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Putting analytics into action in care coordination research: Emerging issues and potential solutions

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Abstract

Care coordination involves shaping patient care activities and sharing information among all participants concerned with a patient's care to achieve safe and effective care. The objectives of care coordination are to promote sharing of patients' clinical information, keep patients and families informed, and manage effective referrals and care transitions. Failures in care coordination account for a large amount of waste per year in the United States. Many innovative healthcare organizations have recently recognized the danger of poorly coordinated care and have implemented analytics to improve it. Therefore, more analytics-based research (especially combining explanatory analytics with predictive analytics) is needed to direct efforts to improve care coordination. This paper focuses on systematically studying the extant literature to understand how analytics play a role in improving care coordination. Our goal is to identify a set of key research questions that would lead to new research areas in the use of analytics for care coordination. Based on these questions, we offer new analytics solution pathways to care coordination problems.

KEYWORDS

business analytics, care coordination, care transition, referral management

> … care coordination is not just a value proposition (higher quality, lower costs) but a patient-safety issue. Patients can be harmed when the many moving parts of their care are out of sync. We owe it to them to coordinate the care we provide and prevent this type of medical error. (Press, 2014, pp. 489–490)

1 | INTRODUCTION

The Institute for Health Improvement (IHI) defines an approach to optimizing health system performance as *Triple Aim* (Institute for Healthcare Improvement, 2021). In this approach, communities must pursue three tenets simultaneously: (a) improve the patient experience of care (including quality and satisfaction), (b) improve the health of populations, and (c) reduce the per capita cost of healthcare. These dimensions are being implemented by healthcare policy experts around the world. Fundamental to this implementation is the need for care coordination and access to and sharing of healthcare information.

Historically, most care coordination programs have targeted patients with chronic conditions, which are costly, especially if managed poorly (McDonald et al., 2007). These issues have challenged healthcare policy makers for many years. In their study of healthcare waste in the United States, Shrank et al. (2019) find that failures in care coordination account for \$27.2 billion to \$78.2 billion in waste per year in the United States. The estimated annual savings from care coordination rectification measures can range from \$29.6 billion to \$38.2 billion annually. The majority of this waste in care coordination can be attributed to the difficulty in implementing care coordination since most primary care practices do not have the proper information infrastructure to coordinate care effectively (Improving Chronic Illness Care, 2021).

Many innovative healthcare organizations are recognizing the danger of poorly coordinated care and implementing analytics to improve it (Kent, 2019; Simpao et al., 2014). In order to address this important practical issue, in this paper, we discuss how business analytics can be leveraged for care coordination research by developing a new classification framework based on a framework created by Whang (1995) in

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the supply chain literature. This care coordination framework helps us classify the extant research studies in care coordination employing business analytics and provides a platform for specifying analytic pathways to future care coordination research solutions. After a systematic review of the literature in analytics used in care coordination, our aim is to show that many care coordination problems have not been addressed, and we offer solution pathways for researchers in this area to follow.

1.1 | The framework

Care coordination is "a deliberate organization of patient care activities between two or more participants (including the patient) involved in a patient's care to facilitate the appropriate delivery of healthcare services. Organizing such care involves … the exchange of information among participants responsible for different aspects of care" (McDonald et al., 2007, p. 5). Care coordination needs to include care goals, care mechanisms, care coordination effects, and care participants. To review the large and diverse body of literature in care coordination, it is useful to develop a classification scheme that provides a categorized and consolidated view of the care coordination studies that have employed business analytics methods.

In this coordination study, we first develop a classification framework for care coordination. According to Bruns (2013), coordination is essential in integrating diverse expertise to develop unique capabilities for addressing complex tasks. Complex tasks often require specialized knowledge and diverse expertise to accomplish. Coordination has been used in many domains, such as building automotive parts (Carlile, 2004), building machines (Bechky, 2003), creating online advertising (Kellogg et al., 2006), and emergency care (Faraj & Xiao, 2006). Coordination in these cases utilizes collaboration among teams. Collaboration among diverse parties with specialized knowledge is needed for tasks requiring certain types of knowledge, which one party could not develop alone. It revolves mostly around how to manage interdependencies among different activities necessary to get to the outcome. However, coordination has also been used in cases where teams share knowledge to learn from each other while competing for resources and external market share (Tsai, 2002).

To study these different coordination approaches, several coordination frameworks have been developed in different domains, including supply chain. A closer examination of these different frameworks suggests that they were formed at two levels: domain level and conceptual level. A domain-level framework deals with a coordination structure that applies to a specific problem at hand, for example, distributed supply chain (Chan & Chan, 2004), construction supply chain (Xue et al., 2005), software development (Chengyao et al., 2008), and disaster management (Kartiwi & Gunawan, 2013). On the other hand, at the conceptual level, a framework deals with multiple problems in a domain or across multiple domains. Frameworks that deal with multiple problems in a domain include those used by Chen (2003), Asian and Nie (2014), and Srivastava (2017); these frameworks manage coordination across different functions of the supply chain, such as logistics, inventory, and product design. Vertical coordination happens between supply chain members located at different levels of the supply chain, for example, between supplier and manufacturer, manufacturer and distributor, and distributor and retailer. Horizontal coordination happens between different supply chain members located at the same level of the supply chain—for example, between various suppliers and manufacturers—mainly for coordinated replenishments and standardized information systems. Various coordination mechanisms such as information technology, contracts, information sharing, and joint decision making are used in such a coordination process.

Whang (1995), on the other hand, has developed a framework that is truly at the conceptual level, which allows us to capture coordination efforts in multiple problem domains. The framework uses coordination type on one axis and people involved in the coordination process on the other. It helps capture coordination operations in multiple domains. We have adopted this framework in our study to understand coordination mechanisms in healthcare delivery. We also like to note that only the classification scheme of this framework has been borrowed to create our own care coordination framework, as shown in Table 1. Because Whang's framework is at the conceptual level, we have to operationalize this framework in the context of healthcare delivery for care coordination.

The cells of the framework along with the two axes depict uniquely how care coordination works in the healthcare delivery domain. To operationalize Whang's framework, we utilize care delivery terminology in defining its axes. One axis in our framework is the care coordination perspective, while the other is the care coordination mechanism. There are three care coordination perspectives: single-provider perspective, cooperative team of providers' perspective, and contracted team of providers' perspective. A perspective abstracts how providers of an organization behave in care coordination efforts. For example, if the care coordination is managed by a single provider, it is a single-provider perspective. Private practice or solo practice is an example of this perspective. In a private practice, a provider practices without any partners and typically with minimal support staff. Care coordination can also be done in cooperative teams. An example of a team is group practice with two or more providers. The teams cooperate to provide medical care. This perspective highlights cooperative coordination and underscores the existence of multiple parties who play different roles in the care coordination operation. Full cooperation among teams is essential in this perspective. Finally, the contracted team of (arms-length) providers' perspective utilizes contracts among teams where each team tries to maximize

TABLE 1 Framework for care coordination based on Whang (1995)

	Coordination within care operation	Cross-functional care coordination	Interorganizational care coordination
Single-provider perspective (coordination is internal)	*Single provider* with *weak* internal care coordination for one disease of a patient	*Single provider* with *medium* internal care coordination for multiple comorbidities of a patient	*Single provider* with *strong* internal care coordination among multiple healthcare facilities for multiple comorbidities of a patient
Cooperative team of providers' perspective	*Siloed providers* with *weak level* of care coordination for one disease of a patient	*Siloed providers* with *medium level* of care coordination for multiple comorbidities of a patient	*Siloed providers* with *strong level* of care coordination among multiple healthcare facilities for multiple comorbidities of a patient
Contracted team of (arms-length) providers' perspective	*Multiple well-connected provider silos* with *weak level* of clinical networks	*Multiple well-connected provider silos* with *medium level* of clinical networks for multiple comorbidities of a patient	*Multiple well-connected provider silos* with *strong level* of clinical networks among multiple healthcare facilities for multiple comorbidities of a patient

its personal objectives. Examples of this kind include HMOs (health maintenance organizations) and ACOs (affordable care organizations). HMOs offer bonuses to improve productivity, while ACOs contract multiple providers, including practices, labs, therapists, and clinics, to manage care. There are three types of care coordination mechanisms: coordination within operation, cross-functional care coordination, and interorganizational care coordination. Each column deals with the types of care needed for a patient. Typically, a patient can have a single disease or multiple diseases that can be cared for by one provider or multiple providers and in one facility or multiple facilities. Details of these subcategories are given below.

1.1.1 | Single-provider perspective

In this perspective, coordination is being done by a single provider. Such a provider could be either a physician, a nurse practitioner, or a registered nurse. In any case, coordination is mostly done mentally and is totally internal to the provider. She deals with three different coordination mechanisms. Based on her experience, the coordination efforts needed for the patient are known and are quite deterministic as the provider has dealt with such diseases many times in the past. Ham and de Silva (2009) call this cell a *single provider with weak internal care coordination*. If the patient has multiple co-morbidities, coordination is more complicated but can still be provided by a provider or a coordinator. Such a care coordination mechanism is also internal and deterministic but is stronger relative to the within care operations cell. We call it *a single provider with medium internal care coordination*. Finally, when the provider deals with external organizations, such as labs, urgent care facilities, skilled nursing facilities (SNFs), and pharmacies for her patients in an interorganizational setting, the coordination is deterministic since she has dealt with these services before. We call this cell a *single provider with strong internal care coordination*.

1.1.2 | Cooperative team of providers' perspective

In this perspective, care coordination is provided to an individual by a collaborative team. Such teams should not be "siloed" (Frost & Sullivan, 2014; Kelly et al., 2019)[1]; they should rather have good communication and team culture. The collaborative teams have one goal, which is to manage and address the patient's care plan.[2] Communication among the teams becomes an important aspect in this type of care coordination. Multiple providers in different care teams inside a medical facility dealing with one disease (like cancer) of a patient need coordination among care teams. Care plan and care coordination need to be formalized so that multiple teams can understand and coordinate. Referral management, care transition management, readmission management, and disease management need to be formalized. Formal care delivery, such as patient-centered medical home (PCMH), is essential at this point. In an interorganizational care setting, multiple provider-based teams from different medical facilities can use IT-enabled systems to deal with patients having multiple comorbidities. We label the three cells as (a) *siloed providers* with *weak levels of care coordination*, (b) *siloed providers* with *medium levels of care coordination*, and (c) *siloed providers* with *strong levels of care coordination*.

1.1.3 | Contracted team of providers' perspective

In this perspective, coordination is generally done among a multitude of teams (or silos) using contract mechanisms, which is different from the cooperative team of providers' perspective. The contracted team of providers' perspective follows the tradition of agency theory (Whang, 1995) to manage and mitigate care plans of patients who can have comorbidities. Like cooperative teams, a contracted team also needs to manage referrals, transitions, readmissions, and diseases, where PCMH is also a must. A legal framework of accountable care organization (ACO), with an emphasis on care integration, can be imposed to cover the risks associated with contracting different teams. An ACO is defined as groups of doctors, hospitals, and other providers that gather voluntarily to give coordinated high-quality care to their Medicare patients (CMS, 2021). Even though communication is essential, the arms-length behavior of the healthcare teams focuses on its own personal objectives and mitigation plan of care. Managing such contracts, as well as managing communications between teams, is an important issue. We label the three cells as (a) *multiple well-connected silos* with *weak levels of clinical networks,* (b) *multiple well-connected silos* with *medium levels of clinical networks,* and (c) *multiple well-connected silos* with *strong levels of clinical networks.* Clinical networks encompass mechanisms like PCMH, care transition management, readmission management, referral management, disease management, and horizontal and vertical integration of care facilities.

Referral management is the process of managing a physician order for a patient to see a specialist or to get certain services. Referral orders are dispensed in both cooperative (without a contract) and contracted situations. However, the management of referral orders may differ. For example, in the cooperative team case, referral orders can be managed in formal team meetings, case conferencing, informal communication with other health professionals, and team-based care delivery. However, in the contracted team approach, referral orders are managed by a mechanism usually set up outside the care teams, either informally or formally (like in HMO or ACO). This is why "referral management" is included in both Sections 1.1.2 and 1.1.3.

