COMPLEX AUTOMATED DECISION PROCESSES AND MITIGATING IMPLICIT STAKEHOLDER BIASES

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By

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On my honor as a University student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments.

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INNOVATIVE ANALYTICS FOR GOLF RECRUITING SYSTEMS AND RISING CONCERNS OVER EXPERTISE AND DATA ANALYSIS IN DECISION-MAKING

The modern proliferation of artificial intelligence deployment throughout the professional services industry has characterized a new era of information technology where society is severely dependent on the insights yielded by data analytics. The use of machine learning in contemporary enterprise processes, from algorithmic trading in the stock market to autonomous vehicles on the road, has created new opportunities for businesses, as exemplified by Loten (2022) with the increasing trend of establishing chief data officer roles at major corporations and governments around the globe. Widespread access to and adoption of these technologies have similarly created complex challenges for industry to resolve, exemplified in a *Wall Street Journal* article that explicates modern consumer expectations: "[Generation Z consumers] won't be attracted by ease and novelty the way earlier generations were. They don't want products that are designed for masses of users. Instead, they are looking for highly personalized experiences" (Narula, 2022).

One example of artificial intelligence diffusion into the private sector is observed with the sports analytics industry, where demand from U.S. universities to recruit the best players using data science has become necessary to maintaining the $18.9 billion-dollar value of NCAA athletic departments around the country (Richter, 2021). One company taking advantage of this new opportunity is GameForge, a Virginia-based golf analytics firm that aims to streamline the recruitment of junior golfers from around the world to U.S. universities. The technical thesis, engages with GameForge to develop a two-sided recruiting system for both college coaches and junior players to use in identifying opportunities for recruitment, taking a systems-based approach to develop new models that assemble to establish (a) a proprietary ranking system that compares junior athletes to one another; (b) a relative SWOT analysis that highlights player strengths and skill gaps; and (c) a recommender system that suggests potential recruits to college coaches and recommends colleges of best fit to junior players.

This novel use of data analytics in sports recruitment is exemplary of a shifting sociotechnical relationship between humans and machines that Jarrahi et. al. (2021) suggests will alter “standard work settings [that] reflect and redefine pre-existing roles, relationships, power dynamics, and information exchanges” (p. 2). The STS research paper explores this relationship further, calling attention to the growing trend of reliance on automated decision systems in every facet of our lives, where the comprehensive reassignment of tasks from humans to machines has transcended productivity to become an essential standard. This trend is complicated by the inadvertent inclusion of implicit biases that can negatively impact how machines make decisions, stemming either from the engineers responsible for these systems or from the inner workings of the system itself. According to Vanderford (2022), “many [corporations] have turned to AI to bulk up… despite perennial warnings from regulators and experts of the potential for algorithm to effectively learn from and then magnify human biases.” The STS topic seeks to answer how biases can be analyzed across different types of automated decision systems to mitigate threats to groups affected by decision outcomes. This STS topic is loosely coupled with the technical thesis, seeking to provide alternative insight into the biases that permeate general decision-making processes yet seeking to include perspectives from both human and machine intervention that diverges from the hands-off approach the technical project maintains. The goal of this work stands to engage modern policy regulators in retrospective thought over the insights garnered from automated decision systems, highlighting the benefits to augment standard human decision-making yet cautioning in the challenges and risks inherent in these systems.

DEPLOYING AUTOMATED DECISION SYSTEMS AND MANAGING BIAS FROM EXPERTISE AND TECHNOLOGY

INTRODUCTION TO THE ROLE OF TECHNOLOGY IN DECISION-MAKING

The continued deployment of automated decision systems into modern business processes prepends a complex pretext to the evolving relationship between humans and technology. The opportunity and availability for bias to infiltrate such decision-making processes requires keen oversight from involved stakeholders and employment of new areas of study for mitigating risks to parties affected by outcomes. Kitchin (2017) argues that engineers and computer systems play unique roles in the creation of algorithmic systems, and that the complex socio-technical relationship between these human and non-human actors provide a more profound understanding of the technologies at-hand. A deeper consideration of this relationship is essential to understanding how information is disseminated between information sources and included in final decisions, which is necessary in ensuring that outcomes are balanced and equitable. Analysis by Brauneis and Goodman (2017) furthers this point through investigation of algorithmically determined decision-making in U.S. local and state governments. This research advocates for enhanced regulatory oversight to safeguard society from the potential risks that new "black-box" technologies can bring about.

MODERN USE OF AUTOMATED DECISION SYSTEMS

Automated decision systems play a pivotal role in the modern age, with extensive applications ranging across various industries and tackling numerous intricate, increasingly complex problems. In her industry-backed audit of the New York City Automated Decision System Task Force, technology policy and civil rights lawyer Rashida Richardson (2019) meticulously defines the concept of an automated decision system as:

> Any software, system, or process that aims to automate, aid, or replace human decision-making. Automated decision systems can include both tools that analyze datasets to generate scores, predictions, classifications, or some recommended action(s) that are used by agencies to make decisions that impact human welfare, and the set of processes involved in implementing these tools (p. 20).

