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Understanding the Effect that Task Complexity has on Automation Potential and Opacity: Implications for Algorithmic Fairness

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Abstract:

Scholars have increasingly focused on understanding different aspects of algorithms since they not only affect individual choices and decisions but also influence and shape societal structures. We can broadly categorize scholarly work on algorithms along the dimensions of economic gain that one achieves through automation and the ethical concerns that stem from such automation. However, the literature largely uses the notion of algorithms in a generic way and overlooks different algorithms' specificity and the type of tasks that they perform. Drawing on a typology of tasks based on task complexity, we suggest that variations in the complexity of tasks contribute to differences in 1) their automation potential and 2) the opacity that results from their automation. We also suggest a framework to assess the likelihood that fairness concerns will emanate from automation of tasks with varying complexity. In this framework, we also recommend affordances for addressing fairness concerns that one may design into systems that automate different types of tasks.

Keywords: Algorithm, Automation, Opacity, Fairness, Task Complexity.

Lionel Robert was the accepting senior editor for this paper.

1 Introduction

Algorithmic retrieval, classification, ranking, and information ordering (Greenfield, 2006; Kitchin, 2017; Kitchin & Dodge, 2011; Manovich, 2013; Polynczuk-Alenius, 2019; Steiner, 2012) not only impact individual choices and decisions (Graham & Henman, 2019) but also influence and shape societal structures (Danaher et al., 2017). As a result, researchers have increasingly begun to focus on understanding algorithms' different aspects¹ (Ananny, 2016; Crawford, 2016; Dwivedi et al., 2019; Introna, 2016; Robert, Bansal, Melville, & Stafford, 2020b).

We can broadly categorize scholarly work on algorithms along the dimensions of economic gain that one achieves through automation and the ethical concerns that stem from such automation (Pasquale, 2015). The economic perspective highlights the efficiency gains that result from reduction in errors that arise due to human judgment and bias (Meadow & Sunstein, 2001) when one employs algorithms for tasks such as searching, classifying, retrieving, ranking, and sorting. These efficiency gains, along with the tirelessness associated with algorithmic work, lead to consequent increases in throughput and work productivity² (Brynjolfsson & McAfee, 2016; Ford, 2015; Meadow & Sunstein, 2001). However, recent research also suggests that not all automation endeavors yield equally encouraging results (Davenport & Ronanki, 2018) and that differences in automation potential—the extent to which a machine (or a computer or algorithm) can carry out the functions that a human agent performed earlier (Parasuraman, Sheridan, & Wickens, 2000)—might exist for different tasks.

The ethical perspective in research on algorithmic automation focuses on concerns that arise from algorithmic automation (Shin, Zhong, & Biocca, 2020). Some concerns include biases in decisions that algorithms make (Introna & Nissenbaum, 2000), discriminatory outcomes (Gillespie, 2017), fairness concerns (Dwork, Hardt, Pitassi, Reingold, & Zemel, 2011), surveillance (Introna & Wood, 2004; Zuboff, 2018) and accountability concerns (Felten, 2012). Research in this stream also argues that algorithms that profit-oriented enterprises control constitute “black boxes” (Hoffmann, 2019; Park & Humphry, 2019; Poon, 2016). Indeed, we can see that many concerns that this research has stream has raised emerge from algorithms' inscrutability (Ziewitz, 2016) due to the opaque manner in which they work (Burrell, 2016). Algorithmic opacity can amplify existing discriminations and inequalities in society and, thereby, raise fairness concerns (Carter, Liu, & Cantrell, 2020; Massanari, 2017; Matamoros-Fernández, 2017; Pasquale, 2015; Thorson, Cotter, Medeiros, & Pak, 2019). Furthermore, as algorithms' opacity increases, it becomes difficult to explain algorithmic outcomes, which in turn, reduces algorithmic accountability (Pasquale, 2015).

These two streams have developed rather individually, and few studies have focused on integrating them (as an exception, see Zarsky, 2016). However, studies in both streams have a common problem: they adopt a generic notion of algorithms. As a result, they have largely ignored different algorithms' specificity and the typical tasks that they perform. Recent work has corroborated this argument by suggesting that artificial intelligence (AI) replaces individuals in jobs fundamentally at the task level rather than at the job level (Arntz, Gregory, & Zierahn, 2017; Huang & Rust, 2018). In this paper, we confirm to the position that the task constitutes as an important characteristic to consider when evaluating algorithmic automation's effects. Put more precisely, in response to the calls to contextualize the factors that influence algorithmic transparency and explainability (Robert, Bansal, & Lütge, 2020a), we argue that a task's nature affects its automation potential and how much opacity arises due to such automation. Therefore, in this study, we focus on understanding 1) different types of tasks' automation potential and 2) the fairness concerns that arise from automation-induced opacity.

We use task complexity (Campbell, 1988; Wood, 1986) as our theoretical foundation to develop a framework. Campbell (1988) categorized tasks into five broad types based on their complexity: 1) simple tasks, 2) problem tasks, 3) decision tasks, 4) judgment tasks, and 5) fuzzy tasks. We show that the variation in automation potential and opacity that arises due to automation associated with these five task types spans the task complexity spectrum. By using task complexity to understand automation potential and opacity

¹ We observe increasing attention on “algorithms” as a scholarly topic in many academic journals, such as from recent calls for special issues on the governing algorithms in *Science Technology and Human Values* in 2015, social power of algorithms in *Information, Communication and Society* in 2017, and so on.

² Such automation examples include manufacturing automation (Groover, 2008), network management automation (Hämäläinen, Sanneck, & Sartori, 2012), stock exchange automation (Naidu & Rozeff, 1994), audit automation (Coderre, 2013), robotic process automation (van der Aalst, Bichler, & Heinzl, 2018), healthcare automation (Galetsi, Katsaliaki, & Kumar, 2020), predictive policing (Hassan et al., 2019; Mantello, 2016)

associated with algorithms, we make three specific contributions to the literature. First, we synthesize research streams that address algorithmic automation and opacity to holistically explain how task complexity affects automation potential and how the associated opaqueness gives rise to fairness concerns. Using this typology, we clarify why AI is associated with higher fairness concerns. Second, using task complexity to understand opacity, we explicate why different task types differ in the likelihood that they will cause fairness concerns. We also delineate fairness across two dimensions—distributive and procedural (Ambrose & Arnaud, 2005; Greenberg & Colquitt, 2013)—and argue that, while some tasks will likely exhibit a greater propensity for distributive fairness concerns, other tasks will likely exhibit a greater propensity for procedural fairness concerns. Third, we provide recommendations to individuals who design algorithmic automation and AI systems about how they can address fairness concerns associated with different task types. We propose that algorithms that automate tasks that differ in complexity require different types of affordances in situations where one needs to address fairness concerns that arise from automation.

This paper proceeds as follows: in Section 2, we briefly describe the literature on algorithmic automation, present algorithmic concerns around fairness, and summarize theoretical knowledge of task complexity. In Section 3, we conceptualize a framework to assess algorithms along two dimensions—automation potential and opacity—while accounting for different levels of task complexity. In Section 4, we discuss the implications that arise when conceptualizing algorithmic automation and AI for research and practice in a task-based manner. In Section 5, we conclude the paper.