1.2 | Search process and data collection

Using the systematic literature review process described by Kampstra et al. (2018), we start our review by collecting papers that use business analytics for care coordination research. Such research sits at the intersection of healthcare, operations, and information systems domains. We perform a systematic scan of online academic and conference databases in these domains. Our aim is to capture a large number of care coordination research articles that use business analytics. We choose Cochrane Library and PubMed Central for collecting healthcare articles in care coordination. We also choose standard databases—ABI/Inform Complete, Google Scholar, ACM Digital, IEEE Xplore, INFORMS Pubs Online (mainly for *Management Science*, *Manufacturing and Service Operations Management*, *Information Systems Research*, *INFORMS Journal of Applied Analytics*), and Wiley Online (mainly for *Production and Operations Management*, *Journal of Operations Management*, and *Decision Sciences*) for technical and mathematical modeling articles in care coordination.

The timeframe for our search is from January 1990 to September 2020. We need a common set of keywords and key phrases for all databases listed above. The objective is to create uniform and standardized search terms, so as to collect the largest possible sample of care coordination research papers. We start with a generic search phrase and then move into more selective phrases to cast a wide net for retrieving relevant articles.

As care coordination is a method used in the healthcare domain, we begin our search with the keyword "healthcare" for all our target online libraries. This produces a very large set of research articles. The largest set of articles is obtained from Google Scholar (1.68 million articles), while the smallest one is obtained from Wiley Online (608 articles) (see Table 2). To narrow the search further and to look for an intersection of healthcare and analytics domains, we start adding keywords such as "analytics" and "business analytics." After several such iterations, we decide to use "care coordination" and "analytics" as our search terms for searching the databases from 1990 to 2020. With the removal of patents and citations, the number of articles from Google Scholar search comes down from 6550 to 6050; we use these 6050 articles for our review. Using several inclusion and exclusion criteria, we reduce the number of articles to 75. Since descriptive analytics is less related to the emerging analytics methods, the list of 75 articles is further reduced by removing five purely descriptive analytics papers (we keep the papers that focus on combining descriptive analytics with explanatory analytics or combining descriptive analytics with predictive analytics), which leads to 70 articles. Details of these steps are given in Supporting Information 1.

We then perform a detailed analysis based on our care coordination framework (see Table 1) to categorize the current research into nine subcategories. This paves the way for us to develop the research challenges in using business analytics for care coordination. Each section below describes the current research activities, the data used in the research, and the analytical methods employed in a particular perspective. The analytical methods are classified as *explanatory analytics* and *predictive analytics* (Shmueli, 2010). In particular, care coordination analytics in our context refers to investigating care coordination issues using explanatory analytics (econometric models focusing on causation) and predictive analytics (machine learning–based models). Each section also focuses on gap analysis, offers future research questions, and proposes solution approaches. Section 2 focuses on the single-provider perspective. Section 3 deals with the cooperative team of providers' perspective. In Section 4, we describe the contracted team of (arms-length) providers' perspective. Finally, in Section 5, we conclude the paper and provide a set of future research directions.

2 | SINGLE-PROVIDER PERSPECTIVE

Consider a provider's office with multiple patients. Some patients are new, while others are seeing her for a long time. A patient can have a single disease or can have multiple comorbidities like diabetes, high blood pressure, and

TABLE 2 Number of documents for keywords in search portal (accessed on September 10, 2020)

Keywords	PubMed Central	Cochran Library (Reviews)	ABI/Inform Complete	Google Scholar	ACM Digital Library	IEEE Xplore	INFORMS Pubs Online	Wiley Online
"healthcare"	996,757	785	1,590,839	1,680,000	20,239	23,939	2154	608
"healthcare" AND "analytics"	12,095	11	12,776	293,000	2423	950	2017	545
"healthcare" AND "business analytics"	144	0	476	9700	132	150	142	545
"care coordination"	10,424	2	4,035	36,300	93	41	17	452
"care coordination" AND "analytics"	638	0	225	6550	16	2	8	13
"care coordination" AND "business analytics"	22	0	2	196	2	0	0	6

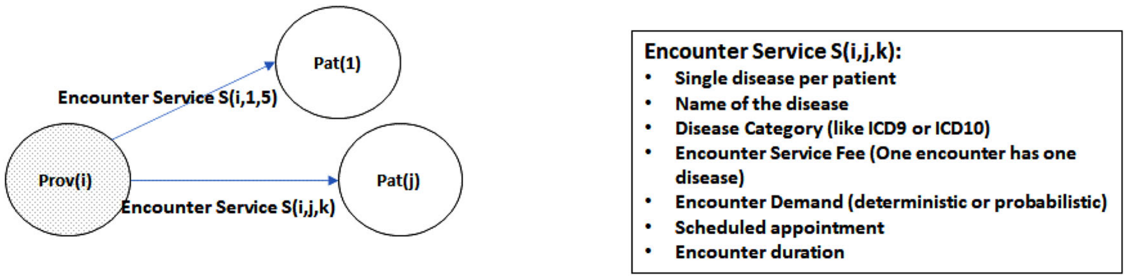

FIGURE 1 Single provider with multiple patients with weak internal care coordination (one disease) [Color figure can be viewed at wileyonlinelibrary.com]

high cholesterol. In either of these cases, the provider is the "central decision-maker," who needs to manage encounters, including managing charts, managing vaccinations, writing prescriptions, and diagnosing diseases. Coordination involves how the provider manages these activities throughout the day. Even though demand for such encounters is stochastic, coordination by the provider is deterministic as she is familiar with her patients and their encounter histories. We begin our discussion with this perspective, starting from *within operations care coordination,* followed by *cross-functional care coordination,* and ending in *interorganizational care coordination* mechanisms.

2.1 | Within operations care coordination mechanism

To understand the coordination approaches in the single provider category using the within operations mechanism, we present a coordination diagram in Figure 1. In this view, a single provider *Prov*(i) manages the care coordination of each of her patients in $\{Pat(j)\}$ having a single disease k (shown by a dashed circle). The coordination is accomplished by creating provider–patient encounters. Each encounter typically includes information on patient demographics, name of the disease, disease category in terms of International Classification of Diseases (ICD) code, service fee for the encounter, service date, and service duration. Even though the demand for service can be stochastic, the coordination managed by the provider is deterministic.

Lanese et al. (2011a, 2011b) describe this type of coordination using a "health coach," who is a medical provider. The data set consists of the entire diabetes patients from the physician's office and includes patient demographic information such as name, age, zip code, insurance, primary and secondary diagnosis, and coding of office visit level. The purpose of the study is to identify and assess the potential benefits, both financial and clinical, of adding a health coach in a primary care practice. The results show that having a health coach was beneficial to patients and give a positive return on investment from the second year onward.

2.2 | Cross-functional care coordination mechanism

In this approach, once again, the coordination is being done by the provider (shown by a dashed circle). This mechanism is similar to the "within operations" coordination mechanism, except that the provider now has to deal with the patient's comorbidities (see Figure 2). The coordination is deterministic, and the demand for encounter service is probabilistic.

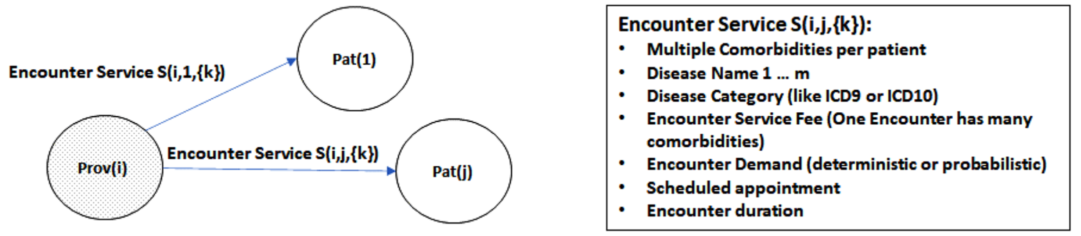

FIGURE 2 Single provider with multiple patients with medium internal care coordination (with comorbidities) [Color figure can be viewed at wileyonlinelibrary.com]

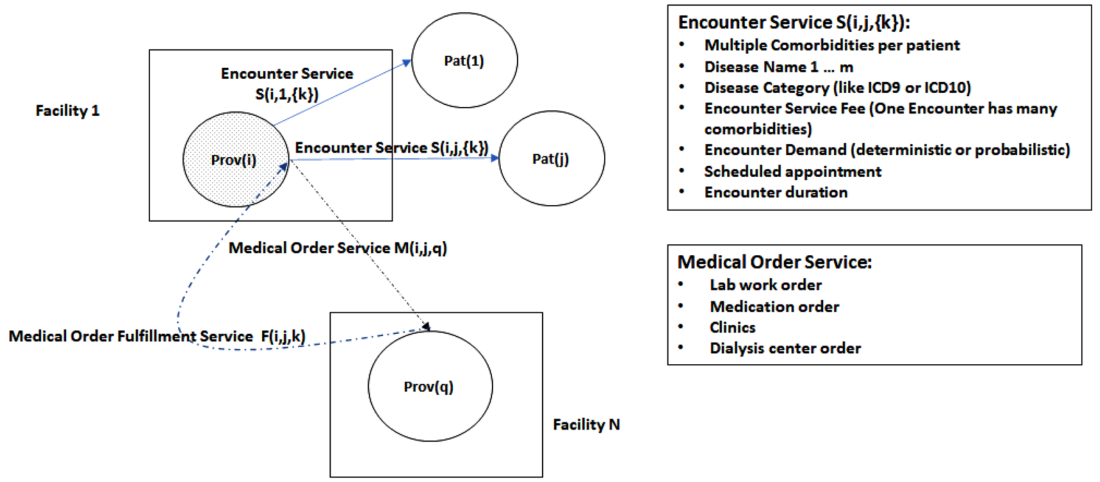

FIGURE 3 Single provider with multiple patients with comorbidities with strong internal care coordination [Color figure can be viewed at wileyonlinelibrary.com]

A survey by Tahan et al. (2015) identifies the essential activities in care coordination needed for a case manager (a provider). They survey 7668 case managers across the nation. The survey tool covers 124 essential coordination activities and 94 case management concepts, along with demographic information. Their study identifies the common activities and knowledge areas necessary for the competent and effective performance of case managers interested in care coordination.

2.3 | Interorganization care coordination mechanism

The final stage of the single-provider perspective deals with interorganizational coordination. Once again, the coordination is performed by provider i in a facility such as a clinic, practice, or hospital (shown by a dashed circle in Figure 3). The provider can have many patients, $\{Pat(j)\}$, each having a set of comorbidities $\{k\}$. The provider coordinates encounters and manages all her orders and their responses from labs, pharmacies, X-ray facilities, dialysis centers, clinics, SNFs, and so forth. Encounters are still deterministic while their demand is stochastic like before.

Ostovari and Yu (2019) assess care coordination among providers and patients in a university-based hospital setting using social network analysis. They find that the degree (connectedness) and the closeness (access) to providers are significant for reducing inpatient hospitalization and emergency department (ED) visits. That is, patients of specialists (like cardiovascular and surgeons) and of providers (like social workers) have a higher rate of hospitalization and ED visits compared to those of primary care providers.

We present a summary of key existing research efforts for the single-provider perspective in Supporting Information Table A.1 (see Supporting Information 2) by highlighting the research scenarios used in extant research, along with the associated research questions, methods, and data sources.