Automated decision systems can be found everywhere: they continue to grow in popularity with passenger and cargo transportation, as McKinsey autonomous vehicle expert Heineke and others (2018) suggest by the twofold increase of the global market for autonomous vehicles from 2018 to 2021, "reaching $35 billion in revenue" (Projected Impact section). Alongside transportation, automated decision systems are standard in corporate supply chain management and delivery, "key to Amazon's retail forecasting on steroids and its push to shave off minutes and seconds in the rush to prepare, pack, and deliver," as detailed by Selyukh (2018) in a publication for NPR (p. 2). In an interview for *The Wall Street Journal*, founder Kevin Parker of the talent recruitment platform HireVue offers compelling evidence for the increased use of artificial intelligence and automation in professional career recruiting, stating "[AI] can sit through a thousand interviews without getting bored or resorting to mental shortcuts" (Vanderford, 2022). Automated decision systems have remained prevalent in the stock market over the past decade, detailed by Markoff (2018) in the growing field of investment known as algorithmic trading that is "essential to accurately order the millions of stock trades that are placed on [the Nasdaq] computer systems every second."

Autonomous technologies seek to drive innovation in the workplace by accelerating decision-making and providing comprehensive answers faster than previously available, easing stress on traditional public and private sector business processes and reducing operating costs and resources. Dunleavy et. al. (2005) emphasize the increased use of automation in governmental decision-making as a response to "disaggregation, competition, and incentivization” in public sector management, yet note that the newer shift to digital governance has brought “adverse indirect effects” to citizens because of “increased institutional and policy complexity” (p. 467). While the increasing reliance on autonomous systems to make decisions proffers great benefits, there are many opportunistic fallacies that can arise, causing terse implications and even severe consequences. As explored by the Harvard Law Review Association (2003) when discussing *Azania v. Indiana*, “the Indiana Supreme Court held that a computer programming error that eliminated a large percentage of black potential jurors from the jury pool in a capital case violated Indiana’s requirement for an ‘impartial and random selection’ process” (p. 2678). This error, which was later determined by investigators to be an unintentional effect from a college student who designed the jury selection software part-time (Oliver, 2020), is one of many examples that have emerged as the adoption of computerized jury coordinators becomes standard in America, “rais[ing] constitutional concerns and threaten[ing] the integrity of the jury system” (Blinder, 2019). Biases and discriminatory decisions can arise in machines in the same fashion it does in humans (Kozyrkov, 2018), demanding critical evaluation and audit of technology-formulated decision-making to ensure fair and impartial outcomes.

CONFLICTING ETHICAL CHALLENGES WITH AUTONOMOUS TECHNOLOGIES

The use of automated decision systems can beget significant ethical and moral implications on users, delegating a responsibility to developers for effective oversight, regulation, and governance of these systems. Resolving the ethical dilemmas that surround automated decision systems can be explored using a guide given by Martin and Schinzinger (2009) in their primer on moral reasoning and ethical frameworks in engineering, which first suggests ascertaining the ethical dilemmas and defining the issues at-hand before moving to collect evidence, propose options, and recommend a solution (p. 38). The problems that arise with automated decision systems are succinctly expressed by Harvard University political philosophy professor Michael Sandel as he expresses the appeals and drawbacks of autonomous decision-making, noting that:

> Part of the appeal of algorithmic decision-making is that it seems to offer an objective way of overcoming human subjectivity, bias and prejudice. But we are discovering that many of the algorithms that decide who should get parole, for example, or who should be presented with employment opportunities or housing… replicate and embed the biases that already exist in our society (Pazzanese, 2020).

The publication enumerates three key areas for ethical consideration on the deployment of automated decision systems: privacy and surveillance, bias and discrimination, and the role of human judgement (Pazzanese, 2020). These issues are not new to complex decision-making processes nor unique to automated decision systems regulation. Brookings Institute fellow Cameron Kerry (2020) emphasizes "the need [for Congress] to consider if or how to address use of personal information in artificial intelligence systems" when deliberating policy options concerning data privacy of current human-controlled information systems. Consumer privacy protection is further advanced by former Federal Trade Commissioner Jon Leibowitz (2022) in discussing the long-standing, bipartisan consensus over data privacy and consumer protections despite minor obstacles that delay effective agenda-setting from Congressional leaders.