2 Theoretical Background

In the 19th century, industrial automation rested on the principle of simplifying a task by breaking it into smaller, highly specialized sequences at the expense of workers' skills; as a result, researchers referred to these technologies as deskilling technologies (Frey & Osborne, 2017, p. 256). These technologies shifted work from artisan shops to factory shop floors where an individual carried out the same repetitive task rather than perform the numerous complex tasks that an individual typically performed in the artisan shop. In turn, recent advancements in computing technology have made it possible to outsource some of these repetitive tasks to algorithms. We define algorithms as “a sequence of unambiguous instructions for solving a problem, that is, for obtaining a required output for any legitimate input in a finite amount of time” (Levitin, 2012). Not only have algorithms become a means for supporting automation and improving productivity, but, with further advancements in computing technology, their capability to perform repetitive tasks has exponentially increased (Ford, 2015). As a result, automation has achieved a scale not previously apprehended (Brynjolfsson & McAfee, 2016). Consequently, automation has moved beyond routine jobs that followed well-defined repetitive procedures as with manufacturing jobs in the 19th century (Acemoglu & Autor, 2011) to potentially include complicated tasks that many considered to necessarily require human involvement, such as driving a car (Frey & Osborne, 2017). The term artificial intelligence (AI) refers to machines (or computers or algorithms) that can perform such tasks; that is, complex tasks that involve cognition, perception, and action (Heer, 2019).

The literature on algorithms in general and AI in particular has broadly explored two dimensions: 1) automation and the efficiency gains that algorithmic automation can produce (Shneiderman, 2020) and 2) ethical concerns that arise due to algorithmic automation (Pasquale, 2015). We briefly discuss these two literature streams in Sections 2.1 and 2.2.

2.1 Algorithms and Automation

Research on the efficiency of algorithms has suggested that algorithms result in higher efficiency in routine personal and professional settings. This research has argued that process automation, achieved through “technology that actively selects data, transforms information, makes decisions, or controls processes” (Lee & See, 2004, p. 50), increases processes' efficiency by reducing errors, working tirelessly, and performing tasks at a faster rate than humans (Hoff & Bashir, 2015; Wajcman, 2019).

As algorithms have slowly entered spaces that human decision making initially dominated, they have augmented human capabilities (Heer, 2019; Jordan, 2019; Li, 2018). However, some researchers have argued that AI will not completely replace humans (Heer, 2019) as we can fully automate only a small percentage of jobs by adapting current technologies. Nonetheless, almost all jobs have some activities or tasks that one could potentially automate (Manyika, 2017). Scholars have suggested that researchers should focus on the task rather than the job to understand which job aspects algorithms could automate

and perform (Arntz et al., 2017). They have further argued that focusing on jobs rather than tasks has led some researchers to seriously overestimate automation's risks.

In a similar vein, Parasuraman et al. (2000) posited that the level of automation in tasks varies along a continuum from completely manual to completely automated decision making. They outlined a 10-level scale for automation level based on whether humans or algorithms control decisions. At lower scale levels (i.e., levels 1 to 5), human control dominates tasks, while the algorithm dominates at higher levels³. Though this framework helps one understand tasks' automation level, it does not explain tasks' complexity and consequent implications. Instead, it focuses mainly on the automation of four broad function classes in human-machine systems: 1) information gathering, 2) information analysis, 3) decision, 4) and action. For example, sensors that automatically collect environmental information or smart electricity meters that automatically compute electricity bills exemplify systems that automate the functions of information gathering and analysis, respectively. However, variations in the permutations and combinations of these functions may make different tasks vary in complexity. In this research, we examine how the complexity associated with a particular task affects its automation potential, an aspect that the literature has not yet adequately explored.

2.2 Algorithms and Fairness

The second literature stream on algorithmic automation has discussed algorithms' wider implications for individual, social, and cultural life (Beer, 2009; Greenfield, 2006; Kitchin, 2017; Kitchin & Dodge, 2011; Manovich, 2013; Polynczuk-Alenius, 2019; Steiner, 2012). For example, researchers have discussed subjects such as "politics of algorithms" (Ziewitz, 2016), "ethicality of algorithms" (Zarsky, 2016), and so on. Scholars in this stream have raised wide-ranging concerns with algorithmic automation, such as surveillance (Introna & Wood, 2004; Zuboff, 2018), accountability (Felten, 2012), and fairness (Dwork et al., 2011). Fairness concerns include those associated with bias (Introna & Nissenbaum, 2000), discrimination (Gillespie, 2017), and transparency (Burrell, 2016). Owing to their black boxed (Pasquale, 2015; van Couvering, 2007) and self-learning nature, researchers have referred to algorithms as inscrutable entities that produce unexpected social influences and outcomes, such as constraints on individual autonomy (Executive Office of the President, 2014; Ziewitz, 2016).

Consider the advanced algorithms that many organizations use to automate their recruitment processes. Through sophisticated mechanisms, these algorithms learn how to identify good candidates using internal organizational databases about performance metrics, tenure records, current and previous employee turnover rates, and sometimes even external information from sources such as social media platforms. By automatically screening applications and providing a shortlist of candidates fit for the job without any human-induced bias, these algorithms can save recruiters' time and money. However, these algorithms' elaborate and complex inner mechanisms often remain unknown, which makes it impossible to ascertain whether they use fair and ethical recruitment practices. Similarly, most algorithms' governance, outcomes, and social influence will likely become a cause of concern (Beer, 2017; Mittelstadt, Allo, Taddeo, Wachter, & Floridi, 2016) due to the complexity associated with these "powerful entities that govern, judge, sort, regulate, classify, influence or otherwise the world" (Barocas, Hood, & Ziewitz, 2013).

Ethical and fairness related issues that arise due to algorithmic task automation have led to an increased interest and discussion among information systems (IS), computer science, law, management, and public policy scholars (Jarrahi, 2018; Robert, Pierce, Marquis, Kim, & Alahmad, 2020c; Veale, van Kleek, & Binns, 2018; Vellido, 2019; Wang & Siau, 2018). However, the literature that has analyzed algorithmic fairness has proposed two opposing arguments. On the one hand, some scholars have argued that algorithmic automation can increase fairness by eliminating human biases (Zarsky, 2016, p. 123). For example, unlike a banker, an algorithm may never offer a loan at a cheaper rate to an individual with higher social capital. On the other hand, other scholars have argued that algorithmic automation and AI can cause greater concerns about fair algorithmic outcomes compared to when humans perform tasks (Martin, 2019; Mateeu & Nguyen, 2019).

³ For example: at level 4, the machine suggests alternative decisions, but the human retains the authority to accept the suggestion or choose an entirely new decision. At higher levels (i.e., levels 6 to 10), algorithmic control dominates the task, and, with each increase in level, the algorithm provides less and less feedback. For example, at level 6, the machine gives a limited amount of time for the operator to veto the decision, and, at level 9, it only informs the operator if it *feels* the need to inform.

