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

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Abstract:

Algorithms today affect not only individual choices and decisions but also influence, shape and guide societies. Scholarship on algorithms is largely divided on the basis of interest in efficiency gains obtained from automation, and ethical concerns with respect to fairness of outcomes of algorithmic automation. Most of this literature uses a generic understand of algorithms, without accounting for the differences among algorithms that might arise due to the differences in tasks that these algorithms automate. Drawing on the notion of task complexity, this research develops a task-based understanding of algorithmic automation, and suggests that differences in complexity across tasks leads to differential automation potential and differential opacity resultant from the automation. It further suggests a framework to assess the likelihood of fairness concerns emanating from the differential opacity across tasks with different complexities. This framework is complemented with propositions for designing specific affordances into information systems that automate tasks in order to address the perceived fairness concerns.

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

1. Introduction

Algorithmic retrieval, classification, ranking, and ordering of information (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, there is a burgeoning interest in research related to understanding different aspects of algorithms[1] (Ananny, 2016; Crawford, 2016; Introna, 2016).

Broadly, scholarly work on algorithms can be categorised along the dimensions of economic gains achieved through automation and ethical concerns stemming from such automation (Pasquale, 2015). The economic perspective highlights the efficiency gains resulting from reduction in errors arising due to human judgement and bias (Meadow & Sunstein, 2001) when algorithms are employed for tasks, such as, searching, classifying, retrieving, ranking, and sorting. These efficiency gains, along with the tirelessness associated with algorithmic work, lead to consequent increase in throughput and productivity of work[2] (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), in turn suggesting that there might exist differences in terms of *automation potential - the extent to which a machine (or*

[1] We observe increasing attention on 'algorithms' as a scholarly topic in many academic journals. This is evident from recent calls for special issues on "The Governing Algorithms" in Science Technology and Human values (2015), "Social Power of Algorithms" in Information, Communication and Society (2017), and so on.

[2] Some of the examples of such automation are: 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)

a computer or an algorithm) can carry out the functions that were performed by a human agent earlier (Parasuraman, Sheridan, & Wickens, 2000) of different types of tasks.

The ethical perspective in research on algorithmic automation focuses on concerns that arise from algorithmic automation (Shin, Zhong, & Biocca, 2020). Some of the concerns include biases in decisions made by algorithms (Introna & Nissenbaum, 2000), discriminatory outcomes (Gillespie, 2017a), fairness concerns (Dwork, Hardt, Pitassi, Reingold, & Zemel, 2011), surveillance (Introna & Wood, 2004; Zuboff, 2018) and accountability concerns (Felten, 2012). Research in this stream argues that algorithms controlled by profit-oriented enterprises are “black boxes” (Hoffmann, 2019; Park & Humphry, 2019; Poon, 2016) and most of these concerns emerge from their inscrutability (Ziewitz, 2016) originating from opaqueness in their workings (Burrell, 2016). Algorithmic opacity can amplify existing discriminations and inequalities in society thereby raising fairness concerns (Massanari, 2017; Matamoros-Fernández, 2017; Pasquale, 2015; Thorson, Cotter, Medeiros, & Pak, 2019) and as the opacity of algorithms increases, it becomes difficult to explain algorithmic outcomes, in turn reducing algorithmic accountability (Pasquale, 2015).

These two streams have developed rather individually and there are few studies that integrate the two bodies of research (for example, see Zarsky 2016 for an integrated approach). A common problem with literature in both these streams is that it is built around a generic notion of algorithms, that is, the specificity of different algorithms, and the typicality of the tasks that they perform have been overlooked. Recent academic literature corroborates this argument by suggesting that job replacement of individuals by Artificial Intelligence (AI) occurs fundamentally at the task level, rather than at the job level (Arntz, Gregory, & Zierahn, 2017; Huang & Rust, 2018). In this research, we tow this line of thought that positions the nature of the task as an important characteristic to consider when evaluating effects of algorithmic automation. Put more precisely, we argue that the nature of task affects its automation potential, as well as the extent of opacity arising due to such automation. Therefore, the objectives of this research are:

Objective 1: To understand the automation potential of different types of tasks;

Objective 2: To understand the fairness concerns arising from opacity, induced by automation of different types of tasks.

We use task complexity (Campbell, 1988; Wood, 1986) as the theoretical foundation to develop a framework to accomplish the aforementioned objectives. Campbell (1988) categorises tasks into five broad types based on their complexity: simple tasks, problem tasks, decision tasks, judgment tasks, and fuzzy tasks. We use these five task types to show the variation in automation potential and opacity associated with tasks across the task complexity spectrum. By using the idea of task complexity to understand automation potential and opacity associated with algorithms, we make three specific contributions. First, we synthesise research streams addressing algorithmic automation and opacity to provide a holistic understanding of how task complexity affects automation potential and associated opaqueness that 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 allows us to explicate why different task types have varying likelihood of fairness concerns. We also delineate fairness across two dimensions – distributive and procedural (Ambrose & Arnaud, 2005; Greenberg & Colquitt, 2013) – and argue that while some tasks are likely to exhibit a greater propensity for distributive fairness concerns, other tasks have a greater likelihood of exhibiting procedural fairness concerns. Third, our framework provides recommendations to designers of algorithmic automation and AI systems regarding addressing fairness concerns associated with different types of tasks. We propose that algorithms used to automate tasks of varying complexity require different types of affordances if fairness concerns arising from automation need to be addressed.

This research article is organised according to the following scheme. We begin with a brief account of the literature on algorithmic automation, algorithmic concerns around fairness and an overview of the theoretical understanding of task complexity in Section 2. In Section 3 we conceptualise a framework to assess algorithms along the dimensions of automation potential and opacity while accounting for different levels of task complexity. This is followed by a discussion on the implications of a task-based understanding of algorithmic automation and AI for research and practice in Section 4. We conclude the paper in Section 5.

2. Theoretical Background

Nineteenth-century industrial automation was grounded on the principle of simplifying a task by breaking the task into smaller highly specialised sequences at the expense of skill, thus, referring to these technologies as deskilling technologies ((Frey & Osborne, 2017), p. 256). These technologies shifted work out of the artisan shops to factory shop floors where an individual carried out the same repetitive task rather than performing a complex interplay of tasks done by an individual in the artisan shop. With advancement in computing technology, it became possible to outsource some of these repetitive tasks to algorithms. Algorithms may be defined 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 means for supporting automation and improving productivity, but, with further advancements in computing technology, the capability of algorithms to perform repetitive tasks has been exponentially increasing (Ford, 2015). This has made automation possible at a scale, something not previously apprehended (Brynjolfsson & McAfee, 2016). Consequently, automation has moved beyond routine jobs that followed well defined repetitive procedures – as was the case with manufacturing jobs (Acemoglu & Autor, 2011) – to potentially including jobs where human involvement was originally considered irreplaceable, like driving a car (Frey & Osborne, 2017). This performance of complex tasks involving cognition, perception, and action by machines based on algorithms is referred to as artificial intelligence (AI) (Heer, 2019).

