Beyond Network Effectiveness: The Case for Network Efficiency and Accuracy

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Abstract

Multi-service coordinated care networks are thought to improve access to care and accountability for human service organizations by centralizing knowledge management and referring clients to appropriate providers. The researchers investigate these referral networks' performance by examining their accuracy at routing clients to the correct provider, their efficiency in terms of time to service, and their effectiveness measured as whether the service request was filled. Using 30 days of service episode data from early 2020 ($N = 1,575$), they compare the 11 networks' performance. Network accuracy positively correlated with network effectiveness and negatively with network efficiency, but efficiency and effectiveness were not correlated. Moreover, network performance significantly varied across service types. The authors end with recommendations for network managers and policy implications.

Beyond Network Effectiveness: The Case for Network Efficiency and Accuracy

Increasingly, nonprofit organizations and government agencies recognize that socially desired outcomes like wellbeing, health, quality of life, and a reduction of community violence require a socio-ecological perspective, sometimes described as social determinants (Agency for Healthcare Research and Quality, 2016; Argita & Hinton, 2018; Centers for Disese Control and Prevention, 2021; Centers for Medicare & Medicaid Services, 2021). A socio-ecological perspective recognizes that several different types of support or interventions are required to improve these social problems (see Salis & Owen, 2015). To deliver these supports and enable clients to navigate fractured social and human services systems, systems of care have emerged. Systems of care, also described as integrated health and human services (Fichtenberg et al., 2020) or service delivery networks (Bunger & Huang, 2019), are referral systems across health and human service agencies supported by technological and human capital. Technological capital includes community referral technologies (Cartier et al., 2019, 2020) and updatable resource directories (Bloom, 2013) while human capital includes community health navigators (Mistry et al., 2021), call center operators (Eddens & Kreuter, 2011), and social workers embedded in agencies (Spencer, 1993).

Federal and state public agencies, foundations, and venture capital firms have encouraged a proliferation of systems of care (Cartier et al., 2019). Increasingly, states and municipalities have multiple overlapping systems of care (e.g., Joint State Government Commission, 2021) and are pushing for greater integration between physical health, mental and behavioral health, and social health services (California Department of Health Care Services, 2022; Crumley et al., 2018; Leveraging Integrated Networks in Communities to Address Social Needs Act, 2021). However, commensurate systems that allow funders, regulators, and communities to evaluate

these systems of care have not kept pace with their proliferation (Fichtenberg et al., 2020). To address this need, we introduce metrics for system evaluation and comparison. We compare a set of networks based on measures of their efficiency, accuracy, and effectiveness. We define efficiency as how quickly a client receives services, accuracy as whether the first referred organization provided services to the client, and effectiveness as whether the client received services.

Research has been scant in connecting clearly defined network functioning (i.e., process) metrics with different operationalizations of network effectiveness (Mayne et al., 2003; Provan & Milward, 2001; Shonk & Bravo, 2010). This paper aims to fill these gaps by using accuracy and efficiency as concrete metrics to understand the influence of network functioning on network effectiveness for referral networks. These metrics capture real-time interactions in the network, offering fertile ground for comparison and clarity in connecting effectiveness to client outputs. Our approach shifts from approaches which emphasize perception and satisfaction to a more operational view of network effectiveness at the whole-network level. We do this through understanding the differences among systems of care based on their performance metrics.

In addition, we explore the impact of different kinds of services on network performance. Saitgalina and Council (2020) noted that services range in complexity and that more complex services may tend to underperform because of the longer time and investment needed to realize a positive result. Considering the present dearth of research on the relationship between service types and network performance, we also explore how performance varies across different services.

This research makes four contributions to public administration research on networks generally and systems of care. First, our study capitalizes on the data available to and used by

network managers to evaluate network functioning and effectiveness. Second, we expand on the concept of service complexity introduced by Saitgalina and Council (2020), demonstrating one way to measure complexity. Third, we explore how service delivery complexity drives performance variations between networks. Finally, we advance network management practice and research by showing the value of nuanced perspectives in evaluating and measuring network functioning.

The paper proceeds as follows. First, we distinguish between the broader concept of service networks and the more transactive referral networks on which service networks rely. We then contextualize the effectiveness of systems of care in the overall literature on network effectiveness and define the network functioning metrics that we use to evaluate networks. Next, we describe the scant research that has explored service complexity and its implications for network performance. Following that, we describe the study we conducted of 11 AmericaServes networks, geographically bound systems of care in 11 geographies that address multiple veterans and military family needs. Then, we describe the results, including how the three metrics are related and the influence of service complexity on the results. Finally, we conclude with a discussion of how detailed views of operational data provide clearer, more actionable insights for researchers, managers, and policymakers and offer ground to continue developing theory around network effectiveness.

Literature Review

Service Networks to Referral Networks

Service networks are a major research stream in public administration (Isett et al., 2011; Lecy et al., 2014). Lorant and colleagues (2019) define service networks as "long-term agreements between organizations or services with the aim of providing patients with a

comprehensive and coordinated range of interventions" (p. 289). Service networks span a variety

of domains including mental health (Huang & Provan, 2007; Lorant et al., 2019; Nicaise et al.,

2013; Provan & Milward, 1995) family and children's services (B. Chen, 2008; B. Chen &

Graddy, 2010; Keast & Brown, 2006), substance use (Kruse et al., 2012; McGihon et al., 2018),

and homeless services (Mosley, 2021). These networks bring together organizations within the

same or adjacent domains to provide comprehensive services for a target population. Research

on service networks examines their effectiveness (B. Chen & Graddy, 2010; Lorant et al., 2019;

Provan & Milward, 1995), the integration and diversity of their services (Bunger & Huang,

2019; Graddy & Chen, 2006; McGihon et al., 2018; Provan & Sebastian, 1998), their size

(Graddy & Chen, 2006), and the volume of clients for whom they provide care (Barnett et al.,

2016; Peters et al., 2018).

     One key relationship within service networks is the referral or the transfer of a client

from one provider organization to another. As Gibbons and Samaddar (2009) define them,

referral networks are "systems of relationships among organizations that allow them to direct

people to appropriate services that are not available at their own facility" (p. 352). Service

networks thus operate on referrals and the transfer of clients to provide the range of necessary

services for a client. For example, Provan and Milward's (1995) seminal piece includes referrals

as part of their study on mental health service networks. Yet, where research tends to take a more

"macro" view of service networks and examines long-term agreements between organizations,

research on referral networks tends to take a more "micro" view of the networks and examines

the flows and movement of referrals.

     Studying referral networks thus creates an opportunity to ask different questions about

how clients move through service networks. For instance, referral networks enable us to ask not

only about the mere receipt of services, but how quickly clients received those services, how many different providers the client touched before receiving services, or what referral patterns emerged. Most of the research on referral networks, however, rests in the domain of healthcare. Moreover, healthcare studies on referrals and referral networks often emphasize the volume of referrals through a specific organization or technology (Barnett et al., 2016; Bowles et al., 2019; Hood-Medland et al., 2019; Peters et al., 2018), whether those referrals resolved the client's needs (Conrad et al., 2003; Saitgalina & Council, 2020), and the quality of information contained within those referrals (Fernández-Méndez et al., 2020; Harahap et al., 2019; Wilberforce et al., 2017). Similar questions could also be asked in human services networks, but we consider what other value might be gained through studying referrals in the multi-sector context of human services.

Studying the flow of referrals across networks can identify potential lags or service gaps, Tausig (1987) describes how unpatterned relations, absent linkages, and conflicted links indicate the absence or fraying of expected referral flows within and across network service types. Examining referral networks can also locate major flows within service networks—pairs of actors between whom many interactions take place—and suggest areas for further network development and network design.

In the following sections, we describe network effectiveness and how to characterize the effectiveness of referral networks. We also define additional metrics unique to referral networks that provide critical information into their operation. We then acknowledge the limited literature on service complexity which describes variations in service delivery arising due to innate differences in services.

