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Uncertainty in healthcare operations: How hospitals weather the perfect storm

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Abstract

We focus on two of the many sources of uncertainty in healthcare operations, *mix uncertainty* – the variation in the complexity of care required by the patient mix, and *volume uncertainty* – the variation in the volume of care demanded by the patient population. Using an interdisciplinary perspective, we study the impact of *mix and volume uncertainties* on two important healthcare outcomes, *length of stay* and *number of procedures*, along with the mitigation impacts of the operational concepts of *related focus* and *utilization* levels. Based on large dataset of 830,853 patient discharges in 26 clinical departments across 731 hospitals in five U.S. Midwest states, our results indicate that *mix and volume uncertainties* each have a significant impact on patient care. We also find that related focus and department utilization levels have a mitigating effect on uncertainty in healthcare settings. Lastly, we find considerable heterogeneity in the effects of uncertainty across hospital types and departments. We discuss key research and managerial implications of our findings.

KEYWORDS
focus, healthcare operations, uncertainty, utilization

Highlights

- Mix Uncertainty, the uncertainty in care delivery operations owing to the variation in the complexity of patient-care needs, triggers more procedures as providers search for information.
- Volume Uncertainty, the uncertainty in care delivery operations owing to the variation in the volume of patients served, drives providers to reduce number of procedures and increases patients' length of stay.
- Related Focus, a department's breadth of expertise in relevant areas, may provide key information that reduces the need for additional procedures and can lower patients' length of stay.

1 | INTRODUCTION

Our great struggle in medicine these days is not just with ignorance and uncertainty. It's also with complexity: how much you have to make sure you have in your head and think about. There are a thousand ways things can go wrong –

Atul Gawande (Surgeon, author)

Healthcare is a significant part of the economy—for example, accounting for 17.3% of U.S. gross domestic product (GDP), healthcare spending grew 4.1% in 2022, reaching $4.5 trillion, about $13,493 per capita (CMS. gov). Given its importance, healthcare operations have received attention from both practitioners and scholars. A fundamental characteristic of healthcare, posing unique challenges to providers (hospitals and clinics), is the uncertainty in care delivery. Seminal work (e.g., Balsa et al., 2003; Wennberg, 1985) contends that uncertainty is the single most important factor affecting physician behaviour. From an operations management (OM) perspective, the many sources of uncertainty in healthcare include demand-side uncertainty (originating from a patient's need for care), supply-side uncertainty (originating from physician and hospital characteristics), and clinical uncertainty (originating from technology, knowledge, and policy), to name a few. In this paper, we focus on the demand-side uncertainty arising from the volume and variety of patient-care needs. Specifically, we focus on *mix uncertainty*, the uncertainty stemming from variation in the complexity of care needs of patients in a hospital department, and *volume uncertainty*, the uncertainty due to variation in the volume of patients served. While an extensive body of research pertains to streamlining healthcare operations (e.g., Devaraj et al., 2013), little research directly addresses the uncertainties in care needs or patient volumes, their impact on the care-delivery process, and mitigating mechanisms.

The demand for (or volume of) care is often unpredictable, which poses a significant source of uncertainty in hospital operations. A growing body of work has examined the impact of demand volume and workload on operational planning and service-delivery outcomes (Powell et al., 2012; Tom & Serguei, 2014). For example, Kuntz et al. (2015) examined the effect of utilization levels on safety outcomes in hospitals, finding evidence for safety tipping points, where mortality increases once patient volumes (utilization) reach a particular level. Similarly, Berry Jaeker and Tucker (2017) found evidence for an 'N-shaped' relationship, where (a) the patient length of stay (*LOS*) increased with occupancy, owing to congestion effects, (b) but then, past a tipping point, exhibited a speed-up effect where the *LOS* decreased, and, (c) past a second tipping point, additional occupancy increased *LOS* owing to saturation effects. Overall, while this body of work has focused on the implications of demand volume for outcomes in healthcare, the implications of *variability* in patient volumes in the care-delivery process are under-examined. Variation in patient volume may considerably disrupt process flows and operational planning, thus making it a key source of uncertainty in the care-delivery process (Devaraj et al., 2013; Jacobs & Swink, 2011). Understanding the implications of *volume uncertainty* in healthcare operations is therefore critical as hospitals struggle to cope with increasing demand for access to care. Our study contributes to addressing this need.

Another important source of uncertainty in hospital operations stems from the variation in patients' care demands, even within a single clinical department. Unlike in a factory setting, in a healthcare setting individual patients have complex care needs, manifest in a multitude of chronic and comorbid conditions. These conditions of varied severity interact to create considerable challenges in both the process and outcomes of care. A rich body of prior research in this area Kc and Terwiesch (2011) has examined the measurement of complexity and its implications for patient routing, care outcomes, and hospital portfolio strategy. For example, Kuntz et al. (2019) argued that organizing hospital services based on the complexity of patient-care needs would improve care quality. More recently, Thirumalai and Devaraj (2024) highlighted the role of focus in mitigating the effects of the complexity of patient-care needs on the costs of care. Clark and Huckman (2012) pointed to the benefits of specialization in focal and related care categories in care delivery for patients needing complex care. Similarly, Sunder and Thirumalai (2024) emphasized the complexity of care needs as a key mechanism for patient choice among hospitals with varied portfolios of care. While this body of research has largely focused on the complexity of care needs, the *variation* in the complexity of patient-care needs and its impact on performance have heretofore not been examined. Our study assesses the *variation in complexity* across patients within a department as a source of *mix uncertainty* and examines its implications for the care-delivery process.

Our study builds on theoretical perspectives from Ramasesh and Browning's (2014) uncertainty framework, hereinafter referred to as the R&B framework, and organizational information processing theory (OIPT) (e.g., Daft & Lengel, 1986; Galbraith, 1977). Specifically, the R&B framework provides the conceptual foundation

to study the sources and measurement of uncertainty. While the R&B framework was primarily developed in the context of projects, we draw upon its conceptualizations for two reasons. First, R&B fully expected it to generalize to other operational settings: "since all types of operations, not just projects, can be characterized by the factors in our framework…, we are optimistic that many insights from this research could be generalized beyond projects" (p. 203, Ramasesh & Browning, 2014). Second, each hospital-patient encounter may be viewed as a project—that is, as temporary work with unique outcomes.[1]

Next, while the R&B framework provides an understanding of the sources of uncertainty, OIPT offers an organization-design perspective for understanding how organizations might mitigate the effects of uncertainty on performance. The primary premise of OIPT is that firms process information to reduce uncertainty, where uncertainty is "the difference between the amount of information required to perform the task and the amount of information already possessed by the organization" (Galbraith, 1977, p. 36). From an OIPT perspective, two mitigating mechanisms are to reduce the need for information processing and/or to increase information-processing capabilities. In this vein, we examine the role of operational factors such as a department's breadth of expertise in related areas of care (related focus) and operational slack (lower resource utilization levels) in mitigating the negative effects of *mix and volume uncertainties* in care delivery.

Three criteria motivated our choices of the outcomes we study. First, given our interest in examining the impact of uncertainty on the process of healthcare delivery, we selected outcome variables at the process level. While prior research (Berry Jaeker & Tucker, 2017; Clark & Huckman, 2012; Kc & Terwiesch, 2009; Kuntz et al., 2015; Thirumalai & Devaraj, 2024) has examined the implications of healthcare policy and operational factors on care-delivery outcomes such as mortality, readmission rates, and the costs of care, relatively little research has examined the process of care. Second, the outcome variables must be proximal (not distal) to the phenomenon we are addressing. Third, our choice of outcome variables is consistent with other process-level studies (e.g., Berry Jaeker & Tucker, 2020; Goodney et al., 2003). To that end, our study examines the implications of *mix and volume uncertainties* for the process of care delivery, specifically looking at the number of procedures (*NPR*) offered to patients and how long patients spend in the system (length of stay, *LOS*). *NPR* is a key driver of process performance and proximal to the process of care. The Institute of Medicine (IOM, 2013) estimated that

unnecessary services and procedures cost more than $200 billion per year in the U.S., and that these extra costs hinder progress in healthcare. An examination of *NPR* is then indicative of the efficiency of the process flow within a care-delivery setting. *LOS* is the time dimension associated with the process of care and is both process-level and proximal. Discharging patients in a timely manner (lower *LOS*) implies both efficiency and effectiveness of service and can lower hospital costs as much as $1729 per patient, with delays costing a hospital an estimated $2.5 million per year (Devaraj et al., 2013). Thus, an examination of *NPR* and *LOS* in our study provides key insights into the process of care delivery.[2]

Using a large dataset of 830,853 patient discharges in 26 clinical departments across 731 hospitals in five U.S. Midwest states, we empirically examine the impact of *mix and volume uncertainties* on the care-delivery process, viz., *NPR* and *LOS*. We use the mean-adjusted *variation* in the complexity of patients served within a primary diagnostic category as a measure of the *mix uncertainty* within a department. Similarly, we use the *variation* in the volume of patients served across time periods within a department as a measure of the *volume uncertainty* within the department. We also examine the mitigating effects of department utilization levels and the operational decision to focus in related areas on addressing uncertainty in healthcare. Lastly, our study also examines heterogeneity in the effects of uncertainty across hospital types and departments.

