towards automation of framing cybernetic systems.

An automated framing system using AI techniques can potentially revolutionize the framing of decisions in organizational decision-making. Developing an automated framing system using AI techniques can significantly improve the framing of decisions in organizational decision-making. Combining machine learning and NLP techniques, such as deep neural networks and transformer architectures, provides a powerful toolset for developing an automated approach to framing. However, several challenges must be addressed, such as ensuring diverse and representative data, fine-tuning the scope, identifying interdependent decisions, evaluating the framing quality, controlling inputs, expressing uncertainty, and seamlessly integrating existing decision-making processes and tools. Future research in this area should focus on addressing these challenges and testing the engineering of the proposed automated framing system and its effectiveness and accuracy.

7. REFERENCES

Baer, M., Dirks, K. T., & Nickerson, J. A. (2013). Microfoundations of strategic problem formulation. *Strategic Management Journal*, *34*(2), 197-214.

Bahoo, S., Cucculelli, M., & Qamar, D. (2023). Artificial intelligence and corporate innovation: A review and research agenda. *Technological Forecasting and Social Change*, *188*, 122264.

Bastons, M. (2008). The role of virtues in the framing of decisions. *Journal of Business Ethics*, *78*, 389-400.

Bowen, K. (2001). The process of problem-formulation. *European Journal of Operational Research*, *128*(2), 258-265.

Brooks, R. A., Selman, B., Dean, T., Horvitz, E., Mitchell, T. M., & Nilsson, N. J. (1996). Challenge problems for artificial intelligence. In *Thirteenth National Conference on Artificial Intelligence-AAAI* (Vol. 4).

Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., ... & Amodei, D. (2020). Language models are few-shot learners. *Advances in neural information processing systems*, *33*, 1877-1901.

Champion, D., & Wilson, J. M. (2010). The impact of contingency factors on validation of problem structuring methods. *Journal of the Operational Research Society*, *61*, 1420-1431.

Chen, M., Tworek, J., Jun, H., Yuan, Q., Pinto, H. P. D. O., Kaplan, J., ... & Zaremba, W. (2021). Evaluating large language models trained on code. *arXiv preprint arXiv:2107.03374*.

Choo, A. S. (2014). Defining problems fast and slow: The u‐shaped effect of problem definition time on project duration. *Production and Operations Management*, *23*(8), 1462-1479.

Clemens, M. (2017). *Idiagram Complexity Examples*. Idiagram. Retrieved March 8, 2023, from https://www.idiagram.com/examples/complexity.html

Dyson, R. G., O'Brien, F. A., & Shah, D. B. (2021). Soft OR and practice: the contribution of the founders of operations research. Operations Research, 69(3), 727-738.

Ellis, B. S., & Herbert, S. (2010). Complex adaptive systems (CAS): an overview of key elements, characteristics and application to management theory. *Journal of Innovation in Health Informatics*, *19*(1), 33-37.

Entman, R. M. (1993). Framing: Toward clarification of a fractured paradigm. *Journal of communication*, *43*(4), 51-58.

Ghosh, S., & Gunning, D. (2019). *Natural Language Processing Fundamentals: Build intelligent applications that can interpret the human language to deliver impactful results*. Packt Publishing Ltd.

Gruetzemacher, R., Dorner, F. E., Bernaola-Alvarez, N., Giattino, C., & Manheim, D. (2021). Forecasting AI progress: A research agenda. *Technological Forecasting and Social Change*, *170*, 120909.

Han, H., & Lai, S. K. (2011). Decision network: a planning tool for making multiple, linked decisions. *Environment and Planning B: Planning and Design*, *38*(1), 115-128.

Hodgkinson, G. P., Bown, N. J., Maule, A. J., Glaister, K. W., & Pearman, A. D. (1999). Breaking the frame: An analysis of strategic cognition and decision making under uncertainty. *Strategic management journal*, *20*(10), 977-985.