2.3.1 | Gap analysis in single-provider perspective

The main concern in this segment is to focus on a provider and understand her coordination efforts. In general, many gaps exist in the care coordination literature, such as lack

TABLE 3 Representative research challenges in single-provider perspective

Perspective/coordination mechanism	Research scenarios	Research questions	Methods	Data sources
Single-provider perspective—within operations	Managing ED visits (patients with no comorbidities)	(a) How does a care coordinator influence the number of ED visits by a patient?	Explanatory/ econometric model	Proprietary data from care coordinator and referral data from hospital
Single-provider perspective—Cross-functional care coordination	Managing ED visits (patients with comorbidities)	(b) What is the likelihood that a patient, if enrolled in the care coordination program, will complete the program with fewer ED visits?	Predictive model	Proprietary data from care coordinator and referral data from hospital
Single-provider perspective—Interorganizational care coordination	Managing ED visits (patients with comorbidities)—coordinator and physicians are in different facilities	(c) What is the likelihood that a patient, once enrolled, will complete the care coordination program with fewer ED visits?	Predictive model	Proprietary data from care coordinator and referral data from hospital

of interoperability, poor primary care management, lack of care coordination framework (Lanese et al., 2011a; 2011b; Ostovari & Yu, 2019; Tahan et al., 2015). Among these, we focus on poor primary care management that results in excessive ED visits. Some patients choose to visit an emergency room for nonurgent situations. All the three research scenarios (Lanese et al., 2011a, 2011b; Ostovari & Yu, 2019; Tahan et al., 2015) presented in Supporting Information Table A.1 focus on managing ED visits. ED visits are expensive, and they force healthcare costs to rise. That is why reduction of ED visits is currently one of the main objectives of the *Triple Aim* in the United States. In order to control such expenses, the provider must navigate the patient properly using care coordination expertise. We, therefore, identify the reduction of ED visits as a research challenge.

2.4 | Research challenges in single-provider perspective

We now present representative research challenges for the single-provider perspective by describing a research scenario along with the associated research questions, data needs, and data analysis methods. According to a single-provider perspective, the coordination is managed by a single decision maker who has all the information about the patient and makes all the care decisions for the patient. As an example, we consider the ED visit problem and the use of care coordination to reduce the number of ED visits (see Table 3).

2.4.1 | Research scenario

The scenario provided covers all three categories in the single-provider perspective. It aims to decrease the number of ED visits by ensuring appropriate follow-up care, upon discharge from the hospital, and connecting these patients to a regular source of primary care and supportive health services using a care coordinator (a provider). The patient can have one or more comorbidities (see Figures 1–3). The encounters include time spent with the patients in determining their needs. The facilities include the hospital and the primary care physician's (PCP) office. The coordination connects frequent ED users who do not have a regular primary care provider to a care coordinator who will work to provide options for accessing regular primary care and health resources to achieve and maintain a positive health status.

2.4.2 | Research questions and data needs

In this research, we identify three research questions that are important in all three coordination mechanisms, as shown in Table 3. Each research question is examined under the following three perspectives: (i) providers are in one facility and patients do not have comorbidities, (ii) providers are in one facility and patients have comorbidities, and (iii) providers are spread out in multiple facilities and patients have comorbidities.

Typically, hospitals recommend patients who are frequent ED visitors to the care coordinator with an objective to encourage the patients to go to PCPs, instead of visiting the ED. The data for this type of problem are at the patient level and can be obtained as proprietary data from the care coordinator. The metadata include patient demographics (id, age, marital status, race, ethnicity, education, and household size); provider demographics; health and risk factors (insurance, number of times of ED visits, reasons for the ED visit—chronic or acute, chronic conditions such as anxiety, asthma, cancer, and chronic obstructive pulmonary disease [COPD]—date of last ED visit, patient making lifestyle changes—stop smoking, willing to increase exercise, etc.); patient barriers (e.g., transportation barrier and communication barrier); coordination mechanisms (e.g., call type, call date, and meeting with patient type); total ED visits; total ED visits before enrollment in the care coordination program; total ED visits after enrollment in the care coordination program; and total PCP appointments.

2.4.3 | Data analytics methods

We propose a generalized explanatory/econometric model to examine Research Question (a) for all three perspectives in Table 3. From the data, we can identify a treatment group (patients who have enrolled in the care coordination program) and a control group (patients who have not enrolled in the care coordination program). Ideally, if it is a randomized trial, we are able to identify the treatment effect by comparing the number of ED visits in the treatment and control groups. However, a typical endogeneity concern is that treated patients might be systematically different from control patients in terms of observable patient demographic characteristics (e.g., age and gender) and disease conditions. For example, high-risk patients might be more likely to be enrolled in the care coordination program. To address this concern, we recommend using a regression method combined with propensity score matching (PSM) (Bapna et al., 2019; Chen et al., 2021b; Cheng et al., 2020; Petryk et al., 2022). The basic idea of this procedure is that we first create more comparable controlled patients for treated patients by using PSM in terms of patient demographic characteristics and disease conditions. Then, one can run a regression based on the matched sample (more balanced sample) to assess the impact of enrolling in the care coordination program.

Specifically, in the first step, we propose running the following logit regression:

$$\text{Logit}\,(enroll_i) = \gamma_0 + \gamma_1 characteristics_i + \gamma_2 condition_i + \gamma_3 hospital_i + \varepsilon_i, \quad (1)$$

where $enroll_i$ is a dummy variable indicating whether patient i enrolls in the program, $characteristics_i$ is a set of variables relating to patient demographic characteristics, $condition_i$ is a set of variables relating to a patient's disease conditions, and $hospital_i$ is a set of variables relating to patient i's hospital characteristics. Using this logit regression, one can generate a predicted propensity score for each patient, which represents the ex ante likelihood of enrolling in the program. In the matching process, we propose matching each treated patient to the most "similar" control patient (closest propensity score), which ensures that we obtain a more balanced matched sample: In the matched sample, treated patients are more similar to control patients in terms of patient demographic characteristics and disease conditions. Although the care coordination enrollment decisions are largely decided by physicians and facility managers, patient characteristics still play an important role in this process. The reason is that physicians and facility managers make enrollment decisions based on observable patient demographic characteristics (e.g., age and gender) and disease conditions, which may cause a selection problem. For example, high-risk patients might be more likely to be enrolled in the care coordination program (Bakst & Longyear, 2020). Our proposed matching method can alleviate this type of selection problem based on observable characteristics.

In the second step, based on the new matched sample, we propose running the following two regression equations:

$$ED_i = \beta_0 + \beta_1 enroll_i + \beta_2 characteristics_i + \beta_3 condition_i + \beta_4 hospital_i + \varepsilon_i, \quad (2)$$

$$ED_i = \beta_0 + \beta_1 enroll_i + \beta_2 characteristics_i + \beta_3 condition_i + \beta_4 hospital_i + \beta_5 enroll_i \times Minority_i + \varepsilon_i, \quad (3)$$

where ED is the number of ED visits for patient i, and $Minority_i$ is a dummy variable indicating whether patient i is a minority patient (Hispanic or African American). The coefficient β_1 in Equation (2) measures the impact of enrolling in the program on the number of ED visits. If $\beta_1 < 0$ and statistically significant, it indicates that a care coordination program can significantly reduce the number of ED visits of a patient. The coefficient β_5 in Equation (3) captures whether the impact of enrolling in the program is larger for a minority patient (Hispanic or African American). If $\beta_5 < 0$ and statistically significant, it indicates that a minority patient (Hispanic or African American) benefits more from a care coordination program: Enrolling in the program leads to a larger reduction in the number of ED visits for a minority patient.

Note that, here, we use a regression method combined with PSM because we assume that only cross-sectional data sets are available. If we are able to obtain a panel data set with the timing of patients enrolling in care coordination programs, we can use a difference-in-differences (DID) method combined with PSM to address selection issues on observables and unobservables. In particular, PSM can address selection issues on observables, and unobserved confounders can be canceled out in the DID regression.

As mentioned earlier, using a regression method combined with PSM can address selection based on observables. As a robustness check to further address selection based on unobservables, we also recommend a quasi-experimental design using a regression method combined with the look-ahead propensity score matching (LA-PSM) (Kumar et al., 2018, 2022; Khurana et al., 2019; Wang et al., 2022). The intuition is to exploit the time sequence of patients enrolling in a care coordination program to construct a more appropriate control group in terms of unobserved patient characteristics. A better control patient is a patient who has not enrolled in a program but will do so in the future. Specifically, to account for unobserved patient characteristics, one can focus on a shorter sample period. The treated patients in this quasi-experimental design are the ones who have enrolled in the program in this shorter sample period. We propose matching each treated patient to a control patient with the closest propensity score among patients who have not enrolled in the program in this shorter sample period but will enroll later. On the one hand, the closest propensity score ensures that the treated and control patients are similar in observable patient characteristics. On the other hand, choosing patients who have not enrolled in the program but will enroll later ensures that the treated and control patients are similar in unobserved patient characteristics. The procedure of a regression method combined with LA-PSM is similar to that of a regression method combined with PSM. In the first step, we propose creating a matched sample based on LA-PSM, and in the second step, we propose rerunning regression Equations (2) and (3) using the matched sample.

If the underlying selection process is known, we can use the Heckman-type model to explicitly account for the selection process and address selection based on observables. In the following discussion, we propose a Heckman-type model to directly specify the selection process. Our main model is still the regression equation (2). However, we directly model whether a patient enrolls in the program by looking at a Probit model. The selection equation is given as follows:

$$w_i^* = \gamma_0 + \gamma_1 characteristics_i + \gamma_2 condition_i + \gamma_3 hospital_i + \gamma_4 External_i + e_i, \quad (4)$$

where w_{it}^* is a latent variable, $External_i$ represents external factors that affect enrollment but not ED visits, and e_i follows a standard normal distribution. The indicator $enroll_i = 1$ if $w_{it}^* \geq 0$; $enroll_i = 0$ otherwise. Taking this selection process into account, we can estimate the selection and main equations jointly, and the selection based on observables is less of a concern.

Next, we propose a predictive model to examine Research Questions (b) and (c) for all three perspectives. Given that the dependent variable in Research Questions (b) and (c) are binary, one can use a logit model to predict the probability. For the robustness of the results, one can also estimate a probit model and a linear probability model. For a logit model, we propose estimating the following two regression equations based on the subsample of enrolled patients:

$$\text{Logit}\,(finish_i) = \gamma_0 + \gamma_1 characteristics_i + \gamma_2 condition_i + \gamma_3 hospital_i + \varepsilon_i, \quad (5)$$

$$\text{Logit}\,(finish\_ed_i) = \gamma_0 + \gamma_1 characteristics_i + \gamma_2 condition_i + \gamma_3 hospital_i + \varepsilon_i, \quad (6)$$

where $finish_i$ is a dummy variable indicating whether patient i finishes the program, and $finish\_ed_i$ is a dummy variable indicating whether patient i finishes the program with fewer ED visits (whether patient i finishes the program with fewer ED visits can be determined by comparing the ED visits of patient i with those of the most similar control patient in our matching process). After estimating Equations (5) and (6), one can obtain the predicted likelihood of a patient finishing the program and the predicted likelihood of a patient finishing the program with fewer ED visits.

3 | COOPERATIVE TEAM OF PROVIDERS' PERSPECTIVE

The emphasis in this section is on *teams*. A team can include a PCP, a specialist, a healthcare coach, a care coordinator, and others. The objective is to utilize a team to coordinate patient care and develop a care plan for the team to use. Even though the providers are siloed, they can form a team along with other healthcare workers. In this team-based environment, coordination is cooperative, implying that team members do not compete with one another, but work together for the good of the patient. Such efforts have been used for studying the implementation of complex care plans (Amir et al., 2015; Ritchie et al., 2016); in managing disease domains such as COPD (Fromer, 2011), pulmonary embolism (Xenos et al., 2019); and in understanding coordination among teams (Treadwell et al., 2015). The demand for encounter services (from primary care providers, specialists, and care coordinators) is stochastic. We discuss the research approaches in this perspective, starting from *within operations coordination* and ending in *interorganizational coordination*.

3.1 | Within operations care coordination mechanism

To understand the coordination approaches in this category, we present a coordination diagram (see Figure 4). In this view, a single provider $Prov(i)$ in a silo of a facility teams up with $\{Prov(q)\}$ in another silo of the same facility to cooperatively manage the care coordination of each of her patients in $\{Pat(j)\}$ (shown as a dashed area in the figure), who has a single disease k. The coordination is managed by creating provider–patient encounters, where a provider could be a primary-care physician, specialist, care coordinator, healthcare coach, pharmacist, or lab manager. Each encounter typically includes patient demographics, name of the disease, disease category (ICD code), service fee for the encounter, service date, and service duration. The demand for encounter services is stochastic.

