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DATA ANALYTICS (AB)USE IN HEALTHCARE FRAUD AUDITS

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ABSTRACT

This study explores how government-adopted audit data analytic tools promote the abuse of power by auditors enabling politically sensitive processes that encourage industry-wide normalization of behavior. In an audit setting, we investigate how a governmental organization enables algorithmic decision-making to alter power relationships to effect organizational and industry-wide change. While prior research has identified discriminatory threats emanating from the deployment of algorithmic decision-making, the effects of algorithmic decision-making on inherently imbalanced power relationships have received scant attention. Our results provide empirical evidence of how systemic and episodic power relationships strengthen each other, thereby enabling the governmental organization to effect social change that might be too politically prohibitive to enact directly. Overall, the results suggest that there are potentially negative effects caused by the use of algorithmic decision-making and the resulting power shifts, and these effects create a different view of the level of purported success attained through auditor use of data analytics.

Key words: Algorithmic decision-making, Data analytics, Government auditors, Healthcare,

Medical fraud detection, Power.

> "Could one imagine a society, or even a group of people, where *nothing* was trusted and where explicit checking and monitoring were more or less constant? . . . The more one thinks about it, the more apparent it is that the imperative 'never trust, always check' could not be a universalizable principle of social order: constant vigilance is somehow autodestructive." (Power, 1999, 3)

1. INTRODUCTION

Under the auspices of promoting efficient and cost-effective monitoring of compliance with federal regulations, the United States (U.S.) Federal Government has recently leveraged data analytics to streamline fraud audits aimed at healthcare providers—a move paralleled by major public accounting firms who recently invested heavily in developing new audit technologies, including data analytics to detect fraud and errors in their clients' financial statements (Eilifsen et al., 2020; see also Deloitte, 2016; EY, 2017; KPMG, 2016; PwC, 2017). The U.S. Small Business Jobs Act of 2010 requires the Centers for Medicare & Medicaid Services (CMS) to implement the Fraud Prevention System (FPS), a data analytic tool designed to identify potential Medicare fraud—which is construed as a pressing problem due to high societal costs (van Capelleveen et al., 2016). Currently, the data analytic tool draws on algorithms to identify reimbursement claims indicative of likely fraud (OIG, 2017) and thus represents a new audit tool whose appropriateness and reliability needs to be critically evaluated (Commerford et al., 2020). The FPS was enacted on June 30, 2011 (DHHS, 2012) and was soon publicized as a major success based on steadily increasing returns on investment (ROI) (CMS, 2015; DHHS, 2012, 2014, 2015) while largely ignoring actual fraud convictions which would indicate true effectiveness (van Capelleveen et al., 2016). Nevertheless, consideration of the success criteria relied upon by the U.S. Government soon triggered interest in deploying similar audit data analytic tools to other U.S. Government programs.

While the U.S. Government advertised the self-identified success of the FPS, researchers have cautioned that algorithmic decision-making warrants particular scrutiny when used by governmental entities whose decisions have implications for society. Despite these calls for scrutiny, prior literature has rather narrowly focused on benefits of implementing advanced data analytic technologies to increase business opportunities and performance (Abbasi et al., 2016; Chen et al., 2012; Grover et al., 2018; Mahama et al., 2020; Peters et al., 2016; Reinking et al., 2020a, 2020b) and, to a limited extent, on the impact of data analytics on auditors' decision making (e.g., Commerford et al., 2020; Eilifsen et al., 2020; Koreff, 2021; Rose et al., 2017). An underlying assumption of these prior studies is that the effects of algorithmic decision-making are limited to the users of the analytics tool and the entity that constitutes the target of the data analysis. We challenge this assumption and explore the propensity of algorithmic decision-making to encourage normalized behavior with potential detrimental outcomes for an entire industry and ultimately society. As such, our motivation is to examine the negative effects of data analytic-driven normalization of behavior.

We examine how government-adopted audit data analytic tools promote abuse of power[1] by auditors and drive processes encouraging industry-wide normalization of behavior. Specifically, we explore how statistical analysis tools utilized in fraud inspection processes prescribed by the U.S. Federal Government are deployed to justify abuse of power via auditor enforcement actions. These are used against healthcare providers in a fashion that stifles their financial viability and shifts power toward larger, albeit not necessarily more effective or efficient, actors. Algorithmic decision-making has the potential to bring out the worst of "The Audit Society" where methods of checking and verification can be perverse, burdensome, and inevitably costly (Power, 1999, 2).

[1] For this study, we follow Hall (1999) who notes that it is commonly understood that power concerns the relationships between two or more individuals, where the actions of one actor impact the actions of the other. In the context of government auditor-auditee relationships, we define 'abuse of power' as a situation in which the exercise of power by the auditor (i.e., the auditor's actions) can justifiably be considered excessively unreasonable or unfair by the auditee. Power dynamics, in our context, refers to the fluid nature of relative power held by various actors within a social setting.

We opted for a qualitative research approach, which can aid in validating theory and enhancing our understanding of power dynamics in an accounting information systems (AIS) setting (Sarker et al., 2018a). While we collected data by reviewing public and proprietary documents and obtaining documents through Freedom of Information Act requests, our primary data stem from 40 semi-structured interviews with individuals employed by organizations subject to a fraud audit.[2] This approach enabled us to obtain first-hand insights from participants in the field (Malsch and Salterio, 2016).

Our results show the capacity of data analytics to allow government auditors to justify sanctions, promote the use of power and abdicate responsibility for the consequences, notwithstanding several shortcomings of the data analytic models when applied in practice. Overall, our findings suggest that the use of advanced audit analytics tools, when legitimated by governmental bodies, not only elevates the systemic power (Clegg, 1989; Kärreman, 2010; Lawrence et al., 2012) bestowed upon authorized users of the technology, but also promotes the abuse of such power. This is consistent with views that governmental audits are not just designed for better financial controls, but to challenge the organizational power and discretion of relatively autonomous groups of experts such as doctors to make them adhere to redefined performance measures and criteria (Power, 1999, p. 98). We show that claims to expert power, justified by access to government-sanctioned audit analytic tools, are used to legitimate enforcement actions that have the potential to trigger radical shifts in industry-wide power dynamics.

Notably, factors such as access to care and changes to the quality of care at providers undergoing a fraud audit are absent in Reports to Congress. These reports focus on ROI rather than

[2] One respondent's employing organization did not go through a fraud audit; however, we proceeded with the interview to understand their perceptions of the threat and nature of the audits as they prepared for the future possibility and likelihood of an audit.

the implications of data-driven fraud audits for the availability of quality healthcare. We argue that technology-driven fraud prevention and detection initiatives normalize behavior (Sargiacomo et al., 2015; Sharma and Lawrence, 2015), which is not always appropriate for highly specialized industries, such as the healthcare industry (Cassel and Reuben, 2011; Marmor et al., 2005; Mashaw and Marmor, 1994). Inappropriate normalization efforts have the potential of marginalizing or even bankrupting various actors within an industry, thereby affecting industry-wide power-dynamics. Moreover, specialization in the healthcare industry advances knowledge to improve society as a whole (Mashaw and Marmor, 1994). Normalization initiatives may discourage providers from specialization, ultimately hindering the advancement of knowledge and the provision of better healthcare, and as a by-product reallocating power to larger, non-specialized providers.

This research makes several important contributions to the AIS literature. First, the research helps address calls to consider audits in governmental contexts (Free et al. 2020; Gendron et al. 2007) as we look specifically at how government auditors appropriate data analytic tools to redefine the audit relationship. Second and more specifically, this study extends prior research which has narrowly focused on the capabilities of various outlier detection algorithms to identify potential Medicaid fraud related to a single type of healthcare providers (i.e., dentists) within a single state (see van Capelleveen et al., 2016).[3] Our study, which explores potential downsides of algorithmic decision-making draws on data related to Medicare as well as Medicaid fraud investigations from a diverse range of healthcare providers across multiple U.S. states. Third, researchers have pointed to the dearth of empirical research on data analytic tools used for auditing purposes and the effect of these new technologies on the conduct of audits (Austin et al., 2019; Eilifsen et al., 2020). Our study addresses those calls for additional research. Fourth, the present

[3] See van Capelleveen et al., (2016) for a review of prior (non-accounting) research on the ability of data mining and outlier detection techniques to improve healthcare fraud identification.

study advances knowledge about the implications of government-encouraged algorithmic decision-making on the power dynamics between auditors acting on behalf of the federal government and constituents. Fifth, our investigation offers future research a better understanding of the transformation of power dynamics within an important social setting (i.e., the healthcare industry) (van Capelleveen et al., 2016) as a result of algorithmic decision-making. Finally, we show implications of using technology to promote change. Our finding that government-encouraged algorithmic decision-making elevates the systemic power of the actors using the technology concerns a manifestation of power that has received little attention in the literature (Simeonova, 2018), even though power and politics associated with information system inventions is a recurring theme in this literature (Avgerou and McGrath, 2007).