Scholars have generally grounded their discussion fairness on two fundamental legal doctrines: distributive fairness and procedural fairness (Ambrose & Arnaud, 2005; Barocas, Hardt, & Narayanan, 2020; Robert et al., 2020c). Distributive fairness deals with fairness associated with allocating outcomes (Alexander & Ruderman, 1987). For example, an organization may ensure distributive fairness via providing the same pay for the same work. A central discussion on gender discrimination concerns distributive fairness as women tend to receive usually significantly less pay than men for the same work (Bishop, 2018). An algorithm that automates performance appraisal in a company might consider women on maternity leave as lower performers compared to men for a given work period, which may, in turn, lead to concerns about distributive fairness if such women receive lower or no pay hikes in comparison to their counterparts. The literature on AI and algorithms has discussed distributive fairness more than other types of fairness and focused mainly on making algorithms select and allocate organizational resources fairly (Robert et al., 2020c). Organizations have primarily achieved fairly distributed outcomes with algorithms via computational models that operationalize equality based on mathematic functions or legal principles (Glymour & Herington, 2019; Madras, Creager, Pitassi, & Zemel, 2019).

Procedural fairness deals with disparate treatment. It focuses on the procedure one employs to reach or decide an outcome rather than the outcome itself. For example, an algorithm that automated performance evaluation through standard KPIs might ignore informal but significant work that managers would otherwise recognize and, thus, create procedural fairness concerns. Research on procedural fairness has focused on automating existing procedures through algorithms rather than employing algorithms to create new procedures and processes. This research has proposed consistency and transparency as two means to achieve procedural fairness⁴ (Brown, Chouldechova, Putnam-Hornstein, Tobin, & Vaithianathan, 2019; Grgić-Hlača, Zafar, Gummadi, & Weller, 2018; Robert et al., 2020c). In other words, algorithms should produce the same output and follow the same procedure every time, and they should follow procedures in a transparent manner.

Achieving fairness through transparency rests on the logic that the more one knows an algorithm's inner workings, the easier it will be to attach accountability to it (Ananny & Crawford, 2018; Martin, 2019). It assumes that, once one reveals an algorithm's inner workings (Christensen & Cheney, 2015, p. 74) to an audience, the audience can not only comprehend the workings but also suggest necessary corrections to them (MacKenzie, 2008; Martin, 2019). However, complexity associated with many algorithms that influence personal and professional life⁵ often make them incomprehensible to humans, which raises concerns about algorithmic accountability. Some scholars have argued that, in the case of algorithms and AI, achieving full transparency may be inadequate, undesirable, and infeasible (Ghani, 2016; Martin, 2019). Furthermore, even though calls for algorithmic transparency have risen (Rader, Cotter, & Cho, 2018; Shin & Park, 2019), one cannot easily make algorithms transparent (Burrell, 2016).

Building on this literature on algorithmic opacity to include algorithms' characteristics and the data scales that algorithms handle, Burrell (2016) argued that contemporary algorithms suffer from the "curse of dimensionality" (Domingos, 2012) and suggested that algorithms—specifically those that deal with big data and AI, are inherently opaque for three broad reasons (see Table 1). First, an organization may protect its algorithms as proprietary information. Second, the difficulty associated with understanding a computer program even if it is open for scrutiny may render it to opaque to technically illiterate individuals. Third, algorithms' characteristics and the data scales that algorithms handle will inevitably make algorithms opaque because the high dimensional optimization conflicts with the scale at which humans reason and interpret semantic information (Burrell 2016)⁶. To optimize the rate at which algorithms consume resources in the presence of multi-dimensionality and address the curse of dimensionality, one often has to use dimensional reduction techniques such as principal component analysis, which may add further to algorithms' opacity. Burrell (2016) suggested that changes in algorithms' logic during their learning phase exacerbate this

⁴ Recent research in algorithmic design has also suggested addressing fairness issues by 1) excluding protected attributes such as race, gender, ethnicity, and their proxies for decision making (Bonchi, Hajian, Mishra, & Ramazzotti, 2017) and 2) training algorithms to ensure that their predictive performance stays the same across groups (Agarwal, Beygelzimer, Dudík, Langford, & Wallach, 2018). However, some studies have argued that such algorithmic designs do not guarantee fair decisions and may instead harm the very groups that they aim to protect (Corbett-Davies & Goel, 2018).

⁵ The algorithms that Google's search engine and Facebook's news feed use have time and again received criticisms (Aswani, Kar, Ilavarasan, & Dwivedi, 2018). For example, in reacting to a Facebook data leak, *The Economist* (2018) has said: "Facebook needs a full, independent examination of its approach to content, privacy, and data... Facebook and other tech firms need to open up [their algorithms] to outsiders, safely and methodically".

⁶ Some scholars have argued that some organizations intentionally make their algorithms opaque to avoid scrutiny and accountability (Martin, 2017; Pasquale, 2015; Burrell, 2016).

opacity. Thus, even if technically literate individuals can initially comprehend a dataset and program's internal logic, the interplay between the two might eventually make the algorithm opaque to these individuals.

The three forms of opacity suggest that different algorithms vary in their opacity and that the extent to which they vary may depend on the task that one uses them for. Consequently, we need to understand how that variation in opacity affects fairness concerns that arise when algorithms automate different tasks. However, the extant literature has not examined opacity associated with algorithmic automation in a task-based manner, which makes it difficult to explicate why algorithms that automate different tasks differ in the fairness concerns they raise. Even though the literature has highlighted that we need to understand AI technologies in a task-based manner to understand why users adopt these technologies (Rzepka & Berger, 2018), researchers have yet to address the issue. We believe that understanding algorithmic automation based on task complexity (Campbell, 1988) can help explain the differential opacity and fairness concerns associated with different kinds of automated tasks. In Table 1, we define the main concepts associated with fairness and opacity that we use in this paper.

Table 1. Fairness and Opacity Types

Concept		Definition	Reference
Fairness	Distributive	The disparate impact: focuses on avoidable or unjustified harm and minimizing differences in outcomes.	Ambrose & Arnaud (2005), Robert et al. (2020)
	Procedural	The disparate treatment: focuses on the procedure one employs to reach or decide an outcome rather than the outcome itself.	
Opacity	First source	Opacity that results from intentional corporate or state secrecy	Burrell (2016)
	Second source	Opacity due to the need for specialized technical literacy	
	Third source	Opacity that arises from the high dimensional optimization that algorithms perform that conflicts with human-scale reasoning	

2.3 Task Complexity

Researchers have long argued that advancements in information technology would have a “considerable effect in [the] office” (Levin, 1956, p. 61) and that it would “suppress most fragmentary and repetitive jobs” (Friedmann, 1992, p. 114) through automation. Consequently, they began to develop models to understand how automation would affect office jobs (Frey & Osborne, 2017; Koorn, Leopold, & Reijers, 2018; Parasuraman et al., 2000; Traumer, Oeste-Reiß, & Leimeister, 2018). While Frey and Osborne (2013) used jobs as the unit of analysis for automation, Arntz et al. (2017) argued that using jobs as a unit of analysis is too coarse grained and rather suggest “task” as an appropriate unit of analysis for studying automation

Early task-automation models simply classified tasks as routine and non-routine (Autor, Levy, & Murnane, 2003). Over time, researchers extended this classification to include further categories such as cognitive, analytical, and interactional tasks (Koorn et al., 2018; Spitz-Oener, 2006). However, most of these frameworks do not clearly specify what constitutes a task and what distinguishes one task type from another. As a result, they fall short in answering why certain tasks are more complex than others.