Adjacently, the role of bias and discrimination in objective human judgement formation is well-documented throughout history, as well as its resolution through effective regulatory oversight and policy formulation. One example of complex decision-making plagued by biased agents is the explosion of the Challenger Space Shuttle in 1986, where key decision-makers withheld data from a teleconference before the launch that would have otherwise suggested postponing liftoff (Ranney, 2012, p. 3). Conversely, effective regulation and committee oversight can lead to indiscriminate and rational decision-making; most notably is the case of the 1976

Cambridge Experimentation Review Board's seven-month, citizen-jury deliberation on the effects of local university recombinant DNA research on public health within the community (Waddell, 1989, p. 9). In both cases, subject matter jurisdiction played a critical role in decision formulation. Success or failure was defined solely by information dissemination, which is resolved in modern decision-making processes through the use of impartial technology.

Data privacy, technology transparency, and algorithmic discrimination necessitate extensive engagement from relevant stakeholders to mitigate the ethical concerns brought about by the use of automated decision systems, calling upon relevant regulators to exercise oversight and intervene where necessary. Jarrahi et. al. (2021) suggests that automated decision systems "can provide more objective and consistent decisions than humans" (p. 3) yet add "to pre-existing power dynamics and regimes of control" (p. 4) between those who make decisions and those affected by the outcomes. However, structural biases can become encoded in autonomous technologies without effective regulation of data aggregation and application processes, either consciously or perfunctorily, leading to skewed results and disparate outcomes. These sentiments call into question the underlying motives of human decision-makers as well as the external validity of decision-making technologies, which can present judgements with serious ramifications. The goal, therefore, of interaction between humans and technology in decision-making should be to galvanize better-informed outcomes through strategic interfacing that circumvents apprehension from relevant stakeholders and those directly affected by decision outcomes. This goal state can be contemplated through the analysis of information sharing between humans and technologies that are involved in decision-making processes, which can then lead to the recommendation of potential efforts to improve decisions and mitigatory actions to minimize the risks of poor decisions.

HUMAN-MACHINE INTERACTION IN DECISION-MAKING PROCESSES

The interaction between humans and technologies as information sources in decision-making processes is characterized by defined relationships of unique actors with distinct agency, which can be analyzed to determine the effect that each actor plays on one another as well as how these actors contribute to bias transfer and outcome determination. The strategic adoption of data analytics as a key stakeholder in contemporary business processes over the past two decades has ameliorated the efficacy and accuracy of strategic decision-making at an executive level, and has further led to the development of commonplace vernacular among those in the field of decision research on four distinguishable decision types. IMD Business School Professor Phil Rosenzweig (2013) elucidates the development of interchange between human and technology decision makers since 2003, describing a framework for categorizing decisions along two dimensions, "the first [control] considers how much we can influence the terms of the decision and the outcome… [and] the second [performance] addresses the way we measure success." This framework suggests four defined types of decisions, as observed in Figure 1. Each decision type has definable traits and, as Rosenzweig writes, particular methodologies for resolution and metrics for analysis that are simple to understand.

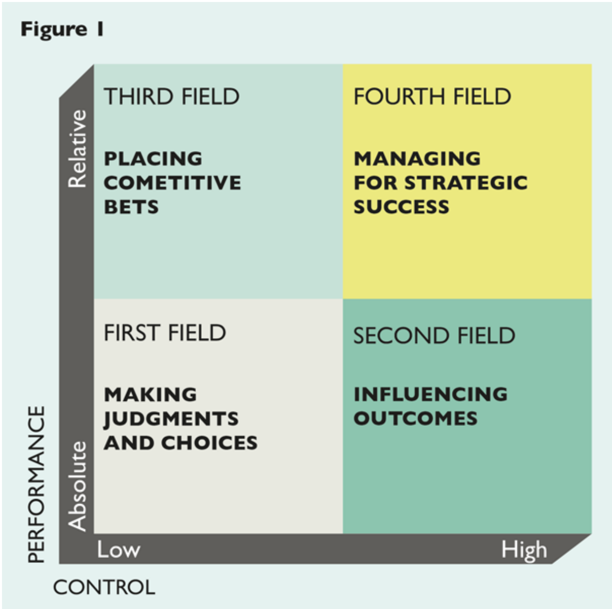

Figure 1: Four Types of Decisions: To get better at making decisions, it's important to recognize the different types. Those in the first field of the matrix – where we have no control over outcomes and our performance isn't absolute – include consumer choices and personal investment decisions. Those in the fourth field – where we can influence outcomes and need to outperform rivals – include the strategic decisions that are most challenging for managers, such as launching a new product or entering a new market (Rosenzweig, 2013).

Rosenzweig's proposed methodology for categorizing decisions advances a top-down approach that classifies the distribution of information into tangible decision categories, which does aid in the review of the sociotechnical relationships of decision-making information sources nor highlight the flow of information, and biases, from these information sources to outcome decisions. Instead, a bottom-up approach should be presented that groups information sources into relevant categories that can demonstrate where potential sources of bias arise from in decision-making processes. Actor Network Theory enables the development of such a model of actors and permits the evaluation of their interaction (Callon & Law, 1997). Figure 2 adopts an actor-network that classifies informative actors by whether they are human or non-human, or their capital type, and where information is sourced from, or their information type, which is crucial to understanding information dissemination as well as viable remediation options.