This research also makes an important contribution to audit research and the discourse on "The Audit Society" (Power, 1999). Power (p. 96) identifies two extreme possibilities of audit failure which are viewed as never likely to be found in pure form. We find both to exist in essentially pure form under the shifting circuits of power surrounding algorithmic decision-making by auditors. First, the audit process can take on a life of its own with its own goals irrespective of the reasons that the auditees exist as a service to society. Second, the audit process becomes the dominant reference point for auditees' organizational activities and effectively colonizes auditee organizations—implanting the values of a third party and a focus on normalization of behavior. Beyond the macro-foundations of the discourse on "The Audit Society", we also provide evidence of how the audit society is created and reinforced at the micro-level as we examine how data analytics that interpret deviations in the audit trail of healthcare organization's transactions as evidence of fraud, actually construct an organizational factivity that all deviations are fraud (Power, 2021).

2. THEORETICAL BACKGROUND

2.1 Power

It is commonly understood that power concerns the relationships between two or more individuals, where actions of one actor impact actions of the other (Hall, 1999). Simple as this sounds, the literature has long recognized that defining and measuring power is a formidable challenge, not least due to the elusive nature of power as a concept with cryptic characteristics that are difficult to label and comprehend (Jasperson et al., 2002). Thus, it is not surprising that numerous conceptualizations of power have emerged in prior literature. For purposes of this study, we draw on two perspectives on power that, while distinct, have been used in conjunction to explain organizational and social change. These two perspectives, which seem to dominate current discourse, are *power as a restraining force* and *power as a productive force* (Kärreman, 2010).

The first conceptualization of power characterizes it as a restraining force used to coerce individuals into acting in compliance with another individual's desire, thereby restraining the actor subject to power from acting according to their own wishes (Kärreman, 2010). This conceptualization aligns with *episodic power*, which emphasizes rather discrete, strategic actions by an actor (Lawrence, Winn, & Jennings, 2001) used to limit others' decision-making alternatives (Lawrence et al., 2005). Thus, the *power as a restraining force / episodic power* viewpoint embraces a "power over" perspective that highlights the advantageous nature of power that allows an actor to regulate the potential actions of other individuals (Lawrence et al., 2012), set agendas, remove opponents, and limit other's decision alternatives (Lawrence et al., 2005). This power over another may be attributable to professional capital—e.g., a physician's power over a patient (Guo et al., 2017). Other examples of this perspective, which encompasses French and Raven's (French and Raven, 1959) concept of "legitimate power," include the power of a teacher over a student, or of a manager over a staff member. Legitimate power, which is closely related to the concept of authority, is often bestowed upon an agent by a legitimizing actor (French and Raven, 1959).

The second conceptualization of power characterizes it as an enabling rather than a restraining force. This conceptualization aligns with the notion of *systemic forms of power*, which "work through the routine, ongoing practices of organizations" (Lawrence et al., 2001, p. 629]. Thus, the *power as a productive force / systemic power* viewpoint embraces a "power to" perspective that highlights the capacity of power to cause or facilitate change. Examples include the power to access information, programs put in place to facilitate social change (Clegg et al., 2006; Cobb, 1984; Lawrence et al., 2012), or the power inherent in an IS that provides encoded decision paths to knowledge workers, thereby guiding them through a limited range of actions (Lawrence et al., 2005). According to this perspective, systemic power ("power to") is considered an integral part of social relationships (Clegg et al., 2006; Kärreman, 2010; Lawrence et al., 2012; Simeonova, 2018), enabling social agents to act in specific ways (Kärreman, 2010; Kärreman and Alvesson, 2009). However, agents who establish systemic forms of power need to be aware of potentially unintentional outcomes, as the long-term impacts of chosen systems and practices often elude their control (Lawrence et al., 2001).

However, a thorough appreciation of the nature of power is limited without an understanding of the interaction between both modes of power. While Cobb, (1984, p. 484) highlights that executing power (i.e., episodic power) critically depends on pre-existing conditions (i.e., systemic power), others have argued that both modes of power operate in circuits: the exercise of episodic power forms the basis for systemic power to operate, which in turn establishes the required legitimacy for agents to exercise episodic power (Clegg, 1989; Lawrence et al., 2012). Those insights are reflected in research that explores the interplay of systemic and episodic power in the context of organizational learning (Lawrence et al., 2005) and radical transformations within professional service firms (Lawrence et al., 2012), and form the basis of our analysis. Figure 1 illustrates the relationship between episodic and systemic power.

[INSERT FIGURE 1 ABOUT HERE]

From an organizational perspective, systemic forms of power include technological systems (Noble, 1984; Shaiken, 1984) that favor certain groups. According to Lawrence et al., systemic power, which can help explain the dynamics of organizational change (Lawrence et al., 2005), takes two distinct forms: (1) "discipline," which, through its impact on identity, affects cost–benefit perceptions associated with individuals' choices; and (2) "domination," which operates through variations of the possibilities available to individuals, frequently through "physical and social technologies that provide the context for action" (Lawrence, 2008, p. 178). Domination is defined by Lawrence et al., (2001, p. 637) as "forms of power that support institutionalization processes through systems of organized, routine practices that do not require agency or choice on the part of those targeted." While systematic discrimination against specific groups reflects a rather obvious form of (institutionalized) domination, more subtle means of domination do exist—for example, governmental use of quantitative descriptors and statistical techniques to label and characterize organizations (Lawrence et al., 2001).[4] Such "actuarial practices" construct target organizations as objects, or pieces of information, the properties of which can be accommodated or exploited (Lawrence et al., 2001).

2.2 Algorithmic decision-making

As technologies may be used to support and rationalize organizational processes and their social implications (Cecez-Kecmanovic, 1994; Cecez-Kecmanovic et al., 2002), researchers have

[4] For additional background on how statistical science is used by auditors to rationalize discriminatory testing see Power (1999).

called for investigations of information technology's effects on society (Sutton, 1993; Sutton et al., 2018; Trauth and Howcroft, 2006). One such technology is the set of algorithms used to support, or even completely automate, human decision-making processes (Arnold and Sutton, 1998; Rikhardsson and Yigitbasioglu, 2018; Sutton et al., 2016). Consistent with Newell & Marabelli (2015), we define algorithmic decision-making as an automated, structured method of identifying patterns within large datasets that are used for decision-making purposes.

Incorporating data analytics into audits can identify the highest risk data for further investigation. Examining highest risk areas can facilitate more efficient and effective audits by enabling auditors to reallocate time spent on labor intensive tasks to judgment intensive tasks (Agnew, 2016; AICPA, 2015; Brown-Liburd et al., 2015; Raphael, 2017). Moreover, while data analytics may permit centralized expertise to be disseminated to lower level auditors (Boland et al., 2019; Dowling, 2009; Dowling and Leech, 2014), they may have unintended consequences, such as causing lower level auditors to insufficiently consider issues beyond identified information (Arnold and Sutton, 1998; Seow, 2011). Although data analytics are able to identify high risk areas from data analyzed, these high risk areas may merely represent false positives (Vasarhelyi et al., 2015; Yoon et al., 2015). Not surprisingly, the rapidly growing reliance on algorithmic decision-making by private and public organizations (Galliers et al., 2017; Kamiran et al., 2013; Kirkpatrick, 2016; Newell and Marabelli, 2015) raises concern with researchers about unintended outcomes (Sutton, 1993; Sutton et al., 2016; Trauth et al., 2018; Zarsky, 2016).

Discriminatory outcomes can be the result of algorithmic bias, which "occurs when the machine learning models reproduce the intentional and unconscious biases of humans making decisions about collecting data, identifying data to be used in algorithms, and deciding how the data is to be used in the algorithm" (Trauth et al., 2018, p. 3). Human error or bias in capturing and/or measuring data that lead to the perception that certain groups of individuals (e.g., ethnic minorities) are disproportionately associated with some forms of undesirable data is often the root cause of data inequality (O'Neil, 2016; Zarsky, 2016). Researchers have thus cautioned against applying algorithmic decision-making to judgment tasks where algorithmic opacity (Burrell, 2016) prevents individuals who use these systems from comprehending how the algorithm arrived at its decision (Arnold and Sutton, 1998; Rikhardsson and Yigitbasioglu, 2018; Sutton et al., 2018). However, even if humans are kept in the loop during the algorithmic decision-making process (and the algorithm's evolution), significant risks remain—research suggests that humans are rather ineffective at overriding automated decisions (Goddard et al., 2014; Markus, 2017).

As discussed earlier, algorithmic decision-making enables actors to justify their actions, even when those actions are inappropriate (i.e., discriminatory) (Newell and Marabelli, 2015). Those findings seem less surprising when viewed in light of social psychology research. While decision-aid users tend to follow decision-aid recommendations passively (Glover et al., 1997), psychology studies show that individuals may rationalize unethical decisions by displacing responsibility (Bandura, 1999, 1991; Bandura et al., 2001) to another individual or to a technological artifact (Nissenbaum, 1996). Thus, data analytics tools can allow actors in a position of power over others to justify their actions based solely on the output of an algorithm, regardless of whether those actions seem appropriate (i.e., ethical) under the specific circumstances. Therefore, we ask the following research question:

RQ: Can algorithmic decision-making enabled by data analytics result in abuse of power and/or shifting power dynamics?