Network Effectiveness and Functioning

Network effectiveness is a robust area of research in public administration that aims to understand why some networks are successful and others are not. What constitutes success, or effectiveness, has been of long-standing debate but we adopt Turrini et al.'s (2010) definition for this paper. Networks are effective when they produce positive outcomes and impact beyond the boundaries of the network (i.e., outside their own membership). Thus, for a network to be effective, the entities within it must act as a coordinated body to achieve overall success despite potential transaction costs to the individual organization (Provan & Milward, 2001). Provan and Milward (2001) noted three different levels at which scholars and practitioners could measure effectiveness. Individual-level effectiveness includes quality and cost of service; network-level effectiveness includes network growth, service integration, and member commitment; and community-level effectiveness includes reductions in problem incidence, costs to the community, and public perceptions.

This study examines individual-level effectiveness, specifically the rate of case closure within each network, but from a whole-network perspective (Kilduff & Tsai, 2003). We opt for case closure since multiple disciplines view the timely closing of a case as a signal of effectiveness, including sales management (Bhattacharjee et al., 2018), criminal justice (Holovko & Shevchenko, 2018), and software engineering (Agrawal, 2019; Zou et al., 2015); yet the network effectiveness literature rarely considers effectiveness in this way (for a limited exception, see Saitgalina & Council, 2020). With the rise of electronic referral systems in systems of care, case closure increasingly signals a network's ability to coordinate service provision across providers. For example, research has found that referral case closure reflects service integration and increased accountability through timely feedback and system

optimization, which correlates with shorter wait times, expedited care, and more accurate appointments that need less follow-up (A. H. Chen et al., 2010; Esquivel et al., 2012; Hysong et al., 2011; Lai et al., 2018). Since case closure affects individuals beyond the scope of the network boundary and has the potential to increase the visibility and legitimacy of the network, we argue that individual-level effectiveness can give way to the higher levels of effectiveness in the context of service and referral networks.

After Provan and Milward's (1995) seminal study, scholars have considered various factors that should influence network effectiveness broadly. Turrini et al. (2010), and later Smith (2020), codified these factors into three groups: 1) network structure, 2) network functioning, and 3) network context. Studies examining network structure consider the role of network size (Provan & Kenis, 2007; Saz-Carranza & Ospina, 2011; Varda & Retrum, 2015), relational structure (Bunger & Huang, 2019; Provan & Sebastian, 1998; Raab et al., 2015), and network governance (Provan & Kenis, 2007; Provan & Lemaire, 2012; Raab et al., 2015). Studies examining network functioning consider trust (Klijn et al., 2010), learning (Provan et al., 2007, 2007), and management (Agranoff, 2007; Agranoff & McGuire, 2001, p. 19; Conrad et al., 2003). Studies examining network context often consider the resource munificence (Human & Provan, 2000; Raab et al., 2015) and the community support of the network (Emerson et al., 2011; Wang, 2016).

We follow Kenis and Raab's (2020) call to return to the work of the network and focus our attention on network functioning. Network functioning describes the operations and work of the network (i.e., the process) which prior research has shown can engage a positive feedback loop of process improving outcomes that improve process (Agrawal, 2019; Gazley & Guo, 2020; Ilgen et al., 2005). Traditionally, scholars have measured network functioning through proxies

like networking and management (Turrini et al., 2010), communication and decision-making (Lucidarme et al., 2016), and relationship development (J. G. Smith, 2020). Additional measures of a network's functioning might be its cost, capacity, engagement, adaptability, and resilience. All these measures are valuable indicators of network functioning and are necessary components for network effectiveness. At the same time, they can be difficult to measure, rely on perceptions, and slow to act upon. This study instead uses operational measures of network functioning accessible via the networks' shared technology platform. Specifically, we focus on two metrics, accuracy and time efficiency, that are relevant to the impact of the network. We detail each of these metrics and their relevance to referral networks and network effectiveness more broadly in the following sections.

Network Accuracy

In social networks, accuracy is understood as the extent to which the actor's perception of the network's structure matches the network's actual structure. For example, Knoben et al. (2018) define accuracy as the "amount of overlap between the network structure as perceived by key organization members and the objective network structure" (p. 472). Their hypothesis establishes that position in the network highly influences this metric. White and Watkins (2000) use a similar definition to analyze people's perception of their peer networks in rural Kenya. Accuracy is a common metric in social networks, often used to identify people who have a clear "picture" of the connections among their peers thereby having access to greater social capital (Brands, 2013; Krackhardt, 1987). Thus, research so far has highlighted the relevance of accuracy in affective- or affinity-based networks but not in more transactional relationships like referral networks.

The definition of accuracy for referral networks differs from the definition of accuracy for social networks. For example, Cheng et al. (2019) measure accuracy in a referral system as the ability of the system to predict relevant items for each user. This difference in definition arises because referrals traditionally involve relationships among organizations whereas affective networks involve relationships among people. Thus, to construct our definition of accuracy, we combine ideas from both social networks and referral networks. We define accuracy in referral networks as successfully routing a client to an organization who provides the services requested. That is, accuracy lies in the choice of an organization that can provide the service requested by the client.

This definition suggests that if organizations in a network have accurate knowledge of the services offered in the network and organizations' capacities, referring organizations should be able to refer a client to an organization to receive the service. On the other hand, if referring organizations lack a clear understanding of the services offered or other organizations' capacities, then referrals may be rejected and require additional follow-up. Thus, an accurate referral represents good knowledge of the network in terms of where to route clients.

Network Efficiency

Network efficiency, by contrast, has been measured in many contexts and, as a result, can be framed in numerous ways. One distinction is *cost efficiency* versus *process efficiency*. Cost efficiency describes the extent to which a network operates at a higher or lower financial cost. Process efficiency, by contrast, describes the extent to which network operations make the best use of their resources in terms of time, effort, or capacity. A common field in which we see network process efficiency is in transportation systems such as airports or bus routing. For example, Fairbrother et al. (2019) model airport congestion, where congestion is the extent to

which demand for landing/takeoff timeslots exceeds the availability of timeslots. An efficient airport thus minimizes that congestion by allocating time slots in a way that maximizes the number of landings/takeoffs.

In other transportation networks, it is common to see similar objectives that seek to minimize the time or the cost of providing the service. For example, a delivery company would like to plan its routes in a cost-efficient manner. Cost might be represented as distance, the number of vehicles used, the number of personnel, among others.

Efficiency also appears in the field of social networks. Such studies typically define efficiency as an actor sending a message to another target actor while minimizing some metric of interest. Often, this metric is the number of intermediaries or hops in the network, though it occasionally also includes time (Killworth et al., 2006; Singh et al., 2010). For example, Tanaka and Horvát (Tanaka & Horvát, 2019) measure efficiency as the average distance between all actors in a network, where distance is the number of intermediaries between two focal actors. Thus, more efficient networks have a smaller average distance while less efficient networks have a larger average distance. In this context then, minimizing the number of intermediaries improves both efficiency and accuracy based on our definition of accuracy.

However, in referral networks, the objective is to quickly connect the client with a provider. Drawing on research from referrals in healthcare (Fernández-Méndez et al., 2020), we define efficiency as the time it takes to connect a client to a service provider. An efficient network should be able to connect its clients with services in the least amount of time possible. There are three possible ways we could characterize efficiency in terms of time: 1) the time from initial referral to initiation of services; 2) the time from initiation of services to completion of services; or 3) the time from initial referral to completion of services. Since different services

require different time investments—for example, providing transportation services will likely

take longer than providing legal services—but should have similar times to connect with a

provider who can offer services, we rely on the first definition of efficiency. That is, we consider

efficiency as the time between an initial referral and the initiation of services with a provider. By

focusing on time to accept and removing the time to resolve the service request from the

efficiency measure, we can compare the efficiency among networks more fairly.