Hodgkinson, G. P., Maule, A. J., Bown, N. J., Pearman, A. D., & Glaister, K. W. (2002). Further reflections on the elimination of framing bias in strategic decision making. *Strategic Management Journal*, *23*(11), 1069-1076.

Howard, R. A. (2000). Decision analysis and law. *Cardozo L. Rev.*, *22*, 1595.

Kotiadis, K., & Mingers, J. (2006). Combining PSMs with hard OR methods: the philosophical and practical challenges. *Journal of the Operational Research Society*, *57*, 856-867.

Kühberger, A. (1995). The framing of decisions: A new look at old problems. *Organizational Behavior and Human Decision Processes*, *62*(2), 230-240.

Kuziemsky, C. (2016, January). Decision-making in healthcare as a complex adaptive system. In *Healthcare Management Forum* (Vol. 29, No. 1, pp. 4-7). Sage CA: Los Angeles, CA: SAGE Publications.

Lin, S., Hilton, J., & Evans, O. (2022). Teaching models to express their uncertainty in words. *arXiv preprint arXiv:2205.14334*.

Lyles, M. A., & Mitroff, I. I. (1980). Organizational problem formulation: An empirical study. *Administrative Science Quarterly*, 102-119.

Marshak, R. J., & Heracleous, L. (2023). The Effect of Evocative Frames on Strategic Decisions. *The Journal of Applied Behavioral Science*, *59*(1), 11-29.

Mårtensson, P., & Lee, A. S. (2004). Dialogical action research at omega corporation. *MIS Quarterly*, 507-536.

McNamee, P., & Celona, J. N. (2007). *Decision analysis for the professional*. SmartOrg, Incorporated.

Midgley, G., Cavana, R. Y., Brocklesby, J., Foote, J. L., Wood, D. R., & Ahuriri-Driscoll, A. (2013). Towards a new framework for evaluating systemic problem structuring methods. *European Journal of Operational Research*, *229*(1), 143-154.

Mingers, J., & Rosenhead, J. (2004). Problem structuring methods in action. *European journal of operational research*, *152*(3), 530-554.

Mojzisch, A., & Schulz-Hardt, S. (2010). Knowing others' preferences degrades the quality of group decisions. *Journal of personality and social psychology*, *98*(5), 794.

Raffel, C., Shazeer, N., Roberts, A., Lee, K., Narang, S., Matena, M., ... & Liu, P. J. (2020). Exploring the limits of transfer learning with a unified text-to-text transformer. *The Journal of Machine Learning Research*, *21*(1), 5485-5551.

Rao, D., & McMahan, B. (2019). *Natural language processing with PyTorch: build intelligent language applications using deep learning*. " O'Reilly Media, Inc.".

Reisman, A., & Oral, M. (2005). Soft systems methodology: A context within a 50-year retrospective of OR/MS. *Interfaces*, *35*(2), 164-178.

Rosenhead, J. (2006). Past, present and future of problem structuring methods. *Journal of the operational research society*, *57*(7), 759-765.

Schwenk, C., & Thomas, H. (1983). Formulating the mess: The role of decision aids in problem formulation. *Omega*, *11*(3), 239-252.

Smith, G. F. (1989). Defining managerial problems: A framework for prescriptive theorizing. *Management science*, *35*(8), 963-981.

Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *science*, *211*(4481), 453-458.

Vajjala, S., Majumder, B., Gupta, A., & Surana, H. (2020). *Practical natural language processing: a comprehensive guide to building real-world NLP systems*. O'Reilly Media.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

White, L. (2006). Evaluating problem-structuring methods: Developing an approach to show the value and effectiveness of PSMs. *Journal of the Operational Research Society*, *57*, 842-855.

Wright, G., & Goodwin, P. (2002). Eliminating a framing bias by using simple instructions to 'think harder' and respondents with managerial experience: Comment on 'breaking the frame'. *Strategic management journal*, *23*(11), 1059-1067.