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The Effects of Operational and Financial Performance Failure on BI&A-Enabled Search Behaviors: A Theory of Performance-Driven Search

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Abstract. Business intelligence and analytics (BI&A) systems enable firms to analyze data and search for insights that could potentially lead to improved organizational performance. While there is evidence that BI&A systems can improve performance through search, our theoretical understanding of how and under what conditions firms leverage BI&A systems to conduct search is rather limited. In particular, while problemistic search theory posits that performance failures motivate search, how firms respond to different types of performance failures remains unclear. We draw on and extend problemistic search theory by theorizing that BI&A-enabled search is influenced by complex interactions between failures in financial and operational performance and performance-related aspirations. We refer to this notion as the Theory of Performance-driven Search (TPS) and test it using longitudinal data gathered for a four-year period from seven U.S. hospitals. We find evidence that firms employ BI&A systems to search in a narrow set of circumstances. We find that performance failures are an important antecedent of BI&A-enabled search. In particular, failures in financial performance, failures in operational performance, and their joint failures are important conditions that trigger BI&A-enabled search. We find that historical and social aspiration levels of financial and operational performance influence BI&A-enabled search during failures in operational performance. We also find that only in organizations experiencing a sustained failure in financial performance do operational performance failures trigger BI&A-enabled search and that the latency of search response is dependent on the speed of failure in financial performance. Through our findings, we make two important contributions: we extend the business value of IT literature by identifying the contextual conditions that trigger BI&A use for search and we extend problemistic search theory by theorizing for the differential effects of operational and financial performance failures.

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Introduction

Organizations have been making significant investments in business intelligence and analytics (BI&A) systems to exploit their data resources (Grover et al. 2018). BI&A are information systems (IS) built on technologies such as big data, analytics, machine learning, and artificial intelligence to integrate data across the enterprise and provide models for data analysis and data visualization capabilities to support managerial decision making (Chen et al. 2012). A key motivation behind such investments is that organizations expect that the analytical and information processing (AIP) capabilities of BI&A systems will be employed to analyze data and *search for insights* (Sharma et al. 2014, Saldanha et al. 2017). Moreover, organizations expect that those insights will be employed to make better decisions and improve performance.

Prior literature on the business value of information technology (BVIT) provides extensive evidence to suggest that, in general, a greater use of IT will lead to improved performances (Devaraj and Kohli 2003, Anand and Fosso Wamba 2013, Schryen 2013). However, while it is tempting to assume that the potential for performance gains offered by BI&A systems will automatically lead to greater use of these systems for search purposes, prior research on the success and failure of IS suggests caution in making that assumption (Sharma et al. 2008, Leonardi and Barley 2010). For instance, literature drawing on the problemistic search theory (PST) suggests that search behavior is satisficing and is not conditioned by gain potential but by a number of other factors including performance and the reward systems in operation (Posen et al. 2018). Further, intuition- and experience-based decision making is still dominant in organizations; analytic decision making is infrequently employed even when the AIP capabilities of BI&A systems are available (Davenport and Bean 2018, Wu et al. 2019).

Consistent with the above expectations of limited use, evidence from the field also suggests that, despite significant investments in BI&A, the impact of BI&A systems on search behavior has been limited, proactive use of these systems for search is limited, and few organizations have been successful in capturing the expected performance outcomes (Ransbotham et al. 2016, Davenport and Bean 2018). Digital-native firms such as Amazon, Google, and Airbnb may be a few exceptions whose digital strategies are embedded into their core competences, and the use of analytics is core to their business model. Taken together, both the research and practitioner literature suggest that understanding the motivations behind BI&A-enabled search is an important research question that needs further investigation.

A productive line of inquiry in past research focused on understanding the motivations of users to explain the limited deployment of available IT-enabled capabilities (Kohli and Kettinger 2004). Following that line of inquiry, the question posed in this paper is as follows: "Under what conditions do organizations exhibit greater leverage of BI&A systems to conduct search?" This question departs from an important related question that has been extensively examined in the BI&A literature: How can BI&A systems improve organizational performance? (Anand et al. 2016, Wu et al. 2019). Thus, our research question pertains to the conditions that motivate BI&A-enabled search and complements the commonly researched question of expected performance outcomes from BI&A capabilities. Moreover, BI&A investments are expected to motivate managers to proactively employ AIP capabilities to *enhance* current performance (Grover et al. 2018). Contrarily, research into problemistic search suggests that managers are likely to use BI&A capabilities in a minimal manner—that is, just enough to *recover* from performance failures. However, under minimal use conditions, firms may not realize the potential value from their BI&A investments. Therefore, understanding the conditions under which managers engage in the use of BI&A systems to search for insights is key to understanding realized performance outcomes of BI&A capabilities.

To examine our research question, we draw on and extend the PST, which proposes that performance failures motivate the search for causes of failure and the exploitation of the knowledge acquired through the search process to improve future performance (Cyert and March 1963, Posen et al. 2018). Although PST recognizes performance failure as a trigger for search, it is silent on which of the performance failures firms respond to and how the type of performance failure affects the organization's search for a solution (Posen et al. 2018). Further, in another research stream that has implications for PST, researchers acknowledge that performance is a multidimensional construct and that it is important to explore the theoretical implications of richer conceptualizations of performance (Venkatraman and Ramanujam 1986, Ittner et al. 2003, Combs et al. 2005, Richard et al. 2009). In particular, separating the theoretical relationships of the two key dimensions of performance—financial performance and operational performance—from various organizational outcomes has resulted in richer explanations of key organizational phenomena (Combs et al. 2005). However, a perusal of the problemistic search literature reveals that, in general, scholars still conceptualize performance as a unidimensional construct—primarily as financial performance (Posen et al. 2018).

Considering performance as a multidimensional construct offers the opportunity to develop richer theory and to better understand how the key dimensions of performance influence BI&A-enabled search. In this study, the PST is extended by theorizing the individual and joint effects of failures in operational performance and financial performance to explain BI&A-enabled search behavior. The proposed theory of performance-driven search (TPS) is then tested using panel data models on monthly longitudinal data collected over four years from seven organizations. As hypothesized, evidence was found that shows organizations leverage BI&A systems for search when failure in operational performance is accompanied by failure in financial performance. It was also found that managers step up ad hoc search for insights under a narrow set of conditions—namely, when there is a joint failure of operational and financial performances. Findings from this study contributes to the BVIT literature by extending our understanding of the contextual conditions under which BI&A systems are used. The PST is also extended by highlighting the distinct effects of different types of performance failures in relation to search. Subsequently, our findings identify specific conditions under which managers are likely (or not likely) to engage in BI&A-enabled search. Therefore, our findings help firms develop appropriate strategies to encourage proactive BI&A use to its full potential and capture value from their investments in BI&A systems.

The Relationship Between BI&A Systems and Search

The role of search in the relationship between BI&A systems and performance has been an important topic in recent literature (Sharma et al. 2014, Anand et al. 2016). Here, "search" refers to the volitional and interactive effort expended by managers in acquiring and analyzing information to understand the cause-effect relationships between performance and factors that affect performance. Further, searching is an unstructured task that is shaped by the nature of the specific problem being addressed (Cyert and March 1963). It involves frequent, iterative, and interactive engagements with BI&A systems and other sources of information (Anand et al. 2016, Wu et al. 2019). It also involves multiple discussions with peers, subordinates, and superiors to problematize, analyze, and synthesize the outcomes of the search into a diagnosis and a solution (Koufteros et al. 2014).

The role of BI&A in facilitating the search for informed decision making has been widely examined (Alter 1980, Davenport 2006). The AIP capabilities of BI&A systems to support search have evolved significantly over the years from the early decision support systems (DSS) and executive support systems (ESS) to the current BI&A 3.0 systems. Early DSS and ESS primarily supported standard reporting based on highly structured transactional data and had limited capabilities for ad hoc search and minimal interactive and visualization capabilities (Watson 2014). However, as IT capabilities improved, later systems—variously referred to as BI&A 1.0 and BI&A 2.0—expanded in functionalities to include advanced data management as well as predictive, prescriptive and text analytics from integrating structured and unstructured data sources. Current BI&A 3.0 systems incorporate much more sophisticated algorithms, machine learning, and artificial intelligence that allow search for context- and customer-specific insights in real time. Corresponding to this evolution, the support for search has become significantly enhanced. Table 1 summarizes the evolution of BI&A systems, their AIP capabilities, and their support for search.

Overall, BI&A systems play a critical role in enabling AIP capabilities and supporting search (Table 1). As can be expected, the maturity of the BI&A systems and the available search capabilities vary across firms and industries. For instance, while e-commerce firms are more likely to have BI&A systems that support search across structured and unstructured data for context and location-specific intelligence on consumers, healthcare firms may focus more on predictive and prescriptive analytics to deliver improved patient treatment and care quality. However, irrespective of the maturity of BI&A systems and the available AIP capabilities, insights for better decision making and improved performance are generated through leveraging the AIP capabilities for search—e.g., by querying data and running ad hoc analyses (Anand et al. 2016).