3. RESEARCH METHOD

The present study is situated in the context of the private/public sector partnership embodied by the U.S. healthcare system. Within the U.S. healthcare system, providers (e.g., hospitals, home health agencies, nursing homes, physician offices) generate revenue by providing services then submitting reimbursement requests to a variety of payers, including government agencies (e.g., Medicare and Medicaid) and insurance companies (e.g., Aetna and UnitedHealthcare). The dollar amount submitted for a reimbursement request is calculated using charge codes. Charge codes are made up of unique billable activities and are impacted by services provided (such as time in an operating room) (Balakrishnan et al., 2018). Reimbursement requests are subject to scrutiny from reimbursement entities for a variety of factors including fraud. Healthcare fraud has a significant societal cost (van Capelleveen et al., 2016): in the 2018 fiscal year, the U.S. Federal Government won or negotiated over $2.3 billion in healthcare fraud judgments and settlements (DHHS & DOJ, 2019). Thus, effective data analytics have the potential to significantly reduce the cost of healthcare fraud. CMS created and implemented the FPS data analytic tool to help identify Medicare fraud. With its introduction, reliance on algorithmic decision-making by government auditors was explicitly dictated by the U.S. Federal Government.

To assist with on-site forensic analysis (i.e., a "government audit"), CMS outsources inspectorial powers (cf. Power, 1999), i.e., audit responsibilities, to teams of auditors, specifically Zone Program Integrity Contractor (ZPIC) firms (CMS, 2007). Once the data analytics identify an outlier, a ZPIC auditor is assigned to examine the outlier and conduct a fraud audit of the healthcare provider to identify a possible pattern of fraudulent claim submissions (DHHS, 2012).

The development and implementation of the FPS highlight how technology can purportedly be used to fight healthcare fraud. The FPS deploys four types of data analytic models to identify potentially fraudulent activities within the Medicare program. The first is a "rules-based" model that uses defined criteria or pre-established rules (Chiu and Jans, 2019; Jans, 2019;

Jans et al., 2014, 2013, 2010) to flag fraudulent claims and behaviors, such as claims billed using a Medicare identification number that has been previously reported as stolen. The second FPS model is an "anomaly" model that detects individual and aggregated abnormal metrics (i.e., ratios) compared with a peer group in the current period—for example, identifying a provider that bills more services in a day than 99% of providers in the same region. The third FPS model is a "predictive" model that uses patterns associated with previously detected frauds to identify similar patterns in the current period. The fourth FPS model is a "network" model that examines links between actors. A network model may be used to identify providers linked to known bad actor, such as through a common address or phone number (DHHS, 2014; Jans et al., 2014).

Four full years of FPS operation have been publicly reported. The reports describe the results of the FPS approach to fraud detection as a major success based on consistently increasing ROI, from 3.3:1 in 2012 to 11.5:1 in 2015 (CMS, 2015; DHHS, 2012, 2014, 2015). Although positive and increasing ROIs are reported in the Reports to Congress (DHHS, 2012, 2014, 2015), examination of only *actual* savings revealed ROIs of 0.51:1, 0.57:1, 0.88:1, and 1.08:1 from 2012 to 2015.[5] Thus, savings did not exceed costs until the fourth year, suggesting that ZPIC auditor activity was not initially cost-effective. Given the purported success of ZPIC Medicare fraud audits (DHHS, 2012, 2014), subcontractor activity has expanded to Medicaid. The creation of Unified Program Integrity Contractors consolidated the ZPIC audit responsiblities with their Medicaid counterparts, yet all contracts were awarded to already utilized ZPIC firms (CMS, 2018).

It should be noted that this expansion of the ZPIC programs are consistent with alleged conflicting motivations for the auditor. While audits are viewed as a remedy for distrust, they can

[5] ROI is calculated based on total estimated savings (actual savings plus projected savings) divided by total estimated costs (development contractor costs, modeling costs, employee salaries and benefits, and investigation costs) (CMS, 2015; DHHS, 2012, 2014, 2015).

also be used to sow distrust where the solution to these pathologies of distrust is yet more and better auditing (Power, 1999, p. 136-7). The auditors are the guardians of distrust, which Power (p. 137) argues is "The Audit Society" in a nutshell.

3.1. METHODOLOGY: A POSITIVIST CROSS-SECTIONAL CASE STUDY

We adopted a positivist case-study approach for this study, as it validates theory and examines relationships among constructs (i.e., power, auditing and AIS) (Sarker et al., 2018b). Using qualitative methods is often a preferable research method for examining emerging phenomena in a natural setting (Benbasat et al., 1987; Eisenhardt, 1989; Power and Gendron, 2015; Sutton et al., 2011); for example, "limited research on outlier techniques in health care fraud … in which experiences of actors and context are important (Benbasat et al., 1987; Yin, 2009)" (van Capelleveen et al., 2016, 21). As organizations are targeted for audit following application of a variety of data analytic methods, and healthcare providers' on-site audit experiences are likely to differ, a cross-sectional case study was selected as the most appropriate method for this research (Benbasat et al., 1987). Semi-structured interviews were utilized to collect data on topics of interest related to respondents' firsthand accounts of being subject to a government audit; however, these interviews also permitted the interviewer to be open and flexible to exploring new insights presented during the interview (Miller and Crabtree, 1994). See Appendix A for the full protocol.

3.1.1 Data collection

We established contact with individuals employed by healthcare providers subject to audit through various sources, including public accounting firms, articles in publicly available sources, and state and subindustry healthcare organizations and conferences. We targeted respondents who could provide direct first-hand knowledge and insight into our research question (Malsch and Salterio, 2016)—specifically, individuals employed by providers subject to the government fraud audits, and thus possessing firsthand knowledge of those audits.

We interviewed 40 individuals from across the U.S. The respondents were primarily C-level executives (or equivalent) or owners of healthcare providers; the remaining respondents were high-ranking clinical personnel, including two administrators (similar to office managers), a consultant, two directors, and a manager.[6] Respondents were located in six of the seven U.S. geographic zones, covering audits by three of the four ZPIC firms.[7] There was substantial diversity among the respondents (see Table 1). We noted no significant differences between different subgroups (i.e., industry type or location) during our analysis.

[INSERT TABLE 1 ABOUT HERE]

The interviews lasted from 31 to 118 minutes and were conducted between March 2015 and May 2019. They were held in respondents' offices, by phone, or in a public location. They were recorded and fully transcribed by one of the researchers or a graduate research assistant.[8]

3.1.2 Data analysis

One of the researchers pilot-coded the initial interviews by examining each sentence and assigning a descriptive label to the content conveyed within it based on an initial set of themes focusing on use of audit data analytics. As additional interviews were conducted and transcribed, the researcher iteratively coded all the interviews by analyzing the data in sequence on a line-by-

[6] Although the directors and manager were not in the "C-suite," they were all employed by organizations of significant size and capacity. Healthcare fraud is particularly prevalent in the home health industry (DHHS & DOJ, 2019; OIG, 2016), therefore it is not surprising that home health providers are targeted by the government auditors and comprise a significant portion of our sample. Prior research expressed the importance of acknowledging the researchers relationship to respondents and organizations (Pratt, 2009). One of the authors previously worked in the healthcare practice of a national professional service firm for approximately two and a half years. None of the authors had a pre-existing relationship with any of the respondents nor organizations prior to the initiation of this study.

[7] The four ZPIC firms are NCI Advancemed, Health Integrity (now Qlarant), Safeguard Services, and Cahaba Safeguard Administrators.

[8] One respondent declined to be recorded. During the interview, the interviewer took handwritten notes and captured direct quotations whenever possible.

line basis, beginning with the first interview. This ensured that increased attention was not given to certain respondents (Miles and Huberman, 1994). During the coding process, we remained open to the emergence of other concepts and relationships and refined the coding scheme as necessary (Sarker et al., 2018b). During this process, power relationships emerged as a theme discussed by respondents. During the coding process, several subcodes were identified. Commonalities among subcodes were identified and subcodes centering on similar topics were collapsed into codes.

Data saturation—the point when additional interviews are neither presenting contradicting information nor adding any significant new information (Malsch and Salterio, 2016; Rahaman et al., 2010; Sutton et al., 2011)—was achieved. We took three main measures to enhance the accuracy, reliability, validity, trustworthiness, and completeness of our findings. First, we triangulated interview data (Dowling and Leech, 2014; Kaplan and Duchon, 1988; Salterio and Denham, 1997; Yin, 2009) with archival documents, such as respondents' communication with the government auditors (primarily e-mails and court documents) and publicly available information sources, such as practitioner websites (i.e., those of attorneys and consultants). Second, a graduate assistant was provided the coding scheme and independently coded all interviews. The assistant coded one transcript and then met with the researcher to discuss discrepancies before proceeding to code remaining transcripts (all discrepancies were resolved). Third, we provided respondents earlier drafts of this study (Guénin-Paracini et al., 2014; Malsch and Salterio, 2016; Trauth and Jessup, 2000) and no concerns regarding content were expressed.

4. FINDINGS

4.1 Use of data analytics

As respondents predominantly portrayed the ZPIC auditors (henceforth "government auditors") in a negative light, we considered whether this negative view was merely attributable to respondent bias from being subject to a government audit or was specific to the government auditors in this study. We examined how respondents discussed their audits with other government agencies (i.e., Department of Justice Office of the Inspector General). We identified a clear distinction in their descriptions, noting that other auditors were described in an overall positive manner. Respondents even expressed support for the intended purpose of the government auditors (to detect Medicare fraud) and expressed their satisfaction with seeing fraudulent providers closed down. This demonstrates that respondents did not highlight government auditors' abuse of power and excessive reliance on algorithmic decision-making merely because they were subject to an audit; rather, they identified these phenomena *only* for the actions of these government auditors.