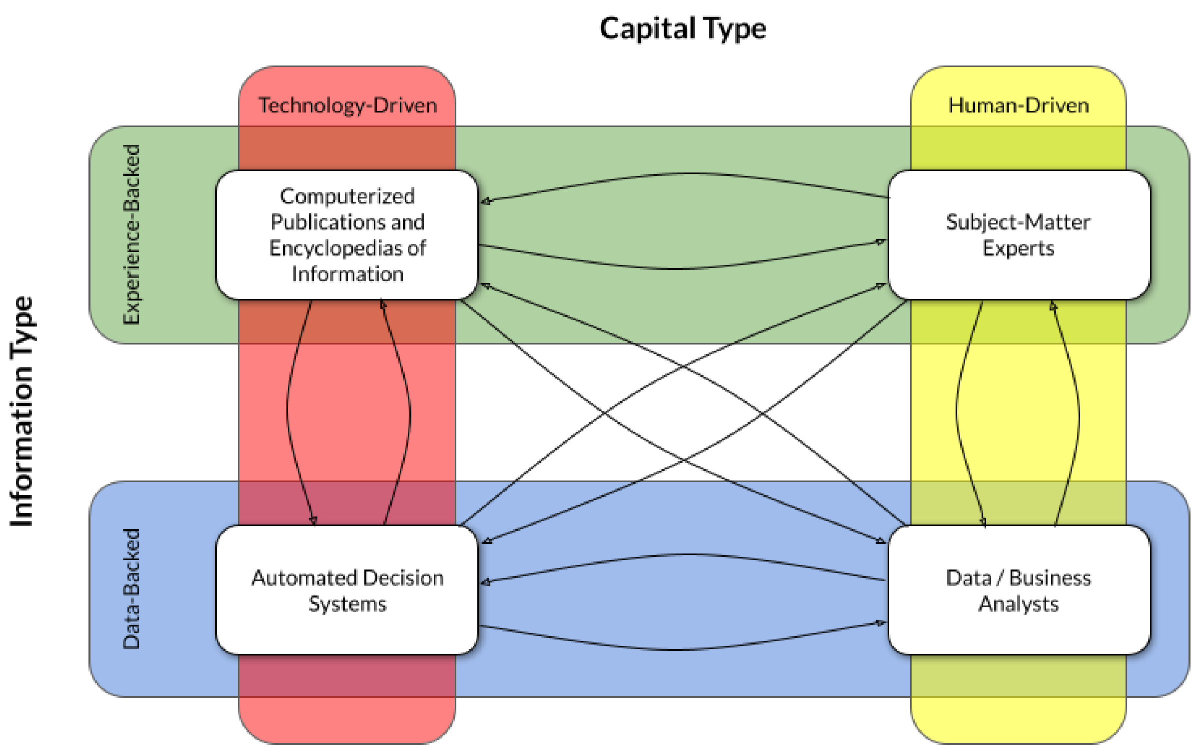

Figure 2: Actor Network of Information Sources: A bottom-up view of information sources can delineate categories that define where information is derived from. Sources can then be grouped by capital type and by information source type. (Wasserman, 2022)

The actor-network given elucidates a simple framework for understanding the interaction between informative actors in a decision-making process, emphasizing exchange and learning between sources that fuels insight development and leads to comprehensive decision-making. information that occurs between one source and another in crafting decisions. Consider the case of autonomous transportation: “computerized publications” might include online resources that discuss control theory, hardware construction, and the mechanical components required for videographic artificial intelligence; and “automated decision systems” include the artificial intelligence that is deployed for recognizing objects and controlling the car. “Subject-matter experts” are the engineers hired to retrofit technology to the car and augment its mechanical systems to work with the onboard artificial intelligence that will drive the car; and “data/business analysts” are the software engineers who design and develop the artificial intelligence to be used in maneuvering the car. This example expresses the complex relationships between informative actors in the formation of an autonomous vehicle, and how actors negotiate within the network exchange information with one another in pursuit of the common goal. With this in mind, these negotiation spaces also hold implicit risk and should be closely scrutinized, as they reflect decision points where miscommunication can lead to improper decision-making and misinformation/disinformation can lead to biased decision-making.