Problemistic Search Theory and Extension

The preceding discussion described search as a volitional task involving a high degree of effort and motivation.

Table 1. Evolution of BI&A Systems, AIP Capabilities, and Support for Search

Systems	Data types	AIP capabilities (examples)	Support for search
BI&A 3.0	Structured and unstructured data	EIS, BI&A 1.0 & 2.0 capabilities Individual-centered analytics Context-relevant analytics Location-aware analytics, etc.	Very high
BI&A 2.0	Structured data and unstructured data (e.g., images, texts, user-generated content)	EIS and BI&A 1.0 capabilities Spatial–temporal analytics Web and social media analytics Sentiment/opinion analytics, etc.	High
BI&A 1.0	Structured data: DBMS-based (e.g., RDBMS, data warehouse)	EIS capabilities Automated and ad hoc reporting Data mining ETL and OLAP Predictive analytics Prescriptive analytics	Medium
Executive information systems	Tacit information and highly structured data	Automated reporting Standard ad hoc report Predefined functionalities	Low
Transaction processing systems	Transactional data	Reporting	Very low

Note. DBMS, database management system; RDBMS, relational database management system; EIS, Executive Information Systems; OLAP, online analytical processing.

Understanding the conditions that motivate BI&A-enabled search is an important theoretical question that remains to be addressed. Prior research on the search behavior of managers argues that in response to failures, "alternatives to the current set of activities do not suddenly appear on the [manager's] desk, they have to be generated through a process of searching" (Greve 2003, p. 14; Posen et al. 2018). A key perspective on what motivates search is offered by the problemistic search theory (PST), which argues that search "is stimulated by a problem . . . and . . . directed toward finding a solution to that problem" (Cyert and March 1963, p. 121). A core premise of PST is that search is triggered by failures in performance—i.e., periods of performance declines and/or performance that is below some aspired level. Further, it posits that performance above some aspired level does not motivate search (Posen et al. 2018). In other words, search is asymmetric with respect to performance. This is paradoxical as high performing organizations are also likely to have invested more in technologies such as BI&A systems to improve search, while their success results in the reduced utilization of the available AIP capabilities to search at the same time. It is further paradoxical as successful firms have more to learn about creating success through the process of search. In contrast, the most that less successful firms can hope to learn from search is about how to avoid failures rather than about how to create successes, yet they are more likely to expend greater search efforts.

There are two possible explanations that explain the asymmetric and seemingly paradoxical relationship between performance and search. One relies on the control theory and the unintended consequences of commonly employed performance control systems. Specifically, firms employ performance goals and reward systems to align the extrinsic motivation of their managers with the goals of the firm (Liang et al. 2007). For instance, a production manager may be rewarded for exceeding some target for capacity utilization, while the CEO may be rewarded for meeting a target in terms of the financial performance of the firm. However, managers are likely to perceive performance below those target levels as failure. Moreover, failure perceptions motivate a response involving the search for insights that could help in explaining and solving the failure problem. In contrast, when managers' performances are above target levels, they are likely to perceive their performance as successes. Under such conditions, managers are likely to exhibit satisficing behavior and not be motivated to search for insights that could further optimize performance and maximize their rewards (O'Connor et al. 2006, Langfield-Smith 2009).

The other explanation for the asymmetric relationship between performance and search is offered by the attribution theory. In contrast to the control theory explanation that relies on extrinsic motivation to explain the relationship, attribution theory offers a complementary explanation that relies on the effects of intrinsic motivation. Attribution theory posits that managers have an ingrained need to be aware of their environment and to develop causal explanations for significant events (Vaara et al. 2014). It proposes that managers tend to attribute failures to external causes over which they have little or no control, while successes are attributed to their own abilities and actions. When managers focus on improving performance, they plan a set of actions to attain aspired performance. If successful outcomes are achieved, they are attributed to the actions they took. However, if the outcomes are not as intended, managers are motivated to search for and identify external causes that might have undermined the expected effects of their actions (Vaara et al. 2014).

In summary, prior research confirms the core propositions of PST that there is an asymmetric relationship between performance and search and, specifically, that performance failures motivate search but success does not (Madsen and Desai 2010, Desai 2016). However, scholars have not extended the PST to account for the effects on search of failures in different performance metrics. Scholars in management, strategy, accounting, and other related disciplines acknowledge that performance is best conceived as a multidimensional construct (Venkatraman and Ramanujam 1986, Brown et al. 2003, Combs et al. 2005). In particular, scholars now distinguish between two broad dimensions of performance: financial performance, which is commonly captured by metrics that include accounting and stock market returns, and operational performance, which is commonly captured by metrics that include various measures of efficiency and resource utilization (Venkatraman and Ramanujam 1986, Melnyk et al. 2004, Combs et al. 2005, McCue and Thompson 2005). It is also widely accepted that financial performance and operational performance are uncorrelated, have different antecedents, and do not exert equivalent effects on organizational outcomes (Combs et al. 2005, McCue and Thompson 2005, Richard et al. 2009, Klingenberg et al. 2013). For instance, drawing on the resource-based view of the firm, scholars have argued that operational performance is influenced by the use of technology and operational innovations driving up resource utilization and operational efficiencies (Combs et al. 2005, Ray et al. 2005).

In contrast, while operational performance is considered a component of financial performance, scholars have argued that financial performance is more influenced by how the surplus from operations is appropriated (Klingenberg et al. 2013). Decisions pertaining to the appropriation of surplus are the purview of top management—for instance, decisions on growth and acquisition strategies, choices of R&D investments, risk profiles of investments, capital structure, financial leverage, and compensation and dividend policies, among others. These decisions, in turn, have an impact on both accounting and stock market returns (Combs et al. 2005, Combs et al. 2006, Klingenberg et al. 2013).

Drawing on the above-mentioned theorizing, scholars have empirically examined the relationships between financial and operational performance. The findings generally support the theoretical expectation that measures of financial and operational performance will not be strongly correlated. For instance, Ittner et al. (2003, p. 78) reported that the nine nonfinancial drivers of operational performance that they captured exhibited significant correlations with each other; in contrast, none of those nine correlated significantly with value drivers of financial performance. Similarly, Klingenberg et al. (2013) found no relationship between the measures of operational performance and measures of financial performance. Scholars have also recognized the implications of the theoretical distinction between financial and operational performance and developed richer theories of individual and joint antecedents and the effects of those two dimensions of performance (Ittner et al. 2003, Koufteros et al. 2014). For instance, Combs et al. (2006) theorized that high-performance work practices such as incentive compensation, employee participation, and flexible work arrangements would have larger effects on operational performance as compared with those on financial performance. Their rationale for that expectation is that work practices immediately impact the motivations and performance of employees, which would reflect in operational improvements. In contrast, financial performance being further removed from work practices would not be as strongly impacted. Similarly, Brown et al. (2003) argued that compensation structures should have different effects on financial performance as compared with operational performance.

Theory of Performance-Driven Search

Effects of Performance Failures on BI&A-Enabled Search

The above discussion on multiple dimensions of performance has important implications for the PST. Prior research in the PST proposes performance failures as an antecedent of search. However, a review of the literature shows that performance is implicitly assumed to be financial performance, and it does not make a distinction between operational and financial performance. Further, performance is operationalized primarily through metrics reflecting financial performance such as return on assets, market-to-book value, and financial growth (Posen et al. 2018). On the other hand, there are a few studies that employ operational metrics such as sales generated by business units as performance measures (Moliterno et al. 2014). However, these studies did not offer a theoretical justification for employing operational instead of financial performance or make a theoretical distinction between the effects of operational and financial performance on search.

Additionally, a review of prior empirical literature also reveals mixed findings (Posen et al. 2018). Within the studies employing financial metrics as a measure of performance, while Parker et al. (2017), among others, reported support for the expected relationship between performance and search, others have also reported nonsupportive or partially supportive findings (Baum et al. 2005, Gaba and Joseph 2013). Similarly, studies employing nonfinancial measures of performance also reported mixed findings: some studies report support for the expected relationship between performance and search (Desai 2015), while other studies reported nonsupportive or partially supportive findings (Mezias et al. 2002). Overall, our review suggests that there is a need to extend the PST to account for the effects of different dimensions of performance failure on BI&A-enabled search.