Referral management is a major issue in this category (Fields, 2018). Referrals can be of two types: *consultation referrals* and *diagnostic referrals*. Consultation referrals are typically referred to specialists in dermatology, gastroenterology, and so forth (Finley, 2013), while the diagnostic referrals are for X-rays, mammograms, ultrasounds, and so forth. Process modeling (Zhong et al., 2017, 2019) has been employed to understand the delay points in the referral process.

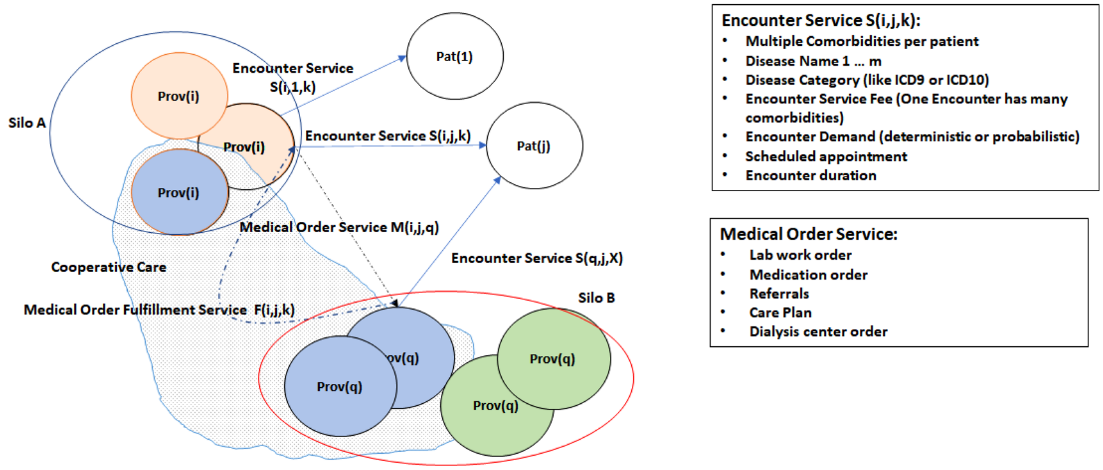

FIGURE 4 Cooperative team of providers with multiple patients with weak level of care coordination (one disease) [Color figure can be viewed at wileyonlinelibrary.com]

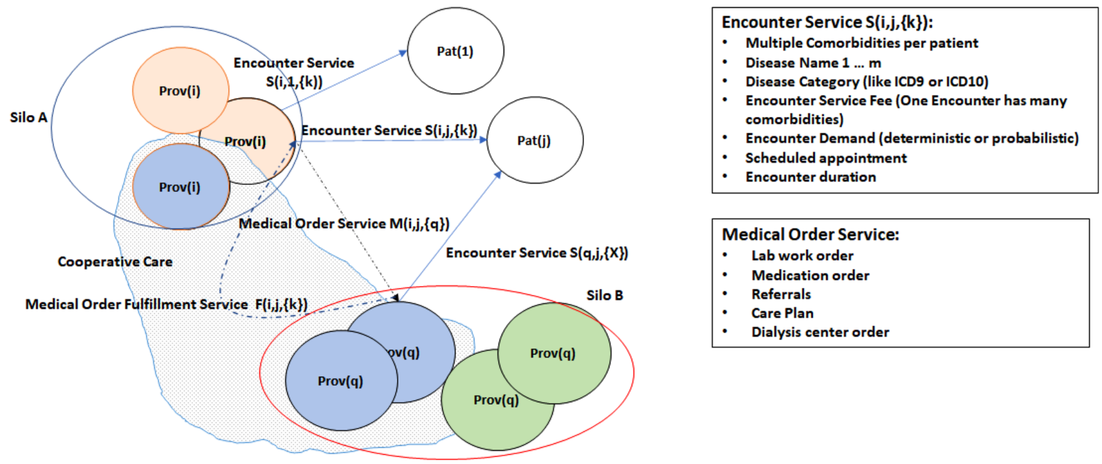

FIGURE 5 Cooperative team of providers with multiple patients with medium level of care coordination (with comorbidities) [Color figure can be viewed at wileyonlinelibrary.com]

3.2 | Cross-functional care coordination mechanism

To understand the coordination approaches in this category, we present a coordination diagram (see Figure 5). This category is very similar to the *within operations category* discussed above, except for the fact that the patients have comorbidities. The demand for encounter services is once again stochastic. Referral management is still an issue in this category. As a part of cross-sectional coordination, Jack et al. (2009) develop hospital discharge interventions to study their effect on readmissions. Using explanatory analytics, they found that such an effort reduces hospital 30-day readmission rates and increases discharge knowledge among the discharged patients. Using natural language processing (NLP) and market basket analysis, Bako et al. (2021) show that safety-net patients tend to be referred to social workers a lot, signifying the complexities of social needs among patients and the potential role for social workers in addressing those needs.

3.3 | Interorganizational care coordination mechanism

This is the final stage in the cooperative team of providers' perspective. We extend the team concept now to different facilities like Facility 1 and Facility N (see Figure 6). It means that a team can be created by picking providers from different facilities, including clinics, SNFs, hospitals, practices, and so forth. The coordination is still cooperative among team members, even though they belong to multiple facilities. A patient can have a single disease or multiple comorbidities. The demand for encounter services is once again stochastic.

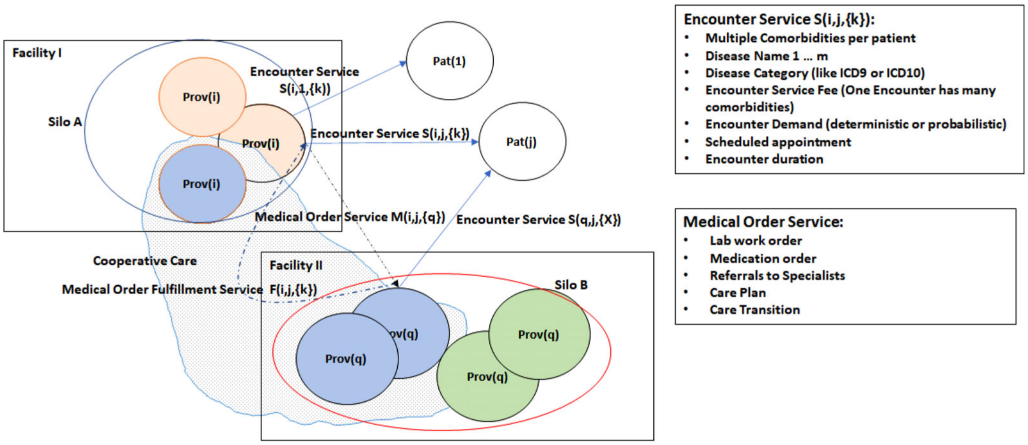

FIGURE 6 Cooperative team of providers with multiple patients with comorbidities with strong level of care coordination [Color figure can be viewed at wileyonlinelibrary.com]

Several interesting research issues have been investigated in this category. Some of them deal with the *efficacy of coordination intervention,* while others deal with the *coordination process* itself.

3.3.1 | Coordination intervention research

This includes those that utilize coordination as a medical intervention. A majority of research in this area relates to determining the efficacy of care coordination interventions by measuring its effect on hospital utilizations, such as quality of care, length of hospital stay, hospital cost, and readmission rates. Gittel et al. (2000) find that the length of hospital stay decreases significantly with coordination. Using the regression discontinuity approach, David et al. (2019) observe that high-risk individuals reduce ED visits and specialist visits. Haas et al. (2013) study risk stratification methods to identify patients in need of care coordination using explanatory analytics. Yosick et al. (2019) conduct a retrospective propensity-adjusted study to quantify cost savings (using ED visits and in-patient admission rates metrics) and resource utilization (using length-of-stay metric) associated with a community-based palliative care coordination program. Using a combination of logistic regression and multivariate regression analysis, the care coordination program has been found to reduce admission rates and hospital stays for those enrolled in the program.

3.3.2 | Coordination process research

This includes the structure of the coordination process, along with several essential tasks such as care transition, referral management, follow-up care, disease management, medication management, and so forth. We describe them as follows.

Care transitions
As patients transition from one facility to another, the issue of care transition becomes important. Coleman (2003) defines care transition as a set of tasks designed to ensure coordination and continuity of care as patients transfer from one facility to another. Care transition has been seen as an intervention tool that has a positive effect of lowering in-patient readmission rate and ED visits, while increasing the quality of life under many different medical conditions (Fisher et al., 2020; Kirkham et al., 2014; Kocher et al., 2013; Kowalkowski et al., 2019; Reeves et al., 2019; Stelfox et al., 2016; Takahashi et al., 2013). Coleman et al. (2004) and Sato et al. (2011) observe that care transitions can have varying patterns once patients are released from acute care hospitals.

Referral management
Coordination through referrals is more complex at this stage as providers belong to different facilities and in different locations (Pham et al., 2009). Referral-based coordination has been measured by the "confirmed referral" metric (Bolland & Wilson, 1994). Predictive models such as decision trees have been used to predict the needs for social service referrals (Kasthurirathne et al., 2018). Explanatory analytics have been used to test whether referral management is associated with a change in outpatient attendance rate (Cox et al., 2011) and to examine the effect of risk stratification on referrals to social services (Vest et al., 2019). Several IT-based referral platforms (Cartier et al., 2020) have also been developed, such as Aunt Bertha (Aunt Bertha for Organizations), Charity Tracker (Home–CharityTracker from Simon Solutions), and Cross TX (Home–CrossTX) to manage referrals. Using regression analysis, Kaur et al. (2017) suggest that higher referral concentration is associated with Medicare cost per bundle.

Follow-up care
Follow-up care is an aspect of care coordination and is typically measured as a binary variable, defined by whether or not

the individual has a completed specialty referral visit within a 28-day period (McDonald et al., 2014). Lynch et al. (2019) build a multivariate logistic regression model to identify the factors (like age, gender, and insurance plan type) associated with follow-up care.

Disease management

To manage the quality of care coordination, disease management is also an issue. Lee et al. (2020) study three types of PCP-care team communications and their effect on disease management. They find that PCP-care team communications play a major role in controlling patients' hypertension and diabetes.

In Supporting Information Table A.2 (see Supporting Information 2), we present a summary of key existing research efforts in the cooperative team of provider perspective by highlighting the research scenarios that have been undertaken, along with the associated research questions, methods, and data sources.

Gap analysis in cooperative team perspective

The main objective of this perspective is to study the influence of cooperative teams on managing care coordination through collaboration. Coordination is managed by teams of decision makers who have all the information about patients and make all care decisions. Several gaps exist in the literature; problems such as referral management (Bako et al., 2021), care transition management (Coleman et al., 2004; Fisher et al., 2020; Kirkham et al., 2014; Kowalkowski et al., 2019; Reeves et al., 2019; Stelfox et al., 2016; Takahashi et al., 2013), follow-up care management (Lynch et al., 2019), and disease management (Lee et al., 2020) need to be addressed in this perspective (see Supporting Information Table A.2). These problems are typically categorized as those that focus on coordination process management and those that focus on studying the effects of coordination intervention. As referral management and care transition are essential for Triple Aim, we present these two as our research challenges.

3.4 | Research challenges in cooperative team of provider perspectives

We now discuss the representative research challenges in this perspective, starting from *within operations coordination* and ending in *interorganizational coordination*. We list a set of research challenges in Table 4.

3.4.1 | Research scenarios

Two scenarios can be attributed to three categories in the cooperative team of provider perspective. First, we focus on the management of the referral process for patients, with or without comorbidities. The referral process gets increasingly complicated if providers happen to be located in multiple facilities. Second, we focus on managing care transitions. Transitions can affect outcome variables such as readmission rate and the number of ED visits.