Our analysis indicates that *mix uncertainty* in patient-care needs triggers more procedures (higher *NPR*), suggestive of the information needs of providers. On the other hand, *volume uncertainty* drives providers to reduce procedures (lower *NPR*) and cause delays (longer *LOS*), suggestive of bottlenecks from variable process flow. We find that breadth of expertise in relevant areas can lower patients' *LOS* and reduce the need for more procedures. In the face of *mix uncertainty*, expertise in related areas may provide key information that reduces the need for additional procedures. We confirm that higher utilization levels motivate a speed-up in healthcare operations, consistent with prior observations in the literature. Lastly, we find considerable heterogeneity in the effects of uncertainty across hospital types and departments within a hospital.

Overall, our study provides further insight into the forces underlying *mix and volume uncertainties* in healthcare. We empirically explore how uncertainty affects healthcare delivery and outcomes. Our study also highlights the role of two operational factors, related focus, and utilization, in mitigating the effects of uncertainty on patient-care delivery.

2 | THEORY AND HYPOTHESES

We draw upon theoretical perspectives from the R&B framework and OIPT to articulate our hypotheses. According to the R&B framework, a key source of uncertainty in operational settings is the variation in the volume and complexity of tasks. Whereas many complexity models (e.g., Kauffman & Levin, 1987) and metrics simply account for the number of elements in a system and the number of relationships among them, the R&B framework defined complexity as a nested function of the complexities and varieties of its elements and their relationships. The framework suggests that increasing variation in the number and types of elements (e.g., patient conditions, medical procedures) and/or relationships (e.g., interactions) would amplify uncertainty. Accounting for the nested complexity enables investigation of how complexity at one level, such as in patients and/or medical procedures, can contribute to uncertainty in a higher-order system such as a hospital-department. Thus, the R&B framework indicates how *variation* in a system's volume and variety of demand can increase uncertainty. In this vein, if a hospital department has to deal with a fluctuating volume of high- and low-complexity patients, it would be more challenging to manage (from an operational perspective) than in a scenario with a consistent stream of either low- or high-complexity patients. Therefore, it is imperative that we examine the *variation* in the volume and nature of patient care needs.

2.1 | Effects of uncertainty on the care-delivery process

Figure 1 shows our conceptual framework, wherein we hypothesize the main effects of two types of uncertainty, *mix uncertainty* (the variation in the complexity of care

demanded) and *volume uncertainty* (the variation in the volume of care demanded), on two outcomes, *NPR* and *LOS*. We then examine the moderating effects of a hospital-department's related focus and resource utilization level. The following discussion develops these hypotheses, while further explanation of the factors themselves is provided in §3. The premise we test in this paper is how the uncertainty due to *variations* in complexity and volume leads to challenges over and above the main effects of complexity and volume, which are both well-studied in the literature.

The uncertainties caused by the fluctuations in complexity and patient volume pose several challenges to the care-delivery process: (a) *administrative challenges* in resource allocation and planning for varying needs; (b) *coordination challenges*, including bringing specialists together, off and on, for patients of varying complexity; (c) *informational challenges* of not having the right information at the right time, especially when faced with a surge in patient volume or complexity; and (d) *clinical challenges*, owing to spillovers (in treating more-complex patients, doctors feel they oftentimes have less time to spend with less-complex patients and their families) or lack of specialty when needed.

We argue that an increase in uncertainty carries significant implications for healthcare outcomes, including *LOS* and *NPR*, for several reasons. First, uncertainty may contribute to a lack of clarity on questions about classifying symptoms, or the causes of illness, and the best mode of treatment. Normally, additional tests might be called for, or responses to particular treatments might provide further clarity (in an effort to close the information gap). In the face of uncertainty, more procedures may substitute for experience. For example, residents within a teaching hospital or providers with less experience may resort to more procedures, with longer lengths of stay, in arriving at appropriate care plans. These situations
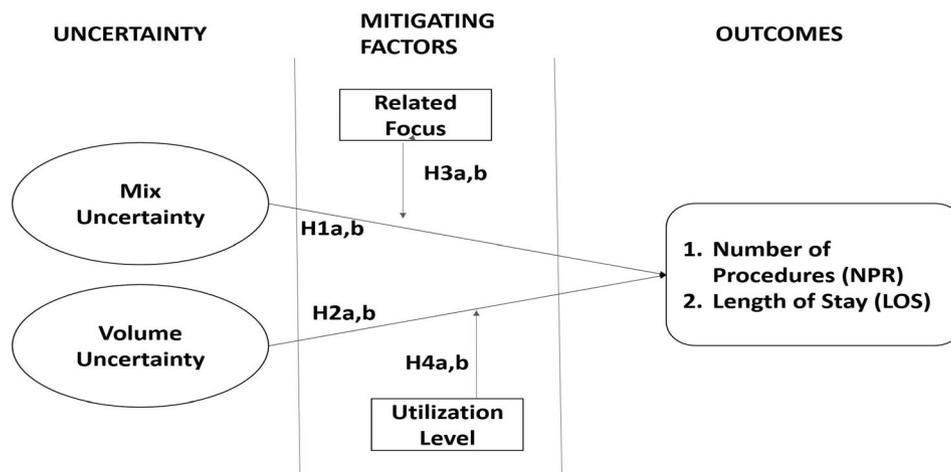

FIGURE 1 Conceptual framework.

prolong the appropriate diagnosis and treatment protocol, increasing both *LOS* and *NPR*. Second, practical uncertainties exist in the structures, processes, and systems of care. These might be ambiguities in procedures to be undertaken or in system guidelines. Second opinions might be considered, or specialists might be sought to gain more clarity. These can be viewed as delays in comparison to a more streamlined and definite process of care, leading to a greater *LOS* and a higher *NPR*. Third, the idiosyncratic, personal characteristics of the interactions between caregiver and patient also harbor uncertainties, including those regarding communication issues and quality-of-life decisions (cf. Healy, 2003). These situations of uncertainty all prolong decision making and call for further evidence (information) to take action, which increases *LOS* and *NPR*.

In the OM literature, Schmenner and Swink (1998) presented the concept of swift and even flow in processes leading to higher productivity. That is, performance improves inversely to the variability of process flow. Sources of variability could be from the demand on the process or from within the steps of the process itself. Devaraj et al. (2013) applied these ideas to examining patient flow in healthcare, finding evidence for a beneficial effect of the reduction in variability of patient flow on healthcare quality. Specifically, they found that while swift flow had a relationship with financial performance, *even* flow was primarily related to quality performance. In our context, the reduction of uncertainty in the volume and mix of patients corresponds to the concept of *even* flow from this stream of literature. Building on this, we expect that uncertainty reduction will have a beneficial effect on healthcare outcomes.

The R&B framework proposed that changes (or variation) in complexity can increase uncertainty, leading to inefficiencies. For example, an organization might organize for efficiency in handling lower-complexity work, while handling the occasional high-complexity situation by exception, and thus, perhaps suboptimally. Thus, an increasingly varied mix of patient complexities could reasonably be expected to reduce performance. While it is possible that low-complexity cases might provide some respite to the medical staff from high-complexity cases, and therefore that greater *mix uncertainty* might lead to better performance, our discussions with medical professionals revealed that increased variation in complexity can lead to challenges in providing patient care because of (a) the coordination challenges arising from varying needs to work with more people (e.g., a diabetic with a dead toe: although this is not a high-complexity patient, doctors have to work with a lot more staff) and (b) medical errors that happen when switching between types of patients.

Based on the above arguments, we hypothesize:

> **Hypothesis 1.** The greater the mix uncertainty, (a) the greater the number of procedures (*NPR*) conducted and (b) the longer the length of stay (*LOS*) of patients.

> **Hypothesis 2.** The greater the volume uncertainty, (a) the greater the number of procedures (*NPR*) conducted and (b) the longer the length of stay (*LOS*) of patients.