Our examination of public documents revealed the government auditors' success in leveraging data analytics to identify Medicare fraud. For example, the government auditors identified that WakeMed hospitals had a large numbers of patients classified as inpatients (indicating overnight admittance) with zero night stays (indicating no overnight admittance) (U.S. District Court for the Eastern District of North Carolina, 2013). Another example is the auditors' identification of Medistat's abnormally high home-health referrals (Health Integrity LLC, 2012). Respondents discussed the benefits of data analytics within their own organization and acknowledged similar success stories and the benefits of government auditors:

> I think the [government auditors'] process when it originally started did a good job of eliminating the bad guys and the fraudsters … it's a good method, they've caught some bad guys, but there needs to be other processes to reconcile the injustices … [government auditor] was VERY successful in knocking out a bunch of the bad guys, very successful. They served their purpose, but they kind of dragged it on too long, they're digging too deep. (Respondent 15, Chief Executive Officer [CEO])

Despite CMS undertaking fraud detection initiatives since the late 1990s,[9] one respondent

[9] See the annual "Health Care Fraud and Abuse Control Program" reports published by the Department of Health and Human Services and Department of Justice since 1997.

pointed out that providers have only recently been financially penalized by CMS based solely on the outcome of statistical analysis. Concerns with the government auditors' selection of statistical methods was a recurring theme among respondents. For example, when the data analytics identified a statistical outlier, that outlier might not have necessarily indicated wrongdoing:

> [J]ust to be presumed guilty by a statistical analytic, has never been done before … every account that was, or every bill that was pulled was denied 100 cents on the dollar, denied, because statistically it didn't make sense to somebody. … There's no concept of an average family because the average family has one and three quarter kids, so it doesn't exist. Statistically you can have an outlier, but that doesn't mean you did anything wrong. (Respondent 8, Financial Director)

As the above quotation indicates, the government auditors seemed dismissive of potential FPS shortcomings and prone to rely on risks identified by the data analytics without sufficient scrutiny. Respondents' frustration with the government auditors' homogenized and ineffective approach to identifying *true* outliers was exacerbated by a perceived lack of openness toward gaining a deeper understanding of the peculiarities of the organization under investigation. Statistical deviations from generic expectations may have straightforward explanations that respondents would have liked to provide, had they been given the opportunity:

> [H]ad they [the government auditors] called the provider up and said, "You know this is what we're seeing in your data" or "This is the complaint or you know, can you help us understand" there's an actual explanation for what's happening. … It's not necessarily indicative of fraud. (Respondent 39, Chief Compliance Officer [CCO])

Several respondents noted that anomaly models (i.e., high or low amounts) spurred their audit. For example, one hospice in the sample was selected for audit due to its patients living too long, as reflected in unusually long Length of Stays (LOS).[10] While a long average LOS at a hospice may be an indicator of fraud (i.e., treating non-terminally ill patients for more than 180

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[10] Hospice providers seek to comfort those expected to pass away within 180 days. The LOS is the number of days the patient received care.

days), high LOS may also be the result of providing high-quality care to patients. A hospice employee explained that professional judgments used to make recommendations for hospice care are not always accurate. Putting an individual in hospice care may actually improve that patient's health. Thus, anomaly models may identify hospices with a high LOS that is attributable to providing high-quality care, not fraud:

> [I]f whatever terminal disease or condition they're suffering from … runs its normal course would you expect this patient to pass away within the next six months. … sometimes it doesn't run its normal course. Sometimes it takes a year or longer. … We go in, we get them on their meds. … We make sure they got oxygen if they need it … We watch their diet. We educate them on those kinds of things. We get a clinical therapist in there … sometimes they start to … improve. (Respondent 4, Chief Financial Officer [CFO])

The implications of such misinterpretation of data analytics can have profound effects on the provision of healthcare services. A hospice in the sample was forced to refuse treatment to certain patients due to the government auditor's accusation that its average LOS was indicative of fraud. One respondent discussed how prolonging patients' lives initiated an audit:

> The patients for the Hospice Medicare benefit is six months or less on a terminal prognosis. Well we had a lot of patients that were over that 180-day mark, and that sparked our [government audit]. (Respondent 3, CEO)

Another respondent described being identified by an anomaly model because their organization had lower costs than similar providers in their region. This CEO expressed frustration with being targeted for having lower expenses than other providers in the area, arguing that their provider was saving the government money. While it seems intuitive that data analytics are used to identify providers with disproportionately high expenses, and thus those that are more likely to engage in fraudulent activities, the identification and audit of providers with disproportionately low expenses may merely target those exhibiting best practices:

> I just didn't feel it was good business practice, having to spend more money to get more money or just trying to grow with volume and spend money … my utilization was always

> low. … claims data showed in one of the counties that I served, showed me as the lowest utilizer of services in the county. The average length of stay in my county was [≈5.5] episodes, so we're talking [≈340] days. My average length of stay was [≈1.1 episodes]. So, my average length of stay was close to or less than [≈80] days. When you add the dollar amounts attached to that, I could have saved the government like a hundred million dollars in one year in one county. (Respondent 12, CEO)

Another CEO stated that their government audit was initiated by disproportionately high revenue growth compared with alleged nationwide industry averages. This respondent then explained that their large increase in revenue was attributable to their organization being a startup that only operated for part of its first year. Accordingly, revenue generation was limited to only that part of the first year, whereas revenue was generated throughout the second year:

> [Government auditor] told us that he had data in front of him and he was very detailed with the numbers. He knew that our revenue for [year 1] was around $270,000 and that our revenue for [year 2] was close to $2 million dollars and that's almost … a 10 times growth, and could I explain that? … we couldn't start billing Medicare until November … I mean we have about four months of operations … in [year 1], and I had one marketer going out and getting referrals as opposed to three marketers in [year 2]. … that's why we grew at the rate we did. And he said that that was way above the national average of growth in the Medicare home care industry. And I said, "Well what is that average? I would like to know" and he goes, "Well … there's nothing published, but that's just higher than expected." (Respondent 34, CEO)

In addition to anomaly models, respondents also discussed the use of network analytics by the government auditors. Respondents noted that physicians unrelated to their organization had been identified by the government auditors as engaging in unusual billing practices. The services delivered by the respondents' organizations to patients referred from those physicians were therefore not reimbursed. Thus, in spite of the referring physician, rather than the organization under the government audit, being suspected of engaging in questionable practices, the organization receiving the referral and providing the treatment faced the consequences in the form of reduced cash flows. Several respondents noted that the government auditors targeted their organization solely based on its indirect association (via referrals) with physicians suspected of unusual billing practices. One respondent recalled this 'guilt by association' experience:

> [N]o home healthcare billing … will be paid with this physician's NPI [National Provider Identifier] attached to the claim, so no one will take care of that patient. … [government auditor] says, "Listen lady, it's not about you, it's about the doctors and as long as you continue to take care of this guy's patients, you're not gonna get paid." (Respondent 28, Administrator)

The third data analytical model identified by respondents as being used by the government auditors was the rules-based model, which applies established flags for potentially fraudulent data values in certain data fields. The rules-based model identifies both physicians and patients suspected of engaging in fraudulent activities and blacklists them. The blacklisted actors identified through the rules-based models become the basis for generating network models, which focus on the actors identified by the rules-based model as likely tied to fraudulent claims. One respondent explained that when a patient is identified by the rules-based model, services provided to them will not be reimbursed to the provider, which may result in providers refusing to treat the patient:

> [The patient's] Medicare is compromised. So she cannot use home-health services … She still has no Medicare and this lady needs the services. … Nobody can touch her. … They [the government auditors] are flagging patients. (Respondent 30, Owner)

The algorithms underlying the three data analytic models used to identify potential healthcare fraud differ in their foci. Results show anomaly models are used to identify providers with abnormally high service treatment periods (based on LOS) and those with unusually low expenses; network models are used to identify patients associated with questionable physicians; and rules-based models identify specific physicians/patients associated with potential fraud.