3.4.2 | Research questions and data needs

We identify three research questions in Table 4. The data in these types of problems are at the patient level and can be obtained as proprietary data from hospitals, or from Health Information Exchanges (HIEs). Another good source of data can come from Medicare sites like https://www.resdac.org/getting-started-cms-data and https://data.cms.gov/provider-data/search. The metadata typically include patient demographics (id, age, marital status, race, ethnicity, education, and household size); provider demographics (urban/rural, practice type, clinics/hospitals, practice size, PCP/specialists, etc.); health and risk factors (insurance, number of times of ED visits, reasons of the ED visit—chronic or acute, chronic conditions like anxiety, asthma, cancer, and COPD—date of last ED visit, patient making lifestyle changes—stop smoking, willing to increase exercise, 30-day readmission flag); patient barriers (e.g., transportation barrier and communication barrier); coordination mechanisms (e.g., call type, call date, patient initial interviews, patient follow-up meetings, referral patterns); total ED visits; total ED visits before enrollment in the care coordination program; total ED visits after enrollment in the care coordination program; and total PCP appointments.

3.4.3 | Data analytics methods

First, we study the issue of rank-ordering specialists in a referral process for patients based on the existing referral data with no comorbidities and with comorbidities in Table 4. We propose a prediction model to examine Research Question (a). The essence of rank-ordering medical specialists is to match a patient with a suitable medical specialist. Patients are different in terms of their features, and medical specialists are different in terms of their experience. In other words, it is a network formation or link prediction problem (Lee et al., 2016). Each node is a patient or a specialist. If a patient is matched with a suitable medical specialist, we call it a good match, which implies that a link is formed between the patient and the specialist. A better matching between patients and specialists, which is based on patients' and specialists' characteristics, can improve healthcare outcomes. Based on the estimation from the existing referral data, we aim to match a new patient with the most suitable existing medical specialist. We start with the case of patients with no comorbidities and formulate our empirical model for estimation. Next, we extend our model to the case of patients with comorbidities.

From the existing referral data, we have a set of patients, $M = \{1, 2, \dots, i, \dots, m\}$, and a set of specialists for one type of disease, $N = \{1, 2, \dots, j, \dots, n\}$ (the case of no comorbidities). Based on the existing referral data and performance measures

TABLE 4 Representative research challenges in cooperative team of provider perspective

Perspective/coordination mechanism	Research scenarios	Research questions	Methods	Data sources
Cooperative team of provider perspective—within operations	Managing referral process (patients with no comorbidities)	(a) How to rank-order specialists in a referral process?	Predictive model	Proprietary data from hospital or HIE; Publicly available CMS-Medicare data (https://www.resdac.org/getting-started-cms-data)
Cooperative team of provider perspective—Cross-functional care coordination	Managing referral process (patients with comorbidities)	(b) How to rank-order specialists in a referral process with comorbidities?	Predictive model	Proprietary data from hospital or HIE; Publicly available CMS-Medicare data (https://www.resdac.org/getting-started-cms-data)
Cooperative team of provider perspective—Interorganizational care coordination	Managing care transition	(c) How does care transition affect ED visits of patients?	Explanatory/econometric model (e.g., a correlated random trend model combined with PSM)	Proprietary data from hospital or HIE; Publicly available CMS-Medicare data (https://www.resdac.org/getting-started-cms-data)

(e.g., the length of stay [LOS]), we can identify whether the match between patient i and specialist j is a good match ($g_{ij} = 1$) or not ($g_{ij} = 0$). We denote u_{ij} as the utility of patient i referred to specialist j:

$$u_{ij} = \beta_0 + \beta_1 P_i + \beta_2 S_j + \beta_3 V_{ij} + \varepsilon_{ij}, \tag{7}$$

where P_i is a vector including patients' demographics and other characteristics in the data, S_j is a vector including specialists' demographics and other characteristics, V_{ij} is a vector of pair-level characteristics (such as specialist j's experience on the disease of patient i), and the error term, ε_{ij}, follows a type I extreme value distribution. In our empirical model, a good match ($g_{ij} = 1$) is formed when $u_{ij} \geq 0$ (and $g_{ij} = 0$ when $u_{ij} < 0$). Since ε_{ij} follows a type I extreme value distribution, we can obtain:

$$\ln \frac{\Pr\left(u_{ij} \geq 0\right)}{1 - \Pr\left(u_{ij} \geq 0\right)} = \beta_0 + \beta_1 P_i + \beta_2 S_j, \tag{8}$$

and run a logit regression:

$$\text{Logit}\left(g_{ij}\right) = \beta_0 + \beta_1 P_i + \beta_2 S_j. \tag{9}$$

Next, we can obtain the estimates for our parameters, β_0, β_1, and β_2. Based on these estimates from the existing referral data, we can predict $g_{m+1,j}$ for a new patient $m + 1$ based on Equation (9) and obtain the predicted value of $g_{m+1,j}$: $\hat{g}_{m+1,j}$, where $j \in N$. We can rank-order specialists according to the value of $\hat{g}_{m+1,j}$.

Then, we study the extension case of patients with comorbidities, which is Research Question (b). We assume that patients have two types of diseases. The case of multiple diseases (≥ 3) will be similar. In this case, there are two sets of specialists for two different types of disease, respectively: $N = \{1, 2, \dots, j, \dots, n\}$ and $W = \{1, 2, \dots, k, \dots, w\}$ (the case of comorbidities). Similarly, based on the existing referral data and performance measures (e.g., the LOS), we can identify whether the match between patient i and specialists j and k is a good match ($g_{ijk} = 1$) or not ($g_{ijk} = 0$). We denote u_{ij} and u_{ik} as the utility of patient i referred to specialists j and k:

$$u_{ij} = \beta_0 + \beta_1 P_i + \beta_2 S_j + \varepsilon_{ij}, \tag{10}$$

$$u_{ik} = \beta_3 + \beta_4 P_i + \beta_5 S_k + \varepsilon_{ik}. \tag{11}$$

Since ε_{ij} and ε_{ik} follow a type I extreme value distribution, we can obtain:

$$\ln \frac{\Pr\left(u_{ij} \geq 0\right)}{1 - \Pr\left(u_{ij} \geq 0\right)} = \beta_0 + \beta_1 P_i + \beta_2 S_j, \tag{12}$$

$$\ln \frac{\Pr(u_{ik} \geq 0)}{1 - \Pr(u_{ik} \geq 0)} = \beta_3 + \beta_4 P_i + \beta_5 S_k. \tag{13}$$

Therefore,

$$\Pr\left(u_{ij} \geq 0\right) = \frac{\exp\left(\beta_0 + \beta_1 P_i + \beta_2 S_j\right)}{1 + \exp\left(\beta_0 + \beta_1 P_i + \beta_2 S_j\right)}, \tag{14}$$

$$\Pr\left(u_{ik} \geq 0\right) = \frac{\exp\left(\beta_3 + \beta_4 P_i + \beta_5 S_k\right)}{1 + \exp\left(\beta_3 + \beta_4 P_i + \beta_5 S_k\right)}. \tag{15}$$

A good match ($g_{ijk} = 1$) is formed when $u_{ij} \geq 0$ and $u_{ik} \geq 0$. Therefore, the probability of a good match is given by:

$$\Pr(u_{ij} \geq 0) \cdot \Pr\left(u_{ik} \geq 0\right) = \frac{\exp\left(\beta_0 + \beta_1 P_i + \beta_2 S_j\right)}{1 + \exp\left(\beta_0 + \beta_1 P_i + \beta_2 S_j\right)} \times \frac{\exp\left(\beta_3 + \beta_4 P_i + \beta_5 S_k\right)}{1 + \exp\left(\beta_3 + \beta_4 P_i + \beta_5 S_k\right)}. \tag{16}$$

We construct the log-likelihood function to estimate the empirical model for matching based on the actual referral data:

$$\mathrm{Ln}L(\theta) = \ln \prod_{i=1}^{m} \prod_{j=1}^{n} \prod_{k=1}^{w} \left[\Pr\left(u_{ij} \geq 0\right) \cdot \Pr\left(u_{ik} \geq 0\right)\right]^{g_{ijk}} \times \left[1 - \Pr\left(u_{ij} \geq 0\right) \cdot \Pr\left(u_{ik} \geq 0\right)\right]^{1-g_{ijk}}. \quad (17)$$

Our estimates of the parameters are chosen to satisfy: $\hat{\theta} = (\hat{\beta}_0, \hat{\beta}_1, \ldots, \hat{\beta}_5) = \mathrm{argmax}_{(\hat{\beta}_0, \hat{\beta}_1, \ldots, \hat{\beta}_5)} \mathrm{Ln}L(\theta)$. Based on these estimates, we can predict the probability of $g_{m+1,j,k}$ for a new patient $m+1$ based on Equation (16), and rank-order specialists according to the values of probability.

Next, we study how care transition affects ED visits of patients for the interorganizational perspective. In the proposed research question, we investigate the role of care transition in reducing ED visits. In the prior studies, the number of ED visits measures the effectiveness of ambulatory care quality (Coller et al., 2020). Literature has examined how age, race, and the type of index hospitalization affect the number of ED visits (Kocher et al., 2013). The proposed question is to quantify the role of care transition.

We propose an explanatory/econometric model to examine Research Question (c). From the data, we can identify a treatment group (patients who have experienced care transition) and a control group (patients who have not). As mentioned earlier, treated patients might be systematically different from control patients in terms of observable patient demographic characteristics (e.g., age and gender) and disease conditions. To address this concern, we recommend using a correlated random trend model combined with PSM. In particular, a correlated random trend model can alleviate time-varying confounders, and PSM can address time-invariant confounders.

Specifically, in the first step, we run the following logit regression:

$$\text{Logit } (CareTran_{it}) = \gamma_0 + \gamma_1 characteristics_{it} + \gamma_2 condition_{it} + \gamma_3 hospital_i + \varepsilon_i, \quad (18)$$

where $CareTran_{it}$ is a dummy variable indicating whether patient i has experienced care transition at time t, $characteristics_{it}$ is a set of variables relating to patient demographic characteristics, $condition_{it}$ is a set of variables relating to a patient's disease conditions, and $hospital_i$ is a set of variables relating to patient i's hospital characteristics. Using this logit regression, one can generate a predicted propensity score for each patient, which represents the ex ante likelihood of enrolling in the program. In the matching stage, we propose matching each treated patient to the most "similar" control patient (closest propensity score) in terms of observable characteristics (including the previous history of patients), which alleviates the concern of confounders, such as improvement of healthcare treatments and previous unsatisfactory patient experience.

In the second step, based on the new matched sample, we propose running the following correlated random trend model (Wooldridge, 2002):

$$ED_{it} = h_i\, t + \beta_0 + \beta_1 CareTran_{it} + \beta_2 characteristics_{it} + \beta_3 condition_{it} + \beta_4 a_i + \varepsilon_i, \quad (19)$$

where ED_{it} is the number of ED visits for patient i at time t, a_i is the patient fixed effect, and h_i is the patient-specific time trend for patient i. This specification allows different patients to follow different trends in a limited but potentially revealing way. The patient-specific time trend addresses unobserved time-varying confounders. The coefficient β_1 in Equation (19) measures the impact of care transition on the number of ED visits.

4 | CONTRACTED TEAM OF (ARMS-LENGTH) PROVIDER PERSPECTIVES

The emphasis of this perspective is on *contracted care using teams*. As before, a team can have providers such as PCPs, specialists, and registered nurses housed in different facilities. The providers are siloed in facilities and are connected by clinical networks (Ham & de Silva, 2009). A clinical network is an integrated delivery system, providing a coordinated continuum of services, which is clinically and fiscally accountable for the health of the population it serves. The integration[3] could be horizontal or vertical. The organizations that are horizontally integrated include organizations that cooperate and work together. The organizations that are vertically integrated, on the other hand, are primary and secondary care organizations that work together. The coordination is implemented using contracts, which could be cooperative or noncooperative. In a cooperative contract, even though there is a physical contract, there is no competition. All participants are willing to make joint agreements via negotiations supported by the coordinators. In a noncooperative physical contract, participants are essentially competitors with multiple goals. Such goals are of many types: patient goals, provider goals, and coordinator goals. Some goals can have precedence, while others could be hierarchical, complementary, or conflicting. Patients, once again, can have a single disease or multiple comorbidities. These kinds of efforts have been used for studying the implementation of chronic care and the use of information technology (Stern, 2017) extensively. To illustrate these, we once again discuss the research approaches in this perspective starting from *within operations coordination* and ending in *interorganizational coordination*.