The literature on algorithms in general, and AI in particular, has broadly explored two dimensions: (1) automation, mainly focusing on efficiency gains from algorithmic automation, and (2) transparency, as an ethical concern arising due to algorithmic automation (Pasquale, 2015). We briefly discuss these two streams of literature in the following sections.

2.1 Algorithms and Automation

Research focusing on the efficiency of algorithms suggests that higher efficiency is achieved by using algorithms in routine personal and professional settings. The premise for the efficiency argument is the belief that process automation, achieved through "technology that actively selects data, transforms information, makes decisions, or controls processes" (Lee & See, 2004, p50), increases the efficiency of the process by reducing errors, working tirelessly, and performing tasks at a faster rate (Hoff & Bashir, 2015; Wajcman, 2019). As algorithms are slowly entering spaces initially dominated by human decision making, they are augmenting human capabilities (Heer, 2019; Jordan, 2019; Li, 2018).

Research further argues that complete replacement of human by AI too far-sighted (Heer, 2019) as only a small percentage of jobs can be fully automated by adapting current technologies. Nonetheless, almost all jobs have some activities or tasks that have the potential to be automated

(Manyika, 2017). The need to understand which aspects of a job possess the potential to get automated and performed by algorithms entails a focus on tasks rather than jobs (Arntz et al., 2017). In fact, economists have argued that focusing on jobs, instead of tasks, has led to a serious overestimation of the risks of automation (Arntz et al. 2017).

Along these lines of thought, Parasuraman et al. (Parasuraman et al., 2000) posit that the level of automation in tasks varies along a continuum from completely manual to completely automated decision making. They outline a 10-level scale for the level of automation based on whether humans or algorithms are in control of the decision. At lower levels of the scale (level 1 to 5), human control dominates the task, while the algorithm dominates at higher levels[3]. Though this framework helps us understand the level of automation of tasks, it has paid scant attention to the complexity associated with tasks, instead focusing mainly on the automation of four broad classes of functions in a human-machine system, namely, information gathering, information analysis, decision, and action. For example, a sensor automating the collection of environmental information or a smart electricity meter automatically computing the electricity bills are instances of automating information gathering and analysis respectively. However, tasks may have varying levels of complexity that are likely to affect these sub-tasks ranging from information gathering to action. Why certain tasks exhibit a higher potential for automation compared to others has not been adequately explored in literature so far. Therefore, in this research, we examine how the complexity associated with a particular task affects the automation potential of the task.

[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 of the scale (level 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.

2.2 Algorithms and Fairness

The second stream of literature on algorithmic automation argues for discussion on the wider implications of algorithms for individual, social and cultural life (Beer, 2009; Greenfield, 2006; Kitchin, 2017; Kitchin & Dodge, 2011; Manovich, 2013; *Polynczuk*-Alenius, 2019; Steiner, 2012), including subject matters 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, 2017b) 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 example of advanced algorithms being used for automating recruitment processes. Through sophisticated mechanisms these algorithms learn how to identify good candidates using internal organisational databases about performance metrics, tenure records, and turnover rates of current and previous employees, and sometimes external information from sources such as social media platforms. The benefit of such 'AI for recruiting' lies in saving recruiters' time and money by automating the task of screening applications, and providing a shortlist of candidates fit for the job without any human-induced bias. However, one of the problems with these algorithms is that the elaborate and complex inner mechanisms of such algorithms are often unknown, making it impossible to ascertain whether they utilise fair and ethical recruitment practices. Similarly, the governance, outcomes, and social influence of most algorithms are likely to 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 arising due to algorithmic automation of tasks have led to an increased interest and discussion among scholars of information systems, computer science, law, management and public policy (Jarrahi, 2018; Robert, Pierce, Marquis, Kim, & Alahmad, 2020; Veale, Van Kleek, & Binns, 2018; Vellido, 2019; Wang & Siau, 2018). However, literature that analyses algorithmic fairness has two opposing arguments. On the one hand, some scholars argue 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, some studies argue that algorithmic automation and AI can cause greater concerns for fairness of algorithmic outcomes than human performance of tasks (Martin, 2019; Mateeu & Nguyen, 2019).

The discussion on fairness is generally grounded on two fundamental legal doctrines (Table 1): distributive fairness and procedural fairness (Ambrose & Arnaud, 2005; Barocas, Hardt, & Narayanan, 2020; Robert et al., 2020). Distributive fairness deals with fairness associated with allocation of outcomes (Alexander & Ruderman, 1987). For example, in an organisational setting, distributive fairness can be in the form of the *same pay for the same work*. One of the central discussions for gender discrimination is about distributive fairness as women tend to be usually paid significantly less than men for the same work (Bishop, 2018). An algorithm automating performance appraisal in a company might consider women who were on maternity leave as lower performers compared to men for a given work period. This may in turn lead to concerns about distributive fairness if such women are given lower or no pay hikes in comparison to their counterparts. Distributive fairness is the most commonly discussed type of fairness in literature on AI and algorithms, and the focus is mainly on making algorithms to select and allocate organisational resources fairly (Robert et al., 2020). The primary mode of achieving a fair distribution of outcomes by algorithms is through computational models operationalising equality defined either mathematically or via legal principles (Glymour & Herington, 2019; Madras, Creager, Pitassi, & Zemel, 2019).

Procedural fairness deals with disparate treatment, where the focus is on the fairness of the procedure employed to reach or decide the outcome, rather than the outcome itself. For example, an algorithm automating performance evaluation through standard KPIs might ignore some informal but significant work done by workers which were otherwise recognised by managers, leading to procedural fairness concerns. Research on procedural fairness focuses on automating existing procedures through algorithms rather than employing algorithms to create new procedures and processes. This research proposes consistency and transparency[4] as two means to achieve procedural fairness (Brown, Chouldechova, Putnam-Hornstein, Tobin, & Vaithianathan, 2019; Grgić-Hlača, Zafar, Gummadi, & Weller, 2018; Robert et al., 2020). That is the algorithms should produce the same output and follow the same procedure every time, and should be transparent in the procedure followed to produce the outcome.

Achieving fairness through transparency is premised on the logic that more the inner workings of the algorithm are known, the easier it will be to attach accountability to it (Ananny & Crawford,

[4] Recent research in algorithmic design aims at addressing fairness issues by (a) excluding protected attributes such as race, gender, ethnicity, and their proxies for decision making (Bonchi, Hajian, Mishra, & Ramazzotti, 2017), (b) training the algorithm to ensure that the predictive performance of algorithms is same across groups (Agarwal, Beygelzimer, Dudík, Langford, & Wallach, 2018). However, some studies argue that such algorithmic designs do not guarantee fair decisions, and may instead harm the very groups that they aim to protect (Corbett-Davies and Goel 2018).