4.2 Abuse of power

Abuse of power also emerged from our analysis as consequences of algorithmic decision-making.[11] Participants lamented about the government auditors constraining cash flows, requesting documentation beyond their jurisdiction and employing intimidation tactics. Subsequently, participants discussed how these actions result in consolidation of power within the industry (see section 4.3 below). The ability to disrupt Medicare reimbursement (DHHS, 2012) creates a resource-dependency relationship between the healthcare providers and government auditors that can reshape providers' service provision. For example, if a provider derives half of their earnings from Medicare, the government auditors can eliminate half of the provider's earnings. A respondent noted that the government auditors exercised their ability to constrain Medicare reimbursement, and gave additional evidence of the government auditors intentionally withholding critical information and abusing their power:

> [T]hey put us on 100% prepayment review, just because they can, and they tell me "We can put you on there for four years, we can have you be on there forever." ... they had never given us a sampling of the 30 initial reviews which you're supposed to by statute. (Respondent 10, Owner)

However, the denial of Medicare reimbursements is not limited to individual provider locations deemed suspicious. The government auditors can increase the financial punishment of a suspected organization by extending Medicare reimbursement constraints to all of the provider's locations nationwide. It is therefore not surprising that this resource dependency resulted in respondents noting that the government auditors abused their power throughout the audit process:

> [T]hese contractors are running rampant and they're breaking the law … There's a lot of power at the ZPIC level right now, and that needs to be balanced … What is currently happening will send ripples through our healthcare system for many years to come. … It is very discouraging to downright criminal the abuse of power that we are currently seeing from the ZPICs and other entities that are letting this happen … It is a battle that you cannot win because by design the rules applied were never drafted to benefit the patient or

[11] We use the term "emerge" to represent properties that are not specified by the algorithmic decision-making literature, but are revealed by our analysis to be salient to respondents' government audit experiences.

provider. (Respondent 14, CFO)

Although the government auditors' jurisdiction has expanded to include Medicaid (CMS, 2018), most respondents were interviewed regarding government audits prior to this expansion. One respondent interviewed before the expansion discussed the government auditors' attempted exercise of power by requesting documentation beyond their jurisdiction:

> [T]he letter originally requested Medicare and Medicaid records, and [attorney] stated that they didn't have authority to request the Medicaid records. (Respondent 16, CCO)

Moreover, respondents noted that intimidation tactics were a standard feature of the government auditors' *modus operandi*—for example, auditors showed up armed at healthcare facilities (Moore Stephens Lovelace, 2013). One respondent reported that the government auditors interviewed a patient at home and verbally abused them to the extent that the patient called police. A review of several archival documents revealed that the government auditors included the CMS logo on their communications with organizations being audited. An agency owner who shared others' awareness of such intimidation practices articulated the perceived purpose of such tactics:

> I think they just use the gestapo tactic to scare people into writing them checks. Showing up like you know, they might as well [have] had ski masks and machine guns. Because that's how they came in … like stormtroopers. (Respondent 1, Owner)

4.3 Consolidation of power

Employees from over three quarters of the organizations interviewed noted that they were aware of several providers who had declared bankruptcy during their government audits, or stated that bankruptcy was a salient fear during their own government audit. Respondents explained that subsequent to a smaller provider declaring bankruptcy, larger providers gained the upper hand in the struggle for market share. Consistent with these explanations, the providers in the sample that declared bankruptcy or sold their company subsequent to their government audits were all small or family-owned businesses:

> [T]hey know that they are really putting us in a situation, and they have that power. … You give power to somebody … to close you down and take everything away. (Respondent 30, Owner)

One respondent explained how larger providers are able to sustain operations during their government audit. While Medicare providers must have a registered, preapproved identifier to receive Medicare reimbursement, larger providers tend to have multiple identifiers. This respondent discussed how larger providers are able to shift reimbursement requests to identifiers *not* under a government audit; however, smaller providers are unable to do so, as they only have one identifier and lack the financial capital to obtain a new one:

> [Attorney] said, so this strategy for people like you who have the resources to take action: we advise them to turn off the lights, roll up the carpet, take the same amount of money they're going to pay lawyers and consultants buy a brand new, clean Medicare number. Transfer all those patients over to that one. Throw the ZPIC letter in the trash and just go right on down the road. … It's a strategy that is deployed by the larger companies who have those resources and [company #1] does it, [company #2] does it, [company #3] does it, [company #4 has] done it. … there's a lot of companies [that have] done it … They have a bank of provider numbers. And so when one gets a dirty … they just close it down. They take the patient population, move them to a new one. … The barrier is cash. (Respondent 40, CEO)

Respondents discussed how the government auditors' actions have a greater impact on smaller providers than on larger providers. The consolidation of market share and power from smaller providers to larger providers was further highlighted by one respondent:

> [I]t's the big guys that are being left … the big players that have you know that are publicly traded, they have bottomless pockets, can throw money at that and survive until the pendulum sways back. … The era of the smaller mom and pops' home-health agency is going away … there's [about 160] agencies in [city] … they're not … shutting down necessarily, they are being gobbled up by the big guys, whether they get sold or acquired, typically is what happens. There's been shut downs, [government auditors] have shut down probably about half a dozen that I can think of in this area … This is the whole process behind Medicare's madness … they can't control 12,600 Medicare agencies nationwide. They can control a couple hundred, and that's what they want. They want the big providers to take over, and then they can control those guys. … they have even said that outside of

> microphones, our association leaders have heard this from the Medicare people …"You have too many agencies, we need to get rid of a bunch." And so, I believe that's part of the [new government audit] program. (Respondent 36, Owner)

With consolidation of market share, fewer specialized niche providers will be available for the general public to choose from for healthcare services:

> I'm not in [big city] … I'm not in a large metropolitan statistical area. There are different things that we have to deal with, and typically they add something to the formulary to look at those rural providers, and look at those things, but it's going to be very sad when we take a vanilla approach to medicine. (Respondent 10, Owner)

5. DISCUSSION

In this study, we examine how government-adopted audit data analytic tools promote abuse of power by auditors and initiate processes encouraging industry-wide normalization of behavior. While prior research identifies discriminatory threats caused by the deployment of algorithmic decision-making, the effects of algorithmic decision-making on inherently imbalanced power relationships, such as those explored in this research, have received limited attention. Our study addresses concerns regarding the social and ethical implications of algorithmic decision-making (Newell and Marabelli, 2015; Sutton, 1993; Sutton et al., 2018, 2016). Our results demonstrate that false positives are used by decision-makers to justify taking action (Newell and Marabelli, 2015), at times without a comprehensive understanding of what the outliers represent (Mayer-Schonberger and Cukier, 2013). For specialized industries, such as healthcare (Cassel and Reuben, 2011; van Capelleveen et al. 2016), consideration should be given to critically evaluating the output of data analytic tools and technology driven fraud detection initiatives seeking to normalize behavior may not be appropriate (Sargiacomo et al., 2015; Sharma and Lawrence, 2015). As risks identified may merely represent false positives, algorithmic decision-making can result in suboptimal outcomes when blindly followed by decision-makers (Arnold and Sutton, 1998).

5.1 Power

As previously discussed, the abuse of power emerged as a theme from our data analysis. Algorithmic decision-making is an integral part of CMS' establishment of systemic power ("power to") for its privatized government auditors. The outputs of the data analytic system give the auditors the right to enter the organization, demand documentary evidence and interviews, and, more importantly, to use the data analytic tool as the sole basis necessary to suspend payments to the organization. The use of statistical outputs to characterize healthcare providers on behalf of the government reflects a subtle form of institutionalized domination where targeted practitioners are constructed as objects (Lawrence et al., 2001). In essence, the auditors are given the "power to" freely audit, but also to freely impose penalties upon the practitioners being audited. The data analytic outputs—statistical outcomes—are frequently the only evidence required to suspend a provider's payments. This power to audit and penalize creates an episodic power relationship between the auditors and the provider. The auditor has "power over" the provider and appears to freely use this power in the relationship. As is not unusual in such relationships, we see perceived abuses of power arise during audits, with the provider often feeling victimized.

Auditors holding a position of power have the ability to engage in actions that influence the actions of less powerful auditees. Such power enables powerful actors to repress, censor, and constrain their subjects (Foucault, 1983). The government auditors in this study are in a position of power to engage in actions affecting the healthcare providers under audit, as highlighted by their ability to recommend providers' temporary and permanent exclusion from Medicare reimbursement (DHHS, 2012). Such resource-dependency relationships enable actors in power to exert unethical demands on their less powerful subjects (Marmor and Morone, 1980; Palmer, 2012), including threatening an indefinite reimbursement suspension, asking for records beyond their jurisdiction and employing gestapo-like tactics. As this study is set in the healthcare industry, the implications of the government auditors' abuse of power may have widespread societal implications, which in some cases may result in loss of life.

Power is legitimized by recognition from a legitimate authority (French and Raven, 1959). As governments are viewed as legitimate actors (French and Raven, 1959), CMS' acceptance of the government auditors' recommendation to constrain Medicare cash flow legitimizes the government auditors' power. Trust placed by CMS in government auditors' recommendations is consistent with prior research suggesting perceptions of competence on the part of (government) agents who deploy a new technology reinforces the trust placed in the technology itself and thus reduces perceptions of power abuse (Avgerou, 2013)—at least from the perspective of the CMS.

The ability of the government auditors to constrain cash flows represents power as a restraining force (episodic power via power "over" another, as discussed in prior research (Lawrence et al., 2012), as providers must act in accordance with government auditors' desires. Episodic power is exercised by actors engaging in self-interested behavior; in the government auditors' case, this is shown by the desire to win Medicaid contracts (CMS, 2018). While the data analytic models used by government auditors differ with respect to the type of data flagged by the underlying algorithm, they all trigger instances of the domination form of systemic power: the algorithmic decisions rendered by these models limit the alternatives available to government auditors, thereby providing additional legitimacy for restraining providers' actions. Consistent with accountants overlooking quality of care delivered by healthcare providers (Pflueger, 2016) and government agencies using quantitative descriptors and statistics to label and characterize subject organizations (Lawrence et al., 2001), the FPS represents a technology enabled tool using these characterizations and in turn enables government auditors to exercise and establish power over healthcare providers. That is, government auditors draw on the FPS "to provide meaning, to exercise power, and to legitimize actions" (Walsham, 2002, p. 935).