Altogether, these three metrics provide an early yet robust view into the relations among

network operations and network effectiveness. Prior research has suggested positive effects of

accuracy on effectiveness (Choi & Brower, 2006; Lucidarme et al., 2016) but a tradeoff between

efficiency and effectiveness (Bayne et al., 2017; Cepiku et al., 2020; Whelan, 2011). Lucidarme

et al. (2016) posit that greater informational accuracy in interorganizational communications

should promote effectiveness, and Choi and Brower (2006) discuss how clearer perceptions of

relationships among actors should improve coordination and collaboration leading to

effectiveness. Conversely, Whelan (2011) and Cepiku et al. (2020) both argue that emphasizing

efficiency in networks could lead to performance detriments (i.e., "faster/cheaper isn't better")

for which Bayne et al. (2017) find some evidence. There is, to the best of the authors'

knowledge, no study yet examines the relation between accuracy and efficiency. The literature

thus remains limited in its understanding of how network functioning influences network

effectiveness, especially from an operational lens. As such, our first question is:

RQ1: What are the relationships among service episode accuracy, efficiency, and

effectiveness?

Service Delivery Complexity

Recently, Saitgalina and Council (2020) in their examination of AmericaServes networks made the argument that services differ in their complexity. Specifically, they classified the services into three groups. They labeled simple services as those which are "basic, clearly defined, and straightforward" (p. 8), moderate as those which "have eligibility requirements … and their outcomes may not be readily available" (p. 8), and complex as those which have "strict eligibility requirements or the nature of the may not yield an immediate result" (p. 8). For the sake of simplicity, we use service complexity, delivery complexity, and service delivery complexity interchangeably. We focus on Saitgalina and Council's description of complexity because of recent policy movements which have been fostering interest and funding for coordinated care approaches (i.e., systems of care, coordinated care networks).

Unlike prior research onto service networks which typically study single-service networks, systems of care are multi-service networks. Gibson (2021) provides definitions for these. Single-service networks, like those studied originally by Provan and Milward (1995), connect organizations who provide the same service or variations of the same service together (e.g., therapy, psychiatry, residential care). Multi-service networks, however, link organizations that provide distinct services (e.g., mental health, housing, employment, financial services), allowing clients to access a variety of different services through interactions with any one provider. As such, there is limited extant research that can provide insights into the evaluation challenges multi-service networks face. Given the recent emergence of multi-service networks and the demonstrated importance of service type on network performance, we ask the following second research question:

RQ2: How does network functioning and effectiveness differ by service type?

Method

Sample / Cases

Our data come from 11 systems of care organized by AmericaServes. AmericaServes is "the [United States'] first coordinated system of public, private, and non-profit organizations working together to serve veterans, transitioning service-members, and their families" (AmericaServes, 2021). The 11 systems, or networks, operate in New York, North Carolina, Pennsylvania, Rhode Island, South Carolina, Texas, and the District of Columbia. The systems offer services in 21 different categories, including financial and income support, physical and mental health care, social and spiritual enrichment, employment assistance, and transportation. They accomplish this by following a centralized intake and referral process.

Clients may enter the network either through interacting with one of the providers in the network or by referring themselves into the network. In either case, the client's service request arrives at the network's Coordination Center, an elected or volunteer provider responsible for routing and monitoring all referrals in the network. The Coordination Center then conducts an intake procedure with the client to identify the client's full set of needs. With the client's needs identified, the Coordination Center then sends referral requests to potential providers within the network. If a provider accepts the referral, then care begins. If a provider rejects the referral, then the Coordination Center continues contacting providers in the network until it connects the client with care.

Their technology provider, Unite Us, maintains the platform through which AmericaServes tracks the progress of referrals and information about both organizations and clients. This data includes client demographics (e.g., age, gender, race, service era, eligibility information), organization attributes (e.g., program offerings, tenure in the network, number of

users), and referral information (e.g., service type, timing, current status, originating and

receiving organization). Notably, the timing data on referrals captures when the referrals first

entered the system and when key updates happened (e.g., rejection, acceptance, closure) to the

referral. Using the referrals' creation times, we took slices of this data from before the start of

each observed state's COVID response. By using data before the onset of COVID, we aim to

reduce the potential influence of circumstances external to the data (e.g., state and federal policy,

networks' crisis responses) on our results.

Data

We drew data from the Unite Us platform during a 30-day window just before states

began responding to the COVID pandemic. Since states responded at different times to the

pandemic, the exact dates of our data vary slightly between networks but range from early

January 2020 to late February 2020 (see Table 1). Drawing our data in this fashion allowed us

access to the most recent data on network operations before being affected by policies and

market changes related to COVID-19. This window provided us with a total of 1,917 service

episodes across all 11 networks. We then dropped all episodes that did not yet have a resolution

status (205 episodes), followed by those that were duplicated or self-resolved by the clients (104

episodes). We also removed 5 out of 21 service types (i.e., entrepreneurship, spiritual

enrichment, sports and recreation, substance use, wellness) from the analysis since they had less

than 15 episodes each (26 episodes). This left us with a final sample size of 1,575 service

episodes across all 11 networks, of which providers accepted 1,032 service episodes.

Measures

Our study focuses on three metrics available in the data that can characterize the

performance and functioning of the observed systems of care: effectiveness, efficiency, and

accuracy. Following the example of other studies on care networks and systems of care (B. Chen & Graddy, 2010; Lorant et al., 2019; Provan & Milward, 1995), we measure effectiveness as the provision of services. The Unite Us data track whether each service episode ultimately resulted in the receipt of services or not. Effectiveness is thus a dichotomous variable at the episode level which we aggregate to a percentage at the network level.

Likewise, for accuracy, the Unite Us data tracks whether each service episode involved a rejection prior to receiving services or not. Specifically, we examine accuracy as a dichotomy— whether the first provider to receive the referral accepted it. However, we note that accuracy might also be defined continuously since it is possible for a referral to cross multiple providers' desks before one eventually accepts it. Due to the rarity of a single episode receiving multiple rejections in our data, we choose to rely on the dichotomous measure. Therefore, accurate referrals have no rejections whereas inaccurate referrals have one or more rejections. We also aggregate this variable to a percentage at the network level.

Finally, we measure efficiency as the time, in days, between initiation of the service request and acceptance of the referral by a provider. We relied on time to accept rather than time to "close the case" since the former indicates the start of service provision and is a common measure of efficiency in healthcare studies (Barnett et al., 2016; Mohammed et al., 2020; Triyono et al., 2018). Since not every service episode resulted in services, we only calculate efficiency for the subset of episodes that resulted in services ($N = 1,575$; $n = 1,032$). To capture efficiency at the network level, we took the median time to accept a referral since our distributions were skewed.

Analysis

Our goal in this study is to gain a deeper understanding of the relationships among operational measures of network functioning and effectiveness, and the role of services in facilitating those relationships. To accomplish this, we conduct two different sets of analyses to address our two research questions. First, we examine our first research question which asks about the relations among accuracy, efficiency, and effectiveness for service episodes through correlational, inferential, and cluster analyses. We compute Pearson's correlations for each pair of metrics for each of the networks and overall, and test for their significance. We then perform inferential tests, Kruskal-Wallis and chi-square specifically, to identify whether there exist significant differences among the observed networks in terms of functioning and effectiveness. Finally, we conduct a cluster analysis using the *NbClust* package in R (Charrad et al., 2014) to further explore how the metrics relate to one another and to identify whether there exist certain performance profiles among the networks. We use *NbClust* as it provides a battery of 30 separate rules by which to determine the appropriate number of clusters. *NbClust* then uses the rule of majority to decide the appropriate cluster count since each test can recommend a different cluster count. In this way, *NbClust* combines the insights provided by various approaches to cluster selection and offers a more consensus-based path by which to conduct cluster analysis. We also compare the network clusters using Kruskal-Wallis and chi-square tests.

To address our second research question, we use a combination of cluster analysis, inferential analysis, and mixed-effects modeling. Cluster analysis allows us to reduce the 15 service categories included in our data to a more manageable number for modeling. We again use *NbClust* for this step. After clustering the services, we perform Kruskal-Wallis and chi-square tests to check for significant differences among the clusters in terms of our network

performance metrics. Finally, we use the identified service clusters as predictors in mixed-effect

models to understand how network functioning and effectiveness differ based on service type.

We use the *lme4* package in R (Bates et al., 2015) to test generalized linear mixed models

(GLMMs), specifically hierarchical logistic regression, for our dichotomous outcomes (i.e.,

accuracy and effectiveness), and regular linear mixed models (LMMs) for efficiency.