Strategic Development: Partnership between Differing Information Sources of Similar Capital Types

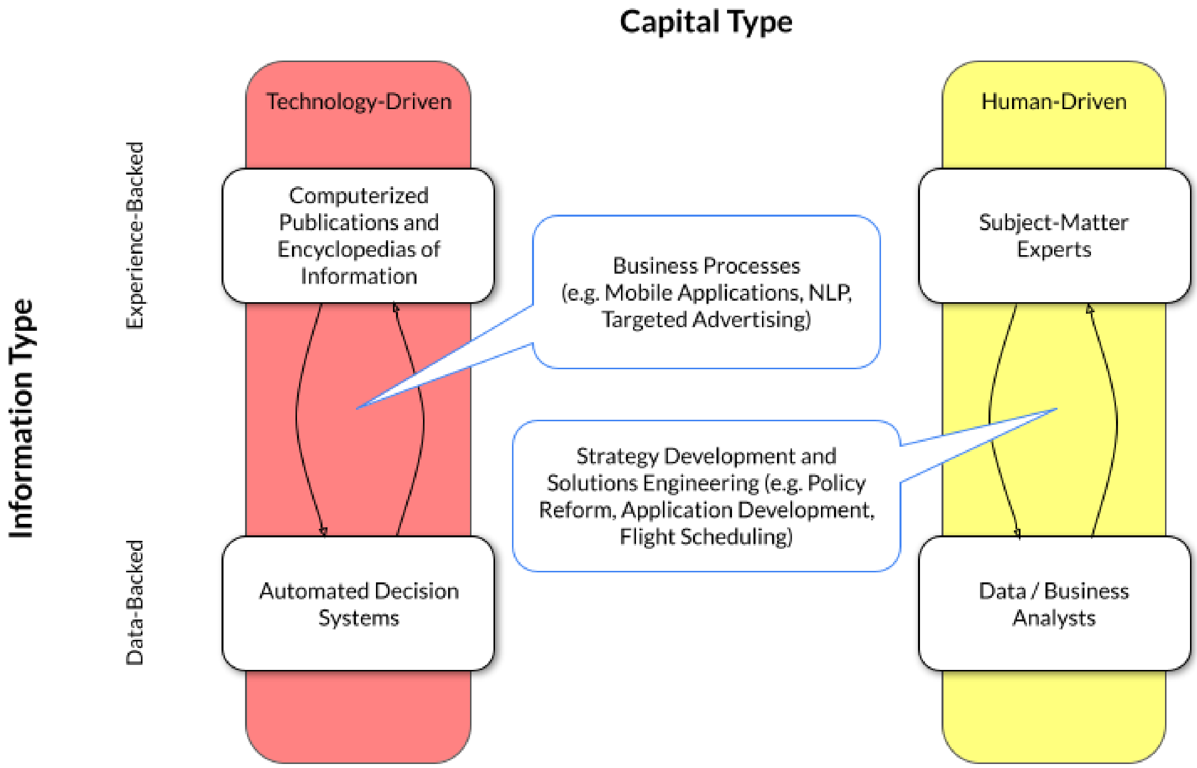

Figure 3: Strategic Partnership in the Negotiation Space: Informative actors of similar capital types feed off one another to create self-fulfilling information cycles that maintain high internal validity. (Wasserman, 2022)

When informative actors of the same capital type collaborate in making decisions, long-term strategic development occurs as domain expertise from each actor leads to sustained growth through self-fulfilling cycles of information exchange that are mostly self-sufficient. One example among technology-driven actors includes voice assistants and natural language processing (NLP), as Forbes technology advisor Bernard Marr (2018) writes:

> [The Amazon Alexa is] only getting stronger as its popularity and the amount of data it gathers increase. Every time Alexa makes a mistake in interpreting your request, that data is used to make the system smarter the next time around. Machine learning is the reason for the rapid improvement in the capabilities of voice-activated user interface.

While this sort of self-sustained development is beneficial for increasing the power of decision-making processes, it can be led awry by skewed data and result in an highly precise but inaccurate decision systems. For this reason, intervention is required by other informative actors to ensure that decisions do not continue to compound over time and decision processes are led back on a self-correcting path. This concept is further explored by March and Olsen (1984), who suggest there are three self-learning cycles pertinent to developing strategies within silos of self-fulling information exchanges while avoiding external stimuli affects: "learning of aspirations affects the definition of subjective success… learning of competencies affects performance outcomes… [and] learning of strategies affects choices" (p. 746). These three learning objectives are key to avoiding bias development in information exchanges where internal validity amongst practitioners can dominate perceptions of best outcomes and lead to poor external generalization.

Knowledge Transfer: Information Exchange between Differing Capital Types of Similar Information Sources