Yet, respondents expressed concerns over the government auditors' mischaracterization of system descriptors and statistics (i.e., false positives)—e.g., when an organization was identified for a government audit due to exhibiting best practices reflected in particularly low expenses. Consistent with Foucault (Foucault, 1977), a respondent expressed the desire to avoid being labeled as "deviant" in the future. Avoiding this label would entail adhering to societal norms, which would, in this scenario, result in incurring additional costs. As a consequence, government resources would be diverted away from education, other social programs, or auditing outliers truly indicative of fraud. This finding is particularly troublesome, since the suspected referral source may itself become a victim of unjustified audit and administrative action, as discussed in the context of false positives. Consequently, instances of episodic power have the potential to form the basis for systemic power to operate, thereby establishing the required legitimacy for government auditors to exercise episodic power. As the results demonstrate, the government auditors' range of action was limited by a technology enabled data analytic tool containing the domination form of systemic power.

Systemic power entails power to access information (Lawrence et al., 2012). The results demonstrate that the government auditors often do not permit providers to offer simple yet important explanations; this constitutes a limitation of the providers' actions via a discrete act by a self-motivated actor (Lawrence et al., 2001). While some respondents discussed the lack of opportunity to provide an explanation for an apparent anomaly identified by the data analytics, even when respondents were able to provide an explanation, they were denied a satisfactory response by the government auditors. This finding is consistent with Power (1999) who notes that the perceived legitimacy of auditors' actions requires that some operational details be kept secret. By keeping information secret that would have allowed the provider to judge the need for more detailed explanations, the government auditors also limited the provider's ability to defend itself against accusations based on data analytics.

Overall, this abuse of power is part of a broader audit system, where the rules and processes governing the auditor-auditee relationship legitimizes the use of technology and algorithmic-decision making. We offer caution to blindly trusting technology in the auditor-auditee context. More effective auditing systems can be achieved by implementing measures to decrease abuse of power through modifying algorithms, and more effective auditor training (including more effective false positive identification).

5.2 Consolidation of power

Episodic power entails an actor's ability to limit others' decision-making alternatives (Lawrence et al., 2005). In this study, episodic power is highlighted by the government auditors' ability to constrain providers' cash flow (DHHS, 2012). Respondents discussed how the government auditors' actions demonstrated episodic power by constraining their organization's ability to operate and forcing bankruptcy declaration. Additionally, the exercise of systemic power enables change, and both types of power operate in circuits with each other (Clegg, 1989; Lawrence et al., 2012). Such change attributable to the government auditors' actions can be seen in the consolidation of power toward larger providers within the healthcare industry.

The exercise of episodic power operating circularly with systemic power is a result of the government auditors' actions. This circular relationship is shown by the government auditors exercising their power (episodic power) to enable change (systemic power) by consolidating power within the healthcare industry toward larger providers via the reduction in the number of smaller providers, a move towards corporate oligopoly. This circular relationship provides additional evidence of certain groups (i.e., larger providers) receiving favorable treatment as a result of actors exercising their power. Exercising power can include use of technological systems (Noble, 1984; Shaiken, 1984). New technologies provide favorable treatment to certain actors by serving certain interests (Cecez-Kecmanovic et al., 2008), shifting power distributions (Joe-Wong and Sen, 2018), and strengthening existing social and control structures (Cecez-Kecmanovic, 2011). Despite the argument that technology should improve quality of life for all (Porra and Hirschheim, 2007), the results of this study suggest that recent changes to conducting government audits—most notably, the introduction of actuarial practices (Lawrence et al., 2001) enabled by data analytics—highlight the use of systemic power and have led to an establishment of a system that favors certain actors.

Industry-specific factors create an abundance of specialization within the healthcare industry (Cassel and Reuben, 2011; Mashaw and Marmor, 1994; van Capelleveen et al., 2016), rendering the adoption of a one-size-fits-all fraud-detection approach inadvisable (SAS, 2014). Specialization in the healthcare industry advances knowledge to improve society as a whole (Mashaw and Marmor, 1994). Therefore, normalization initiatives may not be appropriate (Sargiacomo et al., 2015; Sharma and Lawrence, 2015) and cause providers not to specialize, which ultimately hinders the advancement of knowledge and the provision of innovative healthcare.[12] Such normalization initiatives provide another example of government technology having unintended negative societal effects (Marjanovic and Cecez-Kecmanovic, 2017). The results of this study highlight how a government-endorsed audit data analytic tool consolidates power in an industry toward larger organizations by allowing them to capture market share from

[12] This is consistent with prior research demonstrating that healthcare providers change operations (i.e., patient mix) and financial reporting in response to government regulation(Blanchard et al., 1986; Eldenburg et al., 2017; Eldenburg and Kallapur, 1997; Eldenburg and Soderstrom, 1996; Holzhacker et al., 2015; Kallapur and Eldenburg, 2005; Koreff et al., 2020; Krishnan and Yetman, 2011).

smaller organizations that have been driven out of business. Respondents stated that the elimination of smaller niche providers is an intentional initiative that takes place to the detriment of patients. The consolidation of power to larger providers, moving towards corporate oligopoly, as a result of the government auditors' actions suggests that smaller providers may attempt two courses of action when subject to government audits: (1) expand in size to survive, or (2) declare bankruptcy; the second action appears more prevalent. Results demonstrate that larger organizations are better able to continue operations during a government audit than smaller providers due to greater financial resources (cash). This allows the larger providers to capture more power, via market share, from the smaller bankrupted providers.

Providers may specialize to meet the needs of their target population, since application of generic healthcare services nationwide is unlikely to result in optimal outcomes for patients—for example, the elderly, low-income individuals, and low-education individuals all differ in their healthcare needs (Marmor and Morone, 1980). Thus, even providers delivering high-quality services to their local or niche market, such as markets outside of a large city, may be identified as a statistical outlier by the data analytics and become the target of government auditors. As success of tools such as the FPS are contingent upon the calculation of benefits (Cecez-Kecmanovic et al., 2014), it is important to not only focus on technical aspects when deploying such new technologies, as access to care issues are not included in the ROI calculations presented in Reports to Congress. Although systematic governmental discrimination against specific groups would likely be met with unfavorable public opinion, governments may use quantitative descriptions and statistical techniques to characterize organizations (Lawrence et al., 2001). The ability of auditors to suspend Medicare payments to the provider can financially cripple that provider. Documentary and interview evidence indicates smaller providers that are more susceptible to the auditors' power often either cease operating or merge with other organizations. In some cases, this can leave regions of the country without certain medical options, as a provider that has ceased operations may have been the only provider of certain services within a specific geographic region.

Overall, the intertwined power relationship initiates social change via reshaping the industry landscape. The only means to counter auditors' "power over" providers is to consolidate enough to create a smaller set of large organizations with the power to fight back against auditors' penalties. This often requires sufficient funds to weather years of payment suspension until court resolution is attained, or sufficient financial resources to restart as a different provider registrant. It is not unusual in these cases for penalties to be reduced by 95–100%, but the provider must stay in business long enough to attain judicial remedy.

There is evidence that this consolidation of medical organizations is actually a goal of CMS, as the professional organization representing smaller providers cites Medicare personnel saying that consolidation is desired so they can do business with only a small set of providers, thereby achieving efficiencies. With some political pressures also in place to curtail Medicare expenditures and services, eliminating service provision in some geographic regions may not necessarily be considered a negative by some constituencies. These social outcomes should be considered in future research focused on government use of algorithmic decision-making. Taken together, our results answer the research question by demonstrating that algorithmic decision-making can result in abuse of power while also shifting power dynamics of an entire industry.

5.3 Implications for research and practice

Amid the broad claims of success for the data analytic models adopted by CMS to identify fraud in Medicare claims, this study sought to provide data on the role of power in the deployment, utilization, and impact of information technology within government entities, an area lacking attention in the literature (Jasperson et al., 2002). Of particular interest was attaining an understanding of how algorithmic decision-making via data analytic tools is utilized in practice and how this utilization affects systemic power and its relationship with social change (Clegg, 1989; Lawrence et al., 2005, 2001). In seeking empirical data to enhance our understanding of the intertwined phenomena, we address a concern over the predominance of theoretical-based analyses left wanting in empirical substance (Lawrence et al., 2012).

Recent concerns over algorithmic decision-making have largely been raised over built-in bias (Trauth et al., 2018). The literature's focus on bias generally concentrates on race, gender, social standing, or socioeconomic status (Kamiran et al., 2013; Trauth et al., 2018; Zarsky, 2016). Our empirical data contributes to the literature by identifying a different type of bias built into CMS' data analytics: inherent bias for standardization and efficiency of practice with little regard for specialization, quality differentiation, and effectiveness (Cullinan et al., 2010). We find data analytic tools identify cost leaders, specialized practices for care, unusual success in treatment, and prolonged patient life through quality care as outliers using non-standardized practices and not focusing solely on moving the patient in and out of care. These outliers are viewed as equal levels of fraudulent behavior to practitioners providing false claims or running unnecessary tests, and they appear to be penalized similarly. More conceptually, our findings identify how bias arises from data analytic use on heterogeneous populations to assess operational performance.