2.2 | Mitigating the effects of uncertainty in the care-delivery process

While the R&B framework helps to understand the sources of uncertainty and its implications for care-delivery processes, OIPT (Daft & Lengel, 1986; Dennis & Valacich, 1999; Galbraith, 1974; Galbraith, 1977; Larson et al., 2014) provides an organizational perspective on the role of information processing and factors that can mitigate the effects of uncertainty. As noted earlier, OIPT posits that organizations process information to reduce uncertainty, which is the gap between the knowledge (information) required by an organization and that which it possesses. Two broad mechanisms for mitigating uncertainty in organizations are: (a) reducing the need for information processing and (b) increasing the capacity and capability to process information. A host of studies in the healthcare operations literature (e.g., Berry Jaeker & Tucker, 2020; Ding et al., 2020; Dobrzykowski & Tarafdar, 2015; Wani & Malhotra, 2018) build on theoretical arguments from OIPT, examining information processing as a key mechanism to influence healthcare outcomes. We build on this body of work to examine the role of operational levers, in particular *related focus* and *utilization*, in improving information processing and mitigating the effect of uncertainty in healthcare operations.

2.2.1 | The moderating effects of focus in related areas

Although the concept of focus has its roots in Skinner's (1974) seminal work on focused factories, it has recently gained significant traction in healthcare operations. Focus relates to the narrowing down of tasks by organizational entities to a more limited and consistent set of activities based on a deliberate selection of customer segments, geographies, process technologies, products, and/or service lines (Ding, 2014; Ding et al., 2020;

Huckman & Zinner, 2008; Hyer et al., 2009; Kc & Terwiesch, 2011; Kuntz et al., 2019). Given this extensive body of work on focus, we do not hypothesize the main effect of such focus. However, a more recent and nuanced form of focus is termed "focus in related areas," and there is limited research on this aspect. Clark and Huckman (2012) stated that the practice of care in a focal category may benefit from expertise in other "relevant" categories, which normally manifests as secondary diagnoses. Thus, the concept of *related focus* is a hospital's emphasis on certain, select categories that are clinically associated with and relevant to a focal category (Sunder & Thirumalai, 2024).

Related focus provides a form of complementarity by providing care professionals in a department access to new sources of knowledge and insight about related conditions (Thirumalai & Devaraj, 2024). As an example, many patients with cardiovascular illness also suffer from diabetes, a key area of focus for endocrinologists (Clark & Huckman, 2012). Knowledge about diabetes has the potential to help cardiovascular specialists better understand their own specialized experiences with cardiovascular patients. This is consistent with the concept of "curbside consultations" documented in the medical literature (Manian & Janssen, 1996). Thus, hospitals with high *related focus* may be in a better position to combat the detrimental effects of the variability in the complexity of care.

Applying the propositions of OIPT given above, organizations can mitigate the effects of uncertainty by decreasing their need for information and/or increasing their capability to process information. Related focus can reduce the need for information processing through two of the approaches prescribed by OIPT – increasing lateral connections and creating self-contained tasks. The staffing of care providers in related areas within a department makes it efficient to provide care in a majority of cases where the related specialty is also consulted. An example is a neurology department having a psychiatrist on staff, because neurology patients may need support with mental health. When a care provider has more such *related focus*, the task of providing care is more self-contained in a department and thereby more efficient and effective. In a related manner, the R&B framework includes organizational pathologies of not being open to external information as another driver of uncertainty. In this vein, an organization with higher *related focus* will be more likely to absorb input from related areas, including the "weak signals" that illuminate and help resolve uncertainty.

Based on the above arguments, we hypothesize:

> **Hypothesis 3.** The relationship between mix uncertainty and (a) *NPR* and (b) *LOS* is negatively moderated by the degree of related focus in a hospital-department.

2.2.2 | The moderating effects of utilization level

Workload, utilization level, and organizational slack all relate to the volume of service provided in an organization, which affects organizational performance. R&B noted how both organizational pathologies and individual mindlessness, which often result from the stress and pressure typical of a high-utilization situation, increase uncertainty, because many "knowable unknown unknowns" are left undiscovered without the resources to invest in recognizing them. In healthcare, Kuntz et al. (2015) examined the effect of utilization levels on safety outcomes in hospitals (measured as mortality), finding that when workload or utilization increased, clinical staff was forced to ration resources and became error-prone due to the high stress levels. They found evidence for safety tipping points, where mortality increases after utilization reaches a tipping point.

Prior research on the effects of workload in healthcare settings (e.g., Berry Jaeker & Tucker, 2017; Kuntz et al., 2015) identified speed-up as a behavioral implication of increasing utilization. When providers (clinicians) were faced with increasing demand, they increased their service rates by focusing on critical aspects of care, creating shortcuts and cutting corners (Oliva & Sterman, 2001; Tom & Serguei, 2014). For instance, Berry Jaeker and Tucker (2017) found evidence for an interesting phenomenon, where *LOS* increases as occupancy or utilization increases, but only until a tipping point. After reaching this tipping point, the *LOS* decreased—that is, patients were discharged early to avoid congestion in the system. They also found evidence for a second tipping point, beyond which additional occupancy increased *LOS*. At extreme workload conditions, they may reach an inflection point beyond which speed-up and stress may be associated with a drop in service quality. In other words, there exists a saturation point beyond which speeding up can no longer meet the demand, thus leading to longer *LOS*.

From an organizational response standpoint, at times of extreme workload conditions, hospitals may redirect resources (nurses/physicians), or tap into alternate resources (e.g., non-physician care providers such as nurse practitioners or physician assistants) in the short-term, or use technology (e.g., Tom & Serguei, 2020) to speed up services and deal with demand surges. These behavioral and organizational responses may thus enable providers to respond to surges in workload and uncertainty in demand.

While these earlier studies examined the direct effect of utilization on outcomes, we focus on the moderating role of utilization on the relationship between uncertainty (coming from the variability in volume) and performance (*LOS* and *NPR*). The normal strategies that hospitals pursue to combat high workloads are flexible staffing (Berry Jaeker & Tucker, 2017) and pooling capacity, where hospital clusters cater to demand (Kuntz et al., 2015). However, with high uncertainty in the workload or utilization, it can be extremely challenging for hospitals to implement these strategies (i.e., plan for flexible staffing or pool capacity), because they are aiming at a moving target. So, the effect of the uncertainty resulting from the variability in patient volume has a more drastic effect on *LOS* and the treatment protocols (*NPR*) when utilization levels are high and the environment is more stressful.

The above line of thinking is consistent with OIPT, which suggests that organizations can create slack resources to combat the effect of uncertainty and thereby decrease the need for information processing. That is, low utilization levels allow for greater slack in resources, leading to attenuation of the impact of uncertainty on outcomes. Thus, we hypothesize:

> **Hypothesis 4.** The relationship between volume uncertainty and (a) *NPR* and (b) *LOS* is positively moderated by the utilization level of the hospital-department.

3 | EMPIRICAL DESIGN

The central goal of our empirical analysis is to examine the impact of department-specific characteristics (including *mix and volume uncertainties*, expertise levels, and utilization) on patient-care delivery. Specifically, we examine the direct effects of *mix and volume uncertainties* and the moderating impact of operational levers, including focus and utilization levels, on patient-care delivery. The uncertainty in demand for care, focus, and utilization levels are assessed at the hospital-department level. The implications for care delivery are assessed at the individual-patient level along two dimensions, the number of procedures (*NPR*) performed and length of stay (*LOS*). Below, we describe the data, variables, and model specification.

3.1 | Data

Our research agenda in the study calls for data across hierarchical levels of inpatient care: demand data (mix and volume) and individual-patient demographic and clinical characteristics at the patient level, clinical expertise and utilization at the hospital-department level, and operating characteristics (e.g., profit status, teaching status, location, etc.) at the hospital level. The Nationwide Inpatient Sample (NIS) database from the Agency of Healthcare Research and Quality's (AHRQ) Healthcare Cost and Utilization Project provided our primary source of data for this project. HCUP documentation states that the NIS data is a stratified sample of "discharges from U.S. community hospitals, excluding rehabilitation and long-term acute care hospitals."[3]

Our data comprises patient discharge information from hospitals in five states (Wisconsin, Michigan, Illinois, Indiana, and Ohio) across the U.S. Midwest region. Our sample consists of complete patient-discharge data for 830,853 patients from 731 hospitals in 2015. The patients in our sample are spread across all 26 major diagnostic categories (MDCs).[4] However, since not all hospitals offer care across all MDCs (departments), our sample includes a total of 14,013 unique hospital-MDC combinations. Patient-level data include patient demographics and clinical variables such as patients' admission information, comorbidities, chronic conditions, MDC, primary diagnostic-related group, and disposition at discharge. Due to patient privacy laws, the NIS database does not include identifiers to track patient status prior to admission or subsequent to discharge. The NIS database similarly masks all hospital identifiers to prevent the identification of individual hospitals and the linking of hospital information with outside information, thus preventing the assembly of a longitudinal, panel database of the hospitals. See Table 1 for a demographic summary. The average (median) age of the patients in our sample was 50.3 (56) years.

TABLE 1 Hospital, patient demographic details.