Here, the PST is extended to include the effects of two key dimensions of performance— financial and operational performance. Following the PST, this paper proposes that failures in financial performance will lead to an increased search. Top management pays significant attention to financial performance measures as their targets, and rewards are invariably tied to financial performance (Kraus and Lind 2010). Hence, they are strongly motivated to search for answers when financial performance declines. While the actual search is generally carried out by middle and line managers of the firm, it is executed under the direction of top management. Search may involve exploring, integrating, and analyzing relevant data to identify the internal inefficiencies or changes in market conditions responsible for financial failure. BI&A systems assist managers in this task. For instance, BI&A capabilities such as sentiment/opinion mining could be employed to explore and identify changes in consumer preferences that might have led to the failure. Managers could also explore historical trends in the performance of various processes to identify internal processes that may have contributed to performance decline. Therefore, top management's need to explain failures in financial performance will be reflected in increased BI&A-enabled search effort of the firm. Hence, our first hypothesis is as follows:

Hypothesis 1. *Firms are more likely to exhibit a greater collective increase in BI&A-enabled search when there is a failure in financial performance.*

Extending the PST, we propose that failures in operational performance will also lead to increased search in subsequent periods. While the mechanisms behind this relationship are the same as those proposed in the PST (extrinsic and intrinsic motivations and attribution effects), we propose here that there is an important difference between search as a response to failures in operational performance as compared with failures in financial performance. As argued above, search as a response to failures in financial performance occurs as a result of direction from top management. In contrast, search as a response to failures in operational performance is likely a volitional response of middle and line managers. Specifically, performance metrics for middle and line managers are generally operational in nature. Hence, a failure in operational performance would result in middle and line managers engaging in a greater search, including BI&A-enabled search. Further, prior research has found that various operational performance measures are significantly correlated with each other (Ittner et al. 2003). Consequently, when an aggregate measure of operational performance fails, it is likely that a number of other operational metrics are also failing. Like our arguments for financial performance, we propose that failures in operational performance will motivate search. This will result in a systematic increase in BI&A-enabled search efforts in the firm. Further, search may involve diagnosing and improvising operational processes to its optimal levels. For instance, managers may employ simulation models to examine external processes with different supply chains, distribution channels, and cost of supplies. They can also employ decision models to optimize internal processes related to staff mix, scheduling, procurement, and automate decision making to improve operational performance. Drawing from the above discussion, we propose the following hypothesis:

Hypothesis 2. *Firms are more likely to exhibit a greater collective increase in BI&A-enabled search when there is a failure in operational performance.*

We further extend the PST by proposing that failures in financial and operational performances exert interactive effects on BI&A-enabled search. Specifically, when financial performance is not failing, top management has a positive story to present to their board as targets set by the board have been met. Under this condition, even if operational performance is failing, top management is likely to treat it as a random blip or a learning experience and not be motivated to direct middle and line managers to engage in any additional search (Morris and Moore 2000, Dillon and Tinsley 2008). Conversely, if financial performance is failing but operational performance is not failing, top management still has a good story to present to the board and will try to explain away financial performance failure as being temporary because of external or market conditions (Hayward et al. 2004, Yadav et al. 2007). However, if both financial performance and operational performance fail in the same period, top management is likely to scrutinize operational performance and seek immediate explanations from managers, consequently increasing the collective search effort across the organization. Therefore, we propose the following hypothesis:

Hypothesis 3. *Firms are more likely to exhibit a greater collective increase in BI&A-enabled search when experiencing simultaneous failures in financial performance and failures in operational performance.*

The Role of Aspirations in Motivating BI&A-Enabled Search

Decline in performance is an important heuristic in judging performance as a success or failure. In addition, studies also identify the important role of aspirations in judging performance as a success or a failure (Cyert and March 1963). Aspirations are "the smallest outcome that would be deemed satisfactory by the decision maker [managers]" (Schneider 1992, p. 1053). Managers consider aspiration levels to simplify how they evaluate performance by transforming continuous outcome measures of performance into discrete measures of "success" and "failure" (Cyert and March 1963). However, it is important to distinguish and account for failures as declines in actual performance and declines in performance relative to aspirational levels (the same applies to success judgements as well) because of the adaptable nature of aspirational levels. Moreover, aspiration levels are sometimes lowered to view actual performance as success during the period when actual performances were declining and vice versa. Although operational performance and financial performance may not be correlated, top management recognizes that operational performance still underpins financial performance. Therefore, they are more likely to develop aspirational levels for both performance metrics and are likely to closely monitor the variations in operational performance. When either operational or financial performance relative to aspiration level is as expected, top management is less likely to exert pressure on managers. On the other hand, when either operational or financial performance relative to aspiration level is below expectation, top management is likely to be more sensitive to any declines in operational performance, which would result in a follow-up and scrutinization of performance and the subsequent seeking of remedial actions.

Further, studies also show that top management employs two types of aspiration levels in making success and failure judgments: historical and social (Kim et al. 2015). While historical aspiration levels are based on firms' own past performances, social aspiration levels are based on the performance of a reference group of competitors or peers. Accounting for this distinction is important because the two aspiration levels are derived from different origins and consequently influence BI&A-enabled search efforts differently (Kim et al. 2015, Kuusela et al. 2017). BI&A systems enable managers to conduct an in-depth search of historical information to develop historical aspiration levels of both financial performance and operational performance. Additionally, BI&A systems also allow managers to easily monitor the difference between aspired performance and actual performance. Performance below aspired levels motivates increased search efforts to find insights and to understand the causes of failure.

Like historical aspirations, social aspiration levels help top managements form a baseline performance level that enables them to reflect on how well they are expected to perform (Washburn and Bromiley 2012). Social aspiration levels are shaped by available information on the performance of other organizations, and top management leverages the information and capabilities of BI&A systems to search across heterogeneous data sources to model how competitors and peers are performing relative to their own firm (Xu et al. 2016, Guo et al. 2017). For instance, social media analytics has supplemented traditional competitor analysis with the capabilities to search digital traces of competitor firms. Top managements are thus able to surveil ongoing social media announcements, blogs, and annual reports to infer competitors' performance levels. Additionally, automated crawling and indexing of competitors' websites can yield early warnings of new market actions and update their social aspiration levels. Drawing on the above discussion, we posit that top management forms social aspiration levels from operational and financial performance of competitors and peers (Hu et al. 2017). Therefore, we propose the following four hypotheses related to two types of performances in historical and social aspiration levels:

Hypothesis 4a. *Firms are more likely to exhibit a greater collective increase in BI&A-enabled search when their financial performance is below its historical aspiration level and operational performance is failing in the same period.*

Hypothesis 4b. *Firms are more likely to exhibit a greater collective increase in BI&A-enabled search when their operational performance is below its historical aspiration level and operational performance is failing in the same period.*

Hypothesis 4c. *Firms are more likely to exhibit a greater collective increase in BI&A-enabled search when their financial performance is below its social aspiration level and operational performance is failing in the same period.*

Hypothesis 4d. *Firms are more likely to exhibit a greater collective increase in BI&A-enabled search when their operational performance is below its social aspiration level and operational performance is failing in the same period.*

Time Lags, Latency, and BI&A-Enabled Search

The attribution theory argues that managers interpret stable and increasing performance as evidence of their own success and deem further search for knowledge as unnecessary, even at the risk of ignoring information to the contrary (Hayward et al. 2004, Yadav et al. 2007). We posit that under stable or increasing financial performance, it is less likely that top management will scrutinize and demand an explanation from managers for failures in operational performance. However, stable and increasing financial performance conditions seldom persist for long periods. Over time, organizations will experience a mix of stable, improving, and failing performance. Top management draws on its judgments to categorize some contiguous periods of failure as episodic one-time events and other longer periods of failure as sustained failures. Periods of failure categorized as random episodic failures in financial performance are deemed to not have significant negative consequences and are likely to be ignored or attributed to external causes or one-time events (Hayward et al. 2004, Yadav et al. 2007). Even under conditions of episodic failures in financial performance, unsatisfactory operational performance is often viewed as "opportunities for learning" and treated as stepping stones for future success (Dillon and Tinsley 2008). As a result, accountability for episodic failures in financial performance is attenuated, and consequently, the need for a search is not considered critical.

In contrast to episodic failures in financial performance, sustained failures in financial performance cannot be ignored as they indicate significant gaps in managerial knowledge and the efficacy of decision making (Yu et al. 2019). Under sustained failures in financial performance, operational performance is closely monitored, and the scrutiny of operations returning failing performance is amplified. This greater attention from top management is likely to trigger an intensive search. Therefore, we propose that in firms experiencing sustained failure of financial performance, there should be increased BI&A-enabled search effort in periods following failures in operational performance. Formally, we propose the following:

Hypothesis 5. *Firms are more likely to exhibit a greater collective increase in BI&A-enabled search following failures in operational performance only when they are experiencing a* <u>*sustained*</u> *failure in financial performance.*

Extending Hypothesis 5, we further propose that the latency between failures in operational performance and search effort in firms experiencing sustained failures in financial performance is contingent on how fast financial performance is failing. Specifically, we propose that in firms experiencing sustained failures in financial performance, the faster the financial performance fails, the quicker the search response to any failures in operational performance. Moreover, large and sudden failures indicate significant gaps in managerial knowledge and the need to quickly search for causes of failure. In this regard, performance control systems placed in the organizations to monitor key performance indicators are sensitive to large disruptions and react more quickly to avoid further failures. Further, damage control mechanisms are quickly activated such that the greater the magnitude and faster the failure in financial performance, the greater the sense of urgency to search in response to failures in operational performance as that might contribute to further disruptions (Greve 2003). In this context, a key capability of BI&A systems is its ability to allow managers to react faster by searching for and analyzing information quickly to find insights (Wixom et al. 2013). This "speed to insights" capability allows top managements to calibrate their responses to the magnitude and speed at which financial performance is failing and provides further impetus to employ BI&A systems for search.