Our results also provide future research with a better understanding of the transformation of power dynamics within an important social setting (i.e., the healthcare industry) as a result of algorithmic decision-making. Data analytic models can provide legitimacy, and in turn power, to those empowered to interpret and use the models. Some of our respondents alleged that government entities with the ability to empower those armed with data analytics may be subversively transforming power relationships without overtly having to be accountable—in this case, benefiting larger corporate providers and disadvantaging small- and medium-sized enterprises. Investigating these issues is important, as advanced technologies are increasingly used to justify decisions (Newell and Marabelli, 2015) and disseminate expertise (Dowling and Leech, 2014, 2007) in settings where the long-term ramifications of relying on data analytics are ill-understood (Arnold and Sutton, 1998; Grover et al., 2018; Sutton, 1993; Sutton et al., 2018, 2016).

Accordingly, our research also has implications for practice on several levels. Research on the use of big data and analytics by governmental entities is only beginning to unfold. Governmental entities and their stakeholders (including citizens) need to understand how data and analytics can be used to affect societal relationships. We help address the sparsity of studies that have challenged the decisions made by government agencies based on algorithmic decision-making or considered the associated social and ethical implications (Newell and Marabelli, 2015; Sutton, 1993; Sutton et al., 2018, 2016). By investigating the potential shift in power dynamics attributable to analytic tools used by agents tasked to monitor regulatory compliance, the present research sheds light on recently adopted data analytic applications. This investigation is important, as research shows a power imbalance may enable those imbued with power to engage in amoral practices with potentially adverse social outcomes (Marmor and Morone, 1980; Palmer, 2012).

Our study also has implications for practice more generally, as organizations implement data analytics for monitoring use. First, despite the perception that data analytics will benefit organizations, we highlight the importance of human interaction with data analytic systems to effectively apply such smart technologies (Hancock, 2014). Practitioners in other areas, such as financial fraud, have implemented guidelines for using human brainstorming groups to evaluate potential fraud-source scenarios (Lynch et al., 2009). In the fraud arena investigated in this study, the government auditors may benefit from using brainstorming techniques to consider why data analytics have identified a concern before acting upon them. This could alleviate the common automation bias that leads to overreaction to system alerts (Skitka et al., 1999). Such behavioral supplements to data analytic tools should be more broadly explored (Asatiani et al., 2019).

Further, organizations of all types must be aware of how algorithmic decision-making may be misused to create powerful actors more interested in a personal goal, despite their actions potentially being to the detriment of the organization. Significant data analytic tools should be reviewed on a regular basis to understand the effectiveness of their use. In such reviews, entities should incorporate input from a variety of stakeholders to ensure that necessary, yet uncommon, processes and services are not being impaired by the implementation of analytics.

7. CONCLUSION

Respondents raised several concerns associated with the use of the data analytics and consequent actions by government auditors. Our results provide evidence of rules-based, anomaly, and network models being used to initiate audits, even though these models yield false positives. Further, even when a false positive is identified, a process is initiated that enables the government auditors to wield the power bestowed upon them against organizations they are auditing, ultimately affecting power dynamics within the healthcare industry.

Our research lends support to the argument receiving limited attention in the literature: that data analytics can have unintended and negative consequences (Arnold and Sutton, 1998; Sutton et al., 2018, 2016; Zhou et al., 2018). With a focus on data analytics in an audit setting, our study more broadly contributes to the literature examining dysfunctional side-effects of audits (see Power, 1999). We answer the research question posed and demonstrate that the use of data analytics can promote algorithmic decision-making, resulting in the abuse and consolidation of power. As is generally found during in-depth field studies, the relationships are complex and intertwined. The empirical findings support earlier theorizations that systemic and episodic power operate in circuits, whereby each mode of power is strengthened by the other (Clegg, 1989; Lawrence et al., 2012), leading to organizational transformation and social change (Lawrence et al., 2012, 2005). Some evidence in our context suggests that the governmental entity involved, the legitimizing actor (French and Raven, 1959), effectively utilizes the assignment of systemic ("power to") and episodic ("power over") power against entities under its control to effect social change that, politically, could not be instituted directly by the governmental entity. This establishment of power relationships is greatly enhanced by the use of algorithmic decision-making (Newell and Marabelli, 2015), where the data analytics are incapable of being questioned, as opposed to the human decision-makers they replace.

Overall, our research provides evidence of how systemic and episodic power work in circuits to affect social change. It also highlights how algorithmic decision-making in the form of advanced data analytics can be a powerful force in enabling "power to" and effecting "power over" relationships. This effect of algorithmic decision-making is of particular importance considering the extensive use of data analytics in contemporary organizations, and should be further examined in future research to understand the bounds and magnitude of such effects.

Our research also adds to the understanding of how data analytics can reinforce and even strengthen the pressures of "The Audit Society" (Power, 1999, p. 96). Power notes that there are two extreme possibilities that represent different kinds of audit failure, but that neither is likely to manifest itself in a pure form. First, the audit process could become a world of its own, creating auditable images of performance decoupled from the focus of the auditees' service mission which is the intended subject of audit. We see such an isolated world arising from algorithmic decision making. Second, the audit world spills over and actually defines auditees' organizational activity, effectively colonizing organizations through the audit and redefining organizational values. The audit can be viewed as a failure due to its side effects actually undermining performance—in this case encouraging industry-wide normalization of behavior. Thus, we see how algorithmic decision-making creates circuits of power that actually lead to both types of failure presenting themselves in essentially pure form. Beyond these macro-foundations that have been examined in isolation across many research studies on the 'Audit Society', our findings also contribute to the emerging discourse on the micro-processes that create the 'Audit Society' from the bottom up (Power 2021). Indeed, our findings suggest that data analytics, and the algorithmic decision making associated with these audit procedures, accelerate the interpretation of deviations in audit trails as clear indications of fraud. These findings provide insights into the organic creation of organizational factivity via audit trails that warrant further investigation in future research.

7.1 Limitations

As with any research study, ours is subject to limitations. We considered the potential that respondents in this study were discussing the government auditors' algorithmic decision-making and abuse of power as a mechanism to justify their difficult audit experiences. We are comforted that the findings reported are specific to the government auditors in this study, as respondents discussed audits from other government auditors in a consistently positive light. These insights suggest that the algorithmic decision-making and abuse of power are not merely attributable to being under an audit, but are rather confined to being subject to a fraud audit by the specific auditors in this study.

Despite repeated Freedom of Information Act requests, we were never able to get CMS to disclose the basis for the algorithms underlying the FPS data analytics, including the degree to which artificial intelligence (AI) may or may not have been applied to facilitate data analytic analysis. On the surface, the analytics do not look that sophisticated and government auditors seem to understand the nature of the issues being raised by the analytic. Certainly the government auditors exhibit traits of technology dominance that are consistent with AI-based systems (Arnold and Sutton 1998). Nonetheless, we are unable to assess whether the dominance issues identified in this study might be exacerbated by the use of more advanced AI-based analytics including those that identify problems without being able to explain the basis for the identified fraud issue (Sutton et al. 2018; 2016). Future research should explore the differential effects of more advanced AI-based analytics by auditors as these become more prevalent in audits.

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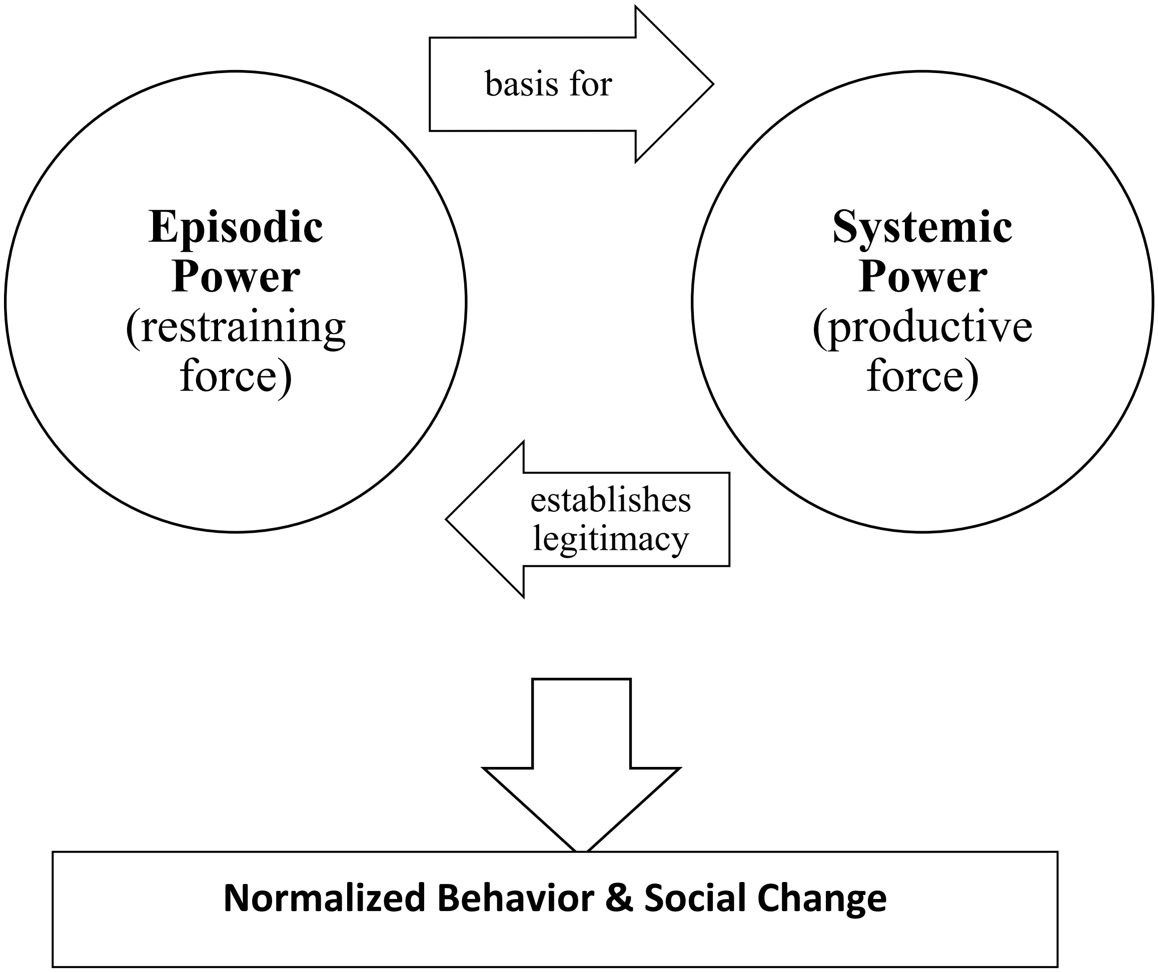
Figure 1