However, research on task characteristics from the organization studies discipline provides theoretical approaches to understand the concept of task and differences between tasks. These approaches include understanding 1) tasks as a pattern of stimuli that one imposes on individuals (task qua task), 2) tasks as behavioral responses that a person emits in order to achieve a specific performance level, 3) tasks as behavior description that a task performer provides, and 4) tasks based on the abilities that one requires to perform that task (Hackman, 1969; McGrath & Altman, 1966). Wood (1986) argued that one can better analyze and operationalize tasks theoretically via combining “behavior as requirements” and “task qua task”⁷.

Campbell (1988) adopted the basic framework that Wood (1986) adopted and suggested a typology of complex tasks via refining the notion of task attributes. He argued that an increase in information load,

⁷ Wood (1986) used the postulates products, acts, and information cues to define tasks. While products refer to a task's measurable outputs (Naylor, Pritchard, & Ilgen, 1980), acts refer to the means to achieve those outputs. Information cues refer to pieces of information about a task that assist an individual in making decisions when performing it.

information diversity, or rate at which information changes can contribute to a task's complexity. These factors can vary owing to four different complexity sources:

- 1) Multiple potential paths to achieving the desired outcome: as the number of paths to reach the outcome increase, the amount of information that one needs to process increases, which, in turn, increases the task's complexity.
- 2) Multiple possible outcomes: as the number of outcomes increases, one needs to process information related to all possible outcomes, which, in turn, increases the task's complexity.
- 3) Conflicting interdependence among paths to outcomes: the outcomes that arise from one desired outcome might negatively influence other desired outcomes (e.g., a focus on quality might decrease how much one produces). In this manner, conflicting paths increase the task's complexity).
- 4) Uncertain or probabilistic links between the paths and outcomes: the amount of information that one needs to process will substantially increase in this case, which will cause an increase in task complexity.

Based on the different possible combinations between these sources (16 to be specific)—that is, whether multiple paths, multiple outcomes, conflicting paths, and uncertainty/probabilistic linkages exist or not—Campbell (1988) proposed a typology of five different tasks that we show in Table 2 (we describe the task types in Section 3).

Though many research papers have adopted (Hærem, Pentland, & Miller, 2015; Liu & Li, 2012; Zigurs & Buckland, 1998) the notion of task complexity that Wood (1986) and Campbell (1988) proposed, few papers have advanced the classification's core ideas⁸. We adopt the original notion of task complexity since it provides a suitable framework to understand the variations in the automation potential and opacity concerns associated with different tasks.

Table 2. Task Complexity Typology (Adapted from Campbell, 1988; Zigurs & Buckland, 1998)

Task type	Complexity source				Examples
	Multiple paths	Multiple outcomes	Conflicting interdependence among paths	Uncertain or probabilistic linkages	
Simple tasks	No	No	No	Not applicable	Coin sorting and finding the maximum number
Problem tasks	Yes	No	Yes or no	Low to high	Chess problems and personnel scheduling
Decision tasks	NR	Yes	Yes or no	Low to high	Employee selection and choosing a house
Judgment tasks	NR	NR*	Yes or no	Low to high	Intelligence analysis and stock market analysis
Fuzzy tasks	Yes	Yes	Yes or no	Low to high	Business ventures

Note: NR means not relevant.

3 Algorithms and Task Complexity

In this section, we describe each task type's complexity sources based on Campbell's (1988) typology and discuss each task type with respect to its automation potential and opacity induced due to its automation. We expect this discussion to contribute to the debate surrounding tasks' automation potential and their associated fairness concerns.

3.1 Simple Tasks

A simple task refers to a task that has a clearly defined path to achieve a single desired outcome. We represent a simple task in Figure 1 where the circle labeled "S" represents the first state, the circle labeled "I" represents an intermediate state, the arrows represent the path, and the doughnut labeled "E" represents

⁸ In a recent work, Hærem et al. (2015) extend the concept of task complexity to group activities.

the end state or the desired outcome. As the number of intermediate steps required to achieve the desired outcome increases, the task's complexity also increases.

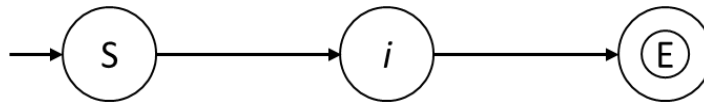


Figure 1. A Simple Task

Since simple tasks have a clearly defined path for achieving their outcome, they have a highly standardized and programmable nature. One can easily formalize them and easily question the outcome of algorithms that perform them. For instance, banking institutions in India used to calculate interest for savings bank accounts semi-annually until late 2010. Bankers used to derive/calculate the interest manually using interest charts and the lowest monthly balance available in the account between the tenth and the last day of the month. With advancements in technology and automation, banking institutions in India now calculate interest based on the available daily balance. While customers and bank officials may lose knowledge about how to compute interest over time due to automation such that the formula for finding interest becomes black boxed, bank officials can nonetheless open up the black boxed formula for inquiry and demonstrate it to consumers in case they suspect computational error. Opacity for a simple task such as this one may at most arise from Burrell's (2016) first opacity source (i.e., corporate or state secrecy). Therefore, we argue that simple tasks have the highest potential for automation and the lowest opacity⁹.

3.2 Problem Tasks

Problem tasks are more complex than a simple task because they involve multiple paths that achieve the same outcome. We represent a problem task in Figure 2 where the circle labeled "S" represents the first state, the doughnut labeled "E" represents the desired outcome, the circle labeled "i" represents an intermediate state in one path to the outcome, and the circles labeled "j" and "k" represent intermediate states in another path to the outcome. The complexity in a problem task arises from the need to evaluate all the paths and then choose the most efficient one. In addition, not all paths may reach the end desired state. An example problem task includes the classic travelling salesman problem, which focuses on determining the least possible distance a salesman needs to travel to visit all cities on a list.

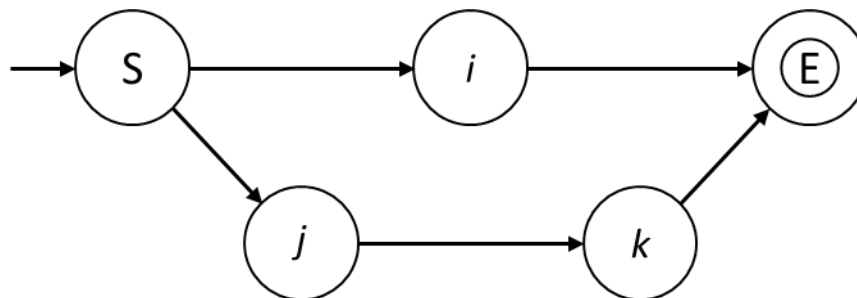


Figure 2. A Problem Task

Unlike the simple task (e.g., to calculate interest) where a single procedure (formula) to calculate the outcome (interest regardless of the account holder's identity) exists, for a problem task such as the travelling salesman problem, multiple ways (algorithms) to find the shortest route and various shortest routes from the source to the destination might exist. Therefore, one cannot straightforwardly find the best possible route in the best possible way as in simple tasks. Nonetheless, one can still represent a problem task as a mathematical/analytical/heuristic model amenable to standardization and automation even though one may not find the exact solution to the model in real time.

⁹ Though automation might induce automation potential and opacity to a different degree for specific tasks that belong to a particular task type (category), we lack the scope to explicate these differences in our framework.