Hospitals	Location – Rural	37%
	Teaching	32%
	Private Non-profit	81.5%
Patients	Female	57%
	White	73.7%
	Black	16.4%
	Hispanic	4.8%
Payor	Medicare	42.6%
	Medicaid	21.7%
	Pvt. Insurance	30.8%

3.2 | Variables

3.2.1 | Mix uncertainty and volume uncertainty

As discussed earlier, we assess uncertainty in the demand for care along two dimensions: *mix uncertainty*, the uncertainty in the care required by patients within a MDC, and *volume uncertainty*, the uncertainty in the volume of care required within a MDC. The operationalization of each in our study is tied to the *variation* in the mix or volume of patients being served within a category. We seek to understand the implications of the uncertainty faced by decision makers that arises from the fluctuations in the complexity and volume of patients served in a department. Instead of a raw measure of variation, we use the coefficient of variation (CV) metric, the ratio of the standard deviation to the mean values, to mean-normalize these metrics in a comparative assessment across categories. The CV is a well-established statistical metric that has been a mainstay in statistical and OM literature (e.g., Feizi et al., 2022; Jalilibal et al., 2021). Below, we describe the measurement of these two dimensions in further detail.

Mix uncertainty reflects the uncertainty arising from heterogeneity in complex care needs across patients. A patient's care needs can be widely heterogeneous because of their varied chronic and comorbid conditions, varied associated diagnoses, and the varied levels of severity and mortality risk in the conditions presented. Even within a single MDC, patients are heterogeneous in their demand for care, owing to the complex cocktail of comorbid, chronic conditions of varied severity. To assess the uncertainty from this heterogeneity, we first create a summary measure of the complexity of patient-care requirements. Our study builds on existing literature (Kuntz et al., 2019; Sunder & Thirumalai, 2024; Thirumalai & Devaraj, 2024) to assess complexity as a reflective score of six clinical indicators that are representative of the complexity of patient-care requirements: (a) the total number of *unique diagnoses* presented by the patient, (b) the number of *chronic conditions* reported, (c) the comorbidity index (summation count of all the *comorbid conditions*), (d) the severity of illness within the diagnostic-related group, (e) the risk of mortality within the diagnostic-related group, and (f) the age of the patient.[5] We then measure *mix uncertainty* as the CV of the complexity of patient-care needs within each department. Let C_{ijk} refer to the complexity of a patient$_i$'s care requirements in (category) MDC$_j$($j = 1, 2, 3, ..., 26$) of hospital$_k$. The *mix uncertainty*, MU_{jk}, of department$_j$($j = 1, 2, 3, ..., 26$) of hospital$_k$ is then:

$$MU_{jk} = \left[\frac{stdev(C_{ijk})}{mean(C_{ijk})} \right]$$

The demand for care within each department each month may be influenced by exogenous environmental and clinical shocks. As noted earlier, fluctuations in demand volumes introduce considerable uncertainty in care-delivery planning, with significant influence on the care-delivery decisions of providers. *Volume uncertainty* indicates the fluctuation in the volume of patients seeking care in a hospital department across time periods. The inpatient discharge summaries in our data include the month of admission. The variation in the aggregate inpatient demand for care across months is then reflective of the uncertainty in volume of care demanded in each department. To assess the uncertainty arising from fluctuations in patient volumes, we calculate the CV of patient volumes in each department, period to period. Let V_{jkt} refer to the volume of patients seeking care in (category) MDC$_j$($j = 1, 2, 3, ..., 26$) of hospital$_k$ in month$_t$. *Volume uncertainty*, VU_{jk}, of department$_j$ of hospital$_k$ is then:

$$VU_{jk} = \left[\frac{stdev(V_{jkt})}{mean(V_{jkt})} \right]$$

3.2.2 | Length of stay (*LOS*) and number of procedures (*NPR*)

The central focus of our empirical analysis is to examine the implications of uncertainty in demand for the process of care delivery. As noted earlier, while prior research in the healthcare operations literature (e.g., Berry Jaeker & Tucker, 2017; Clark & Huckman, 2012; Kc & Terwiesch, 2009; Kuntz et al., 2015; Thirumalai & Devaraj, 2024) has examined a variety of patient-care outcomes such as mortality, readmission rates, and costs of care, the key dependent variables of interest in our study are process-level metrics—*NPR* and *LOS* during an episode of care for an individual patient.

NPR is the total number of clinical procedures billed on the patient record. Analogous to the process steps in a production system, it represents the organizational/employee actions that fill the information gaps and/or represent gains in the work-in-progress, and it forms a key indicator of the overall performance (cf. Berry Jaeker & Tucker, 2020; Hannan, Bernard, et al., 1989). In this vein, Hannan, O'Donnell, et al. (1989) showed that care providers' practice patterns—reflected by the procedures prescribed—accounted for significant variation in outcomes even after controlling for patient characteristics.

LOS is the number of days a patient spends in the hospital as an inpatient. According to AHRQ,[6] patient *LOS* is calculated by subtracting the admission date from the discharge date (same-day discharges coded as 0) on the patient record. *LOS* has been a key variable of interest in multiple studies in the healthcare operations literature (e.g., Berry Jaeker & Tucker, 2017; Kc & Terwiesch, 2009; Kuntz et al., 2015). While lower *LOS* may signal swifter care-delivery operations (without much delay in coordinating services), it is also indicative of a faster recovery and discharge, indicative of quality care. Another reason hospitals strive to decrease *LOS* is to minimize the effect of hospital-acquired complications (HACs). Thus, from an OM perspective, the *LOS* metric simultaneously reflects both the effectiveness and efficiency of care, making it a key variable of interest.

3.2.3 | Mitigating factors: Related focus and utilization

As noted earlier, *related focus* in a category is indicative of a department's expertise across its most-relevant care categories. We build on prior research (e.g., Clark & Huckman, 2012; Thirumalai & Devaraj, 2024) in the empirical calculation of the *related focus* measure. Following this research, for each primary category of care, we consider another category as related if at least 5% of patients in the primary category had secondary diagnoses in the other category. We then calculate *related focus*, Rel_Focus_{jk}, as a summation of the proportions (focus) of hospital patients in all related categories. As discussed in H3, we examine the moderating impact of a department's *related focus*[7] on the effects of *mix uncertainty* on the care-delivery process. We examine this moderating effect by interacting Rel_Focus_{jkt} with MU_{jk}.

Utilization within a hospital department refers to the degree of resource usage relative to its maximum available capacity. We assess the utilization within an individual hospital's departments based on the volume of inpatients that were provided care services relative to the maximum capacity. However, data on maximum available capacity (viz. personnel, facility) across individual departments of hospitals is often unavailable to researchers. Given this challenge, we define peak capacity as the maximum number of inpatients that were served in that department anytime during the 12-month period for which we have data. As noted earlier, our inpatient discharge summaries provide the admission month, which then enables us to identify monthly inpatient volumes in each hospital department. We then assess utilization in a given hospital department in a given month as the ratio of inpatient discharges within the department that month to its peak capacity ($Util_{jkt}$).

As discussed in H4, we examine the moderating impact of utilization levels on the effects of *volume uncertainty* in the care-delivery process. We examine this moderating effect by interacting $Util_{jkt}$ with VU_{jk}. Additionally, prior literature (e.g., Berry Jaeker & Tucker, 2017; Kuntz et al., 2015) has documented the nonlinear impact of workload levels on care delivery. To account for the nonlinear effects of utilization, we include a quadratic term for utilization in our model.

3.2.4 | Control variables

It is conceivable that unobserved, patient-specific heterogeneity may lead to biased estimates of the effects of our key study variables. To that end, our empirical specification includes a host of control variables that account for patients' *demographic*, *clinical*, and *environmental* characteristics. We include fixed intercepts for demographic variables including patient age, race, gender, metropolitan location, and the payor on the patient's record. We also control for the admission type (elective, emergency, or transfer), patient's comorbid conditions, and patient condition at discharge.

Next, to enable a comparative evaluation of the implications of uncertainty and mitigation approaches across hospital departments for patient-care delivery, we account for a host of hospital-, MDC-, DRG-, and time-specific fixed effects (FEs). The hospital FEs account for heterogeneity in hospital structural and operational characteristics. The MDC FEs account for heterogeneity in clinical care characteristics (e.g., in procedures, outcomes, and resource needs) across categories. Similarly, there could be considerable heterogeneity in patients across DRGs within a department. They may differ not only in their clinical care needs (chronic conditions, comorbidity, etc.) but also in their procedural characteristics (e.g., surgical vs. medical treatments). To account for this heterogeneity, we include DRG FEs in our model specification. The DRG-specific intercepts remove the average differences in care characteristics of patients specific to each DRG. Lastly, we include FEs specific to the calendar month and weekend to account for any unobserved heterogeneity across time.