Note: Figure 1 illustrates how instances of episodic power have the potential to form the basis for systemic power to operate, thereby establishing the required legitimacy for government auditors to exercise episodic power (Clegg, 1989; Lawrence et al., 2012). Episodic and systemic power strengthen one another (e.g., Clegg, 1989), leading to social change (Lawrence et al., 2012, 2005).

Table 1 – Interviewee details

#	Job title	Subindustry	Hot spot region[1]	Non-profit	Fines[2]	ZPIC came on site[6]
1	Owner	SNF[3]	Yes	No	Yes	Yes
2	Manager in the revenue cycle	Hospital	No	Yes	No	No
3	CEO	Hospice	Yes	Yes	Yes	Yes
4	CFO	Hospice	Yes	Yes	N/A[4]	N/A[4]
5	CEO	Hospice	No	Yes	No	No
6	Nurse consultant	Home Health	No	No	Yes	Yes
7	Director in care management department	Hospital	No	Yes	No	No
8	Financial Director (CFO equivalent)	SNF[3]	Yes	Yes	Yes	Yes
9	Clinical Care Coordinator	Home Health	Yes	No	Yes	No
10	Owner	Home Health	No	No	Yes	Yes
11	Executive Director	Home Health	No	No	Yes	Yes
12	CEO	Home Health	No	No	Yes	Yes
13	Administrator	Dr. Office	No	No	Yes	Yes
14	CFO	Home Health	Yes	No	Yes	No
15	CEO	Home Health	No	No	Yes	Yes
16	Chief Compliance Officer	Home Health	Yes	No	Yes	Yes
17	Director of Nursing	Home Health	Yes	No	Yes	No
18	Owner	Dr. Office	No	No	Yes	No
19	Chief Operating Officer	DME[5]	No	No	Yes	Yes
20	CEO	DME[5]	No	No	Yes	Yes
21	Clinical administrator	Home Health	No	No	Yes	Yes
22	CEO	Home Health	No	No	Yes	Yes
23	Director in the revenue cycle	Hospital	No	Yes	No	No
24	Director of Compliance	Home Health	No	No	Yes	Yes
25	Director of Nursing	Home Health	Yes	No	Yes	Yes
26	Chief Compliance Officer	DME[5]	No	No	Yes	Yes
27	President	Home Health	No	No	Yes	Yes
28	Administrator	Home Health	Yes	No	Yes	Yes
29	Owner	DME[5]	Yes	No	Yes	Yes
30	Owner	Home Health	Yes	No	Yes	No
31	Chief Operating Officer	Home Health	No	No	No	No
32	CEO	Home Health	No	No	No	Yes
33	Agency director	Home Health	No	Yes	Yes	Yes
34	CEO	Home Health	No	No	Yes	Yes
35	Director of Clinical services	Home Health	Yes	No	Yes	No
36	Owner	Home Health	No	No	Yes	No
37	President	Home Health	Yes	No	Yes	No
38	CEO	Home Health	Yes	No	Yes	No
39	Compliance Officer	Hospice	No	No	Yes	Yes
40	CEO	Home Health	No	Yes	No	No

1 – Hot Spot Region refers to if the provider has at least one location in one of the nine designated hot spots for Medicare Fraud (DHHS, 2012)
2 – This column indicates if the ZPICs levied fines on the interviewee's employer. All fines were related to documentation, none were fraud related
3 – SNF represents a Skilled Nursing Facility, commonly referred to as a nursing home
4 – During the interview, the interviewee revealed that they did not undergo a ZPIC audit. We proceeded with the interview to understand their perceptions of the threat and nature of the audits as they prepare for the future possibility and likelihood of an audit.
5 – DME represents a Durable Medical Equipment company
6 – This column indicates if a ZPIC had a physical presence at the respondent's organization's location at any point during the audit.

Note: More than one individual from some of the providers were interviewed. In total, employees from more than 25 organizations were interviewed.

Appendix A – Interview Protocol

Background of respondents:

1. Please tell me about your job, what you do and what your responsibilities are.
2. What has been your background leading up this point? How did you get to your current job?
3. What is your current title? May I have a business card?
4. How long have you been in this position?

Control items:

1. Can you tell me about what kind of provider you are? (ex: hospital, SNF, physician's office)
2. How many beds do you have? What is the breakdown between SNF, NF, ALF, IL, etc.
3. What county and state are you located in?
4. Is the organization a Non-profit or For-profit provider?
5. Can you talk to me about the level of competition you face in your operating area. (occupancy rates, payer mix, referrals, etc.).

ZPIC Audits:

1. Can you tell me what you know or have heard about ZPIC audits?
2. Can you tell me how and if you changed your activities (corporate compliance, education and training provided to staff) to prepare for them? Are you preparing differently from previous investigations?
3. Can you describe the ZPIC audit(s) experience? (the number of audits, if you received any advance notice, the number of auditors, how long the process was, resources used)
4. Can you tell me how long were they on site for? How much of your time did they require? How did you deal with their requests?
5. Can you tell me what the timeframe was from notice of the ZPIC audit until they showed up and until any issues were resolved? How does this compare to previous investigations?
6. How would you characterize your discussion with the ZPIC auditors? Can you tell me how the ZPICs treated your employees? Were they demanding, accommodating or considerate of your time?
7. Can you tell me if and how you have responded to the ZPIC investigation? Have you done anything differently after the fact? What did you and your colleagues learn from this experience?
8. Can you tell me what you think the likelihood is of them returning?
9. What were the primary issues that the ZPICs brought up? What were their primary findings? Can I see one of the documents that you received? (***Remind the organization to redact resident identifying information***)
10. Can you tell me if you faced any penalties or fines? If so what were they?
11. Can you tell me about the most challenging part of the audit and why it was so challenging?
12. Can you tell me what documents do they usually look at? Can I see one that you were cited on?

13. Can you tell me to whom do they communicate their findings to? Is it a formal report? Who receives the report? Are there different versions. Would you share any of the documents with me?

Societal impact:

1. Have you experienced any unexpected to unanticipated consequences from the ZPIC audit?
2. Has the ZPIC audit impacted the individuals/communities you serve?
3. Did the quality of care change during and after the ZPIC audit?
4. What do you think would happen to the elderly in your region if you went out of business?
5. Did the ZPIC audit put any financial hardship on your organization? Do you think a ZPIC audit could result in bankruptcy?
6. What do you think most of your patients would do if your organization did not exist? What other HC options are available to the community? How could the community be impacted by this lack of service?

Data Analytics:

1. Do you have any insight what initiated your ZPIC investigation?
    a. Do you have any insight what the data analytics identified?
    b. Have auditors used data analytics like this before?
2. Do you have any insight why the government is using data analytics? What are your thoughts on the ZPICs purpose?

Third parties influencing a change in behavior:

1. Did any third parties (external auditors, attorneys, consultants, etc.) give you any notice or warnings about the ZPICs?
2. Did third parties (external auditors, attorneys, consultants, etc.) help you prepare for the ZPICs? Did they provide any advice or counsel for preparation?
3. Did third parties (external auditors, attorneys, consultants, etc.) help you respond to the ZPICs? Did they provide any advice or counsel for response?
4. How would you have liked third parties (external auditors, attorneys, consultants, etc.) to have helped you prepare and respond to the ZPICs?

Leverage, negotiation:

1. Do you have any ability to negotiate with the ZPIC auditors? How does this compare to previous fraud investigators?
2. How would you describe the relationship with your external auditor?
3. How would you describe the relationship with your ZPIC auditor, and previous fraud investigators?
4. Have any other auditors used data analytics? How did that compare to the ZPICs use of data analytics?
5. Does your relationship with the ZPICs differ from previous health care auditors?
    a. After being in the industry for several years, do you think the average provider (not you, someone else) could exert leverage on the ZPICs?