4.1 | Within operations care coordination mechanism

To understand the coordination approaches in this category, we present a coordination diagram in Figure 7. In this view,

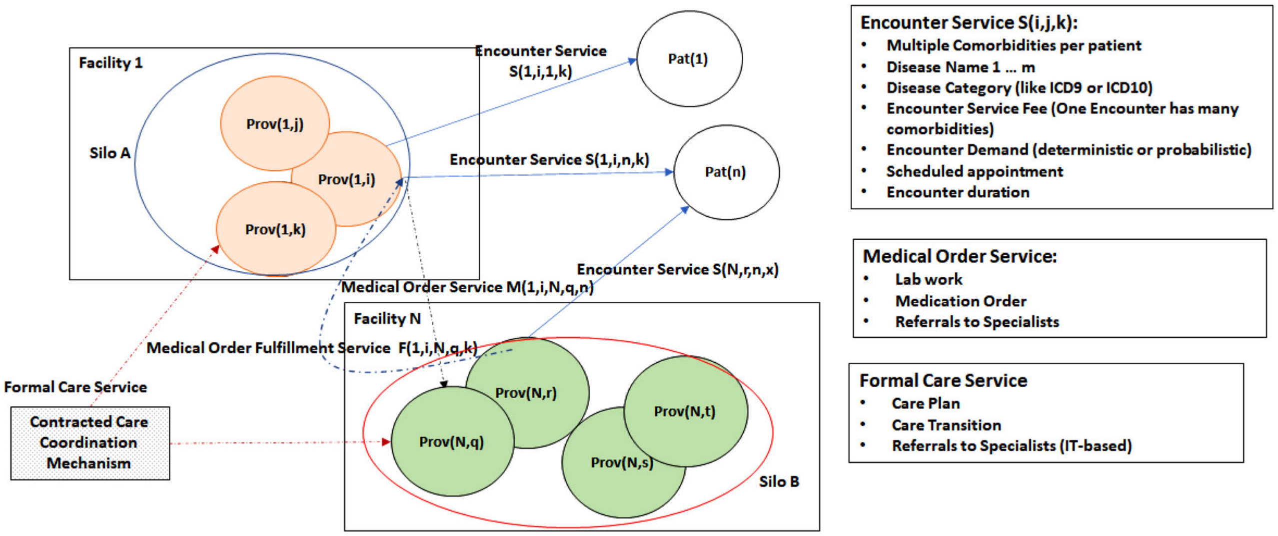

FIGURE 7 Contracted care team of providers with patients with single disease (multiple well-connected provider silos with weak clinical networks) [Color figure can be viewed at wileyonlinelibrary.com]

a provider *Prov*(*i,j*) in Facility *j* teams up with a set of providers {*Prov*(*x,y*)} from {*Facility x*}, along with dedicated care coordinators {*c*} in another facility (*j'*), for each of her patients in {*Pat*(*a*)} who has a disease *k*. Service demand is still stochastic. The coordination is typically accomplished by managing provider–patient encounters where a provider could be a PCP or a specialist in a facility (see the shaded Formal Care Service in Figure 7). Such coordination is employed by creating a contract with coordinators (each coordinator overseeing a bunch of patients from a patient panel) who can use IT-based referral management and IT-based care transition tools that monitor care transitions, manage transition patterns typical for the diseases, manage medications, and so forth.

De Bakkar et al. (2012) study bundled payments for multidisciplinary care for patients with diabetes (and other chronic diseases) to contracting entities called care groups. They find positive consequences, for example, better coordination, better adherence to protocols, and more transparency, along with some negative consequences, such as administrative burden and large price variations. Another good example of this type of care coordination can be found in community-based care coordination programs. Modeling poststroke care transitions with Markov models, Kucukyazici et al. (2011) examine poststroke patients to understand care transition in discharging a patient from a hospital to community-based care facilities.

4.2 | Cross-functional care coordination mechanism

To understand coordination in this category, we present Figure 8. This category is very similar to the *within operations category* (see Section 4.1), except that the patients have comorbidities. The demand for encounter services is once again stochastic. Referral management, disease management, and care transition are still important issues in this category.

Using healthcare coaches, Voss et al. (2011) use care transition intervention (CTI) program to a patient panel chosen from Medicare FFS claims data. They find that the odds of a hospital readmission within 30 days of discharge are significantly lower following hospitalizations, after which individuals receive CTI, compared to the group that do not.

4.3 | Interorganizational care coordination mechanism

This is the final stage in the contracted team of providers' perspective. The contracted standalone care coordination mechanism evolves into the ACO concept. An ACO is a separate entity that is primarily interested in taking responsibilities for the cost and quality of care of an "attributed" patient panel through coordination. A point about enrollment needs to be made here. Enrollment in care coordination is different from one program to the other. For example, in the single-provider perspective, the enrollment in care coordination is managed by the provider herself. She knows which patients need care coordination. At the other extreme, in the contracted team case, enrollment of patients is done through "attribution" of patients to an ACO. However, when a primary care provider participates in an ACO, she may ask patients to select the ACO as their primary care provider. Patients benefit due to a large coverage of physicians. An ACO typically offers education to the physicians like IT planning, care planning, and care coordination; helps create care plans; provides care coordination services; and manages several quality initiatives for the providers (CMS, 2021; Kent, 2019; Salmon et al., 2012). Providers interested in quality measures, getting costs down, increasing patient satisfaction, simpler convenience of referrals, analytics services to

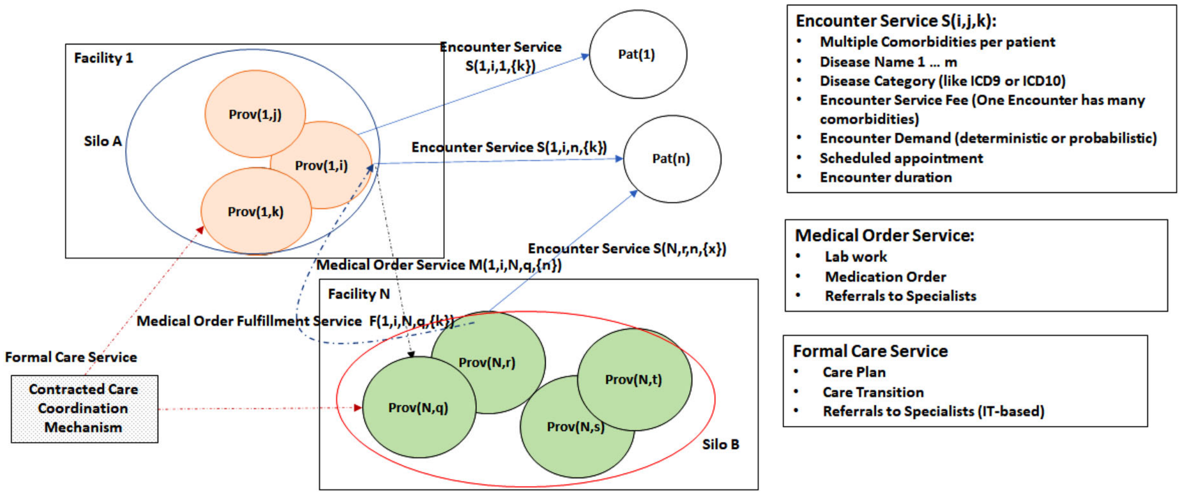

FIGURE 8 Contracted team of providers/multiple patients with comorbidities (multiple well-connected provider silos with medium clinical networks) [Color figure can be viewed at wileyonlinelibrary.com]

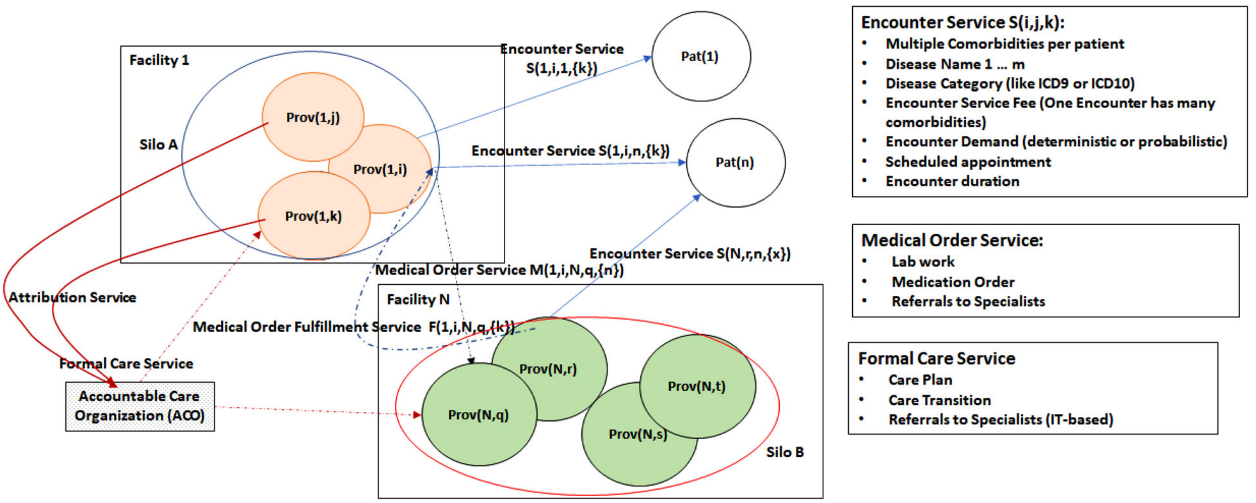

FIGURE 9 Contracted team of providers with multiple patients with comorbidities (multiple well-connected provider silos with strong clinical networks) [Color figure can be viewed at wileyonlinelibrary.com]

reduce risk (medication management, disease management, cost containment, etc.), and seeing better care transition opt for this type of care coordination.

An ACO also supports PCMH-based practice design. Hence, we extend Figure 8 to develop Figure 9. The coordination is done through physical contracts between providers in multiple facilities and an ACO. Patients can have a single disease or many comorbidities. The demand for encounter services is still stochastic. Many interesting research issues have been investigated in this category, which are described below.

4.3.1 | Embedded care coordination by ACO

Instead of having an ACO to coordinate care, Salmon et al. (2012) study Cigna's ACO initiative, which allows registered nurses employed by the practices to serve as embedded care coordinators. The ACO trains these coordinators and offers "practices a care coordination fee on top of standard fee-for service payments. The coordination fee, paid to a practice at the beginning of the year, is designed to help practices make investments that will improve patient care while keeping total medical costs down. Thus, the fee is designed to benefit patients, practices, and the payer alike" (Salmon et al., 2012, p. 2381). The overall goal is for a practice to make improvements in care quality and efficiency that will drive the total medical costs down to attain a net cost saving.

4.3.2 | Centralized care coordination by ACO

Care coordination is typically centralized in an ACO and is run by registered nurses employed by the ACO. According to CMS (2021), Medicare ACOs are groups of doctors, hospitals, and other healthcare providers, who gather together willingly to give superior, coordinated care to their Medicare patients. Many types of ACOs exist. Most of them include PCPs (Salmon et al., 2012). However, various specialized providers (such as dialysis facilities and nephrologists), suppliers, and patients have created specialty-based ACOs like end-stage renal disease (ESRD) seamless care organizations (ESCOs). The ESCOs are accountable for the quality and financial outcomes of their end stage Medicare beneficiaries. Marrufo et al. (2020) demonstrate that such a specialty ACO model focusing on a particular population is still associated with reduced payments and improved quality of care.