Hypothesis 6. *The steeper the sustained failure in financial performance, the faster the BI&A-enabled search response to failure in operational performance.*

Method, Operationalization, and Analyses

Research Setting and Data

We test the proposed hypotheses using longitudinal monthly data collected in 2014 for a period of 49 months in seven independently operated not-for-profit (NFP) U.S. hospitals.[1] All seven independent hospitals utilize a shared service that provides the BI&A system and have access to the same set of AIP capabilities. The system allows managers to view performance data not only of their own hospital but also of their peer hospitals that share the system. The system includes various analytical tools ranging from standard performance reporting to advanced AIP capabilities that allow predictive and prescriptive analytics such as forecasting, analysis of costs, intelligent contract management, and machine learning tools to simulate "what-if" analysis. Managers can use these AIP capabilities to evaluate the impact of services on costs and profits, evaluate contracts, and budget variance and examine their impact on performance. Additionally, the system also maintains a log of usage for each user.

Operationalization of Constructs

BI&A-Enabled Search Effort. BI&A-enabled search effort is referred as the collective effort spent by users in an organization to volitionally employ BI&A systems in an ad hoc manner to acquire and analyze information to discover insights. To be consistent with our definition of search as a volitionally initiated ad hoc use of a BI&A system, the consumption of standard reports generated by the BI&A system were excluded from our measure of search. Further, standard reports are automatically generated by the system, often at predefined intervals, and do not require managerial intervention. While information gleaned from a standard report may induce a search effort, the consumption of standard reports themselves does not fall into the purview of our definition of BI&A-enabled search efforts. Therefore, per our definition, such reports do not constitute ad hoc use and were excluded. Our measure of BI&A-enabled search effort comprises the following three components (Devaraj and Kohli 2003).

The first component is the *number of ad hoc report*s, which is the total number of ad hoc reports generated through the BI&A system in a hospital every month. This measure captures the extent of the collective search effort expended in an organization. To ensure that the reports were indeed ad hoc, two validity checks were conducted. First, all analytics-related reports generated through the BI&A system were inventoried and the hospitals and managers who initiated each report were recorded. This step ensured that we included all reports and all user managers who employed the BI&A system for search. Second, we verified with each manager that the reports generated by them were indeed ad hoc and were employed to support decision making. This step ensured that our count of ad hoc reports represented BI&A-enabled search.

The second component is *CPU time*, which captures the total central processing function (CPU) time consumed in generating the ad hoc reports every month in each hospital. While the count of ad hoc reports captured the number of reports, it does not account for the complexity of the analysis. Moreover, CPU time for a report captures the time it takes to process the variables specified in the report.

The larger the number of variables for analysis, the greater the complexity of the search effort. The last component is the *number of disk input/output* (*I/O*) *cycles*, which captures the total number of disk I/O cycles involved in generating the ad hoc reports every month in each hospital. It captures the number of records that were read from and written to the memory while generating the ad hoc reports. This measure represents the depth of analysis involved in conducting search using the BI&A system.

The number of ad hoc reports, CPU time, and number of disk I/O cycles together measure the extent, complexity, and depth, respectively, of BI&A-enabled search. The three measures reflect the nature of use involving the users, system, and tasks, respectively. As such, our measuring of BI&A-enabled search effort is dimensionally rich as was called for in previous studies (Burton-Jones and Straub 2006). Further, the three measures were standardized to account for the disparities in their scales and an unweighted additive average composite variable was created to measure BI&A-enabled search (Cronbach's $\alpha = 0.81$).

Financial Performance (FP). Financial performance is referred to the hospital's overall financial profitability. Consistent with previous studies, financial performance was operationalized using individual hospital's *net income* (NI) over a month (Devaraj and Kohli 2000). NI reflects the revenues minus expenses for a given period. It is a key performance metric reported by the system and is closely monitored by top management.

Operational Performance (OP). Operational performance pertains to productivity and efficiency related measures—such as regulatory compliance, person-hours per task, product failure rates, process cycle time, and other measures—that capture how well the firm is using its physical and human resources in performing its business processes. Prior research shows that failures in operational performance in the healthcare industry can significantly deter the quality of care, patient satisfaction, and positive patient outcomes (Tucker 2004). Drawing on prior studies in healthcare research, our operational performance comprises two measures: *risk-adjusted length of stay* (*RLOS*) and *risk-adjusted revenue per patient* (*RARP*), which are common metrics employed in hospitals (McDermott and Stock 2007, Nair et al. 2013).

RLOS measures account for the length of stay of patients after adjusting for the complexity of their treatment. Studies in the healthcare sector show that a shorter RLOS reflects a higher quality of care by hospital units (Shi 1996, Anderson et al. 2002, McDermott and Stock 2007). A lower RLOS captures the "timeliness of care" of healthcare operations and processes (IoM 2009, Nair et al. 2013). Timeliness of care refers to reduced wait times, harmful delays for both those who receive and those who provide healthcare, and the extent of conformance to the set guidelines for specific treatments by minimizing delays (Rotter et al. 2008).

On the other hand, RARP captures the average earnings per patient relative to the treatment severity and resources consumed. A higher RARP measures the operational cost efficiencies, which directly relate to avoiding waste of equipment and supplies as well as unwanted tests and treatments. Thus, it measures the extent to which hospitals have adopted "best practices." When hospitals do not adopt best practices, they may overprescribe services or choose inefficient treatments, which can eventually lead to insurance companies delaying or even declining reimbursements. Therefore, RARP is a key metric to evaluate the productivity and efficiency of hospitals' operations (Devaraj and Kohli 2003, Nair et al. 2013). To ensure further robustness, we adjusted the RARP relative to the number of full-time employees (FTE). Realizing a higher RARP with lower FTEs provides a more accurate measurement of the productivity and efficiency of the hospital's operational processes.

Both measures are reported in standard reports generated by the system and are regularly monitored by managers. Failures in these measures are likely the result of underperformance in various functions in a hospital. Managers reviewing those reports can assess how their own function is performing and contributing to the hospital's overall operational performance. Both measures are standardized before creating an unweighted additive average composite measure of operational performance (Cronbach's $\alpha = 0.74$).

Failures in Performance Relative to Historical Aspiration Levels. The historical aspiration level (HAL) refers to the minimum performance level inferred from past performances that is deemed satisfactory by managers. Consistent with previous studies, the historical aspiration was operationalized as a weighted moving average of past performances (Baum et al. 2005, Gaba and Joseph 2013, Kim et al. 2015, Kuusela et al. 2017). This allows for continuous adaption to changes in aspirations over time. The historical aspiration levels of financial and operational performance were operationalized as follows:

$$FP(HAL)_{it} = \alpha FP_{i,t-1} + (1-\alpha) HAL_{i,t-1} \quad (1)$$
$$OP(HAL)_{it} = \alpha OP_{i,t-1} + (1-\alpha) HAL_{i,t-1}, \quad (2)$$

where *HAL* is the historical aspiration level of FP and OP, respectively, of a hospital, *i* is the focal hospital,

t is the time period, and α $(0 < \alpha < 1)$ is the weight given to prior performance and denotes the relative importance of previous performance levels. Higher values of α update historical aspiration at a faster rate, thus placing more importance on recent performance. Consistent with prior research, fixed values of α—0.75, 0.50, and 0.25—were chosen to adjust the relative weightage of prior performance in the previous three periods, respectively (Baum et al. 2005, Kim et al. 2015, Kuusela et al. 2017).

Moreover, FP was categorized as a success or failure in a period by comparing the actual FP in that period to the historical aspiration of FP relevant to that period (Equation 3). Similarly, OP was categorized as a success or failure in a period by comparing the actual OP in that period to the historical aspiration level of OP relevant to that period (Equation 4). Like the approach in prior research, the spline function in Equations 3 and 4 allows the coefficient to change at a predetermined point (Marsh and Cormier 2001, Kim et al. 2015). This enables the categorization of performance as above or below the historical aspiration level.

$$FFP(HAL) = \begin{cases} 2, \text{ if } (FP_{it} - FP(HAL)_{it} \geq 0), \text{ i.e., success} \\ 1, \text{ if } (FP_{it} - FP(HAL)_{it} < 0), \text{ i.e., failure} \end{cases} \tag{3}$$

$$FOP(HAL) = \begin{cases} 2, \text{ if } (OP_{it} - OP(HAL)_{it} \geq 0), \text{ i.e., success} \\ 1, \text{ if } (OP_{it} - OP(HAL)_{it} < 0), \text{ i.e., failure,} \end{cases} \tag{4}$$

where $FFP(HAL)$ and $FOP(HAL)$ are failures in financial and operational performance, respectively, as assessed against their historical aspiration levels. For ease of interpretation and to obtain absolute values, performances above HAL (i.e., success) were assigned a value of two, while performances below HAL (i.e., failure) were assigned a value of one.