4 | ANALYSIS

4.1 | Descriptive statistics

Tables 2 and 3 provide descriptive statistics for the key variables in the study sample. Although we had data from 731 hospitals across 26 categories, as noted earlier, not all hospitals offer care in all departments (i.e., not all

hospitals had patient admissions across all departments). This resulted in a sample of 14,013 unique hospital departments with patient admissions. Furthermore, across the individual departments which did admit patients, some had infrequent patient volumes (e.g., patients admitted just once during the year or a fixed number of patient admissions in different months of the year). Since the measure of *volume uncertainty* assesses the variation in the volume of patients served in these hospital-departments, these observations have a value of zero for volume-uncertainty in our data, which is represented by the density around zero.[8] Figure 2 provides the frequency distributions of *mix uncertainty* (*MU*) and *volume uncertainty* (*VU*).

The plots reveal that the values of *MU* are more dispersed than those of *VU*. *MU* is assessed as the ratio of the standard deviation (SD) of complexity of patient-care requirements to the mean complexity value in that category of care within the hospital. Note that the complexity of care is assessed as a regression factor score, which is likely to have negative values. Thus, while the SD values are non-negative, the mean values are negative in some cases, which makes the *MU* values negative. *MU* in hospital departments has an average value of 1.24 across departments.[9] On a comparative note, *VU*, the CV of the volume of patients in hospital departments across the time periods, is 0.25. The rather large difference in CV suggests that, while the demand volume is relatively stable within and across departments, there is considerable variation in the complexity of patients' care requirements within and across departments (see Figure 2). Thus, the descriptive summary suggests that *MU* may present a greater challenge than *VU* in hospital departments.

TABLE 2 Descriptive statistics.

Variable	No. of obs	Mean	Std. dev.
Hospital-Department Level			
Mix_Uncertainty	11,223	1.237	2.283
Vol_Uncertainty	12,273	0.252	0.152
Related_Focus	14,013	0.420	0.156
Dept_Utilization	14,013	0.835	0.223
Patient-Level			
NPR	830,853	1.584	2.190
LOS	830,842	4.441	5.825

TABLE 3 Correlation matrix.

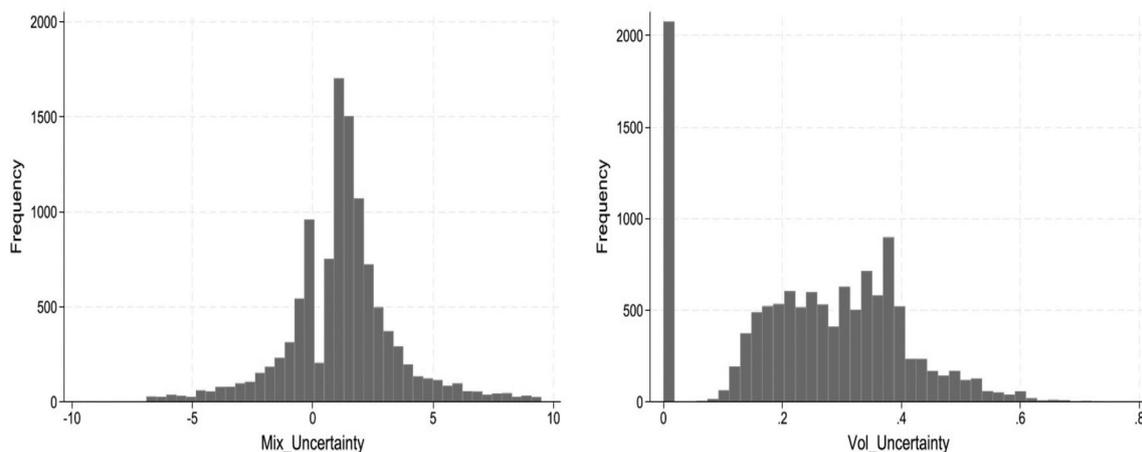|	*Mix_Uncertainty*	*Vol_Uncertainty*	*Related_Focus*	*Dept_Utilization*	*NPR*	*LOS*
Mix_Uncertainty	1					
Vol_Uncertainty	0.097	1				
Related_Focus	0.080	0.003	1			
Dept_Utilization	−0.071	−0.407	0.001	1		
NPR	−0.056	0.026	−0.106	−0.068	1	
LOS	0.042	0.010	0.082	−0.036	0.185	1

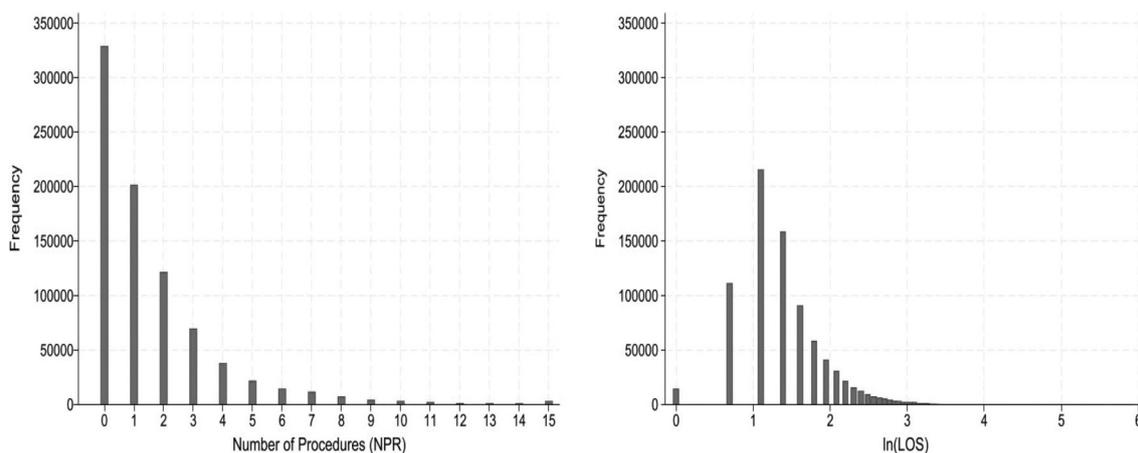**FIGURE 2** Mix and volume uncertainty.

FIGURE 3 *NPR* and ln(*LOS*).

Figure 3 shows the distributions of patients' *NPR* and ln(*LOS*). The average *LOS* in our sample is about 4.5 days, with 90% of patients staying fewer than nine days, while the average *NPR* received by a patient is two, with 90% receiving four or fewer.

4.2 | Results

To examine the effects of uncertainty on (1) *NPR*, a count variable, we follow a Poisson model specification, whereas for (2) *LOS* we follow a commonly used approach of taking the natural logarithm of the variable, ln(*LOS*), to reduce the skewness in the distribution (Kc & Terwiesch, 2011, 2009). *LOS* values tend to be highly skewed, with some patients discharged the same day of admission and others staying over an extended duration (lasting months). This transformation enables us to model logarithmic *LOS* as a linear regression (cf. Berry Jaeker & Tucker, 2017).

Table 4 presents the results from the estimation of the empirical models in our study. Models 1–2 provide the results from estimating the model for *NPR*, where Model 1 presents the main effects and Model 2 presents the main and interaction effects.[10] Similarly, Models 3–4 present the results for ln(*LOS*). Estimation of the models for *NPR* followed a Poisson regression, while that for *LOS* was modeled as a log-linear regression. The results (see Figure 4 for the marginal effects plot) from these models suggest the following key insights.

The results (see Model 2) indicate a positive and significant coefficient[11] $(0.05, p < 0.01)$ for the main effect of *MU* on *NPR*, while the coefficient for the main effect of *MU* on *LOS* is not significant. This result suggests that, with increased variation in the complexity of patient-care requirements, providers tend to order more treatment procedures, with no significant effect on the *LOS*. This finding is consistent with our theorizing about the information-seeking behavior (e.g., more tests and procedures) of agents in the presence of uncertainty and supports Hypothesis H1(a).

The coefficients of the main effects of *related focus* for both *NPR* and *LOS* are negative and significant $(-80.6, p < 0.01; -0.246, p < 0.01)$, suggesting that, ceteris paribus, expertise in related areas enables providers to reduce *LOS* while also performing fewer procedures. This signals the efficiency and effectiveness benefits of breadth of expertise in relevant areas. This finding is consistent with arguments in the literature on the benefits of *related focus* (e.g., Clark & Huckman, 2012; Sfekas, 2019; Thirumalai & Devaraj, 2024). A wider breadth of expertise could reasonably be expected to help any organization deal with complex information needs. The additional breadth of expertise may essentially serve as a proxy source of information, reducing the need for information search.

The coefficients of the interaction effects of *related focus* and *MU* are negative and significant, suggesting that *related focus* moderates the effect of *MU* on *NPR* by reducing *NPR*. While *mix uncertainty* may trigger more procedures (seeking information), providers with expertise in related areas may be less susceptible to such procedure surges in the face of uncertainty. By providing the necessary information and insight, this breadth of expertise may enable these departments to design a treatment plan without first requiring more *NPR*, especially when faced with uncertainty. This finding supports H3(a).