Results

Descriptive Statistics

Before exploring the results of our cluster analysis, we describe the observed networks

(see Table 2). The networks average 143 total service episodes during our observation window

with as few as 34 episodes and as many as 407. On average, the networks resolve 71.6% ($SD =$

14.2%) of referrals with 87.8% ($SD = 8.74$%) of referrals accepted by the first provider within

2.82 days ($SD = 1.45$). These values indicate that the systems of care perform relatively well and

successfully connect veterans to necessary care. Most service episodes result in care within just a

couple days and with the first organization asked to provide care. This means most clients

entering the network will commence care with a provider after 2-4 days and will then have that

provider's services resolve their needs.

Inferential tests examining the metrics across networks also find significant differences in

how networks perform. A Kruskal-Wallis test shows that the networks vary significantly in terms

of their efficiency ($\chi^2 = 68.98$, $p < 0.001$, $n = 1,575$). Likewise, chi-square tests show significant

variation across the networks for both accuracy ($\chi^2 = 131.97$, $p < 0.001$, $n = 1,575$) and

effectiveness ($\chi^2 = 115.87$, $p < 0.001$, $n = 1,032$). Collectively, these results mean that, despite

average trends indicating success, some networks are faster, more accurate, or more effective

than others. In the cluster analyses in the following sections, we aim to uncover whether there

exist performance profiles for these variations and what role services play in those performance

variations.

Relations Among Network Functioning and Effectiveness

To tackle our first research question, we first examine the correlations among the three

metrics we described. We find that the observed outcomes are lowly to moderately correlated, as

shown in Table 3. Efficiency and accuracy are negatively correlated across our 11 networks with

an overall correlation of -0.11. This is surprising since we would expect that referrals which are

accurate would also be more efficient. Instead, we find that referrals which receive care from the

first requested provider (rather than the second, third, or so on) tend to receive a response slower

than referrals which receive care from subsequent requests. This may suggest limited capacity

for certain services (i.e., wait times for low-supply services) or providers feeling uncomfortable

rejecting referrals (i.e., wait times for fear of reprisal).

By contrast, accuracy is positively correlated with effectiveness with a coefficient of

0.30. This indicates that referrals which enter care on the first try typically result in services that

resolve the client's request. This finding aligns with Choi and Brower's (2006) suggestion that

organizations with clearer perceptions of network relations coordinate and collaborate better.

When the Coordination Center knows the capacities and services of its network providers, it can

better refer to services that address clients' needs.

We also find no correlation between efficiency and effectiveness among the referral

networks. Correlations range from -0.07 to 0.23 but are all non-significant, with the overall

correlation being 0.00. We therefore find no direct link between efficiency and effectiveness as

expected by prior theory (Bayne et al., 2017; Cepiku et al., 2020; Whelan, 2011). However, the

negative correlation between efficiency and accuracy may suggest an indirect path through

which efficiency impairs network effectiveness. It may thus be the case that the Coordination Center has accurate knowledge of who is the best provider for the client (i.e., can resolve the case effectively) and that quicker entry into an alternative program may not offer the best results for the client.

To better understand the observed variations in network performance, we conducted inferential tests and a cluster analysis. Inferential tests revealed significant variation among the networks on efficiency ($\chi^2 = 54.08$, $p < 0.001$), accuracy ($\chi^2 = 90.58$, $p < 0.001$), and effectiveness ($\chi^2 = 82.11$, $p < 0.001$). The goal of the cluster analysis then is to assign the networks to groups based on their similarities across the performance dimensions (i.e., efficiency, accuracy, effectiveness). Using the *NbClust* package in R (Charrad et al., 2014), we tested the appropriateness of 2-, 3-, and 4-cluster solutions. For the 11 networks, 9 tests proposed a 2-cluster solution, 11 tests proposed a 3-cluster solution, and 2 tests proposed a 4-cluster solution. Following the rule of majority in *NbClust* we adopt a 3-cluster solution. Fortunately, the 3-cluster solution also appeared to be the most substantively meaningful of the options.

The results, shown in Table 2 and Table 4 and visualized in Figure 1, show clear, spatially proximal groups based on our three outcome dimensions. Cluster N1, colored red, is the least efficient (>4 days) and accurate (76.5%) but is relatively effective overall (68.5%). Cluster N2, colored blue, has middling efficiency (<3 days) and accuracy (86.6%) but is the least effective (58.2%). Cluster N3, colored green, is the most efficient (~1 day), accurate (95.3%), and effective (82.8%).

Respectively, we name the three network clusters "low-efficiency", "low-effectiveness", and "well-rounded" based on their performance profiles. However, we hedge discussions about any cluster being superior or higher performing than another cluster because the distributions of

service types across clusters are unequal. This point is crucial because some services are more complex than others (e.g., housing vs. income, healthcare vs. food). We, therefore, examine the service types represented in our data and cluster them together based on our outcome metrics as well as the total number of episodes. In doing so, we seek to discern the relationship between the distribution of service types within these network clusters.

The Effect of Services on Network Functioning and Effectiveness

Our first step in understanding the influence of services on network performance was to cluster the 15 services into a more manageable set. When clustering the services, we again tested for 2-, 3-, and 4-cluster solutions using *NbClust* (Charrad et al., 2014). Of the *NbClust* tests, 7 recommended 2-cluster solutions, 11 recommended 3-cluster solutions, and 4 recommended 4-cluster solutions. Following the majority rule used by *NbClust*, we opt for a 3-cluster solution. The service clusters use the same dimensions as the network clusters (i.e., efficiency, effectiveness, and accuracy) plus the total number of episodes for each service type. The resulting clusters can be seen in Table 5 and visualized in Figure 2.

The first service cluster, colored orange in Figure 2, contains good-based offerings (i.e., clothing & household goods, food assistance, income support) and simple, short-term services (i.e., physical health, social enrichment, transportation). Also included in the first service cluster are employment and benefits navigation, services for which there are dedicated VA programs, national nonprofit organizations, and codified procedures for referral and service provision. Because the services captured in the first cluster have so much structure and availability, we label this cluster as "low complexity" in the sense that they are less complex to deliver relative to other services. The second cluster contains some services for which there are dedicated VA programs but require greater time investment, additional supporting documentation, or both. For

example, the G.I. Bill grants veterans access to education benefits, but activating those benefits successfully takes time and veterans may need guidance in how to use them. Meanwhile, utilities assistance typically involves financial assistance with utilities but requires clients to collect documentation to support the case for assistance. Since these services in the second cluster are service- rather than goods-based, require greater investment of time and effort, but have structures in place to support their delivery, we refer to these as "mid complexity." The last service cluster then includes just three services: housing & shelter, legal, and money management. The Supportive Services for Veteran Families (SSVF) program managed by the VA helps veterans and their families access housing but may require clients to wait weeks or months for a slot to open. Money management services are also longer-term and legal services vary in their availability and structure to support referrals. As a result, we refer to this cluster as "high complexity."

The service clusters' performance on network effectiveness and functioning metrics reflects this spectrum of complexity. Low-complexity services are highly efficient (1.35 days), accurate (93.1%), and effective (77.9%). Mid-complexity services, as the name implies, have middling efficiency (3.46 days), accuracy (87%), and effectiveness (68.2%). High-complexity services then are the least efficient (5.97 days), accurate (70.6%), and effective (56.8%). Figure 2 also shows how the different services spread out in an almost conical fashion, worsening on one or more dimensions, as they move from the innermost, low-complexity cluster to the outermost, high-complexity cluster. One surprising result is that high-complexity services have the second-highest volume of episodes. This suggests that, for at least one high-complexity service, there is significant need within the veteran population but either insufficient supply or inefficient streamlining of the process by which to access those services.