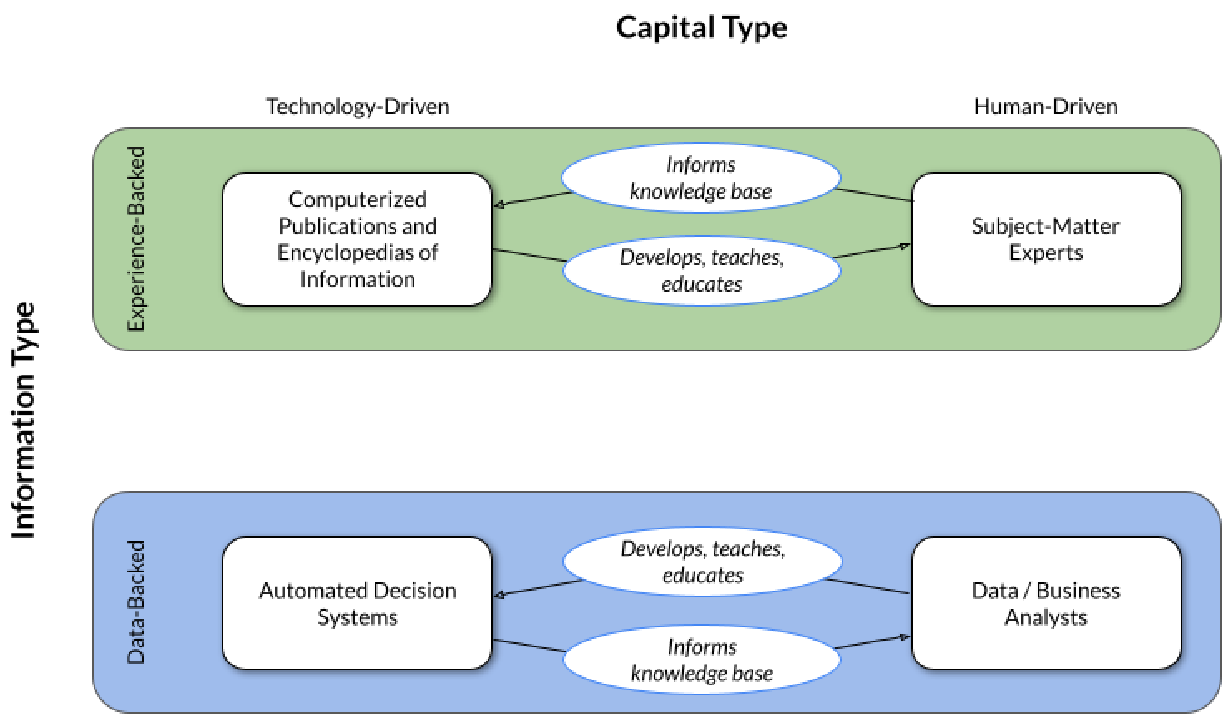

Figure 4: Knowledge Transfer in the Negotiation Space: Informative actors that derive information from the same sources can lead to development for each actor involved. (Wasserman, 2022)

When collaboration occurs between informative actors who derive information from the same sources, highly-specialized knowledge is transferred between such actors, leading to development of institutional knowledge on either end of the interaction. One instance among data-backed informative actors might include a researcher who is developing a machine learning model for predicting housing prices in their hometown. The computer scientist develops and teaches the machine learning algorithms, which then informs the computer scientist of possible solutions. In this negotiation space, the human-driven informative actor directs the technology to carryout specific actions with given specifications and fit criteria, either developing it from the ground up or augmenting it to include more information, such as how a subject-expert might author additional information on a Wikipedia page. In return, the technology-driven informative actor delivers information quickly and efficiently back to the human operator.

This feedback loop provides many opportunities for bias to cloud the dissemination of valid information, either implicitly through interjection by the human operator or perpetuation by a piece of technology. In one instance, a human-driven informative actor maintains some degree of bias that is incorporated into a piece of technology then learned and perpetuated without hesitation, while in another setting, the technology employs skewed data in the creation of biased model that appears unimpaired and delivered such to the subject-matter expert. In either instance, the containment and self-confirmation of discriminatory outcomes is stuck in a recurrent loop of disinformation until mediation occurs to remedy the bias. This concept is raised to a higher degree by decision modeling and data analytics experts Ross and Taylor (2021) who discuss differing levels of human intervention in automated decision systems, which they argue are dependent upon situational context (p. 2). They go on to add that “a fully black box system that was based on proprietary algorithms… [is] unmanageable in practice… An algorithmic decision might be too opaque to pass regulatory scrutiny or to be explained to unhappy customers." Often, the highly-technical work that is developed in this negotiation space is too complex for information recipients who do not have some basis for understanding of the information at-hand, leading to a point of miscommunication where external actors cannot receive information without effective translation nor ascertain what incorrect information looks like and know when to intervene.