The negative and significant coefficient $(-17.0, p < 0.01)$ for the main effect of *VU* on *NPR* suggests that, with increased fluctuation in the volume of patient care demanded in hospital-departments, providers tend to "speed up" operations by performing fewer

TABLE 4 Effects of mix- and volume-uncertainty.

Variables	NPR		ln(LOS)	
	(1)	(2)	(3)	(4)
MU	0.005**	0.05***	−2.22e-5**	−4.52e-5
	(0.002)	(0.017)	(1.05e-5)	(5.56e-5)
Rel_Focus	−81.0***	−80.6***	−0.245***	−0.246***
	(9.93)	(9.93)	0.0499)	(0.0499)
MU × Rel_Focus		−0.067**		9.96e-5
		(0.032)		(11.1e-5)
VU	0.0225	−17.0***	0.114***	0.117***
	(1.89)	(4.74)	(0.009)	(0.026)
Util	15.5***	2.40	0.0902***	0.0928***
	(4.0)	(4.98)	(0.021)	(0.0279)
Util × Util	11.5***	−6.98**	−0.053***	−0.054***
	(2.63)	(2.82)	(0.014)	(0.016)
VU × Util		24.6***		−0.427
		(0.056)		(0.030)
Fixed Effects				
FE: Comorbidities	✓	✓	✓	✓
FE: Primary DRG	✓	✓	✓	✓
FE: MDC	✓	✓	✓	✓
FE: Hospital	✓	✓	✓	✓
Controls				
Patient Complexity, Department Focus, Patient Gender, Patient Race				
Elective Admission, Emergency Admission, Transfer_In, Transfer_Out				
Payor, Admission Month, Weekend Admission, Hospital Birth				
Disposition at Discharge, Endogeneity Correction				
Fit Statistics				
N	768,903	768,903	768,897	768,897
Log Pseudo Likelihood	−1021002.7	−1020987.5	−478075.9	−478073.0

Note: Coefficients represent % change in outcomes, Standard errors in parentheses. Coefficient estimates of FEs and control variables not included for brevity of exposition. *$p < .10$; **$p < .05$; ***$p < .01$.

procedures. The reduction in service caused by cutting corners and decrease in non-critical activity when faced with erratic demand surges is consistent with prior literature on the behavioral implications of workload pressures (e.g., Oliva & Sterman, 2001; Repenning & Sterman, 2001).

Furthermore, under conditions of high *VU*, patients tend to have longer *LOS*, as observed in the positive and significant coefficient for the main effect of *VU* on *LOS* ($0.117, p < 0.01$). Specifically, a one-SD increase in *VU* is associated with a 1.01% (about 76 min) increase in *LOS*. This is consistent with the "swift and even flow" arguments in the literature (e.g., Devaraj et al., 2013;

Schmenner & Swink, 1998) that identify challenges such as system slow-down, resource bottlenecks, and waiting when the demand fluctuates and process flow is variable. These findings support H2(a,b).

The positive and significant coefficient ($0.0928, p < 0.01$) of department utilization on *LOS* indicates that patients tend to spend more time in the system when the workload is high. Note that this may be reflective of queuing in the system, since patients are not necessarily receiving more procedures here. On the contrary, the negative and significant coefficients of the quadratic utilization term ($−6.98, p < 0.05$ and $−0.0543, p < 0.01$, respectively) highlight the implications of very high
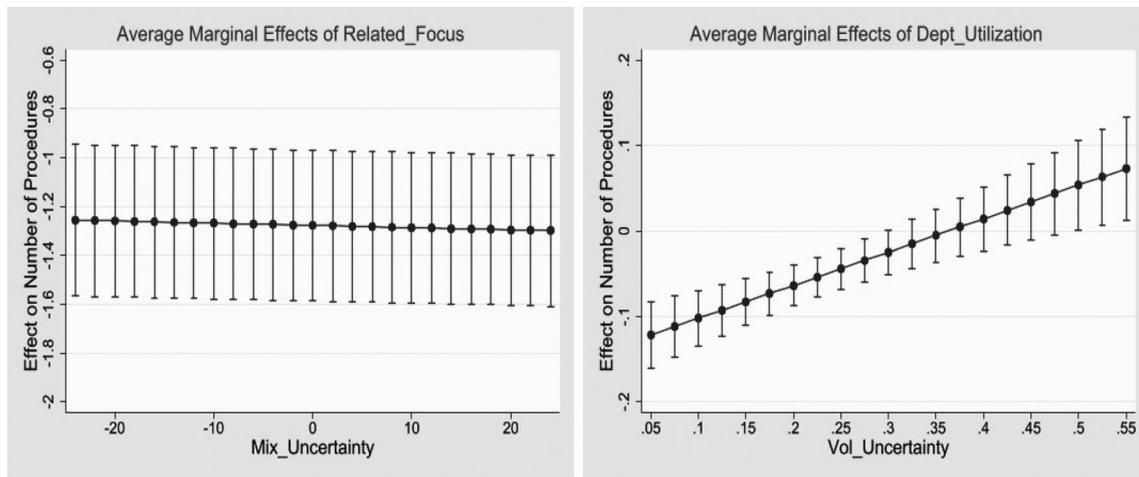
FIGURE 4   Marginal effects.

workload in healthcare. These results indicate that under conditions of high workload, there is a speed-up effect with patients receiving fewer procedures and faster discharge. This is consistent with prior literature (e.g., Berry Jaeker & Tucker, 2017; Kuntz et al., 2019) that highlights service providers cutting corners and pruning their service offering in an attempt to speed up in the face of heightened workload conditions.

Lastly, our results highlight a nuanced response by providers to the double trouble of both uncertainty and system overload. Specifically, we find that the interaction term is positive and significant, suggesting that providers increased the *NPR* offered. While more procedures may often indicate delays, the coefficient of the interaction effect of uncertainty and utilization on *LOS* is not significant. This pattern of coefficients—that is, more procedures with no corresponding change in duration under conditions of double trouble—suggests that providers may attempt to clear the system by arriving at a diagnostic and treatment plan more quickly by running more procedures. This finding supports H4(a).
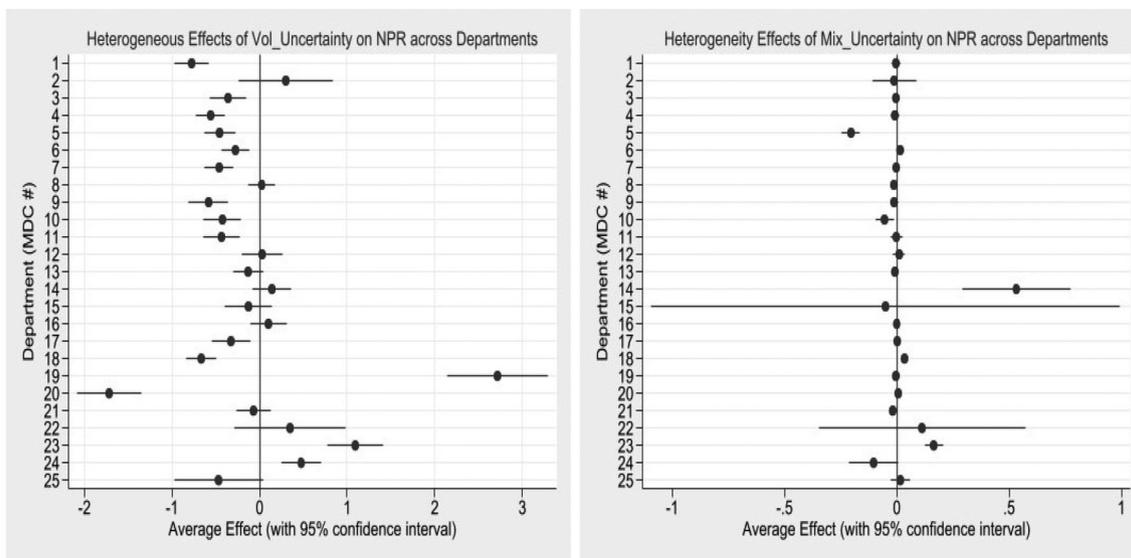
4.3 | Post-hoc tests and robustness checks