Hence, we consider problem tasks as having slightly lower automation potential than simple tasks (maybe at level 8 or 9). We can also consider problem tasks as more opaque than simple tasks. In addition to the possibility that opacity can stem from Burrell's (2016) first source (i.e., corporate secrecy), opacity for problem tasks primarily arises from the second source (i.e., the need for specialized technical literacy). However, one can still open up algorithms that perform problem tasks and make them understandable with a little technical literacy. Hence, we consider them as having low opacity though slightly more than simple tasks.

3.3 Decision Tasks

Decision tasks involve multiple possible outcomes. To complete these tasks, one needs to choose the most desirable alternative (that optimizes or maximizes utility) among many available alternatives, which often involves trade-offs along multiple dimensions. We represent a decision task in Figure 3 where the circle labeled "S" represents the starting state, the circle labeled "i" represents an intermediate state, and the doughnuts labeled "E1" to "E6" represent multiple possible outcomes. At the intermediate state "i", a decision point, one needs to make a choice between states E1 and E2. One may achieve E1 or E2 as the eventual outcome, or the path that one chooses afterwards may further lead to another end states (i.e., E3, E4, E5, or E6).

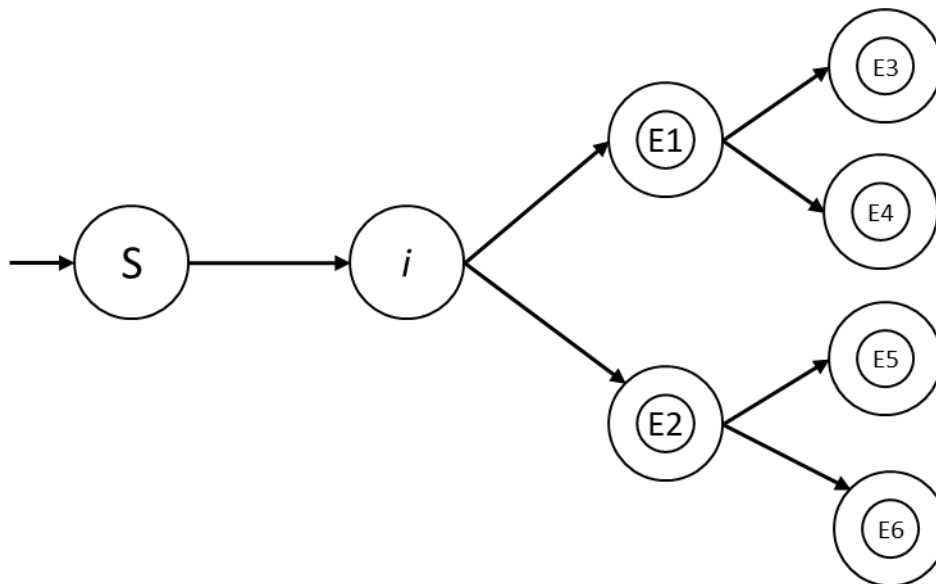


Figure 3. A Decision Task

Each outcome among the multiple possible outcomes for a decision task may need a different information stream, though one may lack clear or the necessary information to complete the task. A lack of clear or necessary information may contribute to the task's complexity but still keep it amenable to automation. Different decision tasks may also increase in complexity when uncertainty or conflicting interdependence among outcomes exists (Campbell, 1988, p. 47). Conflicting interdependencies and uncertainty may also require high dimensional optimization, which conflicts with the scale at which humans reason and interpret semantic information (Burrell, 2016). A recommender system that a websites uses exemplifies a decision task. A recommender system suggests content to an individual user based on the user's consumption pattern and the similarity between the user and other users. To make such complex (though often standardized) recommendations, an algorithm requires a large volume of information, which further contributes to the task's complexity. Further still, conflicting interdependencies—where one recommendation precludes the recommender system from showing other recommendations—exacerbates this complexity. Corporate secrecy associated with the algorithms used, technical illiteracy to understand the complex computations, and the high dimensional optimization involved definitely contribute to the opacity of automated decision tasks. Accordingly, we consider decision tasks to have lower automation potential compared to simple and problem tasks due to their higher complexity. Similarly, we consider them to have higher opacity compared to simple and problem tasks due to their need for high dimensional optimization, the need for technical literacy to understand the complex algorithms that conduct them, and corporate secrecy.

3.4 Judgment Tasks

A judgment task requires one to integrate and process information from diverse sources to subsequently make a judgment about the likelihood that a future event will occur (Campbell, 1988). The information itself is usually uncertain, contradictory, historical, and, in many situations, insufficient to predict the future, which contributes to the task's complexity. As a result, uncertain linkages between the task's intermediate steps emerge. The notions of multiple paths and multiple desired outcomes do not apply to judgment tasks (Campbell, 1988). We represent a basic judgment task in Figure 4 where the circle labeled "S" represents the starting state, the circles labeled "i" and "j" represent intermediate states, and the doughnut labeled "E" represents the end state. In this case, the path between state j and the end state remains uncertain, which the dotted line represents.

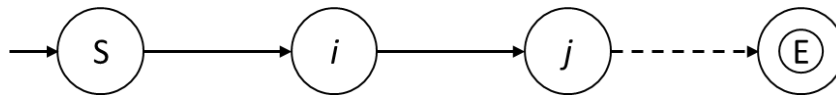


Figure 4. A Judgment Task

The large amount of information that one requires to make predictions/judgments contributes to judgment tasks' complexity, which makes machine learning (ML) algorithms the preferred agents for these tasks as opposed to humans. Furthermore, bounded rationality and inherent human biases do not constrain these algorithms (Meadow & Sunstein, 2001). However, judgment tasks also have significant risk (of making/not making the correct judgment) due to which one cannot automate all judgment tasks. This risk explains why automation in judgment tasks range from highly automated in some tasks to a human-machine partnership in others. ML algorithms' dynamic nature coupled with the informational uncertainties involved in judgment tasks make such tasks more opaque compared to simple and problem tasks with the opacity arising due to technical illiteracy, high dimensional optimization, and corporate secrecy in most cases (Burrell, 2016).

For instance, consider high-frequency trading (HFT) and credit appraisal. In HFT, a form of automatic trading, an algorithm processes information from diverse, historic, and often uncertain sources and learns to make high volumes of profitable trade judgments at very high speed (in fraction of seconds) while minimizing risk. Credit appraisal requires one to decide whether to extend a loan by computing the probability that an application will default by using information on an applicant's demographics, credit history, past financial behavior. Complexity arises due to uncertainty with respect to different information types' (variables) relevance to and importance in (weights) predicting a future default. Since both these judgment tasks involve processing highly uncertain information to arrive at a judgment, they have lower automation potential than simple, problem, and decision tasks. Further, these judgment tasks have higher opacity than simple, problem, and decision tasks since they may encounter opacity from all three opacity sources (Burrell, 2016). However, the two examples we discuss (HFT and credit lending) both differ in their social embeddedness and the extent to which the judgment will affect society. A human-machine partnership is the more desirable option for many judgment tasks, such as credit lending and decisions about whether to grant or deny someone bail, due to their higher social embeddedness.