Inferential tests of the service clusters further reveal the significance of the differences. A Kruskal-Wallis test shows significant variation among the clusters in terms of efficiency ($\chi2 = 58.82$, p < 0.001). Chi-square tests then show significant variation among the clusters on both accuracy ($\chi2 = 118.76$, p < 0.001) and effectiveness ($\chi2 = 59.02$, p < 0.001). The service clusters are therefore both descriptively and statistically distinct from one another. On its own, this finding suggests that we should be wary when comparing networks to one another using aggregate or composite measures as the services the networks provide may not be reasonably comparable.

With the clusters identified, we further explore their influence on network functioning and effectiveness through both standard and generalized linear mixed models (i.e., LMMs; GLMMs) using *lme4* (Bates et al., 2015). For all of our models, we opt to include service complexity as a categorical predictor rather than an ordinal predictor since the cluster analysis cannot fully identify an ordered relationship between the levels despite offering preliminary evidence of an ordered relation. Table 6 shows the results of the models for all three outcomes.

Our first model tests the effect of service cluster on network effectiveness and finds that networks resolve significantly fewer requests for mid-complexity (OR = 0.66, $p = 0.02$) and high-complexity services (OR = 0.39, $p < 0.001$) compared to requests for low-complexity services. Specifically, networks are two-thirds as likely to resolve mid-complexity and one-third as likely to resolve high-complexity service requests relative to low-complexity services.

The second model which links service cluster to network accuracy similarly finds that requests for mid-complexity (OR = 0.52, $p = 0.01$) and high-complexity (OR = 0.23, $p < 0.001$) are significantly less accurate relative to requests for low-complexity services. On average, Coordination Centers are half as likely to direct requests for mid-complexity services to an

appropriate provider on the first try, and only one-quarter as likely for high-complexity services. Given the positive correlation (see Table 3) between accuracy and effectiveness, this finding highlights the potential for clients requesting high-complexity services like housing or legal assistance to slip through the cracks.

The final model then examines the relationship between service complexity and network efficiency. Since efficiency is a continuous measure, the interpretation of our results are slightly different from the previous two models. We find that, compared to requests for low-complexity services, requests for both mid-complexity ($B = 4.67$) and high-complexity ($B = 4.55$) are slower by over 4 days on average. Here, we again turn our attention to the correlations in Table 3, specifically the negative correlation between efficiency and accuracy. We note that although requests are slower for mid- and high-complexity requests, this could signify effort on behalf of the Coordination Centers to compensate for the difficulty of the request and ensure that those requests ultimately receive services.

Collectively, the results across Tables 2 through 6 and Figures 1 and 2 show that the relations among network effectiveness, network functioning, and service type are complex. We find that accuracy, rather than efficiency, plays a direct role in influencing network effectiveness. Although accurate referrals tend to be slower, they also are more likely to be resolved. Examining the networks on all three outcomes at once rather than individually reveals that there are typical performance profiles—low-effectiveness, low-efficiency, and well-rounded—which indicate that composite, aggregate, or singular performance metrics may insufficiently describe networks' performance. Our last set of results then demonstrates that 1) services are not equal and 2) the complexity in delivering those services matters. Network performance thus cannot and

should not be reduced to a single metric. Instead, nuanced views that highlight network strengths and challenges are key. We expand on these findings in our discussion.

Discussion

This paper evaluates systems of care with special attention to how the process of collaboration can be observed by capturing operational interactions in the network, such as the routing of clients (Provan et al., 2009). This analysis surfaces an under-researched lens of network functioning through interactions and/or tasks, highlighting how referrals provide critical insight into the operation of collaborative systems of care. In doing so, we empirically examine the influence of network functioning on network effectiveness as modeled by Turrini et al. (2010). Moreover, we move past methods that conceptualize network functioning as broader processes such as trust, stability, or learning (J. G. Smith, 2020; Turrini et al., 2010) to examine functioning as the day-to-day work of the network (Kenis & Raab, 2020). We then explore how the daily work of the network connects to its overall, whole-network effectiveness (Kenis & Provan, 2009; Kilduff & Tsai, 2003; Provan & Milward, 1995). Our analysis thus expands the literatures on network functioning and network effectiveness.

By examining network functioning as the more transactional, interactional elements of networks rather than longer-term processes of collaboration, we can shed light on how networks function in real time. We look beyond network characteristics (J. G. Smith, 2020; Turrini et al., 2010) and individual leadership (Agranoff, 2007; McGuire & Silvia, 2009) through accuracy, efficiency, and effectiveness metrics for individual service episodes that the networks process. These metrics provide a lens to better understand how referral network processes perform across key indicators and how the services provided (i.e., distribution of labor Kenis & Raab, 2020) influences referral network performance. Moreover, the data in this study capitalize on a rapidly

growing market of technologies aimed at facilitating coordinated care networks and referral

management (Goldberg & Nash, 2021).

By comparing 11 whole networks (Provan et al., 2007) aiming to create positive wrap-

around care for veterans and their families, we demonstrate how these metrics explicitly capture

outputs in systems of care. This research expands the study of network effectiveness by focusing

on the ways that providers route referrals in the network (i.e., accuracy) and the responsiveness

of those providers to the referrals made (i.e., efficiency). We then connect these operational

metrics with actual receipt of services (i.e., effectiveness) rather than treating success as the

provider agreeing to provide services. As additional research on AmericaServes has shown, a

provider agreeing to provide services does not mean the client successfully follows through and

receives those services (Gibson, 2021). Therefore, this study also adds to the scant literature that

treats network effectiveness as the client receiving the service they sought (Conrad et al., 2003;

Saitgalina & Council, 2020).

Taking this operational perspective to network functioning reveals discrepancies between

provider matches, uncovers what areas providers might be underperforming in case resolution,

and informs management solutions as the work is occurring. The network cluster analysis shows

that networks can exhibit similar performance profiles (i.e., well-rounded, low-effectiveness,

low-efficiency) and the correlational analysis demonstrates that not all operational efforts align

with overall effectiveness. Table 3 shows that, for networks, better accuracy generally leads to

more effective referrals; however, accuracy may be at odds with efficiency. Less accurate

referrals tend to have a shorter time to care whereas more accurate referrals tend to have a longer

time to care. Yet, accurate referrals are more likely to result in service provision than inaccurate

referrals. Additionally, efficiency exhibits no correlation at all with effectiveness as we measure

it suggesting that time to care as a goal is separate from case resolution. Our results add context to prior research that theorizes an efficiency-effectiveness tradeoff (Bayne et al., 2017; Cepiku et al., 2020; Whelan, 2011) by showing that efficiency may impact effectiveness indirectly with network accuracy as one possible pathway.

Moreover, we find that networks can be characterized into distinct groups based on their performance across multiple metrics. We specifically identified well-rounded, low-efficiency, and low-effectiveness groups of networks, but studies employing a wider or different set of metrics may uncover other groups. However, we add a note of caution in interpreting these results, since service type is related to network performance. Specifically, networks that provide a higher percentage of complex services would have poorer performance, suggesting that an over reliance on these performance metrics without accounting for service type could provide perverse incentives.

Our analysis also provides theoretical support of how distribution and service type influence accuracy, efficiency, and effectiveness in a system of care. Services increase in complexity based on the extent to which they require customization, expertise, and involve complicated delivery processes (Saitgalina & Council, 2020; Zou et al., 2019). By clustering the service types based on the performance of requests for each service type, we expand on Saitgalina and Council's (2020) qualitative grouping to reveal how certain services quantitatively are more or less complex to *deliver* relative to other services. We emphasize complexity in terms of delivery here rather than the service itself because it is the actual provision and availability of services that creates challenges rather than the *connection* to the service provider. Theoretically, this finding suggests that network outcomes cannot be divorced from the real work of the network, providing additional support for the inclusion of tasks in the evaluation of networks

(Kenis & Raab, 2020). This is especially important as national policy in the U.S. continues to push for the development of coordinated care approaches that integrate health and social care (California Department of Health Care Services, 2022; Crumley et al., 2018; Leveraging Integrated Networks in Communities to Address Social Needs Act, 2021).