2018; Martin, 2019). The epistemological foundation of this argument of deriving accountability from transparency is based on the assumption that once the inner workings of the algorithm are revealed (Christensen & Cheney, 2015, p74) to an audience, the audience is capable of not only comprehending the workings but also suggesting necessary corrections in the algorithms (MacKenzie, 2008; Martin, 2019). However, complexity associated with many algorithms that influence personal and professional life[5], often, make them incomprehensible for humans, thus, raising concerns about algorithmic accountability. Some scholars argue that in the case of algorithms and AI, achieving full transparency may be inadequate, undesirable, and infeasible (Ghani, 2016; Martin, 2019). Furthermore, even though the call for algorithmic transparency is on the rise (Rader, Cotter, & Cho, 2018; Shin & Park, 2019), making algorithms transparent is not that simple (Burrell, 2016).

Building on this literature on algorithmic opacity to include the characteristics of algorithms and scale of data being handled by algorithms, Burrell (2016) argues that modern algorithms suffer from the 'curse of dimensionality' (Domingos, 2012) and suggests that algorithms, specifically those dealing with big data and AI, are inherently opaque for three broad reasons (Table 1). First, an organisation may protect the algorithms as proprietary information. Second, the difficulty associated with understanding a computer program even if it is open for scrutiny may render it to be opaque to technically illiterate individuals. Third, the characteristics of algorithms and scale of information they handle will inevitably make algorithms opaque because the high dimensional

[5] The algorithms running in the backdrop of Google's Search Engine and Facebook's News Feed have time and again become the subject of critique (Aswani, Kar, Ilavarasan, & Dwivedi, 2018). For example, reacting to the issue of a Facebook data leak, The Economist says, "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" (The Economist, 2018).

optimisation is at odds with the human scale reasoning and semantic interpretation *(ibid)*[6]. Often, to optimise resource utilisation in the presence of multi-dimensionality, dimensional reduction techniques such as Principal Component Analysis may have to be used (to address the curse of dimensionality), which may add further to the opacity of algorithms. She suggests that this opacity is exacerbated by the internal logic of the algorithm getting altered during the learning phase of the algorithms. Thus, even if the dataset and the internal program logic is comprehensible to a few technically literate individuals initially, the interplay between the two might eventually make the algorithm opaque even to these individuals.

The existence of three forms of opacity suggests that all algorithms are not equally opaque, and the degree of opaqueness may vary depending on the nature of task that the algorithm is used for. Consequently, there is a need to understand fairness concerns arising from varying levels of opacity introduced by algorithmic automation of different tasks. However, extant literature lacks a task-based understanding of opacity associated with algorithmic automation, further making it difficult to explicate the reasons for varying levels of fairness concerns associated with algorithmic automation of different tasks. Even though the importance of a task-based understanding of AI technologies has been highlighted in literature to understand user adoption of these technologies (Rzepka & Berger, 2018), it continues to remain unaddressed. We believe that a "task complexity" (Campbell, 1988) based understanding of algorithmic automation can further our understanding of the differential opacity and fairness concerns associated with different kinds of automated tasks. Thus, in this paper, we attempt to provide a task-based understanding of algorithmic opacity which will in turn help in making task complexity central to the analysis of the fairness of algorithmic

[6] Some scholars argue that although algorithmic opacity originating from protection of proprietary information or as a corporate strategy is an intentional tool designed to avoid scrutiny and accountability (Martin 2017, Diakopoulos 2015, Pasquale 2015, Burell 2016).

automation. Table 1 specifies the definitions of the main concepts associated with fairness and opacity used in this research.

Table 1 Fairness and Opacity Types

Concept		Definition	Reference
Fairness	**Distributive**	The disparate impact. The focus is on avoidable or unjustified harm and minimising the differences in the outcome.	Ambrose & Arnaud, 2005; Robert et al. 2020
	Procedural	The disparate treatment. The focus is on the fairness of the procedure employed to reach or decide the outcome, rather than the outcome itself.	
Opacity	**Source 1**	Opacity as part of the intentional corporate or state secrecy	Burrell 2016
	Source 2	Opacity due to the need for specialised technical illiteracy	
	Source 3	Opacity that arises from the characteristics of machine learning algorithms and the scale required to apply them usefully.	

2.3 Task Complexity

It has long been argued that advancement in information technology would have a *considerable effect in office* (Levin, 1956, p61) and that it would *suppress most fragmentary and repetitive jobs* (Friedmann, 1992, p114) through automation. Consequently, models to understand how jobs in office would get affected by automation began to be developed (Frey & Osborne, 2017; Koorn, Leopold, & Reijers, 2018; Parasuraman et al., 2000; Traumer, Oeste-Reiß, & Leimeister, 2018). While Frey and Osborne (2013) use jobs as the unit of analysis for automation, Arntz et al. (2017) argue that jobs as a unit of analysis is too coarse-grained., and suggest ‘task’ as an appropriate unit of analysis for studying automation

Early models of task automation began with a simple classification of tasks as routine and non-routine (Autor, Levy, & Murnane, 2003). Over time this classification was extended to include further categories like cognitive, analytical, and interactional tasks (Koorn et al., 2018; Spitz-Oener, 2006). However, most of these frameworks lack the micro-foundations of what constitutes a task and what distinguishes one type of task from another. As a result, these frameworks fell short in answering why certain tasks are more complex than others.

However, research on task characteristics, developed in the discipline of Organization Studies, provides us with theoretical approaches to understand the concept of task and differences between tasks. Some of these approaches include (1) task as a pattern of stimuli imposed on the individual (task qua task), (2) task as behavioural responses emitted by a person in order to achieve a specific level of performance, (3) task as behaviour description provided by the task performer, and (4) task described on the abilities required to perform that task (Hackman, 1969; McGrath and Altman, 1966). Wood (1986) argues that a combination of "behaviour as requirements" and "task qua task" has a better potential to analyse and operationalise the notion of tasks theoretically[7].

Campbell (1988) adopted the basic framework proposed by Wood (1986) and suggested a typology of complex tasks through a refined notion of task attributes. He argues that an increase in information load, information diversity, or rate of change in information can contribute to the complexity of a task. These factors can vary owing to different task circumstances, specifically, (a) multiple potential paths to achieving the desired outcome, (b) multiple possible outcomes, (c) conflicting interdependence among paths to outcomes, and (d) uncertain or probabilistic links between the path and outcomes.