Decision Formation: Contextualization and Recommendation between Disparate Actors

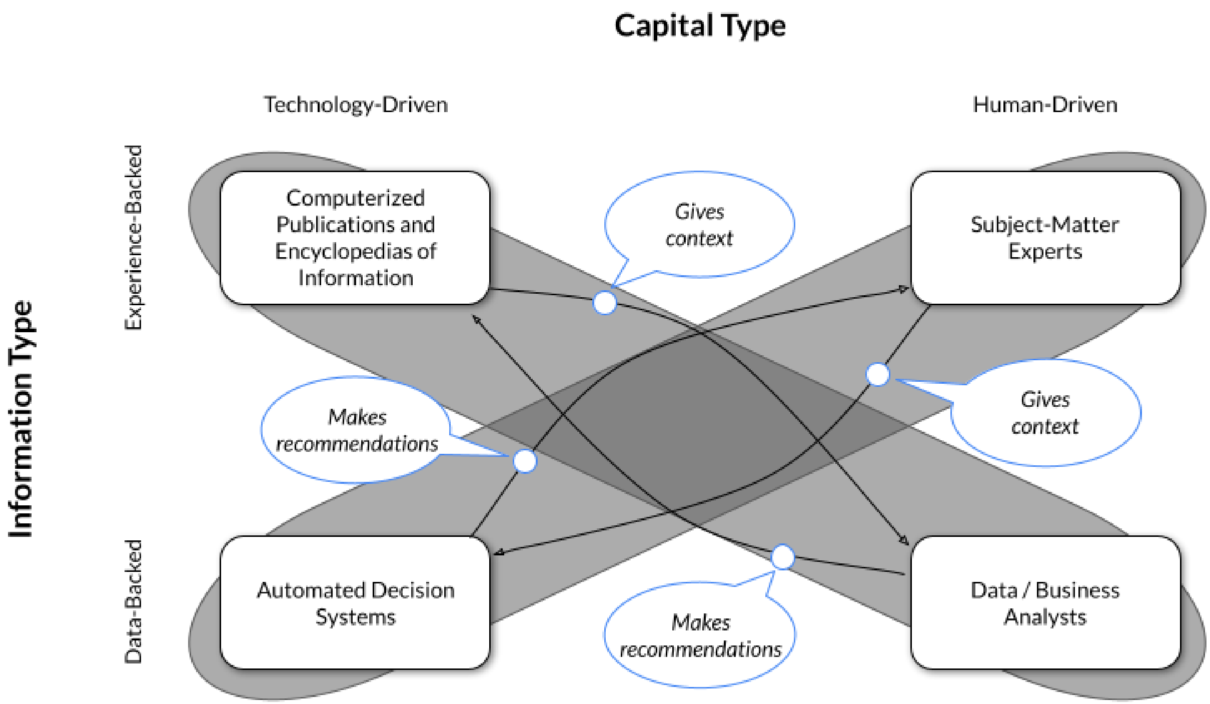

Figure 5: Contextualization and Recommendation in the Negotiation Space: Through interdisciplinary engagement between informative actors, dynamic decisions can be made (Wasserman, 2022)

This final representation of the actor-network showcases cross-disciplinary engagement of informative actors across the spectrum, which leads to decision outcomes that incorporate higher degrees of detail due to the complexity of discourse and involvement between actors. As opposing actors are not best suited to engage tangentially across the network, they must take intermediary steps to better understand and communicate across the network, incorporating at least two other actors within the negotiation space to develop a solution. With more informative actors involved, more information is included in the decision-making process and greater detail is incorporated into the final outcome.

In an article outlining the role of data analysts, Google Chief Data Scientist Cassie Kozyrkov (2018) raises the importance of continuing to engage human opinion and creativity through an analogy of cooking:

> The machine learning engineer is great at tinkering in the kitchen, but right now they're standing in front of a huge, dark warehouse full of potential ingredients. They could either start grabbing them haphazardly and dragging them back to their kitchens, or they could send a sprinter armed with a flashlight through the warehouse first.

Engaging another informative actor with firsthand knowledge on the topic will allow for better understanding and scoping of the problem at-hand, formalizing a decision that incorporates information from a wide variety of disparate sources. Additionally, while bias might be prevalent, its risks are mitigated through effective debate in negotiation space by informative actors that maintain alternative views of the same problem. This is critical in comprehending steps for mitigation that are crucial in resolving bias development of human and non-human actors, namely through algorithmic management and behavioral economics.

TARGETING BIASES THROUGH EMPLOYING ALGORITHMIC MANAGEMENT AND BEHAVIORAL ECONOMICS

As automated decision systems continue to grow in popularity and are adopted into public and private sector roles, implicit biases that come from human and non-human actors must be minimized to reduce the risks that come from poor decision-making and protect society from detrimental outcomes. The proposed actor-network suggests that informative actors in modern decision-making processes can be classified into discrete categories and used in discourse concerning the effects these actors play in disseminating information. The same analysis can be used to propose remediation efforts that target these actors, and more specifically, pursue the biases that come from these actors. This effort considers the separation of informative actors into human and non-human information sources, as outlined in Figure 3, due to the increasing accreditation of algorithmic management and behavioral economics as areas of study appropriate for targeting bias propagation in technology and in people.