Failures in Performance Relative to Social Aspiration Levels. Social aspiration level (SAL) refers to the minimum performance level inferred from the performances of peer organizations that is deemed satisfactory by managers (Baum et al. 2005, Gaba and Joseph 2013). In a multifirm context, such as this study, firms tend to calibrate their aspiration levels based on peer firms in the network rather than the population of firms external to the network (Washburn and Bromiley 2012, Moliterno et al. 2014). In a multifirm context, firms within a group compete with each other for corporate resources and operate to look more favorable than their peers to the corporate parent (Gaba and Joseph 2013, Hu et al. 2017). Given that our data are from a multifirm context, an appropriate reference point for calibrating social aspirations is to base it on the concurrent performance levels of all other hospitals in the network (Hu et al. 2017). Therefore, consistent with previous studies, the aspirational levels of FP and OP are set to the average of all other hospitals in the network, respectively, as shown in Equations 5 and 6. For FP, to reduce any firm-specific biases, the *profit margin* percentage was used as our FP measure for each individual hospital.

$$FP(SAL)_{it} = \left(\sum_j FP_{jt}\right) / K_H - 1 \tag{5}$$

$$OP(SAL)_{it} = \left(\sum_j OP_{jt}\right) / K_H - 1, \tag{6}$$

where j (equal to six in our study) refers to the other hospitals in the group against whom performance is compared and K_H (equal to seven in our study) is the total number of hospitals in the network.

FP in a period was categorized as a success or failure by comparing the actual FP in that period with the social aspiration level of FP relevant to that period (Equation 7). Similarly, OP in a period was categorized as a success or failure by comparing the actual OP in that period with the social aspiration levels of OP relevant to that period (Equation 8). Further, like Equations 3 and 4, the spline function in Equations 7 and 8 allows the coefficient to change at a predetermined point. This enables us to categorize performance as above or below SAL.

$$FFP(SAL) = \begin{cases} 2, \text{ if } (FP_{it} - FP(SAL)_{it} \geq 0), \text{ i.e., success} \\ 1, \text{ if } (FP_{it} - FP(SAL)_{it} < 0), \text{ i.e., failure} \end{cases} \tag{7}$$

$$FOP(SAL) = \begin{cases} 2, \text{ if } (OP_{it} - OP(SAL)_{it} \geq 0), \text{ i.e., success} \\ 1, \text{ if } (OP_{it} - OP(SAL)_{it} < 0), \text{ i.e., failure} \end{cases} \tag{8}$$

For ease of interpretation and to obtain absolute values, a value of two was assigned for performances above SAL and a value of one for performances below SAL.

Sustained Failure in Financial Performance. To test Hypotheses 5 and 6, it is necessary to identify hospitals in our sample that are experiencing sustained failures in financial performance. Whether a firm is experiencing sustained failure or just a random blip in performance is a matter of judgment that can vary among managers. However, certain trends in FP are likely to induce a high level of consensus among managers on whether a firm is experiencing sustained failure or only a random episode of failure. Three such conditions were considered to identify hospitals that are experiencing sustained failure: (i) whether a hospital has been consistently missing aspired performance levels, (ii) whether a hospital has been consistently performing at lower efficiency levels than its peers, and (iii) whether a hospital has been having consistently declining performance over time. Each of these three conditions mimics judgment rules and heuristics commonly employed by managers in evaluating performance (Arrfelt et al. 2015).[2]

First, to infer which hospitals are consistently meeting or missing aspired performance levels over the four-year period of our study, the success and failure categorizations of FP were categorized based on both historical and social aspirations. Specifically, a *performance attainment index* was constructed, and the average value for each month was computed from the spline functions that compare FP levels for each month against its HAL and SAL. For each month that a hospital meets its aspiration level, it receives a score of one and a score of zero if it does not. For each month, each hospital receives two scores—one based on HAL and the other based on SAL. Hence, the *performance attainment index*, which is the average of values over a month, ranges from zero to one. When averaged over a year, index values that are closer to zero indicate temporal persistence in failing to reach the aspired performance for that year.

Hospitals that return low and declining scores on the index over the four years are likely to be categorized as "experiencing sustained failure." In contrast, hospitals that return values approaching one indicate high levels of temporal persistence in attaining aspired performance levels and are unlikely to be categorized as experiencing sustained failure. Further, because aspiration levels update continuously, this index also controls for any seasonal and cyclic trends within each year that may influence managers' judgments of performance. The index—based on averaging judgements of success and failure based on both historical and social aspirations—captures the complexity of managerial judgments that go into performance evaluation.

Second, to infer whether a hospital has been consistently performing at lower efficiency levels than its peers, a data envelopment analysis (DEA) was conducted (Hollingsworth 2003, Deidda et al. 2014). DEA has been extensively employed in practice, particularly in the healthcare industry, to measure and analyze the efficiency levels of healthcare services (Hollingsworth 2003, Hollingsworth 2008). Therefore, this technique simulates the judgments of top managements.

Finally, to infer whether a hospital has been having a consistently declining performance over time, a time-series analysis of monthly data on FP was conducted. Table 2 reports the results of the findings of analysis of performance attainment index, DEA, and time-series analysis. Our categorization of hospitals as "experiencing sustained failure" and "not experiencing sustained failure" was based on a triangulation of findings from the three analytical methods. Given that the three analyses are based on different input data and analytical techniques, the findings from the triangulation of the three analyses results in categorizations that are robust against construct validity threats.

The results in Table 2 show that hospitals O1 and O2 returned the lowest average index score for each of the four years. It is also important to note that the index score also declines over time. This analysis indicates that these two hospitals have been experiencing sustained failure, while the results of the DEA analysis show that over the four-year period, hospitals O1 and O2 have been performing at low efficiency levels. On the other hand, the results from the time-series analysis indicate that only these two specific hospitals return significant negative coefficients for firm performance over time. For a further robustness check, the difference-in-slope analysis between O1 and O2 were tested to determine which hospitals faced a significantly faster sustained failure. The test revealed that the slope for O1 was significantly steeper than the slope for O2 ($t = -3.07$, $p \leq 0.05$), suggesting that O1 was facing a significantly faster and sustained performance failure than O2. The findings from all three analyses consistently identify hospitals O1 and O2 as the only two hospitals that are experiencing sustained failure unlike the other five hospitals (O3–O7).

Control Variables

Five main control variables were included to account for factors that reflect changes in services and FP:

1. *Rate of reimbursement* (RoR) captures the amount reimbursed by insurers to the hospital for patient services. Although related to revenue, reimbursement rates vary depending on contractual terms with insurers and can influence NI.
2. *Medicaid* captures the number of patients who were insured through the state-funded Medicaid program. Medicaid was included because the level of reimbursement amount for services to patients in the Medicaid program is generally lower than the level of reimbursement amount for patients covered by commercial insurance plans. Therefore, a higher proportion of Medicaid patients can affect a hospital's financial performance.
3. A hospital's *Casemix* score is an index—with the base as one—that captures the aggregated allocation of resources in the treatment of patients. Generally, a hospital that treats sicker patients will have a higher Casemix score because sicker patients require more resources.
4. The *number of beds* reflects the size of the hospitals and has been shown to impact the cost performance of hospitals (Nair et al. 2013).

Table 2. Categorizing Trends in Financial Performance

	Performance attainment index (PAI)						
Hospital	Year 1	Year 2	Year 3	Year 4	Overall average	DEA ranks (θ)	Time-series trends (coefficient)
O1	**0.38**	**0.38**	**0.33**	**0.17**	**0.31**	**7**	**–28,650****
O2	**0.63**	**0.54**	**0.46**	**0.32**	**0.49**	**6**	**–7,060****
O3	0.63	0.38	0.55	NSD	0.52	5	–1,135
O4	0.5	0.5	0.46	0.71	0.51	4	–1,929
O5	0.55	0.59	0.57	0.67	0.58	3	32,541
O6	0.63	0.58	0.84	0.67	0.68	2	1,934
O7	0.59	0.67	0.75	0.84	0.72	1	17,274**

Notes. θ = 7 indicates the lowest-performing hospital and θ = 1 indicates the highest-performing hospital. NSD, no sufficient data.
$^{**}p \leq 0.05$.

5. *City size* was used as a control because previous studies have shown that hospitals serving in areas with a larger population can derive improved operational and clinical performance by selectively admitting low risk and less complicated cases (Lee et al. 2009, Kc and Terwiesch 2011).

Taken together, our controls account for differences among hospitals that could affect patient revenue and hospital performance (Ding 2014). (See Online Appendix 1 for correlation matrix.)