3.5 Fuzzy Tasks

Fuzzy tasks have many desired outcomes and multiple (often uncertain and/or conflicting) paths to achieve them. We represent a fuzzy task in Figure 5 where the circle labeled "S" represents the starting state, the circles labeled "i", "j", and "k" represent intermediate states, and the doughnuts labeled "E1" to "E6" represent multiple outcomes or ending states. Fuzzy tasks require information that pertains to all paths and

to all possible permutations and path combinations that lead to all possible outcomes so that one can identify the outcome with the maximum benefit. Compared to simple, problem, decision, and judgment tasks, fuzzy tasks have the highest complexity since they demand that one processes information from multiple sources through multiple permutations and combinations to arrive at the optimal choice. The information that one needs to process may come in many (both structured and unstructured) forms and from varied sources. The complexity increases further when uncertain or conflicting paths exist.

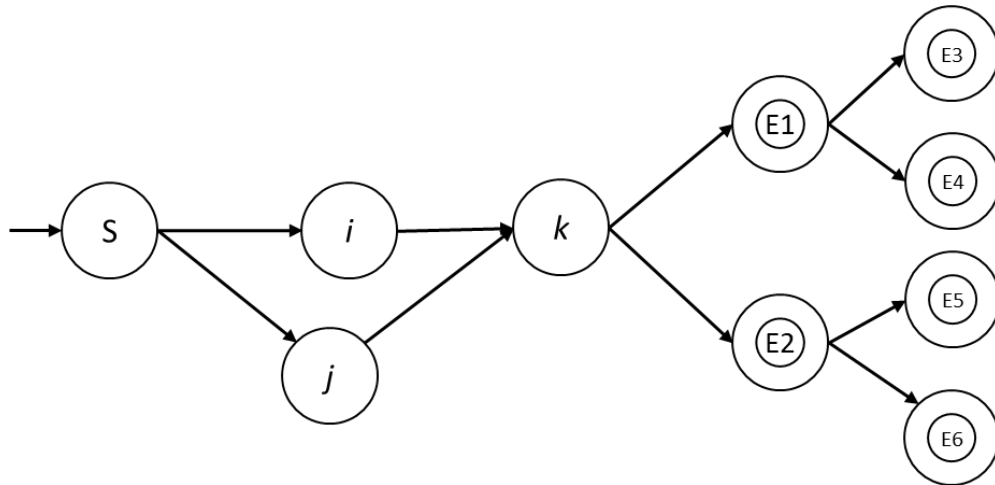
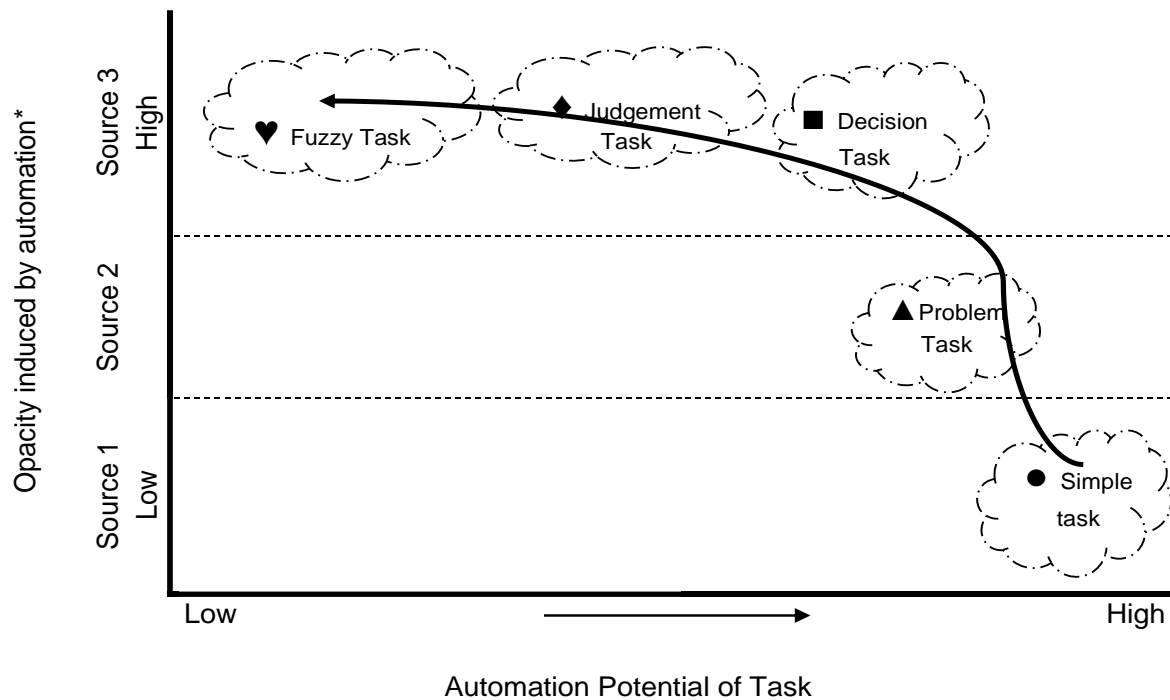


Figure 5. A Fuzzy Task

Despite advances in machine learning, the combinatorial processing of unstructured information makes fuzzy tasks poor candidates for complete automation. However, algorithms' ability to quickly process large amounts of information and reduce it to a form and size that people can manually handle makes these tasks amenable for partial automation (e.g., via decision support systems). Consider, for example, self-driving cars. Most advanced cars come with a semi-auto driving mode that uses algorithms to ensure a safer driving experience via algorithmically processing data from sources as varied as global positioning systems (GPS), satellites, sensors installed on the car, and historical data. In this case, complexity arises from not only the multiple information sources and information uncertainty but also the complicated combinatorial computations that one needs to perform in near real time. As a result, algorithms have not yet been able to replace human drivers; instead, they augment drivers' capability to deal with various possible scenarios when driving by predicting and pre-empting certain situations. Hence, fuzzy tasks have the lowest automation potential compared to simple, problem, decision, and judgment tasks. Furthermore, fuzzy tasks have the highest opacity compared to the other tasks since they will likely encounter all three opacity sources that Burrell (2016) suggested. Note that, like judgment tasks, many fuzzy tasks are also socially embedded and may have wide-reaching social impacts, which makes even partially automating these tasks socially undesirable. Therefore, even if algorithms gain the ability to fully automate fuzzy tasks such as driving, their social acceptability might still remain problematic due to ethical dilemmas such as the trolley problem (i.e., a problem in which one needs to decide on the action to take when one cannot avoid a collision).

Based on the above discussion, we now position the five different task types in a grid along the automation potential and opacity dimensions in Figure 6. We observe that, depending on a task's nature, an algorithm's automation potential and the opacity that automation induces vary. In Table 3, we also summarize the relationship between task complexity, automation potential, and opacity.