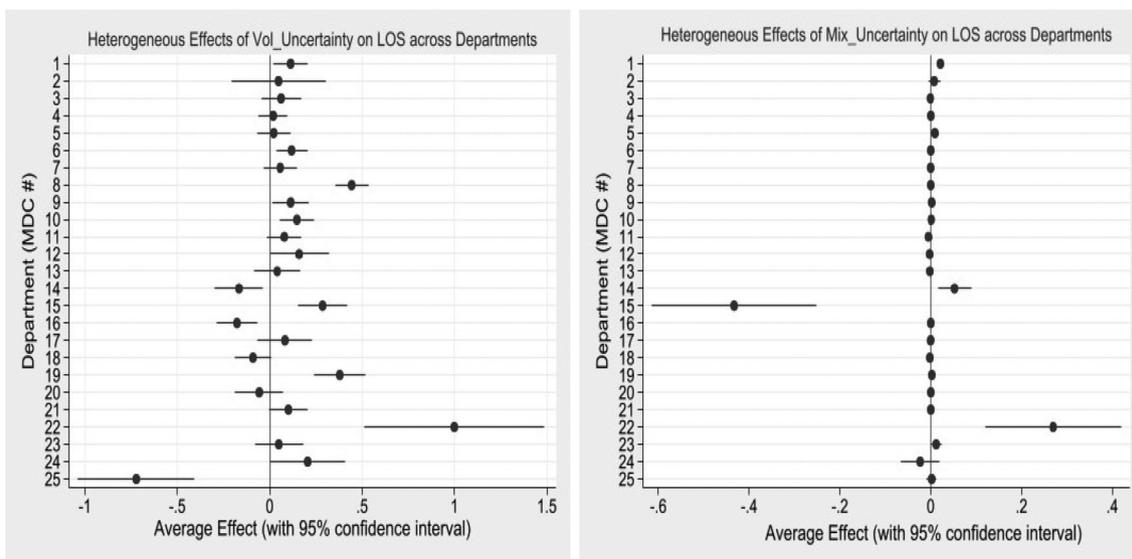### 4.3.1 | Heterogeneous effects of uncertainty across departments

The analysis presented above provides an empirical assessment of how *mix and volume uncertainties* affect care delivery in inpatient settings, and how hospitals could mitigate these effects via operational decisions pertaining to focus in relevant areas and utilization levels in departments. While the insights from this analysis are broadly applicable to various clinical departments

(MDCs), it is conceivable that the effects of uncertainty may be heterogeneous across departments, owing to their differences in care characteristics. For example, the average complexity of care needs or the efficacy of care-delivery practices may be quite varied across departments. Consider, for example, Orthopedics versus Cardiology departments. Both departments may have patients with complex needs but may vary in terms of clinical care pathways, resource requirements, treatment, and recovery prognosis. While our analysis includes MDC FEs to account for such differences on average, it is conceivable that, beyond intercept differences, the slopes examined in the study may still be heterogeneous across departments. Therefore, we further explore such differences.

To examine the heterogeneity in the hypothesized effects across hospital departments, we interact the uncertainty variables with department-specific dummies to obtain separate, MDC-specific estimates for uncertainty effects. Figure 5 shows the average effects (with 95% confidence intervals) of *MU* and *VU* on *NPR* and *LOS* across departments. While the effect of *MU* is positive and significant on average, as observed in our main analysis, there are departments (e.g., MDC#5 – Cardiology, MDC#10 – Endocrinology) for which the observed effects are negative. This suggests that while *MU* tends to increase the *NPR* offered to patients in most departments, this effect is reversed or largely non-significant in some departments. Similarly, while the effects of *VU* are largely negative across departments, as observed in our main analysis, in a few instances (e.g., Burns unit) it tends to increase *NPR*. These results point to heterogeneity in the uncertainty effects across departments. While an examination of the clinical drivers of these differences in the effects of uncertainty is beyond the scope of this work, it points to the fallacy of a one-size-fits-all approach to departments in policy decisions. This

(a) Implications for NPR

(b) Implications for LOS

FIGURE 5 Heterogeneous effects of *volume and mix uncertainties* across departments.

heterogeneity in the effect of uncertainty across departments underscores the need to further examine the sources and consequences of such category-level variation for care design and delivery.

4.3.2 | Heterogeneous effects of uncertainty across hospitals

Our analysis controlled for hospital-specific, unique structural, and operational characteristics via the use of hospital FEs. While hospital dummy variables remove the intercept differences across hospitals, similar to the discussion above, it is possible that hospitals with varied

ownership, location, and/or teaching status may have heterogeneous uncertainty effects (slope coefficients). For example, it is conceivable that the effects of uncertainty may be varied at teaching hospitals owing to the presence of formal residency programs. Residents in teaching hospitals may rely on more *NPR* as an uncertainty reduction mechanism in the care-delivery process. To explore this heterogeneity in the impact of uncertainty, we interacted the uncertainty variables with the indicators of hospital ownership, location, and teaching status. Our results indicate key differences in the effects of uncertainty across hospital types. For example, relative to government hospitals, private-non-profit hospitals tend to discharge patients faster in response to fluctuating demands.

On the contrary, relative to rural hospitals, urban hospitals (both teaching and non-teaching) tend to offer fewer *NPR* and yet longer *LOS*, indicating the buildup of queues and waiting time in these systems. Additionally, our results indicate that in the face of *MU*, teaching hospitals did indeed offer more procedures to their patients, on average, than non-teaching hospitals. The heterogeneous effects of uncertainty across hospital types underscore the need for health policy that is tailored to hospital type and the need for further research in this area to understand the sources and consequences of such heterogeneity.

4.3.3 | Category- versus DRG-level analysis: Rationale and robustness

Our analysis examines the effects of category-level uncertainty on the care-delivery process and the moderating effects of related focus and utilization levels within the category. Our choice of studying the sources and mitigation of uncertainty at the category (MDC) vis-à-vis DRG-level is driven by the following rationale. Hospital care-delivery services (inpatient and outpatient) are most commonly organized into medical specialty areas (or departments).[12] Individual clinical specialties are then provided resources to offer care services across the various DRGs within each broader specialty. As part of their portfolio strategy, hospitals may decide to selectively grow emphasis in certain departments (e.g., a cancer center or an orthopedics center), allocating a greater proportion of hospital resources (toward facility, technology, and equipment) to those departments based on planned or emergent capacity needs. Similarly, clinicians (doctors, specialists, and nursing staff) are hired to specific departments owing to their training and expertise within a category. Clinicians provide services across multiple, related conditions within a broad category (e.g., a cardiologist serves patients across a variety of DRGs within the cardiology department), not specific to any one of the over 700+ DRGs. A department faces considerable uncertainty in the volume and mix of patients it serves, and it strives to match demand with appropriate supply. The operational levers of related focus and utilization levels are department-level factors that serve to mitigate the effects of uncertainty. Furthermore, patients often present multiple conditions (chronic, comorbid) that are manifest as multiple DRGs (primary and secondary), and patient admissions are specific to a MDC (department) that is most suited to their primary condition. Thus, care-delivery operations are largely situated at the department (MDC) level for the varied procedures needed by patients. Therefore, from an organizational planning, operational decision making, and resource allocation standpoint, it is appropriate to focus on the MDC level instead of the DRG level. Our conversations with practitioners and healthcare administrators served to echo many of these aspects, reinforcing the need for a department-level analysis.

Nevertheless, as a robustness check, we re-ran the main study analysis using measures of uncertainty assessed at the DRG level. Specifically, we assess DRG MU (drg_MU_{ij}) as within-DRG variation in the complexity of patients served (SD of complexity of patients in the DRG normalized by the mean complexity in that DRG) and the DRG VU (drg_VU_{ij}) as the variation in the volume of patients with that primary DRG (SD of volume of patients with that primary DRG normalized by the mean volume in that DRG) across time periods. While we examine the moderating influence of expertise diversity viz. *related focus* (across categories of care) in addressing the diverse care needs of patients as hypothesized and tested earlier, we now additionally account for task focus (focus on the DRG) vis-à-vis department-level focus for this analysis. We also examined the moderating influence of resource utilization levels within the department on the impact of *VU* within the DRG.

Table A-2 (see Online Appendix A) provides a comparative evaluation of the results from this analysis and the results discussed in the study. The results at the DRG level (columns 1 & 3) indicate that *MU* within a DRG increases *LOS*, and *related focus* moderates this effect. We also note that the effect of *MU* is exacerbated by increasing utilization levels. Similarly, while *VU* within a DRG does decrease the *NPR*, under conditions of high utilization providers seem to "speed up" services by increasing the *NPR* to quicken the diagnostic and treatment process. The numerical results at the DRG level are *not* intended to replicate or mirror those from the MDC level, since they correspond to different levels of aggregation. However, they are highly consistent in reflecting the broad challenges owing to *mix and volume uncertainties* and the role of operational levers in mitigating these effects, reinforcing the robustness of the key arguments in our analysis.

5 | CONCLUSION

Uncertainty in healthcare is a critical issue that presents considerable challenges in the efficiency and effectiveness of care-delivery operations. Mitigation of these challenges requires a multidisciplinary perspective. We build on the perspectives of OIPT and the R&B framework of uncertainty to derive new insights about the effects of uncertainties and mitigating mechanisms in healthcare.