Beyond the substantial differences identified between different kinds of services, our analysis also demonstrated that service complexity significantly impacts network performance. As service complexity increases, effectiveness, accuracy, and efficiency all worsen. This aligns with Saitgalina and Council's (2020) findings which showed that networks performed better on mid- and low-complexity services on both case resolution and case duration. However, there remain open questions as to why these services are more difficult to deliver, what interventions are necessary to ease delivery of those services, and how networks align their efforts between the labor requisite for complex services relative to their reward (Kenis & Raab, 2020). As multi-service networks (Gibson, 2021) continue to grow in popularity, research that grapples with challenges of joining dissimilar services together under one umbrella will be crucial.

Collectively, this study makes the point that nuance is key. Evaluating networks based on aggregate, singular, omnibus metrics can easily cloud where networks are performing well and where they are struggling. Aggregate measures thus hide weak points of generally higher-performing networks (e.g., well-rounded networks) and overshadow the strong suits of networks that do not match that high-performance profile. Such blurring can then lead to mismanagement of the networks and unfair reward structures (Kenis & Raab, 2020). In turn, mismanagement and misalignment of rewards combined with the "thin markets" (S. R. Smith & Smyth, 1996) that human service organizations face can lead to cream-skimming, colloquially called "gaming the system," (Guul et al., 2021; Jilke et al., 2018; Koning & Heinrich, 2013) behaviors as networks

vie to meet performance milestones. These systemic issues ultimately penalize the beneficiaries of those services by limiting the services available in communities and the types of clients served.

Overall, our work makes four key contributions to the public administration literature and to practice in systems of care. First, our study breaks from the tradition of survey and interview research that dominates the literature and capitalizes on the transactional, time-stamped data captured by the networks' community referral technology. These kinds of data are increasingly common among systems of care and permit researchers a "micro" view of networks' operations, making questions related to the "black box" of network governance and functioning tractable. Using such field data also makes the research findings more tangible to practitioners and policymakers.

Second, our study expands the notion of service complexity and provides a preliminary clustering to show different services can be faster or easier, slower or harder to deliver. Goods-based (i.e., clothing & household goods, food assistance, income support) and simple, short-term services (i.e., physical health, social enrichment, transportation) were classified as low complexity. Mid-complexity services included education, individual & family support, mental/behavioral health, and utilities. Notably, these services require additional time investment or documentation to determine eligibility. Housing & shelter, legal, and money management were high complexity services. Each of these services were harder to access or had significant wait times.

Third, we connect service complexity to network performance, demonstrating that as complexity rises, performance falls across an array of metrics. We find that, despite the efforts of the observed networks to provide comprehensive wrap-around services, their performance tends

to be consistently higher in certain service domains relative to others. This suggests either capacity, coordination, or delivery challenges that lead to network specialization, which runs counter to the goal of these networks.

Finally, our study advances both public administration theory and network management practice. We define a major challenge facing systems of care (i.e., service complexity) in both their operation and evaluation, and make recommendations for how network managers can capitalize on data collected via referral technologies to improve service provision in their networks.

Management Insights

From our findings, we highlight two major insights for management. First, the results of our correlational analysis (see Table 3) show tradeoffs between the three performance metrics we observed. Accurate referrals promote case resolution but tend to have a longer time to care compared to inaccurate referrals. Time to care then, surprisingly, does not affect case resolution or receipt of services. Therefore, managers of coordinated care networks need to be mindful of how their various goals (e.g., efficiency, accuracy, effectiveness) interact and tradeoff with one another. Our findings simply translate to "faster is not better." At the same time, extensive wait times are not ideal either. Providers often describe how delays in access to care can lead clients to not follow-through to the point of services. Network managers thus need to adjust their goals and operations in ways that promote service delivery while also maintaining a sufficient degree of speed so as to promote client follow-through.

Second, managers need to capitalize on the nuance available in the data collected by coordinated care technologies. As we show (see Table 2), despite all 11 networks here following the same service delivery model, they exhibit different performance *profiles*. We cannot reduce

performance to a single number or indicator that describes the overall effectiveness of the

networks. Instead, we find that each network has areas in which it excels and in which it

struggles. Network management therefore does not mean managing the *whole* network (Kilduff

& Tsai, 2003) but managing targeted sections of the network that improve the whole network's

performance. Using such data in a nuanced fashion can identify areas in which the network needs

to foster new partnerships to grow its capacity, to work with current partners to understand the

causes behind performance struggles, and to review its current operational procedures. Detailed

views of data provide managers with more actionable insights and can reduce managerial burden

by focusing managers' efforts rather than relying on blanket approaches to management.

Policy Insights

This work also highlights two major points for policymakers. First, evaluations of

networks should extend beyond just network outcomes. Network functioning, particularly

operational views of network functioning (Kenis & Raab, 2020), have implications for network

effectiveness. Health care research on referrals has emphasized wait time (i.e., the time between

a request for care and receipt of services) as a key metric (Barnett et al., 2016; Fernández-

Méndez et al., 2020; Mohammed et al., 2020; Warren et al., 2011). We find that wait time (i.e.,

efficiency) does not correlate with effectiveness, yet providers have mentioned that wait times

can lead clients to not follow through on services (Gibson, 2021). Accuracy and efficiency might

then be pathways to effectiveness for coordinated care networks. Whole Person Care in

California (California Department of Health Care Services, 2022) which is supported by CMMS

1115 (Crumley et al., 2018) does not currently consider the role process plays in making

networks effective. Current and future policy can both benefit by encouraging grantees and

contracted networks to include process metrics in their data infrastructure as these metrics

provide invaluable and timely insights that allow managers to course-correct programs in a prospective rather than retrospective fashion.

Second, and related to process metrics, we recommend that policy encourages systems to address, rather than penalize, more complex services and client populations. Using a single metric, rather than a profile of process and outcome metrics, may promote undesirable behaviors through misplaced worker incentives. Skimming occurs when individuals manipulate or game incentive structures to achieve better performance outcomes (Guul et al., 2021; Jilke et al., 2018; Koning & Heinrich, 2013). For example, the recent LINC Act (Butler & Sheriff, 2021) aims to support the development of coordinated care networks in the U.S. If implementations of the policy rely solely on case resolution as the evaluation metric, this will incentivize networks to provide the services that are the easiest to resolve to the populations that are easiest to access. Policy that includes multiple measures of effectiveness can generate more precise evidence of network functioning and effectiveness and respond with more appropriate network interventions to achieve expected community outcomes. Additionally, policy can include line items to reimburse networks at higher rates for more complex services, for example. These recommendations can conserve time, effort, and resources that more general or blanket interventions would consume.

Limitations and Future Research

We also note several limitations with our current study. First, our study examines efficiency, accuracy, and effectiveness using dichotomous measures for the latter two. Studies adopting continuous measures of accuracy and effectiveness could further clarify the relationships among service complexity, network functioning, and network effectiveness. Networks also have values beyond these three metrics including engagement, equitable

participation, resilience, and capacity. These are other elements of network functioning which community referral technologies may already capture or proxy. Continuing to capitalize on the data available to managers in the field with the rigor upheld by researchers paves the way for impactful research that generates actionable insights for both managers and policymakers.

Second, the network outcomes proposed in this research describe service episodes. Our analysis provides insights into how performance and complexity vary by service, but future research could adopt a client-centered perspective. For example, by considering the sequence of services that clients request and receive, researchers can develop longitudinal measures of network success based on client trajectories rather than on episodic features. Understanding whether there is a systematic sequence of requests may help systems predict and offer services to clients earlier to promote self-sufficiency and stability and whether this varies by client type. Such systems would align with healthcare efforts in developing "smart" referral systems (Bowles et al., 2019; Triyono et al., 2018). Longitudinal, client-centered efforts also surface the need for new metrics that capture the degree to which networks are able, through coordinated activity, to produce better long-term outcomes.

Third, future research could investigate how networks respond to changes in demand as a result of environmental events, such as natural disasters, global pandemics, and seasonality. Human service networks exhibited high demand for some services (e.g., mid-complexity) and low demand for others (e.g., high-complexity) yet demand may change in response to external events. For example, housing assistance may be in greater demand when weather is extreme and food assistance requests may be more frequent when children are out of school and thus lose access to federal food assistance programs. Future research should examine the characteristics of

networks whose outcomes are more resilient to rapidly changing demands. Again, standardizing data would allow for better analysis of surges relative to base levels of demand.