●: Simple Task ▲: Problem Task; ■: Decision Task; ◆: Judgement Task; ♥: Fuzzy Task
 Arrow (→): Arrow indicates the direction of the increasing task complexity
 * Opacity levels are derived from the three forms of opacities discussed by Burrell (2016)

Figure 6. Task Relations according to Automation Potential and Opacity

Table 3. Influence that Task Complexity has on Automation and Opacity

Task type	Automation potential	Opacity	Examples	Primary source of complexity	Primary source of opacity
Simple tasks	High	Low	Interest calculation	None	Corporate secrecy
Problem tasks	High	Medium	Finding the shortest route (e.g., Waze)	Multiple paths	Technical illiteracy
Decision tasks	Medium	High	Recommender systems (e.g., Google search / Facebook news recommendations)	Multiple Outcomes	High dimensional optimization
Judgment tasks	Low	High	High-frequency trading / credit appraisal	Interdependent and/or uncertain linkages	
Fuzzy tasks	Very low	High	Autonomous driving	All sources	

4 Task Complexity, Artificial Intelligence, and Fairness Concerns

In this research, we use Campbell’s (1998) typology of five task types based on their complexity to understand how a task’s nature affects both its automation potential and the opacity that arises from such automation. In this section, we elaborate our study’s implications.

4.1 Task Complexity and Artificial Intelligence

Our research contributes towards current debates about adopting and implementing artificial intelligence (AI) for social and organizational tasks. While many organizations have begun to invest in AI technology and fervently explored AI system use cases, they have adopted AI relatively slowly. AI—which we define as machines performing cognition, perception, and action (Heer, 2019)—primarily deals with automation of judgment and fuzzy tasks that possess high complexity and low automation potential owing to uncertainty and conflicting interdependence between paths to outcomes.

While research in general has contended that algorithmic automation leads to an increase in throughput and work productivity (Brynjolfsson & McAfee, 2016; Ford, 2015; Meadow & Sunstein, 2001), recent research has suggested that all automation endeavors do not yield equally encouraging results (Davenport & Ronanki, 2018). For example, Davenport and Ronanki (2018) found that a cancer center's investment in AI systems did not help it detect cancer but that its investment in automating its backroom increased cost efficiency and patient satisfaction. Based on our work, we can explain their findings as follows: backroom tasks constitute simple tasks and, hence, possess higher automation potential, which makes them good candidates for automation. However, using AI to detect cancer constitutes a fuzzy task that possesses much more complexity compared to a simple task, and, thus, has a lower automation potential.

Researchers have also shown algorithmic automation to be associated with an increase in efficiency due to a reduction in errors and tireless and fast work performance (Hoff & Bashir, 2015; Wajcman, 2019). For example, researchers have contended that deep AI technologies may improve the efficacy of the task of drug selection to about 60 to 70 percent compared to about 20 to 30 percent currently when clinicians recommend combinations of drugs for treatment (Singh, 2020). Even though one cannot easily automate such tasks, automating them may produce a significant consequent increase in efficiency. However, one should note that the task-based manner in which we examine automation in this paper has a limited ability to address questions regarding which tasks when automated would yield maximum efficiency gains.

Our examination also implies that all opacity sources associated with judgment and fuzzy tasks (i.e., corporate secrecy, technical illiteracy, and high-dimensional optimization (Burrell, 2016)) will likely affect AI). Hence, AI systems will likely be highly opaque, which raises concerns about ethics and their eventual social desirability. Our framework can further our current knowledge of AI adoption by explicating the specific concerns for fairness associated with AI and design solutions that might alleviate those concerns (see Section 4.2).

4.2 Task Complexity and Likelihood of Fairness Concerns: Implications for Designing Task-aware Technology Artefacts

Based on our task complexity-based understanding of algorithmic automation, we can better explain why all algorithmic automation may not be equally problematic from an ethical and social desirability perspective (e.g., Martin, 2019). In this section, we discuss how different tasks may be associated with different concerns for algorithmic fairness. We then extend that discussion to indicate the implications that a task complexity based-understanding of algorithmic automation has for technology artefact design.

Scholarship on designing artefacts has drawn inspiration from the concept of affordance, which researchers developed in ecological psychology (Gibson, 1986) and refers to a relationship between an object's properties and a user's properties that determines how the user may use the object (Norman, 2013). IS scholars have appropriated this concept to refer to the goal-oriented action that a technical object offers to a specified user group (Markus & Silver, 2008). Some studies have recently called for scholars to pay more attention to the affordances that AI-enabled systems offer to their users that enhance user experience, user acceptance, willingness to delegate decision making, and trust in such systems (Rzepka & Berger, 2018; Sundar, 2020).

Research on affordances in the AI and automation domain has focused on how AI systems can perceive their environment in terms of affordances (Min, Yi, Luo, Zhu, & Bi, 2016; Nye & Silverman, 2012), how big data analytics affords opportunities for informed decision making (Zeng, Tim, Yu, & Liu, 2020), and innovation (Achmat & Brown, 2019; Lehrer, Wieneke, vom Brocke, Jung, & Seidel, 2018). Recently, scholars have also argued in favor of supporting AI fairness and transparency by designing AI systems that afford transparency, explainability, visualization, and voice (Robert et al., 2020c). While these scholars have researched the AI domain for human-resources management, we believe that these affordances, to an extent, address fairness concerns associated with automation and AI in general. Transparency affords

fairness by making underlying AI mechanics visible and known. Explainability affords fairness by describing AI decisions and actions that impact individuals in human terms. Visualization affords fairness by representing information visually so that one can understand AI decisions' multidimensionality. Finally, voice affords fairness by providing the opportunity for feedback to AI.

We argue that the AI affordances that Robert et al. (2020c) developed coupled with our task complexity-based understanding of fairness concerns associated with different task types can help designers design automated systems. For each task type, we propose the affordances that designers need to incorporate into an automated system to address fairness concerns. Hence, we argue in favor of using a task-aware methodology for designing technology artefacts.

4.2.1 Simple Tasks

Simple tasks lack all four complexity sources that Campbell (1988) discussed. When one automates a simple task, the automation follows a common, consistent procedure to achieve the single desired outcome, which reduces the chance that it will produce a biased outcome and ensures consistent allocation. Simple tasks have only one source of opacity (if any): the need for corporate secrecy (Burrell, 2016). As a result, procedural fairness concerns have a low probability to emerge in such tasks when automated. Similarly, the lack of multiple desired outcomes that may exhibit a negative relationship with one another indicates that distributive fairness concerns will not likely emerge automated simple tasks. Since automated simple tasks will likely pose low fairness concerns, they represent the best candidates for automation. We propose that, by making a automated simple task's underlying mechanics visible and transparent, one can address the procedural fairness concerns (if any) that arise due to opacity. Hence, we posit that:

P1: One must incorporate the transparency affordance in a system that automates a simple task in order to address any procedural fairness concerns.

4.2.2 Problem Tasks

Multiple paths to a single desired outcome constitute problem tasks' defining feature. Automating these tasks requires an algorithm to computationally evaluate, execute, and compare multiple paths across the entire solution space to arrive at the desired outcome (Campbell, 1988). The possibility of exhaustive comparison leaves little possibility of bias or inconsistent allocations due to automation. Therefore, distributive fairness concerns associated with the outcome will not likely emerge when one automates these tasks. However, from the perspective of procedural fairness, some concerns owing to the mathematical/analytical/heuristic formulation of these tasks may arise. Opacity may arise from users' lack of skill to understand coded logics in addition to the need for corporate secrecy (Burrell, 2016). Hence, to address procedural fairness concerns associated with automating these tasks, one needs to not only enable transparency but also design affordances that explain the computational logic in human terms. Hence, we posit:

P2: One must incorporate the transparency and explainability affordances into a system that automates a problem task in order to address procedural fairness concerns.