Data Analysis

The data employed in this research have a cross-sectional dimension (multiple hospitals) and a temporal dimension (longitudinal-monthly data). Tests of Hypotheses 1–5 involve combining the longitudinal data across the seven hospitals. Given the panel nature of the data, testing the hypotheses involves controlling for unobserved heterogeneity and other differences within the hospitals that may influence the BI&A-enabled search effort. When examining how BI&A-enabled search efforts change in response to the financial and operational performances of the firm, a fixed effects model (FEM) with robust standard errors (RSE) clustered on the organizational identifiers was employed to observe within-firm changes (Greene 2000, Wooldridge 2010). Our empirical specification for FEM is as follows (Model 3, Table 3):

$$\begin{aligned} &BI\&A\text{-}enabledSearchEffort_{it} \\ &\quad = \beta_1 + \beta_2 FP_{it} + \beta_3 OP_{it} + \beta_4 FFP(HAL)_{it} \\ &\qquad + \beta_5 FOP(HAL)_{it} + \beta_6 FFP(SAL)_{it} + \beta_7 FOP(SAL)_{it} \\ &\qquad + \beta_8 (OP{*}FP)_{it} + \beta_9 (OP{*}FFP(HAL))_{it} \\ &\qquad + \beta_{10}(OP{*}FOP(HAL))_{it} + \beta_{11}(OP{*}FFP(SAL))_{it} \\ &\qquad + \beta_{12}(OP{*}FOP(SAL))_{it} + \beta_{13} RoR_{it} \\ &\qquad + \beta_{14} Medicaid_{it} + \beta_{15} Casemix_{it} + \alpha_i + \lambda_t + e_{it}, \end{aligned} \tag{9}$$

where *BI&A-enabled Search Effort*$_{it}$ is the value of the construct for the ith hospital at time t. β_1–β_{15} are the standardized coefficients. *FP* and *OP* are financial and operational performance, respectively. *FFP*(*HAL*) and *FOP*(*HAL*) are the failure (success) assessments of financial and operational performance, respectively, based on comparison against historical aspirations levels; and *FFP*(*SAL*) and *FOP*(*SAL*) are the corresponding assessments against social aspiration levels. *RoR* is the rate of reimbursement, while *Medicaid* measures the number of patients whose healthcare is funded by the state government and *Casemix* captures the complexity of the treatment received by patients. The firm fixed effects (α_i) absorbs any permanent unobserved heterogeneity, and time fixed effects (λ_t) absorbs time-specific shocks experienced by all firms.

The FEM employed to test Hypotheses 1–4 provides an *all-inclusive* within-hospital analysis aggregated across all hospitals. Although this analysis provides us with an understanding of the joint effect of performance on BI&A-enabled search efforts and provides for the generalizability of our results, the effects of idiosyncratic organizational contexts—such as firms experiencing sustained failures versus firms not experiencing sustained failures—on search efforts as theorized in Hypotheses 5 and 6 are difficult to extract and observe in FEMs. Furthermore, because the effects of performance failure on search efforts are likely to be lagged, it is difficult to determine the latency of responses (lags). Moreover, Hypothesis 5 was tested using a random effects model (REM) by introducing a dummy variable to distinguish between firms experiencing sustained failures and not sustained failures. Further, additional controls for hospital size and city size were included in the random effects model as they are time-invariants. However, the results are reported at the aggregated level (Model 4, Table 3).

To formally test Hypotheses 5 and 6, finite distributed lag models (FDLM) were employed (Arellano 2003, Wooldridge 2010). With FDLM, the limitations posed in the fixed and random effect estimators were overcome, and it was possible to account for

Table 3. Panel Regression Analyses for BI&A-Enabled Search Effort

		Model 1 (fixed effects)		Model 2 (fixed effects)		Model 3 (fixed effects)		Model 4 (random effects)	
Main effects	Hypothesis	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Financial performance (FP)	H1	–0.003	0.035	0.008	0.072	–0.414***	0.074	–0.341**	0.157
Operational performance (OP)	H2	–0.023	0.117	–0.14**	0.069	–0.587**	0.138	–0.596***	0.109
FFP(HAL)				–0.051	0.06	–0.231**	0.088	–0.298**	0.095
FOP(HAL)				–0.009	0.06	–0.21***	0.021	–0.204**	0.105
FFP(SAL)				–0.266	0.213	–0.194**	0.071	–0.222	0.192
FOP(SAL)				0.387	0.218	–0.057	0.051	0.006	0.233
Interaction effects									
OP × FP	H3					0.442**	0.108	0.371**	0.162
OP × FFP(HAL)	H4a					0.269**	0.115	0.334**	0.119
OP × FOP(HAL)	H4b					0.248**	0.102	0.200	0.134
OP × FFP(SAL)	H4c					0.139**	0.054	0.238**	0.132
OP × FOP(SAL)	H4d					0.279**	0.096	0.229	0.207
OP × Sustained failure	H5							0.504**	0.188
Control variables									
Rate of reimbursement		–0.024	0.155	0.197**	0.072	–0.028	0.107	0.105	0.073
Medicaid		0.171	0.152	0.09	0.069	0.098	0.121	–0.067	0.073
Casemix		–0.041	0.128	–0.197**	0.068	–0.099	0.129	–0.157**	0.078
Hospital size								0.081	0.071
City size								–0.120	0.086
Organizations		7		7		7		7	
Time period									
N		280		269		269		269	
R^2									
Within		0.016		0.012		0.211		0.186	
Between		0.188		0.594		0.521		0.846	
Overall		0.046		0.16		0.28		0.350	

Notes. BI&A-enabled search effort is the dependent variable. S.E., standard error; Coeff., coefficient.
$^{**}p \leq 0.05$; $^{***}p \leq 0.001$.

the effects on search efforts between the "sustained failures" group and the "not sustained failure" group. Accounting for such nuances provides a richer explanation of the patterns of relationship between performance and search effort. Therefore, to test Hypotheses 5 and 6, FDLM was employed to examine the lagged relationship between performance and search effort for each individual hospital. Specifically, such conclusions were drawn based on FP conditions that vary across individual hospitals (Kmenta 1971).

$$\begin{aligned} &\textit{BI\&A-enabled Search Effort}_t \\ &\quad = \propto + \sum_{i=0}^{\infty} \beta_i \, OP_{t-i} + u_t \end{aligned} \tag{10}$$

For Hypothesis 5 to be supported, β_i must be (1) negative and significant over *multiple* lags only in hospitals experiencing sustained failure—that is, Hospitals O1 and O2—and (2) nonsignificant or positively significant for hospitals not experiencing sustained failures. For Hypothesis 6 to be supported, β_i must show negative and significant value for hospital O1 in earlier lags than for hospital O2. (See Online Appendices 2 and 3 for details on diagnostics and robustness checks.)

Results

In Table 3, the results of the fixed effects (Models 1–3) and random effects analysis (Model 4) are presented. In Model 3, the results show negative and significant effects between FP and BI&A-enabled search and OP and BI&A-enabled search, respectively, *supporting Hypotheses* 1 *and* 2. In the interaction results, outputs from FEM show the positive and significant interaction effect of failures on the following: OP and FP, OP and FFP (HAL), OP and FOP (HAL), OP and FFP (SAL), and OP and FOP (SAL) on BI&A-enabled search effort, *supporting Hypotheses* 3–4d, *respectively*.

Results from the REM, reported in Model 4, show that firms that experience failures in operational performance are more likely to significantly increase BI&A-enabled search effort when they experience sustained failures in financial performance, *supporting Hypothesis* 5. Additional support for Hypothesis 5 is also found in the FDLM analyses of individual hospitals (Table 4). The lag coefficients for hospital O1 and O2—which are the only two hospitals in the sample that experienced sustained financial performance failures (Table 4, Model 1)—are negative and significant over multiple periods. In contrast, there are

Table 4. FDL Analyses for BI&A-Enabled Search Effort

	Model 1		Model 2				
Hospital	O1	O2	O3	O4	O5	O6	O7
Lags	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
0	–0.224	0.071	–0.312	0.328	–0.562	–0.21	0.141
1	–0.23	0.063	–0.166	–0.012	–0.125	–0.453	0.235
2	–0.324**	0.066	–0.191	–0.022	–0.154	–0.05	0.24
3	–0.382***	–0.031	–0.528	–0.148	–0.22	0.08	0.313
4	–0.311***	–0.223	–0.354	–0.045	0.11	0.043	0.464
5	–0.347***	–0.291	–0.09	0.125	0.017	0.099	0.027
6	–0.401***	–0.347**	–0.098	0.289	0.111	0.176	0.364
7	–0.417***	–0.426**	0.15	0.553	–0.735	0.174	0.343
8	–0.421***	–0.276**	0.374	0.672	–0.855	0.294	0.622
Categorization of FP (Table 2)	SF	SF	NSF	NSF	NSF	NSF	NSF
AIC/FPE	8	8	8	8	8	8	8