Echoing across all these different directions is the need for research to adopt standards for describing the services that networks perform based on their complexity. These standards should also align with how policymakers and practitioners evaluate networks and should be accessible to policymakers and practitioners who participate in and manage networks. Without such standardization, network effectiveness research will continue to focus on case studies, limiting its generalizability. Open Referral Project's Human Services Data Specification standards or FindHelps's creative commons licensed Human Services Taxonomy offer two examples. By choosing a standard categorization system of human services, new knowledge can be gained about the types of activities, systems, and interventions that reliably improve network outcomes, without encouraging networks to favor easier services.

Conclusion

Our study is among the first to capitalize on real-time, grounded data to understand how the work of systems of care affects their overall performance. To capture this, we introduced two dimensions of network functioning, accuracy, and efficiency, established their relevance to the context of systems of care, and demonstrated how these dimensions differed from yet fed into traditional measures of network effectiveness. We also described the concept of service complexity and showed how our data reveals complexity through worsening performance.

As programs and policies like California's Whole Person Care (California Department of Health Care Services, 2022), the Centers' for Medicare and Medicaid Section 1115 Waivers (Crumley et al., 2018), and the LINC Act (Butler & Sheriff, 2021) continue to grow, research and evaluation that reveals rather than disguises complexity is paramount. Comparing systems

on aggregate measures, particularly a single aggregate measure, may provide incomplete or even unfair judgments of their performance, missing the areas in which they flourish and excel.

Moreover, if service complexity is not considered, these evaluations may then encourage networks to engage in cream-skimming behaviors where networks prioritize less complex service types. A nuanced view can identify where systems of care flourish or struggle, enabling more targeted interventions and more informed policy. We believe such data-driven insights increase the comprehensiveness of wrap-around services and reduce fragmentation in systems of care, realizing increased client access to care and better use of public dollars to support clients and communities. Further, by tracking collaboration via referral movements through systems of care, scholars can continue to empirically examine the process of governance and ultimately develop a more robust and palpable understanding of network effectiveness.

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Appendix: Tables & Figures

Table 1

Data Sampling by Network

Network	# Service Episodes	# Episodes Accepted	Data Window
2	201	171	01/11/2020–02/11/2020
3	407	344	01/14/2020–02/14/2020
4	151	99	01/03/2020–02/03/2020
5	34	5	01/06/2020–02/06/2020
7	95	38	01/11/2020–02/11/2020
10	218	108	01/22/2020–02/22/2020
11	60	54	01/01/2020–02/01/2020
12	205	110	01/06/2020–02/06/2020
13	104	45	01/09/2020–02/09/2020
14	57	53	01/02/2020–02/02/2020
18	43	5	01/20/2020–02/20/2020
Total	1,575	1,032	

Note. Dates are in month/day/year format. We compute effectiveness and accuracy using the total number of service episodes, and efficiency using the number of accepted service episodes.

Table 2

Dependent Variables by Network

Network	Cluster	Efficiency***	Accuracy***	Effectiveness***
4	N1	3.97	83.44	82.12
7	N1	5.24	86.32	69.47
10	N1	4.62	67.43	58.72
12	N2	2.82	86.83	60.98
13	N2	3.01	81.73	50.96
14	N2	3.70	92.98	56.14
18	N2	1.85	88.37	65.12
2	N3	1.84	93.03	86.07
3	N3	0.94	97.05	80.10
5	N3	1.85	100.0	94.12
11	N3	0.98	88.33	83.33
Overall	–	2.82	87.78	71.56
Statistic				
Kruskal-Wallis	–	68.98	–	–
Chi-square	–	–	131.92	115.87
p	–	<0.001	<0.001	<0.001

Note. Efficiency is measured as the median time in days to accept a referral, and accuracy and effectiveness are measured as percentages. Outcomes compared via Kruskal-Wallis and chi-square test. $N = 1,575$. $p = *** < 0.001$.

Table 3

Correlations of Dependent Variables by Network

Network	Efficiency ✕ Accuracy	Efficiency ✕ Effectiveness	Accuracy ✕ Effectiveness
2	-0.10	-0.07	0.18**
3	—	0.01	0.20***
4	-0.35***	-0.02	0.03
5	—	—	—
7	—	0.17	0.35***
10	-0.07	-0.04	0.49***
11	0.02	-0.01	0.54***
12	—	0.14	0.27***
13	0.03	0.05	0.24**
14	0.03	0.23	0.31*
18	—	—	-0.11
Overall	-0.11***	0.00	0.30***

Note. $N = 1{,}676$. $p = * < 0.05$, $** < 0.01$, $*** < 0.001$. Network 5 had perfect accuracy, so it is not possible to compute correlation values related to accuracy for Network 5.

Table 4

Dependent Variable Mean Value by Network Cluster

Network Cluster	# Episodes	Code	Efficiency***	Accuracy***	Effectiveness***
Low-efficiency	464	N1	4.22	76.5	68.5
Low-effectiveness	409	N2	2.87	86.6	58.2
Well-rounded	702	N3	1.01	95.3	82.8
Statistic					
Kruskal-Wallis	1,032	–	54.08	–	–
Chi-square	1,575	–	–	90.58	82.11
p	–	–	<0.001	<0.001	<0.001

Note. Efficiency is measured as the median time in days to accept a referral, and accuracy and effectiveness are measured as percentages. Accuracy and effectiveness compared using chi-square tests ($N = 1,575$); efficiency compared using Kruskal-Wallis test ($N = 1,032$). $p =$ *** < 0.001.

Table 5

Dependent Variable Mean Value by Service Cluster

Cluster	Service Types	Efficiency***	Accuracy***	Effectiveness***	Size
Low complexity (orange)	• Benefits navigation • Clothing & household goods • Employment • Food assistance • Income support • Physical health • Social enrichment • Transportation	1.35	93.1	77.9	1,043
Mid complexity (purple)	• Education • Individual & family support • Mental/behavioral health • Utilities	3.46	87.0	68.2	192
High complexity (gold)	• Housing & shelter • Legal • Money management	5.97	70.6	56.8	340
Statistic					
Kruskal-Wallis	–	58.82	–	–	1,032
Chi-square	–	–	118.76	59.02	1,575
p	–	<0.001	<0.001	<0.001	–