4.2.3 Decision Tasks

Decision tasks feature multiple possible outcomes (Campbell, 1988). They often involve uncertainty and conflicting interdependence in paths to outcomes and complicated trade-offs between them. Automating a decision task requires an algorithm to computationally execute all paths to all desired outcomes and, thus, achieve an eventual outcome at the cost of other desired outcomes. Hence, automating decision tasks may give rise to some concerns about distributive fairness. Automating decision tasks often requires high-dimensional algorithmic computations that cognitively conflict with human reasoning and interpretations (Burrell, 2016). Hence, opacity for automated decision tasks arises not only from corporate secrecy and users' technical illiteracy but also from the mismatch between the high-dimensional computations that algorithms perform and limitations in human reasoning and semantic interpretation (Burrell, 2016). Accordingly, to address procedural fairness concerns associated with automating these tasks, one needs to incorporate not only the transparency and explainability affordances but also affordances that represent intermediate steps of the high-dimensionally computed outcomes visually for analysis and comparison in systems that perform them. Further, to alleviate concerns about distributive fairness, we suggest that one needs to incorporate the comparability affordance, which we define as the possibility to compare outcomes using what-if analysis and simulate multiple scenarios on actual data that the automated system uses, into

the automated system. This comparability capability, when actualized in tandem with the visualization affordance, can specifically help in alleviating concerns with respect to distributive fairness. Hence, we posit:

- P3a:** One must incorporate the transparency, explainability, and visualization affordances into a system that automates a decision task in order to address procedural fairness concerns.
- P3b:** One must incorporate the visualization and comparability affordances into a system that automates a decision task in order to address distributive fairness concerns.

4.2.4 Judgment and Fuzzy Tasks

Judgment tasks and fuzzy tasks feature conflicting interdependence between paths and probabilistic and/or uncertain linkages between paths and outcomes. For these tasks, algorithms need to perform high-dimensional optimization, which makes it difficult to discern the actual path that they use to reach the outcome. Hence, automating judgment and fuzzy tasks through AI systems likely raises concerns about procedural fairness due to users' and even technology designers' inability to understand how they perform high-dimensional computations (Burrell, 2016). The socially embedded assumptions that AI systems make in order to contend with information's uncertainty and stochasticity further exacerbate concerns about procedural fairness. In addition, when conflicting interdependence exists between paths to multiple outcomes, AI systems achieve one outcome at the cost of other desired outcomes, which raises concerns about distributive fairness. The high likelihood for concerns about both procedural and distributive fairness to emerge when AI automates judgment and fuzzy tasks makes AI a highly contentious topic with respect to ethical concerns (e.g., Zarsky, 2016; Sweeney, 2013; Noble, 2018; Martin 2019).

Consider the example algorithmic judgment in courts of law to decide whether to grant or deny someone bail. The system that automates this judgment task has to account for the task's uncertainties and stochasticity by making possibly socially embedded assumptions, which could result in the system systematically marginalizing certain historically disadvantaged groups further and, thus, in concerns about distributive and procedural justice (Zarsky, 2016, Park & Humphry, 2019). Similarly, consider autonomous cars and the ethical dilemma associated with the trolley problem. One cannot possibly solve the ethical dilemma associated with such a case computationally, which means a system would need to use some socially embedded assumptions that further aggravate concerns about procedural and distributive fairness.

The stochastic and uncertain information that AI systems use and the socially embedded assumptions they make means one cannot simply incorporate the transparency, explainability, and visualization affordances in such systems to alleviate fairness concerns. We argue that the voice affordance can address procedural and distributive fairness concerns to some extent. Further, an affordance for comparability coupled with the visualization affordance can specifically help to alleviate concerns with respect to distributive unfairness.

- P4a:** One must incorporate the transparency, explainability, visualization, and voice affordances into a system that automates judgment or/and fuzzy tasks in order to address procedural fairness concerns.
- P4b:** One must incorporate the visualization, comparability, and voice affordances into a system that automates judgment or/and fuzzy task in order to address distributive fairness concerns.

We summarize the likelihood of concerns about distributive and procedural fairness across task types by using different colors (blue: negligible likelihood of concerns; green: low likelihood of concerns; yellow: medium likelihood of concerns; orange: high likelihood of concern). In the figure, we also list the affordances that one needs to incorporate into an automated system to alleviate distributive and procedural fairness concerns.

	Simple Task	Problem Task	Decision Task	Judgment or Fuzzy Task
Distributive Fairness			Transparency Explainability Visualization	Transparency Explainability Visualization Voice
Procedural Fairness	Transparency	Transparency Explainability	Visualization Comparability	Visualization Comparability Voice

Legend:	Likelihood of concerns	Negligible	Low
		Medium	High

Figure 7. Distributive and Procedural Fairness Concerns across Task Types and Necessary Affordances that Address These Concerns

Using affordances to address fairness concerns that arise from algorithmic automation and AI also highlights the heterogeneity among task performers (i.e., technology users). Since affordance represents a relational notion, it means that actualizing an affordance accounts for a user's capabilities and a technical object's properties/features (Leonardi, 2011; Markus & Silver, 2008)—in this case, the information system that automates tasks algorithmically. Hence, simply incorporating an affordance into an automated system does not sufficiently actualize an affordance that addresses fairness concerns. For example, even if one makes an algorithm's code public, users who do not possess the skill to read and understand it will not be able to actualize the transparency affordance (Strong et al., 2014), which explains why all the propositions that we formulate in this section mention the necessary affordances to address fairness concerns that pertain to different task complexities and not the sufficient ones.

The fact that technology affordances are relational also underscores their contingent nature; that is, affordances merely constitute *potentials* for action and need not always be actualized (Strong et al., 2014). We believe that this aspect has strong repercussions for all ethical and moral concerns, such as fairness and accountability (Orr & Davis, 2020; Robert et al., 2020c), associated with algorithmic automation even for the simplest tasks. Specifically, fixing ethical accountability for corporations that design and use algorithmic automation and AI becomes untenable given responsibility's distributed nature (across users, designers, and technological artefacts) (Orr & Davis, 2020) and affordance actualization's contingent nature (across users and technological artefacts). Therefore, we argue that designing affordances that enhance the degree to which users perceive automated and AI systems as fair constitutes a necessary first step to alleviate associated ethical and moral concerns. Furthermore, these affordances must be coupled with due legal and regulatory oversight in order to protect users' interests and drive them to adopt automated and AI-based information systems (Pumplun, Tauchert, & Heidt, 2020).

5 Conclusion

In this paper, we examine the variations in algorithmic automation potential and opacity and fairness concerns associated with such automation across different tasks. To do so, we developed a framework based on the complexity-based task typology from Campbell (1988). This framework helps to explain the reasons for differences in different tasks' automation potential and opaqueness across the task-complexity spectrum. Further, we use this framework to explicate why different task types vary in the likelihood that they will exhibit fairness concerns. We analyze the fairness concerns across two legal doctrines, distributive and procedural fairness, and show variations in them across the task-complexity spectrum. We also provide recommendations to actors who design algorithmic automation and AI systems for addressing fairness concerns associated with different task types. We propose that algorithms that automate tasks that vary in

complexity require different types of affordances if one needs to address fairness concerns that arise from automation.

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