Notes. BI&A-enabled search effort is the dependent variable. Coeff., coefficient; SF, sustained failure; NSF, not sustained failure; AIC/FPE, Akaike information criteria/final prediction error lag tests.
$^{**}p \leq 0.05$; $^{***}p \leq 0.001$.

no significant negative lags over multiple periods in the other hospitals (O3–O7, Model 2, Table 4) that did not experience sustained failures. Therefore, *Hypothesis* 5 *is supported*. The corresponding interaction effects for Hypotheses 3–5 is shown in Figure 1.[3]

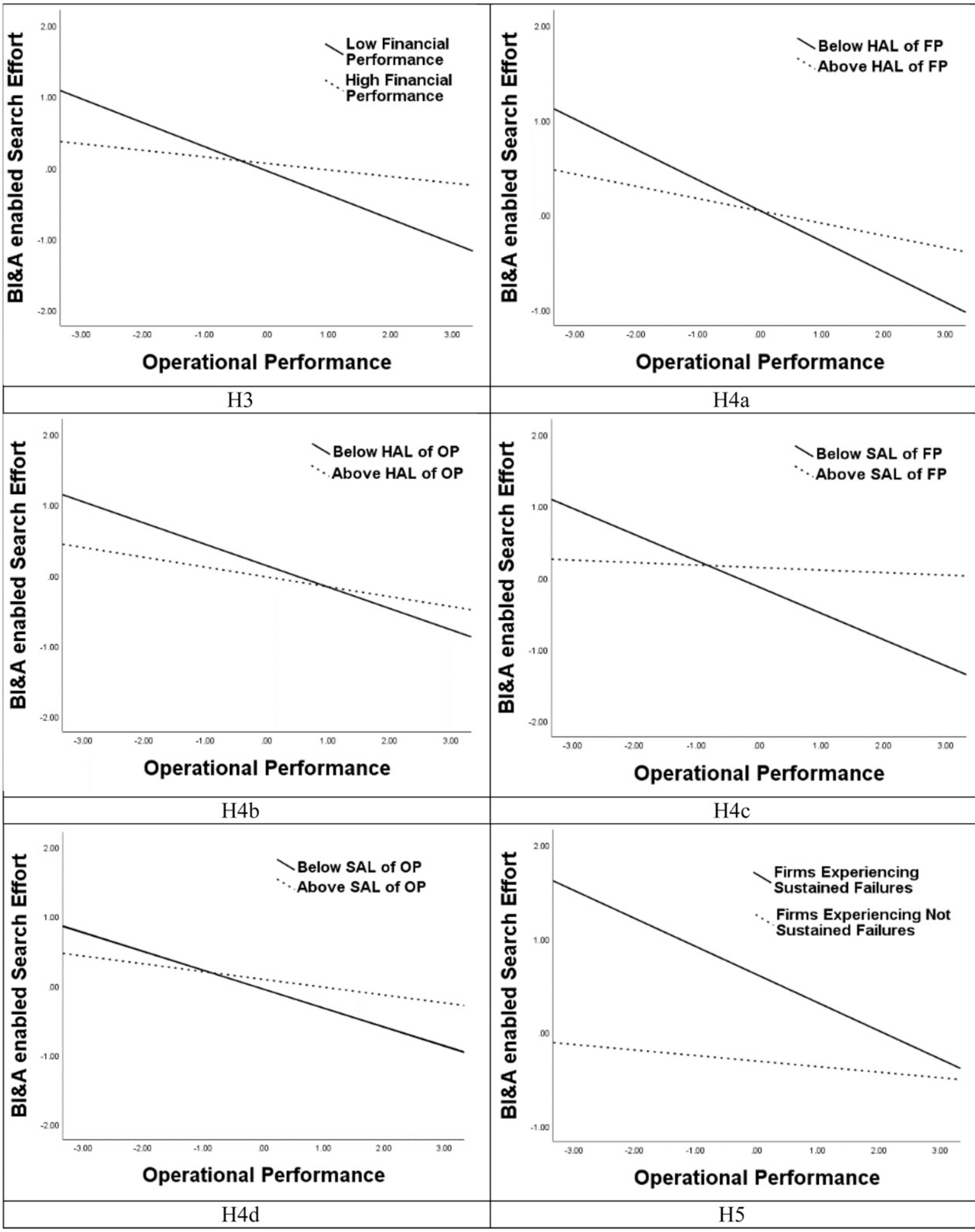
Finally, hospital O1 returns significant lags from lag periods two to eight, while O2 returns significant lags for lag periods six to eight. This finding indicates that O1—which experienced a faster sustained financial performance failure than O2—responded to failures in operational performance with significant search efforts faster than O2 (Table 4, Model 1). Therefore, *Hypothesis* 6 *is supported.*

Discussion

Managerial search—the process of uncovering insights through the use of BI&A systems and developing solutions to improve performance—underpins the creation of value from investments in BI&A systems (Sharma et al. 2014, Anand et al. 2016). However, a theoretical understanding of the conditions under which managers use (or do not use) BI&A systems and their motivation behind search are still underexplored. By and large, prior research has focused on understanding the consequential effects of the use of BI&A systems—for instance, identifying types of BI&A systems and how they could potentially influence performance improvements (Chen et al. 2012), conceptualizing different capabilities that manifest from BI&A system use (Saldanha et al. 2017), and identifying the conditions that can facilitate the BI&A-enabled value chain from BI&A investments to positive outcomes (Sharma et al. 2014, Grover et al. 2018). However, an implicit assumption in those streams of research is that following the investment or adoption of BI&A systems, managers will proactively exploit the capabilities of BI&A systems to search and improve performance. However, prior research and anecdotal evidence on the use of BI&A systems suggests that proactive use is limited and that understanding the motivation behind BI&A-enabled search remains an important research question.

In this study, the above gap is addressed by drawing on the PST to posit that a significant factor influencing BI&A use (i.e., BI&A-enabled search) is variations in performance. Extending prior research on BI&A-enabled search, contingent models of the effects of performance failures on BI&A-enabled search were theorized upon. Empirical analyses provide strong support for the theory developed in this paper. In particular, this study shows that failures in financial and operational performance and their joint failures are important conditions that stimulate BI&A-enabled search. It was also theorized and found that performance data in BI&A systems shape the formation of historical and social aspiration levels of financial and operational performance and that those aspiration levels influence assessments of performance failure and, in turn, influence managerial search. Further, it was also theorized and evidence was found that it is only in organizations experiencing a sustained failure in financial performance that operational performance failures trigger BI&A-enabled search and that the speed of search response is dependent on the speed of failure in financial performance. Thus, our results suggest that BI&A-enabled search is motivated by a narrow set of conditions related to performance failures. These results have implications for research examining value creation from BI&A investments and may help identify the role of additional contingencies that influence that relationship.

Figure 1. Interaction Plots



Theoretical Contributions and Implications

This paper adds to growing literature examining the factors that contribute to *realizing* the *potential* value created by investments in BI&A systems. It argues that changes to performance control systems and specifically systems for rewarding success and punishing failure can help firms *realize* their *potential* value. Moreover, Anand et al. (2016) reported that the agility of resource allocation processes contributes to creating value from investments in BI&A systems.

Similarly, Mikalef et al. (2019) have found that relational practices—such as formally bringing IT managers and line managers together and formalizing their respective roles and responsibilities—contribute to superior performance. Further, Jensen et al. (2019) argue that as the realization of business benefits from BI&A investments is contingent on organizational changes rather than on the functionalities of the technology per se, the ability of the firms to manage changes is critical to realizing value from BI&A systems. Taken together, this stream of literature highlights the complexity of successfully realizing value from investments in BI&A systems. Specifically, it suggests that realizing value involves significant interdependent changes in IT and the firm's strategy, structure, and management processes (Sharma et al. 2008). It also highlights the role of metastructuration actions—such as changes in structures and performance control systems—in realizing value in the face of complex interdependencies (Sharma and Yetton 2003, Vidgen et al. 2017). Acknowledging that complexity, Otondo (2019) warns that if BI&A research and practice are not able to bridge the gap between the potential and realized value of BI&A, it could well become irrelevant for organizations.

Current research suggests that while financial performance is invariably tied to the incentives of top management, nonfinancial metrics of performance are not tied to their incentives and do not influence their behavior, even in firms that collect and report data on nonfinancial metrics (Kraus and Lind 2010). Our theorizing and findings from this research suggest various research directions to investigate how to make search more responsive to failures in nonfinancial metrics. Future research could examine whether structures that support availability of nonfinancial performance data can increase IT-enabled search. Further studies may also examine whether performance on nonfinancial metrics needs to be tied to the incentives from top management to encourage more IT-enabled search. The broader research question it raises is whether making performance visible through digital artifacts is sufficient to influence behavior or whether making incentives contingent on performance is needed to influence behavior. The combined effect of monitoring of nonfinancial performance measures and incentive structures is an important area for future research.