The first circumstance discusses *multiple paths* to achieve the desired outcome. As the number of paths to reach the outcome increases or when there is an associated efficiency criterion embedded

[7] Wood (1986) used the postulates of *products, acts, and information cues* to define tasks. While products are the measurable outputs of the task performed (Naylor et al.1980), the acts are means to achieve those outputs. *Information cues* are pieces of information about the task which assist an individual in making decisions during performance of the task.

in the task, the amount of information that needs to be processed increases, in turn, increasing the complexity of the task. The second circumstance is that of attaining *multiple possible outcomes*. As the number of outcomes increases, information related to all possible outcomes needs to be processed, thus, increasing the complexity of the task. The third task situation focuses on the possibility of the *conflicting or inverse relationship among paths to outcomes* arising since one desired outcome might negatively influence the other desired outcome. For instance, the focus on quality might decrease the quantity of production. In this manner, conflicting paths increase the complexity of the task. Finally, when the *chosen path cannot guarantee the desired outcome* with certainty, the amount of information that needs to be processed will substantially increase, causing an increase in task complexity.

Based on the different possible combinations (sixteen to be specific) of the presence or absence of the task circumstances, that is, presence or absence of multiple paths, multiple outcomes, conflicting paths and uncertainty/probabilistic linkages, Campbell (1988) proposed five different task types (Table 2).

Though many research articles have adopted (Hærem, Pentland, & Miller, 2015; Liu & Li, 2012; Zigurs & Buckland, 1998) the notion of task complexity proposed by Wood (1986) and Campbell (1988), there are not many articles advancing the core ideas of the classification[8]. We adopt the original notion of task complexity since it provides us with a suitable framework to understand the variations in the automation potential and opacity concerns associated with different tasks. In the next section, we explore how these different types of tasks vary along the dimensions of automation potential and opacity.

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

Table 2: Complex Task Classifications (Adopted from Campbell 1988 and Zigurs & Buckland 1998)

	Multiple Paths	Multiple Outcomes	Conflicting Interdependence Among Paths	Uncertain or Probabilistic Linkages	Examples
Simple Tasks	No	No	No	Not Applicable	Coin Sorting; Finding Maximum Number;
Problem Tasks	Yes	No	Yes or No	Low to high	Chess problems; Personnel scheduling
Decision Tasks	NR*	Yes	Yes or No	Low to high	Employee Selection; Choosing a house
Judgement Tasks	NR*	NR*	Yes or No	Low to high	Intelligence Analysis; Stock market analysis
Fuzzy Tasks	Yes	Yes	Yes or No	Low to high	Business Ventures

**NR – Not Relevant*

3. Algorithms and Task Complexity

In this section, we further a task complexity based understanding of algorithmic automation by conceptualising a grid with the algorithmic attributes of automation potential and opacity induced due to automation as its two dimensions. This grid, based on Campbell's (1988) typology of tasks, is expected to contribute to the debate around automation potential of tasks and their associated fairness concerns.

3.1 Simple Tasks

A simple task is one which has a clearly defined path to achieve a single desired outcome. Figure 1 represents a simple task, where circles represent intermediary steps, arrows represent the path, and doughnut represents the desired outcome. As the number of intermediary acts required to achieve the desired outcome increase, the complexity of the task also increases.

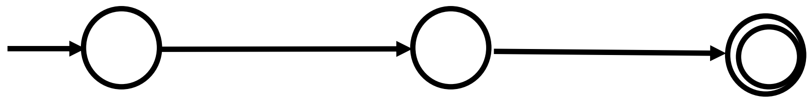

Figure 1: A simple representation of simple task

Since the path to achieve the outcome is clearly defined for a simple task, such a task is highly standardised and programmable. It can be easily formalised, and the outcome of the algorithm easily questioned. For instance, in the traditional Indian banking setup, the interest on the savings bank account was calculated semi-annually until late 2010. As reported by a bank manager, 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 advancement in technology and automation, interest is now calculated based on the available daily balance. While there is a possibility that, owing to automation, the customers and the bank officials may over time lose the know-how of computing interest, eventually causing the sophisticated formula of finding interest to be black-boxed, it can nonetheless be opened up for inquiry and demonstrated to the consumer for any computational error. Opacity for a simple task like this may at most arise from Burell's (2016) first source of opacity – corporate or state secrecy. Therefore, we argue that simple tasks may be represented in the bottom right quadrant of the grid, denoting the highest potential for automation and the lowest level of opacity[9].

3.2 Problem Tasks

A problem task is more complex than a simple task because it involves multiple paths that achieve the same outcome. Figure 2 represents a problem task. The complexity in a problem task arises from the need to evaluate all the paths and then choose the one which is most efficient. In addition,

[9] Different task types are represented as area within the grid. Through there might exist differences in terms of automation potential and opacity induced by automation for specific tasks belonging to a particular task type (category) our framework is limited in scope to explicate these differences.

not all paths may reach the end desired state. An example of a problem task is the classic Travelling Salesman Problem, where the objective for the salesman is to visit all cities in a list by travelling the least possible distance.

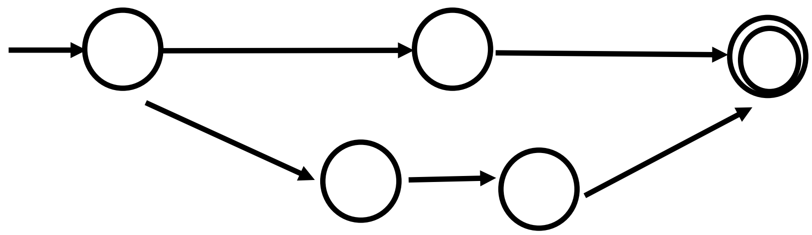

Figure 2: A simple representation of problem task

Unlike the simple task like interest calculation where there is a single procedure (formula) to calculate the interest irrespective of who the account holder is, for a problem task like the Travelling Salesman Problem, there might be multiple ways (algorithms) to find the shortest route, and there might be various shortest routes to reach from source to destination. Therefore, finding the best possible route in the best possible way is not as straight forwards as simple tasks. Nonetheless, a problem task can still be represented in the form of a mathematical/analytical/heuristic model amenable to standardisation and automation, even though the exact solution to the model may not be found in real-time.

Hence, we place problem tasks on the grid a little to the left of simple tasks along the axis of automation (maybe 8 to 9 out of 10 in terms of automation). Problem tasks are more complex than simple tasks and may be considered more opaque than simple tasks. In addition to the possibility of opacity stemming from Burrell’s (2016) first source corporate secrecy, opacity for problem tasks primarily arises from the second source of opacity discussed by Burell (2016), that is, the need for specialised skills to understand the programming language and mathematical formulation of the logic. However, these algorithms can still be opened up and made understandable with a little technical literacy. Hence, we place them low on the dimension of opacity, though slightly higher than simple tasks, on the grid.