Note. Complexity refers to the complexity in service delivery, rather than the services themselves. Efficiency is measured as the median time in days to accept a referral, and accuracy and effectiveness are measured as percentages. Service episodes for entrepreneurship, spiritual enrichment, sports and recreation, substance use, and wellness were excluded from the analysis. Sample size is smaller for Kruskal-Wallis test since not all service episodes were accepted. $p =$ *** < 0.001.
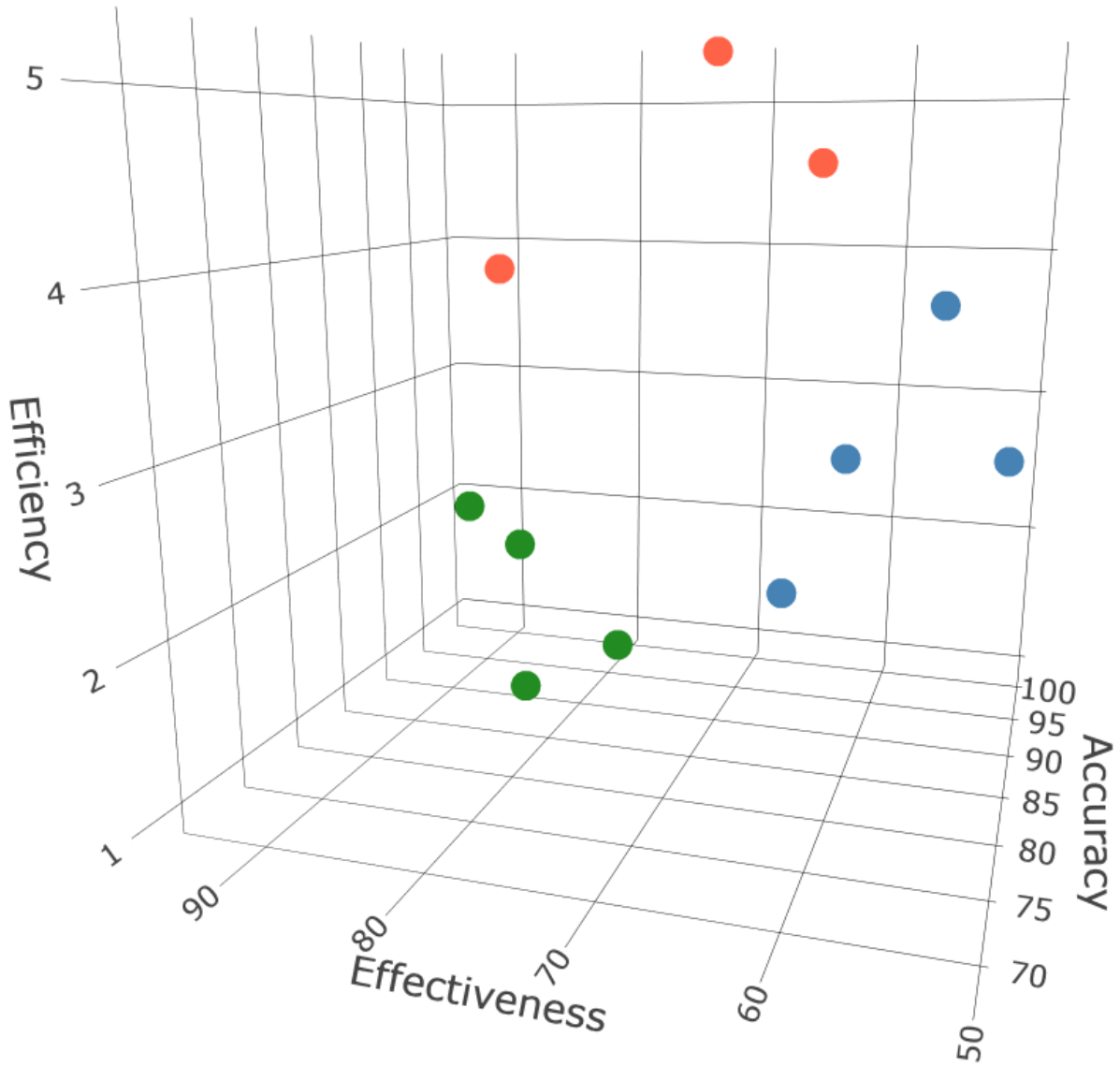
Table 6

Generalized Linear Mixed Model Results for Network Effectiveness and Functioning

Effect	Estimate	SE	OR	*t*	*z*	*p*	95% CI
Effectiveness							
Service Cluster (M)	-0.41	0.18	0.66	–	-2.29	0.02	[-0.76, -0.05]
Service Cluster (H)	-0.94	0.14	0.39	–	-6.47	<0.001	[-1.22, -0.65]
Accuracy							
Service Cluster (M)	-0.65	0.25	0.52	–	-2.57	0.01	[-1.14, -0.14]
Service Cluster (H)	-1.46	0.18	0.23	–	-8.04	<0.001	[-1.83, -1.11]
Efficiency							
Service Cluster (M)	4.67	1.06	–	4.41	–	–	[2.58, 6.74]
Service Cluster (H)	4.55	0.91	–	5.02	–	–	[2.79, 6.37]

Note. The predictions for effectiveness and accuracy use generalized linear mixed models (GLMM), specifically hierarchical logistic regression since effectiveness and accuracy are dichotomous variables. The predictions for efficiency use standard linear mixed models (LMM), also called hierarchical linear modeling (HLM). Computation of *p*-values are contentious in GLMM and LMM so we also present the 95% confidence intervals to demonstrate significance.
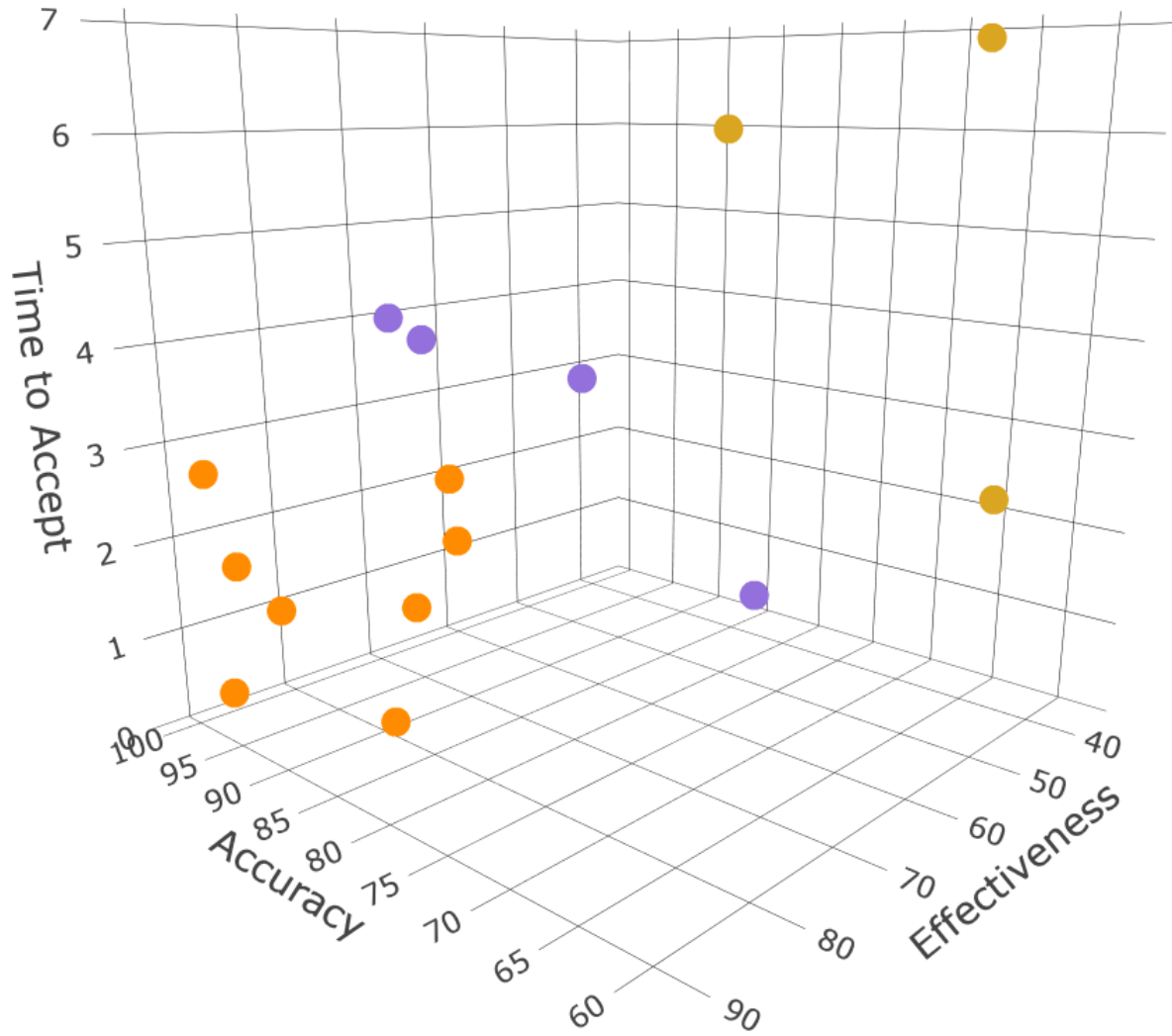
Figure 1

Cluster Analysis of Networks

Note. Optimal performance is at the bottom, back, left corner. Color represents network cluster.

Low-efficiency = red, low-effectiveness = blue, well-rounded = green.

Figure 2

Cluster Analysis of Services

Note. Optimal performance is in the bottom-left corner. Color represents service cluster. Low-complexity = orange, mid-complexity = purple, high-complexity = gold.