4.3.3 | Care integration in ACO

Integration of care is increasingly becoming important as hospitals are facing value-based payment reforms. As a result, hospitals have turned their attention to postdischarge care. One way to manage this kind of care is through care coordination using *vertical integration*. For example, a hospital can vertically integrate through the legal acquisition of postacute care providers or through more informal settings where legally separate organizations can share providers across facilities. Konetzka et al. (2018) detect that vertically integrated facilities earn more in Medicare payments than similar facilities that are not integrated. The larger Medicare payments are due to longer LOS in the postacute care facilities. Horizontal integration, on the other hand, is implemented when organizations acquire or integrate with other organizations that provide the same or similar services (Heeringa et al., 2020). Using horizontal integration, Veterans Health Administration has created nation-wide primary care and mental health integration initiative. Leung et al. (2019) discover that such integration realizes "each percentage-point increase in the proportion of clinic patients seen by these providers was associated with 11 percent more mental health and 40 percent more primary care visits but also with 9 percent higher average total costs per patient per year" (p. 1281).

4.3.4 | Referral analytics in ACO

The study of referral patterns is important for ACOs, too. In order to study referral analytics, Ru et al. (2017) emphasize the need for integration of data from an ACO with data from CMS. As research in ACO has concentrated mostly on cost reductions with PCPs, it is important to investigate cost reductions using specialist office visits. Shetty et al. (2019) examine this issue and find that 40% to 44.9% of specialist encounters have significantly lower healthcare expenditures compared to ACOs with lower or higher encounters.

We present a summary of existing research efforts in the contracted team of providers' perspective in Supporting Information Table A.3 (see Supporting Information 2) below by highlighting the research scenarios used in extant research along with associated research questions, methods, and data sources.

4.3.5 | Gap analysis in contracted team of provider perspective

The main focus of this perspective is to employ a separate contracted entity that manages the coordination of patients. The contracted entity ranges from a loosely organized contracted group that supports a coordination mechanism to a formally organized group such as an ACO. Several problem types/gaps are quite common in this perspective. They range from the effectiveness of contracted coordination program (Kucukyazici et al., 2011) to the effectiveness of care transition program (Voss et al., 2011) along with care integration (Konetzka et al., 2018; Leung et al., 2019) and referral analytics (Ru et al., 2017). ACOs are designed to achieve the Triple Aim of better health, improving patient experience, and lowering costs by shifting financial responsibility for patient outcomes to the providers, rather than payers. Improvement of patient experience can be achieved by vertical integration of care. Case managers in ACOs play a pivotal role during care transitions by focusing on the goals of Triple Aim that assess patients and identify those who are at high risk, reconcile medications, and facilitate the education of patients and their support systems to improve self-management. We focus in this section on these two gaps and present the research challenges in care transition and care integration.

4.4 | Research challenges in contracted team of (arms-length) provider perspectives

According to the contracted team of provider perspective, the coordination is managed by a separate entity, which could be a group of coordinators in a different facility or an ACO. As described in Section 4.3, many types of problems can be addressed in this perspective, for example, embedded coordination, centralized coordination, referral analytics, and care integration. We identify three research questions in Table 5. The first two questions focus on whether care transition in a community-based setting can help readmission costs. Care transition deals with a patient's transition from one facility to another. The question posed in Table A.3 in the Supporting Information, however, focuses on community-based coordination program. A community-based coordination covers many aspects such as health disablers, community features that make disease management easier, health enablers, family resources, coordination intervention, community-based healthcare education, and others.

4.4.1 | Research scenarios

Two scenarios can be attributed to three categories in the contracted team of provider perspective. First, we focus on the

TABLE 5 Representative research challenges in contracted team of provider perspectives

Perspective/coordination mechanism	Research scenarios	Research questions	Methods	Data sources
Contracted team of (arms-length) healthcare providers—coordination within care operation	Efficacy of care transition (patients with no comorbidities)	(a) Can a community-based care transition help reduce hospital readmission costs for patients with no comorbidities?	Explanatory/econometric model	Proprietary data from hospital or HIE or ACO; Publicly available CMS-Medicare data (https://www.resdac.org/getting-started-cms-data)
Contracted team of (arms-length) healthcare providers—cross-functional care coordination	Efficacy of care transition (patients with comorbidities)	(b) Can a community-based care transition help reduce hospital readmission costs for patients with comorbidities?	Explanatory/econometric model	Proprietary data from hospital or HIE or ACO; Publicly available CMS-Medicare data (https://www.resdac.org/getting-started-cms-data)
Contracted team of (arms-length) healthcare providers—interorganizational care coordination	Care integration	(c) Does vertical integration reduce hospital readmission rates for an ACO?	Explanatory/machine learning–based econometric model, machine learning–based predictive analytics (e.g., GSCM and MCM)	Proprietary data from hospital or HIE or ACO; Publicly available CMS-Medicare data (https://www.resdac.org/getting-started-cms-data)

efficacy of coordination using the ACO paradigm. This scenario allows us to study the effectiveness of coordination for patients with or without comorbidities. Second, care facility integration needs to be studied to assess the efficacy of vertical and horizontal care integration in care coordination.

4.4.2 | Research questions and data needs

We identify three research questions in Table 5. The existing literature (see Table A.3 in the Supporting Information) focuses on the use of community-based coordination programs in improving health outcomes. In contrast, the first two research questions we pose in Table 5 focus on a specific type of cost: Can a community-based care transition help reduce hospital readmission costs for patients with no comorbidities? Hence, our focus is on reducing hospital readmission costs through community-based care transition programs. The third question examines the effect of vertical integration on hospital readmission rates for an ACO. The data in these types of problems are at the patient level and can be obtained as proprietary data from hospitals, HIEs, or ACOs. Another good source of data is Medicare sites such as https://www.resdac.org/getting-started-cms-data, https://data.cms.gov/provider-data/search. The metadata typically include patient demographics, provider demographics, health and risk factors, patient barriers, coordination mechanisms, total ED visits, total ED visits before enrollment in the care coordination program, total ED visits after enrollment in the care coordination program, and total PCP appointments.

4.4.3 | Data analytics methods

First, we focus on community-based care transition. Can it help reduce hospital readmission costs for patients with and without comorbidities? We propose an explanatory/econometric model to examine Research Questions (a) and (b). Note that the hospitalization cost of similar procedures does not vary too much across facilities. For instance, Medicare has a standard set of rates for procedure codes. Therefore, the costs of procedures do not vary widely across facilities (MedicareInsurance, 2022). A patient covered by a private insurance company may witness some cost variations across facilities, but even in that case, the patient's share is usually limited to a fixed copay/coinsurance rate (Henry, 2015). From the data, we can identify a treatment group (patients who have experienced a community-based care transition) and a control group (patients who have experienced a non–community-based care transition). The ideal causal identification is to compare the treatment group with themselves but in the condition that they had not received the treatment. To obtain the unobservable counterfactual, we follow the idea of synthetic control (Abadie et al., 2010) to construct a weighted combination of control units used as the comparison unit. As there are multiple treated units in our case, we recommend using the generalized synthetic control method (GSCM) (Xu, 2017). This extended version relaxes the critical assumption of a single treated unit in the classic synthetic control method. The intuition behind the GSCM is to synthesize a weighted control unit that closely matches the data pattern of the outcome variable (in our case, it is hospitalization cost) in the pretreatment period for the treated unit. Then the outcome variable of the synthetic control unit in the posttreatment period is taken as the counterfactual prediction for the treated unit. Because the GSCM models the trend of the outcome variable, it can naturally account for the effects of both observable and unobservable confounders changing over time.

In the GSCM framework, we propose running the following interactive fixed effects model:

$$\begin{aligned} HospCost_{it} = {} & \beta_0 + \beta_1 ComCareTran_{it} + \beta_2 characteristics_{it} \\ & + \beta_3 condition_{it} + \lambda_i f_t + \alpha_i + \omega_t + \varepsilon_i, \end{aligned} \tag{20}$$

where α_i is the patient-level fixed effect, ω_t is the time fixed effect, $HospCost_{it}$ is the hospital readmission cost for patient i at time t, $ComCareTran_{it}$ is a dummy variable indicating whether patient i has experienced community-based care transition at time t, $characteristics_{it}$ is a set of variables relating to patient demographic characteristics, $condition_{it}$ is a set of variables relating to a patient's disease conditions, f_t represents the vector of unobserved time-varying factors, and λ_i is the vector of factor loadings. The GSCM estimation can be implemented by using the available "gsynth" package in R (Xu, 2017). We recommend estimating Equation (20) for the samples of patients with comorbidities and no comorbidities separately to obtain the estimates. The coefficient β_1 in Equation (20) measures the impact of community-based care transition on the hospitalization cost.

Next, we study the effect of vertical integration on the care coordination. We ask if vertical integration can reduce hospital readmission rates for an ACO. We propose an explanatory/econometric model to examine Research Question (c). From the data, we can identify treated hospitals that have experienced vertical integrations and control hospitals that have not experienced vertical integration. To address the effects of both observable and unobservable confounders changing over time, we can use the GSCM framework mentioned earlier and the following interactive fixed effects model:

$$Readmission_{it} = \beta_0 + \beta_1 VerInte_{it} + \beta_2 hospital_{it} + \lambda_i f_t + \varepsilon_i, \tag{21}$$

where $Readmission_{it}$ is the readmission rate of hospital i at time t, $VerInte_{it}$ is a dummy variable indicating whether hospital i has experienced vertical integration, $hospital_{it}$ includes time-varing hospital characteristics, f_t represents the vector of unobserved time-varying factors, and λ_i is the vector of factor loadings. The coefficient β_1 in Equation (21) measures the impact of vertical integration on readmission rate.

Note that our proposed econometric models are quite flexible and can be adapted into different contexts as long as we have a panel data set with control and treatment groups. The purpose of proposing econometric models in our study is to help researchers see the potential applications of recently developed explanatory analytics estimators. Explanatory analytics and predictive analytics are complementary, and both are very useful in studying care coordination. The winner of the 2011 Turing Award, Judea Pearl, argues that the future development of AI depends on the causal revolution: Without understanding the underlying causation, prediction performance could suffer when a structural change occurs (Pearl & Mackenzie, 2018). Recently, various causal machine learning estimators have been developed to combine explanatory analytics rooted in the econometrics literature with predictive analytics rooted in computer science and statistics literature (Athey et al., 2021). We also recommend using the matrix completion method (MCM), a new causal machine learning approach developed by Athey et al. (2021), to further explore the robustness of the results. Like the GSCM, the MCM also aims at predicting the counterfactual outcomes for the treatment group in the posttreatment period and can account for unobserved time-varying characteristics. The MCM gains insights from machine learning literature and treats the problem of counterfactual prediction as a problem of completing an $N \times T$ matrix with missing elements, where missing appears when the treatment indicator $VerInte_{it} = 1$. The untreated potential outcome matrix $Readmission(0)_{N\times T}$ is assumed to be as follows (Athey et al., 2021):

$$Readmission(0)_{N\times T} = L_{N\times T} + \varepsilon_{N\times T}, \mathbb{E}\left[\varepsilon|L\right] = 0, \tag{22}$$

where $L_{N\times T}$ denotes an $N \times T$ target matrix to be estimated and ε represents a matrix of measurement errors. As with standard factor models, L can be decomposed as: $L = U_{N\times R} F'_{T\times R}$, where $F_{T\times R}$ is a matrix of time-varying factors and $U_{N\times R}$ denotes a matrix of heterogeneous factor loadings. The MCM attempts to directly estimate L by minimizing the following regularized object function:

$$\hat{L} = \arg\min_L \left[\sum_{(i,t)\epsilon C} \frac{(Readmission_{it} - L_{it})^2}{|C|} + \theta||L||_1\right], \tag{23}$$

where $C = \{(i,t)|Readmission_{it} = 0\}$ and $|C|$ represents the number of elements in C. θ is the penalty term and $\|L\|_1$ denotes the nuclear norm. Then an iterative algorithm is used to obtain $\hat{L}$, which is proved to be asymptotically unbiased. Interested readers can refer to Athey et al. (2021) for technical and proof details. The average treatment effect on the treated (ATT) at time t, which is the impact of vertical integration on readmission, can be calculated based on the average differences between the outcome of a treated unit $Readmission_{it}(1)$ and its constructed counterfactual $Readmission_{it}(0)$.