3.3 Decision Tasks

Decision tasks involve multiple possible outcomes and it is essential to choose the most desirable alternative (that optimises or maximises utility) among many available alternatives, often involving trade-offs along multiple dimensions. Figure 3 represents a decision task. Step-2 in this figure is a decision point where a choice between step-3 and step-4 needs to be made, each of these steps 3 and 4 will further lead to multiple different end states.

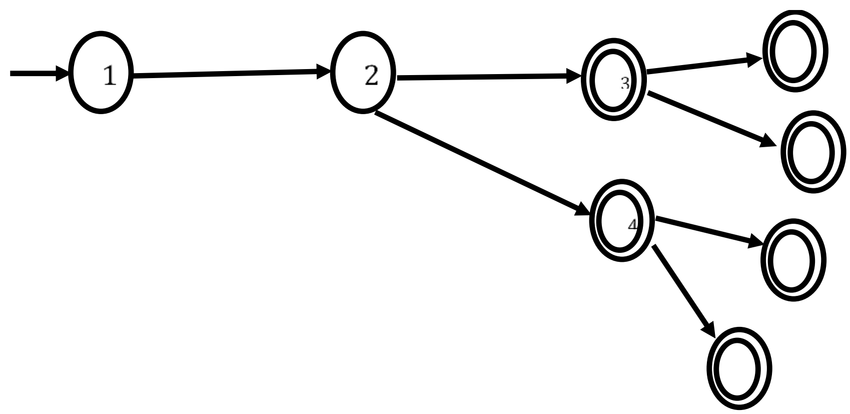

Figure 3: *A simple representation of decision task*

Each outcome amongst the multiple possible outcomes for a decision task may need a different information stream, though there might be lack of clarity in terms of information required or lack of availability of the required information. This may contribute to the complexity of the task, while still keeping it amenable to automation. Within the category of decision tasks, complexity of different tasks may increase with the presence of conflicting interdependence among outcomes or presence of uncertainty (Campbell 1988, p. 47). Conflicting interdependencies and uncertainty may also require high dimensional optimisation which is at odds with the human scale reasoning and semantic interpretation. An example of a decision task is recommender systems used on websites. A recommender system suggests content to an individual user based on the user's consumption pattern as well as the similarity between the user and other users. This task requires a large volume of information to perform complex, though often standardised, computations to make recommendations for each individual user contributing to complexity. This complexity is further exacerbated by conflicting interdependencies, where one recommendation precludes other recommendations from being shown. Whether or not opacity for this task arises due to corporate secrecy associated with the algorithms used, technical illiteracy to understand the complex computations, as well as the high dimensional optimisation involved definitely contribute to opacity of automated decision tasks.

When placing on the grid, decision tasks may be placed to the left of simple and problem tasks along the dimension of automation potential owing to the higher complexity due to conflicting interdependencies and uncertainty to arrive at the outcome. Similarly, decision tasks may be placed above simple and problem tasks along the dimension of opacity owing to the higher opacity arising from high dimensional optimisation in addition to corporate secrecy and technical illiteracy.

3.4 Algorithmic Attributes and Judgement Tasks

A judgement task requires integrating and processing information from diverse sources to subsequently make a judgment about the likelihood of a future event (Campbell, 1988). The information is itself usually uncertain, contradictory, and historical, and in many situations, insufficient to predict the future, contributing to the complexity of the task. This results in uncertain linkages between intermediate steps of the task. The notion of multiple paths and multiple desired outcomes are irrelevant for such tasks (Campbell, 1988). Figure 4 represents a basic judgement task wherein the path between step-3 and the end state is not certain, and is, hence, represented by a dotted line.

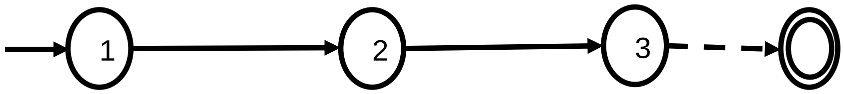

Figure 4: *A simple representation of Judgment Task*

The large quantum of information required for making predictions/judgments contributes to complexity of judgment tasks, making machine learning (ML) algorithms the preferred agents for these tasks as opposed to humans. These algorithms are also not constrained by bounded rationality and inherent human biases (Meadow & Sunstein, 2001). However, judgment tasks are also associated with high quantum of risk (of making/not making the correct judgment), due to which not all judgment tasks can be automated. That is why automation in judgement tasks range from highly automated in some tasks to a human-machine partnership in others. The dynamic nature of machine learning algorithms coupled with the informational uncertainties involved in a judgment task, make such a task more opaque compared to problem, and simple tasks with the opacity arising due to technical illiteracy, high dimensional optimisation, as well as, corporate secrecy in most cases (Burell 2016).

For instance, consider the examples of high-frequency trading (HFT) and credit appraisal. HFT is a form of automatic trading where 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 (within fraction of seconds) while minimising risk. Credit appraisal requires deciding whether to extend a loan by computing the probability of default by using information on demographics, credit history, and past financial behavior of an applicant. Complexity arises due to uncertainty with respect to the relevance and importance (weights) of different types of information (variables) to predict a future default. Since, both HFT and credit lending involve processing highly uncertain information to arrive at a judgment, they have lower automation potential than decision, problem, and simple tasks. Judgment tasks like these may, therefore, be placed to the left of decision tasks along the dimension of automation potential on the grid. Further, judgment tasks may be placed above problem and simple tasks along the opacity dimension as opacity may arise from all the three sources discussed by Burrell (2016). However, the two examples of HFT and credit lending are both distinct in terms of their social embeddedness and social impact of the judgment made. Due to this, human-machine partnership is still desirable for many judgment tasks, such as credit lending and ‘bail or jail’.

3.5 Algorithmic Attributes and Fuzzy Tasks

Fuzzy tasks have many desired outcomes and multiple, often uncertain and/or conflicting, paths to achieve them. Figure 6 represents a fuzzy task. Fuzzy tasks require information pertaining to all paths, and all possible permutations and combinations of paths leading to all the possible outcomes, so that the outcome that maximises benefit can be identified. Compared to other tasks discussed earlier, the complexity of fuzzy tasks is highest, since, they demand information to be processed combinatorially to arrive at the optimal choice. The information required to be processed may come in multifarious forms, both structured and unstructured, from varied sources. The complexity increases further if the paths are uncertain or there exist conflicting paths.