5.1 | Contributions to theory

While prior research has accounted for the volume and severity of patient-care requirements on the care-delivery process (e.g., Devaraj et al., 2013; Ding et al., 2020; Ding & Peng, 2022; Peng et al., 2020), our study is among the first to explicitly conceptualize and empirically measure key aspects of uncertainty in healthcare delivery. Our study draws on key concepts from prior literature on complex systems (e.g., Ramasesh & Browning, 2014) to conceptualize uncertainty in care delivery from two additional sources of variation heretofore unaddressed in the literature: *mix uncertainty*, the variability in the complexity of care provided to the patients in each department, and *volume uncertainty*, the variability in the volume of patients served in each department. We build on healthcare operations literature to then conceptualize the implications of these two forms of uncertainty for process-level care-delivery outcomes, including *NPR* and *LOS*. An empirical assessment of the effects of uncertainty on care delivery is a heretofore unexplored area and a unique contribution of our research.

While prior research has examined the clinical benefits of *related focus* in narrow settings (e.g., Cardiology in Clark & Huckman, 2012, or OB-GYN in Sfekas, 2019), an assessment of the role of *related focus* capability in mitigating the effects of *mix uncertainty* on care-delivery outcomes across departments is a unique contribution of this study. Similarly, while a growing body of research (Berry Jaeker & Tucker, 2017; Kuntz et al., 2015) has examined the implications of utilization, our research complements this body of work by highlighting its moderating effects in healthcare settings characterized by high levels of uncertainty.

5.2 | Implications for practice

One of the most challenging problems facing healthcare practitioners is coping with the uncertainty stemming from demand (mix and volume). To get a handle on this implies measuring the level of exposure to uncertainty in care-delivery operations. As the adage goes, that which one can measure one can improve. To that end, our study provides an objective measure of uncertainty based on a multi-dimensional assessment of complexity. Next, while uncertainty in demand mix and volumes is largely a given in operational settings such as healthcare,[13] our study still provides valuable insights in managing the effects of uncertainty in care settings. From a practice standpoint, two key operational strategies that hospitals can leverage to mitigate the effects of uncertainty include:

5.2.1 | Related focus

We propose that developing a breadth of expertise in related areas of care can be an effective way to combat uncertainty in each department. Our research indicates that hospitals with greater expertise in related areas (high *related focus*) tend to have shorter *LOS* and fewer *NPR*. The breadth of expertise is also found to mitigate the effects of *MU*, pointing to the beneficial impacts of *related focus* across the spectrum of uncertainty. Hospital administrators looking to move the needle on *LOS* and *NPR* might seek not only to expand the skill set of providers in related specialties but also to create coordination mechanisms (e.g., physician teams) to tap into the breadth of expertise.

5.2.2 | Operational slack

Another factor that affects the relationship between the uncertainty and outcomes is the utilization levels in departments. High levels of utilization further exacerbate the negative effects of uncertainty on performance. Building slack into the system by way of scheduling practices, flexible staffing, demand pooling, or increasing the role of non-physician practitioners (physician assistants) in care delivery may serve alleviate the effects of uncertainty.

Using counterfactual analysis, we illustrate the scope of the effect sizes observed in our study. Assuming an average acute-care hospital discharges about 7000 patients per year, with an average length of stay of 4.5 days per patient, the savings from reduced mix and volume uncertainty translate to serving 31 and 82 additional patients, respectively, per hospital per year. With an average revenue of $15,000 per inpatient, this translates to about $1.7 M in additional annual revenues per hospital.

5.3 | Limitations and extensions

Our study illuminates several other useful opportunities for research from conceptual, data, and empirical standpoints, including some that would address limitations of our study. First, from a conceptual standpoint, while our focus on uncertainty is restricted to the care-delivery process, other forms of uncertainty (e.g., market uncertainty) are also important and interesting, and future research may address these. Second, from a data standpoint, to test the robustness of our results, we replicated our study using another dataset from the U.S. Pacific states of Alaska, Washington, Oregon, California, and Hawaii. We

found consistent results. While replicating the full analysis across regions is computationally intensive, especially for non-linear models involving count outcomes and mortality metrics on large datasets, future research may broaden the generalizability of the results. Third, from an empirical specification standpoint, our performance measures, *LOS* and *NPR*, are proxies for efficiency and effectiveness of care, respectively. Future studies should explore effects of uncertainty on other measures of performance, such as costs of care and mortality/readmission.

On a related note, our study relies on the MDC categories as defined by the Center for Medicare and Medicaid Services (CMS) to identify the various departments of care in an acute-care hospital. Per CMS, all principal diagnoses are classified into 26 MDCs that are often associated with departments (or clinical specialties) within hospitals. Specifically, "the diagnoses in each MDC correspond to a single organ system or etiology and in general are associated with a particular medical specialty... each MDC was constructed to correspond to a major organ system (e.g., Respiratory System, Circulatory System, Digestive System) rather than etiology (e.g., malignancies, infectious diseases). This approach was used since clinical care is generally organized in accordance with the organ system affected, and not the etiology." This categorization of MDCs is the standard approach to charting and discharge records for patients across hospitals in the U.S. Our study assesses the uncertainty, related focus, and utilization constructs at this level of aggregation for each of these categories. That said, it is conceivable that hospitals may organizationally group a subset of MDCs into a department (e.g., 11, 12, and/or 13 could be grouped into a Fertility, Urology, or Obstetrics and Gynecology – OBGYN department) for idiosyncratic reasons unobservable by the researchers. Note, however, that since our measures are tied back to patient-level discharge records across hospitals that all follow the same MDC categorization by CMS, they remain reliable and informative of the study's effects of interest. Furthermore, any idiosyncratic advantages or disadvantages in hospital outcomes arising from such differing categorizations may be empirically accounted for in the hospital FEs. However, to the extent that future research can gain access to hospital-specific groupings of MDCs, replicating our study for robustness may be valuable.

Another aspect from an empirical specification standpoint is the decision time scale for examining the variation in patient volumes within a category. This variation can be within a day, week, or year. In our study, we examine variation in volume of patients within each category of care across months within a year. While this temporal variation is at a higher level relative to day/week, variation across months within a year is in sync with the time scale for decisions related to strategic resource allocations and utilization decisions. We do have information on whether the patient visit was during the weekend, which we include as a control variable. Other time scales may each reflect a unique type of variability, but given data limitations (lack of data at the level of hours within a day or daily within a week), we are unable to conduct analysis at these micro time scales. Future research at these micro levels may provide further insights.

Fourth, from a implications perspective, our findings that uncertainty has a heterogeneous effect across departments and hospital types suggests the need to examine further the sources and consequences of such heterogeneity. It is conceivable that the benefits of expertise in related areas may also vary across these departments. While our analysis suggests the benefits of *related focus*, on average (across departments), its beneficial effects may be heterogeneous across departments, forming a subject for further research.

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ENDNOTES

[1] A project is defined as "A temporary endeavor undertaken to create a unique product, service, or result" (PMI, 2021, p. 4).

[2] Financial metrics such as patient revenue and other hospital-level metrics are not well-suited for our study as they are affected by many other factors not proximal to the process of care.

[3] https://hcup-us.ahrq.gov/nisoverview.jsp.

[4] Table A-1 in the Online Appendix A provides a full listing of all MDCs and their corresponding department definitions.

[5] We used factor analysis with the "Principal Factors" extraction method with Orthogonal Quartimax for the rotation. A single factor (with an eigenvalue >1.0) emerged from this analysis (see Figure A-1, Online Appendix A for confirmatory factor analysis). Factor scores were then obtained for each patient as a (regression) composite of these indicators, which formed our measure of complexity for each patient.

[6] https://www.hcup-us.ahrq.gov/db/vars/los/nisnote.jsp.

[7] The rich set of fixed effects at the hospital, MDC, and diagnostic related group (DRG) levels in our model specification serve to control for unobserved heterogeneity in the related focus strategy of a hospital-department. However, to account for (any remaining sources of) endogeneity in related focus, we follow a control function methodology using instrumental variables. Online Appendix A provides a brief description of this approach.

8 As a robustness check, we repeated the study analysis excluding the 'zero' volume uncertainty observations. Results from this analysis were highly consistent with our study findings.

9 We use the 95% interquartile range for this average to isolate the effect of outliers.

10 The estimated variance inflation factors of the key study variables in our main effects models were less than 2, alleviating any concerns of multi-collinearity.

11 Coefficient estimates represent % change in outcomes.

12 The Center for Medicare and Medicaid Services (CMS) broadly categorizes healthcare services into 26 Major Diagnostic Categories (MDCs) for inpatient care (https://www.cms.gov/icd10m/version37-fullcode-cms/fullcode_cms/P0001.html).

13 An examination of demand-generating mechanisms (e.g., strategic positioning, quality signaling, socio-economic and demographic factors) and drivers of uncertainty is beyond the scope of this work.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.