An earlier stream of research into decision support systems has also extensively examined the role of IT-enabled search in decision making (Arnott and Pervan 2005). Further, Simon's intelligence-design-choice (IDC) framework has been employed extensively in that research stream to model and describe managerial decision processes (Simon 1976, Sharma et al. 2014). A perusal of Table 1 reveals that a majority of the AIP capabilities of modern BI&A systems, such as OLAP, automated and ad hoc reporting, social media analytics, sentiment analytics, and location- and context-aware analytics, supporting the intelligence phase—that is, the identification of problems that require attention. In contrast, there is much less emphasis on AIP capabilities such as simulation and predictive models that could potentially support the design phase—that is, developing and evaluating possible courses of action. There is even lesser emphasis on prescriptive capabilities (such as simulation and optimization models) that could potentially support the choice phase—that is, the evaluating and choosing of an appropriate course of action. An important question for future research is whether investments in each phase contribute equally to value creation or whether further investments in capabilities supporting the design and choice phases can enhance the value that can be realized from investments in capabilities supporting the intelligence phase. An equally important question for future research is whether BI&A capabilities supporting each phase are equally motivating for managers or whether the inclusion of capabilities supporting the design and choice phases can make it more motivating for managers to use BI&A systems. In this context, the job characteristics theory suggests that the inclusion of capabilities supporting the design and choice phases could make it more motivating for managers to use BI&A systems as it is likely to enhance the experienced meaningfulness of work by improving core job characteristics such as skill variety, task identity, task significance, and autonomy (Hackman and Oldham 1976, Hackman and Oldham 1980).

IT use has been a central construct in various research streams (Burton-Jones and Grange 2012). IT is known to play a critical role in enhancing managers' ability to sense opportunities (Roberts et al. 2016). Prior research distinguishes between routinized IT use, where managers use IT in a routine and standardized way to support their work, and innovative IT use, where managers use IT in novel ways to search for solutions and sense opportunities (Li et al. 2013). However, prior research has generally overlooked the theoretical implications of this distinction and employed an aggregated measure of IT use that includes both types of use. In contrast, our operationalization of BI&A-enabled search as ad hoc BI&A use acknowledges that distinction and is consistent with the innovative use of IT-enabled search (Li et al. 2013, Roberts et al. 2016). Nevertheless, future research needs to build on this distinction and develop finer-grained theories of the different antecedents and outcomes of routinized and innovative use of BI&A systems.

Going forward, an important extension to the theory developed here could be to understand the impact of performance failures on different types of IT-enabled search. Specifically, similar to what this study does by conceptualizing performance as a multidimensional construct, future research could develop finer-grained theories of specific dimensions of search. For instance, prior research has already identified multiple dimensions of search, such as local and distant search, explorative and exploitative search, and external and internal boundary-spanning search (Rosenkopf and Almeida 2003, Raisch et al. 2009, Uotila et al. 2009, Afuah and Tucci 2012). Thus, theorizing on the differential effects of performance failures on different dimensions of search could further extend our understanding of the use of IT systems for search.

Additionally, behavioral theory and the information-processing views of firms can also help in investigating how the data in IT systems influences the formation of aspiration levels. The operationalization of aspiration levels in this study assumes that they are conditioned by their own past performances and of their peers based on data available in the BI&A system. Future research could investigate how different presentations of their own and peers' performance could shape aspiration levels and, ultimately, the use of IT systems for search.

Lastly, while the primary focus of this study has been to draw upon PST and develop a theory of BI&A-enabled search, it also makes important contributions to the PST. Although the PST has been widely employed within management literature, recent research argues that it needs to be refreshed in two important ways: the measurement of core constructs and refinement of theory (Posen et al. 2018). Our study contributes to both. First, prior research on problemistic search employs a narrow and unidimensional conceptualization of performance, which is financial performance (Chen 2008, Bromiley and Washburn 2011, Gaba and Joseph 2013, Joseph et al. 2016, Sengul and Obloj 2017). This is consistent with the broader research in management, strategy, accounting, and other disciplines that consider performance to be synonymous with financial performance (Venkatraman and Ramanujam 1986, Bharadwaj 2000, Klingenberg et al. 2013, Mithas and Rust 2016). Drawing on concurrent literature that explores and identifies multiple dimensions of performance, performance in this study was conceptualized along two dimensions: financial and operational performance. This lays the foundation for extending and enriching PST. Second, the PST was refined by theorizing on the independent and joint effects of financial and operational performances. Extending the conceptualization of performance is particularly important in the current analytics-on-demand environment where data on multiple metrics are easily available. It is also important as organizations experience external pressures to broaden their focus from maximizing shareholder value, for instance, to their environmental performance, carbon footprint, and corporate social responsibility. Further, by extending prior theory, this paper proposed that problemistic search is triggered not just by failures in financial performance but also by a complex function of various types of performance failures and related aspirations. Indeed, the extension to theory developed here could potentially explain the mixed findings in prior studies that Posen et al. (2018) argue could be due to a narrow conceptualization of performance employed in prior research.

Limitations

One limitation of this study is that our sample consists of a single type of organization—NFP hospitals. This may appear to limit the generalizability of our findings. However, as discussed earlier, NFPs do operate in a competitive environment and compete for contracts with other for-profit and NFP hospitals. As such, they deploy BI&A systems and performance management strategies similar to for-profit hospitals (Clement et al. 1997, Kohli and Kettinger 2004). While prior research has found differences in the performance of for-profit and not-for-profit hospitals (McCue and Thompson 2005), this does not pose a validity threat to our findings as all hospitals in our sample are NFPs. However, our theory does need to be tested in for-profit firms.

Our sample consists of one type of BI&A system and one level of analytics maturity across the hospitals in our sample. While this limitation does suggest a need to test our theory in other contexts, it also eliminates a potential validity threat arising from varying system types and maturity levels across the firms in our sample.

Another limitation of this study is that our measure of use was operationalized as a BI&A-enabled search effort and while it was a diverse and multidimensional measure, it may not be as dimensionally rich as proposed by scholars (Burton-Jones and Grange 2012). Against this limitation, this paper submits that our usage measure involves the *actual use* of the BI&A system for generating ad hoc reports—a very specific measure for operationalizing BI&A-enabled search. As such, our use measure is richer than most self-reported or perceived measures or even archival measures of use that have been employed in previous research (Sharma et al. 2009).

Implications for Practice

An important finding of this study is that BI&A systems are likely to be used for search under a narrow set of conditions—that is, when both financial performance and operational performance are failing. This suggests that firms may not be realizing the potential value from their investments in BI&A systems. The theory proposed here suggests possible remedies. Specifically, it suggests that changes to performance control systems could motivate the greater use of BI&A systems under a wider set of conditions. For instance, one such change could be for organizations to require managers to produce "success reports," just as they are required to produce "failure reports" in many organizations (Kaplan and Rabin Fastman 2003, Cannon and Edmondson 2005). This is because scrutinizing success with as much rigor as is commonly devoted to scrutinizing failure could help organizations draw valid and valuable lessons for improving performance. Another possible intervention could be to shape aspiration levels by providing more data on high-performing peers and competitors or industry best practices. However, such changes are deep organizational changes and would require the strong support of top management for them to be successful (Sharma and Yetton 2003, Sharma et al. 2008).

Conclusion

Organizations expect that investments in the BI&A system will lead to the use of such systems to search for insights and improve future performance. However, in contrast to existing wisdom and conventional thought, this paper found that BI&A systems are used for search only under a narrow set of conditions—specifically, when both operational and financial performances are failing. However, organizations could drive up the use of BI&A systems to search for insights through judicious changes to their performance control systems.

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Endnotes

[1] Unlike non-profit entities, NFP hospitals operate like for-profit hospitals, compete with for-profit hospitals in investing in IT, hiring physicians and staffs, and patient services; charge market rates for their services to remain competitive; and are reimbursed by insurance companies at the same rate as for-profit hospitals. The primary difference is that profits of for-profit hospitals are disbursed to the stakeholders, whereas profits in NFP hospitals are disbursed to the activities of the mission. NFP hospitals must follow the same accreditation regulations as for-profit hospitals, and they compete for quality and safety rankings just as for-profit hospitals do. Therefore, managers in NFP hospitals operate in the same competitive market forces as for-profit hospitals.

[2] Consistent with our conditions for sustained failure, a hospital manager confirmed that he was conducting an intensive search through BI&A system to seek answers as to why a hospital was losing money while competitors were doing fine, and why this hospital has repeatedly missed projected performance targets. This manager speculated that outside factors, such as reimbursement, may be to blame. This is consistent with the predictions of attribution theory that managers attribute failure to external causes.

[3] As BI&A is primarily used by managers at the operational level, our focal interest was to examine the interaction graphs between OP and BI&A-enabled search in combination with FP. We also plotted interaction graphs between FP and BI&A-enabled search in combination with OP to check for consistency.

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