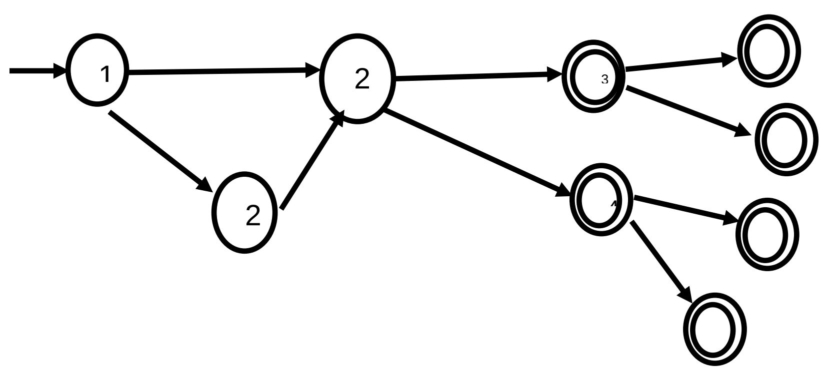

Figure 5: A Representation of Fuzzy Task

Despite advances in machine learning, the need to combinatorially process unstructured information makes fuzzy tasks poor candidates for complete automation. However, the ability of algorithms to quickly process large amounts of information and reduce it to a form and size that can be manually handled makes these tasks amenable for partial automation giving rise to 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 by algorithmic processing of data from sources as varied as GPS systems, satellites, sensors installed on the car and historical data. Complexity, in this case, arises not only from the multiplicity of information sources and uncertainty of information, but also the complicated combinatorial computations to be performed in near real-time. As a result of the complexity, the algorithm has not yet been able to replace the human driver; instead, it augments the driver's capability to deal with (by predicting and pre-empting) various possible scenarios during a ride. Hence, fuzzy task may be positioned further to the left of judgment tasks along the dimension of automation potential on the grid. In terms of opacity, algorithmic automation of fuzzy tasks is likely to encounter all three sources of opacity suggested by Burrell (2016) – corporate secrecy, technical illiteracy and high dimensional computations. As a result, these tasks may be positioned alongside judgment tasks on the dimension of algorithmic opacity in the grid. It is important to note here that, like judgment tasks, many fuzzy tasks are also socially embedded and may have wide-reaching social impact. This makes even partial automation of these tasks socially undesirable. Therefore, even when algorithms may become capable of fully automating fuzzy tasks such as driving, their social acceptability might still remain problematic owing to ethical dilemmas such as the trolley problem. Figure 6 positions the five different types of tasks along the two dimensions of automation and opacity as already discussed above. We observe that depending on the nature of the task, an algorithm's automation potential and the opacity induced by automation vary.

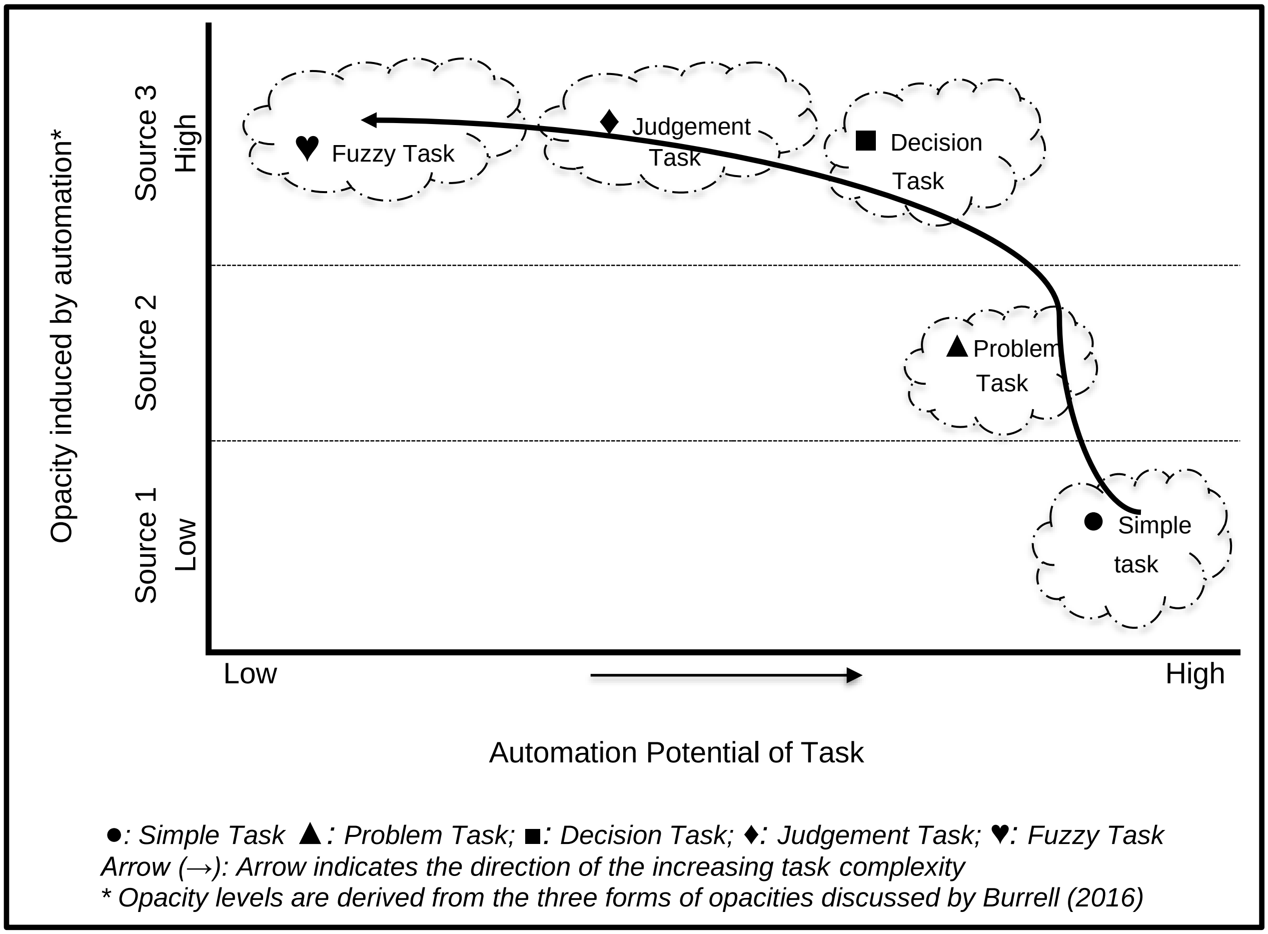

Figure 6: Relations of Task along the Automation potential and Opacity

Table 3: Summary of Influence of Task Complexity on Fairness

	Automation Potential	Opacity	Examples	Source of Complexity	Source of Opacity
Simple Tasks	High	Low	Kiva robots – Amazon's Fulfilment Centres	None	Corporate Secrecy
Problem Tasks	High	Medium	Waze - Finding the shortest route in the new age	Multiple Paths	Technical Illiteracy
Decision Tasks	Medium	High	Recommender System - Google Search/Facebook News Recommendations	Multiple Outcomes	High dimensional computations
Judgement Tasks	Low	High	High-Frequency Trading /Credit Appraisal	Uncertain or Probabilistic Linkages	
Fuzzy Tasks	Very Low	High	Autonomous Driving	Conflicting Interdependence Among Paths	

4 Task Complexity, Artificial Intelligence and Fairness Concerns

In this research we use Campbell's (1998) typology of five types of tasks based on their complexity to understand how the nature of a task affects, both, its automation potential, as well as, the extent of opacity arising due to such automation. In this section we will elaborate the implications of our research.