In addition, we can also examine the robustness of our results by looking at a set of recently developed counterfactual estimators, which belongs to the causal machine learning approach (Liu et al., 2021; Pan & Qiu, 2022). Counterfactual estimators aim to estimate the average effect of the treatment on the treated units by imputing the missing potential outcomes or counterfactuals. Unlike a conventional two-way fixed effects model, counterfactual estimators take observations under the treatment condition (in our context, $VerInte_{it} = 1$) as missing data and directly estimate their counterfactuals: the readmission rates for the treated hospitals if they have not experienced vertical integration. Essentially, counterfactual estimators convert the original causal identification problem into a "prediction" problem: Using the observations in untreated conditions (in our context, $VerInte_{it} = 0$) to predict the missing outcomes of treated observations in counterfactual conditions (Liu et al., 2021; Pan & Qiu, 2022). This approach addresses unobserved, time-varying confounders using a latent factor approach.

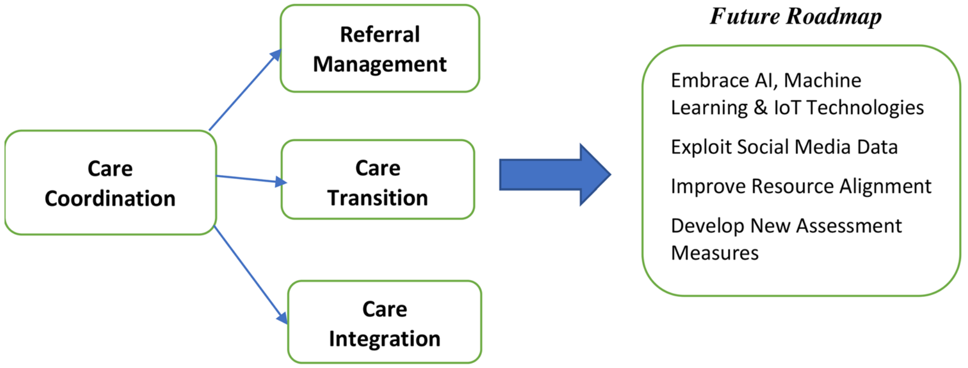

FIGURE 10 Future roadmap for care coordination research [Color figure can be viewed at wileyonlinelibrary.com]

5 | FUTURE ROADMAP

As the care coordination field continues to grow rapidly, there is a growing need to rely on advanced business analytics methods, social media data, real-time patient information, and new care assessment methods for realizing its full potential. We present a future roadmap for care coordination research in Figure 10, which shows the three focus areas for research listed in our framework—referral management, care transition, and care integration—and identifies the initiatives that need to be launched in the future. In the following subsections, we discuss these initiatives.

5.1 | Embrace artificial intelligence (AI), machine learning, and Internet of Things (IoT)

Advanced technologies such as AI, machine learning, and IoT could emerge as powerful enablers for care coordination. Healthcare organizations should embrace these technologies to facilitate information flow between providers, patients, and facilities (Chen et al., 2021a). This will help address issues related to EHR-based care coordination systems, which include clinical workflow barriers, data limitations, and limited ability to share information across different facilities. With respect to the *Cooperative Team of Provider* perspective, future research could dwell on addressing questions on predicting the quality outcome of a specialist based on her referral pattern or on the effects of referral history on readmission rates. With respect to the *Contracted Team of Provider* perspective (refer to our framework in Table 1), follow-up research questions on whether community-based care helps reduce hospital costs could examine whether such care mechanisms can help reduce specific costs, such as those related to readmission and mortality rates. Addressing such questions, which rely on cross-boundary measurement, could be facilitated with the use of IoT sensors and devices. AI and machine learning techniques could be deployed for understanding the process and analyzing the effects of coordination across the different care interfaces, spanning multiple providers and facilities.

Patients could be provided with IoT wearable devices that capture vitals such as weight, temperature, blood pressure, heart rate, respiratory rate, and oxygen saturation. Provider facilities could be equipped with sensors for collecting information from blood tests, point-of-care glucose, urine tests, ultrasounds, X-rays, MRI and CT scans, and EKG/telemetry data. An IoT hub could be used to capture data from those sensors, as well as the data from EHRs on referrals and care transitions. An IoT-based data analytics platform could be employed for applying stream analytics to process real-time data from sensors and then apply machine learning methods for detecting clinical anomalies in the patient's overall health. Streaming analytics is the ability to continually conduct statistical analytics while moving within the stream of data; it enables real-time analytics of live streaming data. Predictive machine learning models could be built dynamically during the stream analytics phase based on the streaming data and the historical data (e.g., referral history, patient encounter history) to provide proactive decision support for important problems such as an increase in readmission/mortality rates or a decrease in provider sign-up when an ACO engages in care integration efforts.

Consider a patient who experiences a sudden drop in blood count, postsurgery; that information would be transmitted in real time by the patient's wearable device to a predictive machine learning model, which could dynamically decide on whether they should be sent to an acute rehabilitation facility or not. Consider another patient who experiences a change in vital signs. A machine learning model could be used to predict readmission risk for the patient and then recommend whether to schedule a follow-up appointment at an outpatient facility to prevent inpatient readmission. More advanced AI technologies such as virtual reality (VR), augmented reality (AR), and mixed reality (MR) open up exciting future research opportunities. Consider an operating room where a patient is about to undergo surgery. If the care coordination process involves a contracted team of providers in an interorganizational setting, multiple physicians, clinicians, and other providers across different facilities can leverage the power of an MR system to view and interact with the vital signs and surgical plan in real time and provide immediate assistance to the surgeon. An interesting research question then is to examine if advanced technologies such as VR, AR, and MR are able to bring down readmission, mortality, and postsurgical infection rates.

The use of such intelligent real-time analytics techniques for anomaly detection will help address several meaningful use objectives and clinical quality outcomes related to care coordination, such as identify patients who should receive reminders for preventive/follow-up care; perform medication reconciliation for patient transitions of care to the provider or ED/inpatient hospital admissions; real-time transfer of referral/care transition data across PCPs, specialists, providers, and facilities; and predicting readmission/mortality rates based on referrals and care transitions.

5.2 | Exploit social media data

Social media platforms could be exploited for assessing care coordination goals and plans for patients (Fan et al., 2022; Kumar & Qiu, 2022; Strekalova et al., 2018). In addition to data from EHR systems, IoT sensor devices, and mobile devices, future research should tap into the unstructured data available in various online patient forums for addressing important care coordination research questions. One type of forum is online review platforms, where patients post reviews of physicians and hospitals. Some examples of online platforms where patients post reviews are Yelp.com, RateMDs.com, and Vitals.com.

Machine learning techniques could be applied to extract latent topics in patient reviews. Leveraging topic modeling, an unsupervised learning technique, to extract latent topics that highlight patient needs, goals, and concerns could facilitate communication between patients, physicians, and providers. The latent Dirichlet allocation (LDA) method (Blei et al., 2003; Kwark et al., 2021; Pu et al., 2020, 2022; Shi et al., 2021), which is an unsupervised method that extracts a predefined number of hidden topics from documents, could be employed. Those topics could then be interpreted and labeled by human coders based on their content. With respect to the *Cooperative Team of Provider* perspective, an interesting future research direction would be to investigate which topics related to care transition (e.g., discharge planning, effective communication, follow-up appointment, and medication review) have a significant influence on a hospital's objective quality performance measures, such as the time spent in ED, readmission rate, and mortality rate. The findings from such investigations would help hospitals focus on specific areas of care transition and launch quality improvement initiatives.

Using econometric models, the relationship between patient reviews and clinical health outcomes, such as readmission rate, mortality rate, and overall hospital rating, could also be analyzed (Saifee et al., 2020). Analysis of longitudinal review data collected from online review platforms will provide a comprehensive and better view of a patient's experience of care coordination services over time. Physicians and hospitals could exploit the results from such an analysis to understand patient needs and plan for proactive care. Reviews and ratings of specialists and medical facilities could also provide valuable inputs for referrals and care transitions.

5.3 | Improve resource alignment

Linking the right resources to meet patient needs remains to be one of the major barriers in care coordination. Several types of resources could be used to facilitate care coordination, including financial resources, educational resources, social services, support groups, transportation support, and multidisciplinary boards (Qiu et al., 2022). Promoting a more efficient use of healthcare resources is likely to generate significant cost savings among beneficiaries (Pezzin et al., 2018).

One way to improve resource alignment is through the implementation of programs that address patients' social conditions. New technology platforms, such as AuntBertha, CharityTracker, CrossTx, Healthify, and Signify Community, have emerged to facilitate referrals to community-based social services organizations (Cartier et al., 2020). With respect to the *Cooperative Team of Provider* perspective, such platforms could prove to be useful in answering questions on the influence of past referrals on hospital costs, health quality outcomes, readmission rates, and so forth. Another way to improve resource alignment is HIE, which addresses the fragmentation of patient medical records (Demirezen et al., 2016). Since there are difficulties in sharing medical records, it would be interesting to examine how privacy concerns and HIE affect the performance of care coordination.

5.4 | Develop new assessment measures

One of the problems associated with current EHR-based care coordination measures is that it is difficult to create, maintain, and share a longitudinal, comprehensive plan of care. Also, much of the information needed for care coordination is available in an unstructured text format (clinical notes) or is not stored at all. There is, therefore, an urgent need to develop measures that use unstructured data and capture the dynamic aspects of healthcare data.

None of the current EHR-based assessment measures evaluate communication among care coordination team members (e.g., providers and staff within a practice). In particular, none of them evaluate interpersonal communication, whether within a healthcare team or across healthcare teams. Given these gaps, it is important to develop measures that can effectively capture the interpersonal and dynamic processes between healthcare professionals and patient/family, as well as those across healthcare teams/settings. There is a need to develop measures based on the patient/family and healthcare professional perspectives, in addition to the EHR (system representative) perspective. Such measures would help us address research questions on whether the level of interpersonal communication, both within and between healthcare teams, influences health quality outcomes. Evaluating communication across different healthcare teams or settings would also address issues relating to care integration, for example, how comprehensive, shared, and proactive a plan of care is.

5.5 | Closing remarks

In this study, we develop a framework for examining business analytics research in the domain of healthcare coordination. Our framework includes three care coordination perspectives: single-provider perspective, cooperative team of providers–based perspective, and contracted team of providers' perspective. Within each perspective, we consider three care coordination mechanisms: coordination within care operation, cross-functional care coordination, and interorganizational care coordination. Our framework provides a classification scheme for extant research by helping us describe the different research scenarios under which prior care coordination research has been conducted and then, within each scenario, identify the research questions that have been addressed, as well as the methods and data sources employed to address those questions. This framework helped us identify several important research challenges and propose a set of methods (explanatory models, predictive models, and descriptive models) and data sources that could be leveraged by future research for exploiting the power of business analytics in care coordination.

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ENDNOTES

[1] The term "silo" has often been used in the healthcare literature (Frost & Sullivan, 2014) to emphasize the lack of communication between healthcare entities. The reasons for this lack of communication could be technical, behavioral, organizational, and other issues.

[2] In our framework, the cooperative team perspective includes the noncontracted approach as the main emphasis is on collaboration among teams. In other words, all members of a team share the same objective, although they work separately. For example, a primary care provider can refer a patient to a specialist who is not in her network and still collaborate to provide care to the patient. Note that disparate healthcare entities that are not part of the same network or contract agreement might not be able to effectively coordinate with each other due to the lack of incentives.

[3] The reason we did not bring up integration at the team level in Section 3 is because integration in teams is horizontal and no explicit legal contracts are executed (Vigran et al. 2015).

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SUPPORTING INFORMATION

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

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