Algorithmic management, as defined by Jarrahi et. al (2021) is considered “a sociotechnical process emerging from the continuous interaction of organizational members and the algorithms that mediate their work” (p. 2), inclusive of the seemingly biased decisions that human and non-human informative actors effectuate in search of the most viable solution. One case study for consideration of algorithmic management is the development of CAPTCHA technology, or Completely Automated Public Turing Test To Tell Computers and Humans Apart, particularly in its growth following acquisition by Google in 2009 (Vox, 2021). CAPTCHAs, more commonly known by the simple test given throughout Internet browsing activities that begins by suggesting “I am not a robot,” has undergone three major evolutions since its inception in 2000. The first version, which required users to type strings of characters into a textbox, was found to greatly outperform humans in reading distorted text. A 2014 machine learning study from Google (Goodfellow et. al, 2014) found that humans could decipher garbled text with 33% accuracy whereas the machine could decode the same text with an accuracy rate of 99.8% (p. 8). This simplistic technology follows integral methodologies that Jarrahi and others suggest are key tenets to effective algorithmic management: first, the technology does not greatly interrupt or impede the relationship between managers and workers in accomplishing its own goals, namely by enabling societal use of the Internet and securing sites from bot traffic while developing better neural networks through supervised learning. Second, the technology maintains a formal level of algorithmic competency that allows workers to "understand and interact with the algorithmic systems" in the development of symbiotic relationships (Jarrahi et. al., 2021, p. 6). CAPTCHAs might be aggravating to users, but they are straightforward enough for users to pass through. Finally, the algorithmic systems provide results that reduce aversion and complacency because they are developed by a wide range of users. According to CloudFlare research engineer Thibault Meunier (2021), CAPTCHAs are solved approximately every thirty-two seconds by the world's 4.6 billion Internet users. The distributed array of responses minimize the incorporation of skewed data or biases because many human actors are involved in its development. Algorithmic management provides a framework for technology-based informative actors to be effectively audited by oversight committees and regulators to determine the influence of bias in decision-making processes.

Conversely, behavioral economics provides a playbook for the same regulatory bodies to course-correct behavior from human-based informative actors that does not reflect both precise and accurate decision-making. Behavioral economics advances the concept that humans are rational thinkers with consistent behaviors that are predictable in nature and easily manipulated through a process called nudging (Schrager, 2021). Behavioral economics has become increasingly popular and is known more formally as the basis of esteemed author Michael Lewis' books *Moneyball* and *The Undoing Project*. In his novels, Lewis cites cognitive biases as a barrier to effective decision-making that humans develop over time as they experience more and more surrounding a given topic (Lewis, 2003; Lewis, 2016). Cognitive biases have grown and persisted as fundamental psychological mechanisms for survival throughout human evolution (Santos & Rosati, 2015, p. 4); they are "the shortcuts and rules of thumb by which we make judgements and predictions," states American author Ben Yagoda (2018). These heuristics have aided humans for centuries, but have hindered our ability to be impartial in decision-making. Israeli psychologists Daniel Kahneman and Amos Tversky have demonstrated through their Nobel-winning research that humans make predictable, erroneous judgements when obliged to contemplate ambiguous evidence or challenging decisions (Thaler & Sunstein, 2003). These cognitive biases have recently been challenged through research in behavioral economics, specifically in the field of nudging. Similar to algorithmic management, nudging is "used to help people make better decisions, rather than manipulate them" through "communicat[ing] risk in ways that are more likely to make sense to people," as policy researcher and economist Allison Schrager points out (2021). Risks are often presented in as probabilities and complex numbers that the layman may not directly understand, suggests mathematics professor John Allen Paulos in his novel *Innumeracy*. Paulos (1988) continues by arguing that organizations looking to more effectively present data on dangerous topics to society should endeavor to understand how people look at data and adopt more intuitive methods for communicating and sharing information (p. 100-102). Through incremental change that incorporates behavioral economics as well as algorithmic management, public and private organizations can establish effective decision-making systems that lessen the risks of bias by targeting the sources they derive from.

FUTURE CONSIDERATIONS FOR STS ANALYSIS OF BIAS IN DECISION-MAKING

Algorithmic management and behavioral economics are emerging fields and continue to make developments every day; their suggestion as solutions for mitigating the effect of bias in automated decision systems and decision-making processes at-large should continue to be re-evaluated as the fields continue to grow. Further research in the area of mitigating implicit stakeholder bias in complex decision systems should continue to evolve as the developments in these respective fields evolve. One such milestone might include such a time when federal

Congressional bodies are able to pass holistic legislation on data management and consumer privacy in the United States, or at such a time when behavioral economics delivers new insights as a field of practice; many mainstream practitioners, such as Walmart's Global Head of Behavioral Science Jason Hreha, have suggested that behavioral economics does not satisfy the promises it suggests (Schrager, 2021), necessitating further research and development in the field. The use of automated decision systems will continue to integrate further and further into modern decision-making processes, and research on this topic should continue to be conducted as new innovations in and deployments of autonomous technologies are announced, to ensure that these technologies deliver fair and impartial decisions to people affected around the globe.

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