4.1 Task Complexity and Artificial Intelligence

Our research contributes towards the current debates clouding the adoption and implementation of Artificial Intelligence for social and organisational tasks. While many organisations have started investing in AI technology and are fervently exploring use cases of Artificial Intelligence systems, AI adoption has been relatively slow. AI primarily involves judgment and fuzzy tasks – performance of cognition, perception, and action by machines (Heer, 2019) – that are associated with high complexity and low automation potential owing to uncertainty and conflicting interdependence between paths to outcomes.

While research, in general, contends that algorithmic automation leads to increase in throughput and productivity of work (Brynjolfsson & McAfee, 2016; Ford, 2015; Meadow & Sunstein, 2001), recent research also suggests that all automation endeavours do not yield equally encouraging results (Davenport & Ronanki, 2018). For example, Davenport and Ronanki (2018) in their research show that while investments on AI systems for cancer detection did not deliver results, backroom automation was not only cost-efficient but also increased patient satisfaction. Our task complexity based analytical exposition of algorithmic automation explains this as follows. Backroom tasks are simple tasks and, hence, possess higher automation potential making then good candidates for automation. However, use of AI for cancer detection is a fuzzy task, possesses more complexity compared to a simple task and thus has a lower automation potential.

Algorithmic automation has also been shown to be associated with increase in efficiency due to reduction in errors, and tireless and fast performance of work (Hoff & Bashir, 2015; Wajcman, 2019). For example, it is contended that the use of deep AI technologies may improve the rate of cancer treatment to about 60-70%, which is only about 20-30% currently when clinicians recommend combinations of drugs (Singh, 2020). Even though it is difficult to automate such tasks, consequent increase in efficiency, if and when these tasks get automated, may be huge. It is important to understand, however, that the task complexity based understanding of automation that we propose is limited in its ability to address questions regarding which tasks when automated would yield maximum efficiency gains.

The task complexity based understanding of automation also implies that AI is likely to be fraught with all sources of opacity associated with judgment and fuzzy tasks, that is, corporate secrecy, technical illiteracy, and high-dimensional optimisation (Burrell 2016). Hence, AI systems are likely to be highly opaque raising concerns about ethics and their eventual social desirability. Our framework can further add to the current understanding of AI adoption by explicating the specific concerns for fairness associated with AI, as well as, design solutions that might alleviate those concerns, as explained below.

4.2 Task complexity and likelihood of fairness concerns: Implications for designing task-aware technology artefacts

A task complexity based understanding of algorithmic automation allows us to supplement the understanding about why all instances of algorithmic automation may not be equally problematic from an ethical and social desirability perspective (for example, Martin 2018). In this section, we will discuss how different tasks may be associated with different concerns algorithmic fairness. We then extend this discussion to indicate the implications of a task complexity based understanding of algorithmic automation for technology artefact design.

Scholarship on designing artefacts has drawn inspiration from the concept of affordance – developed in ecological psychology (Gibson, 1986) – defined as a relationship between the properties of an object and the capabilities of a user, determining how the object may be used (Norman, 2013). Scholars of Information Systems have appropriated this concept to imply the possibilities for goal-oriented action offered by a technical object to a specified user group (Markus & Silver, 2008). Recently, scholars have called for greater attention to the affordances offered by AI-enabled systems 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 domain of AI and automation has focused on how AI-based 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 favour of supporting AI fairness and transparency by designing AI systems that afford transparency, explainability, visualization and voice (Robert et al., 2020). While these scholars have researched the domain of AI 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 impacting individuals in human terms. Visualization affords fairness by representing information visually to make sense of the multi-dimensionality of AI decisions. And voice affords fairness by providing the opportunity for feedback to the AI.

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

Simple Task: For simple tasks, none of the four sources of complexity discussed by Campbell (1988) is present. When a simple task is automated, a common consistent procedure is followed for achieving the single desired outcome, reducing the possibility of a biased outcome and ensuring consistent allocation. The only source of opacity, if any, for such tasks may be attributed to the need for corporate secrecy (Burrell, 2016). As a result, the likelihood of procedural fairness concerns in such tasks, when automated, is low. Similarly, the lack of multiple desired outcomes that may exhibit negative relationship with each other, indicates that distributive fairness concerns are unlikely for automated simple tasks. Since automated simple tasks are likely to pose low fairness concerns, they are the best candidates for automation. We propose that by making the underlying mechanics of the automated simple task visible and transparent, the procedural fairness concerns, if any, arising due to opacity can be addressed. Hence, we posit that:

> *Proposition 1: The affordance of transparency must necessarily be designed into a system that automates a simple task in order to address any procedural fairness concerns.*

Problem Task: The defining feature of problem tasks is the multiplicity of paths to a single desired outcome. Automation of these tasks entails computational evaluation, execution, and comparison of multiple paths across the entire solution space to arrive at the desired outcome (Campbell, 1988).

The possibility of exhaustive comparison leaved little possibility of bias or inconsistent allocations due to automation. Therefore, the distributive fairness concerns associated with the outcome is unlikely when these tasks are automated. However, from the perspective of procedural fairness there might arise some concerns owing to the mathematical/analytical/heuristic formulation of these tasks. Opacity may arise from users' lack of skill to understand coded logics, in addition to that imposed by the need for corporate secrecy (Burrell 2016). Hence, to address procedural fairness concerns associated with automation of these tasks, not only is there a need to enable transparency, but also design affordances that explain the computational logic in human terms. Hence, we posit:

> *Proposition 2: The affordances of transparency and explainability must necessarily be designed into a system that automates a problem task in order to address procedural fairness concerns.*

Decision Task: Decision tasks are defined by multiplicity of paths and multiple outcomes (Campbell 1988) often involving conflicting interdependence and uncertainty of paths and complicated trade-offs between the outcomes. Automation of a decision task requires the algorithm to computationally execute all the paths to all the desired outcomes, causing the eventual outcome to be achieved at the cost of other desired outcomes. Hence, there is a likelihood of automated decision tasks giving rise to some concerns about distributive fairness. Automation of decision tasks often requires high-dimensional algorithmic computations which cognitively mismatch with human reasoning and interpretations (Burrell 2016). Opacity for automated decision tasks, hence, arises not only from corporate secrecy and users' technical illiteracy, but also form the mismatch between the high-dimensional computations performed by algorithms and limitations on human reasoning and semantic interpretation (Burrell, 2016). Hence, to address procedural fairness concerns associated with automation of these tasks, not only is there a need to design the affordances of transparency and explainability, but also affordances that represent the high-dimensionally computed outcomes visually for analysis and comparison. Further, to alleviate concerns about distributive fairness, we suggest that the affordance of comparability, defined as *the possibility to compare outcomes using what-if analysis and simulate multiple scenarios on actual data* used by the automated system, need to be designed into the automated system. This affordance of comparability, when actualized in tandem with the affordance of visualization, can specifically help in alleviating concerns with respect to distributive unfairness. Hence, we posit:

> *Proposition 3a: The affordances of transparency, explainability, and visualization must necessarily be designed into a system that automates a decision task in order to address procedural fairness concerns.*

> *Proposition 3b: The affordances of visualization and comparability must necessarily be designed into a system that automates a decision task in order to address distributive fairness concerns.*

Judgment and Fuzzy Tasks: Judgment tasks and fuzzy tasks are characterized by the presence of conflicting interdependence between paths, and probabilistic and/or uncertain linkages between paths and outcomes. For these tasks, the algorithm needs to perform high-dimensional optimization making it difficult to discern the actual path used by the algorithm to reach the outcome. Hence, automation of judgment and fuzzy tasks through AI-systems is associated with high likelihood of concerns about procedural fairness due to the inability of users and, often technology designers as well, to make sense of how the high-dimensional computations are being carried out (Burrell, 2016). Concerns for procedural fairness are further exacerbated due to the socially embedded assumptions made by AI-systems in order to contend with the uncertainty and stochasticity of information. In addition, when conflicting interdependence exists between paths to multiple outcomes, one outcome is achieved at the cost of other desired outcomes, associating AI-systems with a high likelihood of concerns about distributive fairness. The high likelihood of concerns for both procedural and distributive fairness makes AI a highly contentious topic with respect to ethical concerns (for example, Zarsky 2016, Sweeney, 2013, Noble 2018, Martin 2019). Consider the example algorithmic judgment in courts of law to decide 'Bail or Jail'. The system that automates this judgment task has to account for most of the uncertainties and stochasticity of the task by making assumptions that might be socially embedded, resulting in a systematic marginalization of certain historically disadvantaged groups to a further state of disadvantage, thereby, raising concerns about distributive and procedural justice (Zarsky 2016, Park & Humphry, 2019). Similarly, consider the example of autonomous cars, particularly the ethical dilemma associate with the 'trolly problem', where the algorithm is expected decide a course of action when a collision is unavoidable. The ethical dilemma associated with such a case is impossible to resolve computationally, leading to the use of some socially embedded assumptions that further aggravates concerns about procedural and distributive fairness.

The use of stochastic and uncertain information along with socially embedded assumptions in AI-systems makes it insufficient to design just the affordances for transparency, explainability, and visualization to alleviate fairness concerns. We argue that the affordance of voicing feedback to the AI-based system can address procedural and distributive fairness concerns to some extent. Further, the affordance of comparability coupled with the affordance of visualization can specifically help in alleviating concerns with respect to distributive unfairness.

Proposition 4a: The affordances of transparency, explainability, visualization, and voice must necessarily be designed into a system that automates judgment or/and fuzzy tasks to address procedural fairness concerns.

Proposition 4b: The affordances of visualization, comparability, and voice must necessarily be designed into a system that automates judgment or/and fuzzy task to address distributive fairness concerns.

Figure 7 summarizes the likelihood of concerns about distributive and procedural fairness across task types by using different colors to depict the magnitude of concerns (blue – negligible likelihood of concerns; green – low likelihood of concerns; yellow – medium likelihood of concerns; orange – high likelihood of concern). This figure also lists the affordances that need to be designed into an automated system to alleviate distributive and procedural fairness concerns.

Fairness Concerns	Simple Task	Problem Task	Decision Task	Judgement and Fuzzy Task
Likelihood of concerns about distributive fairness			Transparency Explainability Visualization	Transparency Explainability Visualization Voice
Likelihood of concerns about procedural fairness	Transparency	Transparency Explainanility	Visualization Comparability	Visualization Comparability Voice

Legend:	Magnitude of Concerns	Negligible	Low
		Medium	High

Figure 7: Distributive and procedural fairness concerns across task types and necessary affordance that address these concerns

Another important implication that can be derived from the use of the concept of affordances to address fairness concerns arising due to algorithmic automation and AI is highlighting the presence of heterogeneity among task-performers (that is, the technology users). Since, affordance is a relational notion, it means that actualization of an affordance accounts for the capabilities of a user and the properties/features of the technical object (Leonardi, 2011; Markus & Silver, 2008), in this case the information system that automates tasks algorithmically. Hence, simply designing an affordance into an automated system is not sufficient for actualizing an affordance that addresses fairness concerns. For example, even if the code for an algorithm is made public, users who do not possess the skill to read and understand the code will not be able to actualize the affordance of transparency (Strong et al., 2014). That is why all the propositions formulated in this section mention the necessary affordances to address fairness concerns pertaining to different task complexities, and not the sufficient ones.

Affordances of technology being relational also underscores the contingent nature of affordances, where affordances are mere *potentials* for action, and need not always get actualized (Strong et al., 2014). We believe that this aspect has strong repercussions for all ethical and moral concerns, like fairness and accountability (Orr & Davis, 2020; Robert et al., 2020), associated with algorithmic automation even for the simplest of tasks. Specifically, fixing ethical accountability on the corporations that design and use algorithmic automation and AI becomes untenable given not only the distributed nature of responsibility (across users, designers, and technological artefacts) (Orr & Davis, 2020), but also the contingent nature of affordance actualization (across users and technological artefacts). We, therefore, argue that designing affordances that enhance the perception of fairness of automated and AI-based systems is only a necessary first step to alleviate associated ethical and moral concerns. These affordances must be coupled with due legal and regulatory oversight in order to protect users' interests and drive adoption of automated and AI-based information systems (Pumplun, Tauchert, & Heidt, 2020).

5. Conclusion

The objective of this essay was to examine the variations in algorithmic automation potential and its varying influence on the opacity and fairness concerns of such automations. To examine this, we developed a framework using the task complexity as the theoretical foundations. With the assistance of five task types propounded by Campbell (Campbell, 1988) we show the variation in automation potential and opacity associated with tasks across the task complexity spectrum. This exposition assists us in understanding the underlying task specific reasons for difference in automation potential and associated opaqueness. Further, we use the same framework to explicate why different tasks types have varying likelihood of fairness concerns. We analyses the fairness concerns across distributive and procedural fairness and show variations in these two types of fairness concerns across the task complexity spectrum. Finally, we use our framework to provide recommendations to designers of algorithmic automations and AI systems regarding addressing fairness concerns associated with different types of tasks. We propose that algorithms used to automate tasks of varying complexity require different types of affordances if fairness concerns arising from automation need to be addressed.

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