A DECENTRALIZED UBER?
OPERATIONAL ANALYSIS OF COOPERATIVE RIDESOURCING -
A CASE STUDY OF ARCADE CITY IN AUSTIN, TEXAS

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ABSTRACT
This paper examines the operational qualities of Arcade City (AC) Austin, a decentralized ridesourcing cooperative that emerged in mid-2016 when Uber and Lyft temporarily left the Austin market. Platform cooperatives are an emerging alternative to more commercial 'sharing economy' platforms. They are democratically governed and cooperatively owned and aim to allow users and society at large to benefit from the shifting of transactions to the digital realm. AC Austin consists of a 42,000-member Facebook group that has no centralized management structure and relies on the group's drivers and moderators to coordinate on-demand rides, deliveries, and other services between requesters and drivers. We collected trip-level request data from three weeks of operations in April and May 2018. The analysis reveals that 96% of all requests received a response from a driver or moderator and 80% of all requests were successfully completed. The average time it takes for a driver to respond to requests is 5.5 minutes and the average overall wait time is just under 15 minutes. In addition, we find that requests with driver response times longer than 14 minutes or overall wait times longer than 24 minutes are much more unlikely to be successfully completed than those with response and wait times under these thresholds. These operational results reveal ridesourcing travel behavior insights that are typically not publicly released, due to propriety concerns of commercial ridesourcing companies. Overall, the results show that the decentralized cooperative ridesourcing model can be surprisingly effective at serving rides and other requests.

INTRODUCTION

Digital sharing platforms have expanded in popularity over the past decade as technology has increased connectivity and reduced transaction costs, making sharing assets and services cheaper and easier than before *(1)*. These platforms have proliferated in the transportation industry over the last two decades in the form of shared mobility services, which refer to the shared use of a vehicle, bicycle, or other mode that enables users to gain short-term access to transportation modes on an as-needed basis *(2)*. This includes modes like carsharing, bikesharing, carpooling, microtransit, and ridesourcing (also known as Transportation Network companies like Uber and Lyft). Some of these shared mobility services operate in a peer-to-peer (P2P) manner, with vehicle owners or transportation service providers connecting with renters or users, typically through a centralized digital platform that processes transactions and manages logistics. The most prominent example of P2P shared mobility are ridesourcing services like Uber and Lyft. Ridesourcing services use smartphone apps to connect drivers using their personal vehicle with passengers requesting rides. P2P ridesourcing launched in San Francisco during summer 2012 with the introduction of Lyft and uberX *(3)* and the model has expanded rapidly around the world over the last six years. However, serious problems can arise through P2P platforms when consolidated power is held by a small number of platform owners who often use unfair and extractive techniques to benefit themselves and their shareholders as opposed to the platform users and society as a whole. Ridesourcing companies are no exception, and there have been many equity, labor, and environmental concerns regarding the operations of these companies.

Platform cooperatives are an emerging approach to more centralized 'sharing economy' companies that involve cooperatively owned, democratically governed platforms to facilitate the sale of goods or exchange of services. The goal of platform cooperatives is to decentralize the power of protocols and platforms to allow users and society at large to benefit from the shifting of transactions to the digital realm *(4)*. In addition, emerging technologies like blockchain and distributed ledgers could help enable platform cooperative models through the disintermediation of transactions. Although ridesourcing services are a commonly cited possible application for platform cooperatives, there are very few organizations actually operating as ridesourcing cooperatives, at present. In May 2016, Uber and Lyft exited the Austin, Texas market when the city voted for stricter fingerprint background checks for drivers *(5)*. More than a half dozen other ridesourcing organizations emerged in their absence, including Arcade City (AC) Austin, a decentralized ridesourcing cooperative which serves as a platform for coordinating on-demand rides, deliveries, and other services between requesters and drivers. AC Austin consists of a 42,000-member Facebook group that is not incorporated, has no centralized management structure, and relies on the group's members and moderators to keep operations running smoothly. Drivers on the group typically charge a rate of $2 per mile with a $10 minimum charge. AC Austin is one of the only ridesourcing platforms that entered Austin in mid-2016 which is still operating today since Uber and Lyft returned to Austin in May 2017 when state law superseded Austin's city laws *(6)*. The group is also one of the only examples in the world of a decentralized ridesourcing organization serving on-demand rides and requests.

For this reason, decentralized cooperative ridesourcing and shared mobility models have almost no existing research coverage, at present. Therefore, we believe that our evaluation of AC Austin's operations fills knowledge gaps and provides important and novel insights into the benefits and drawbacks of decentralized ridesourcing as compared to more prevalent centralized commercial approaches. By examining the operational qualities of AC Austin, we uncover key metrics behind how and why this unique operating model has succeeded in Austin and we offer the first known analysis of important operational aspects for sustaining decentralized ridesourcing networks.

This paper uses data collected over three weeks of continuous operations from mid-April to early-May 2018. We collected trip-level data (trip requests and driver responses) directly from posts on AC Austin's Facebook page. We explore metrics such as: number of active drivers and requesters, response time to requests, and wait times. Since no central operator matches requesters with drivers, there are a number of metrics that are unique to AC Austin's decentralized operating model, including: helper and moderator request assistance and its effectiveness, number of drivers responding per request, failed trip requests and reason for failure, special requests like food delivery, moving help, and others, and the portion of rides scheduled in advance (as opposed to on-demand). We also examine these metrics temporally, as appropriate. Our analysis reveals the scale of AC Austin's operations and provides valuable insight into the factors that lead to lower response and wait times and successful requester-driver matching.

The first section of this article reviews literature on transportation and platform cooperatives as well as efforts using blockchain in shared mobility applications. Next, we describe the study methodology and its limitations. The results are presented in the following section, including an analysis of the number of participants and requests, request types, and the operational and matching effectiveness enabled by the platform. Data collection, curated aggregation, and crosstabulation are the main methods used in the analysis. Key findings are summarized and discussed in the conclusion.

BACKGROUND

Cooperatives have organized throughout history, typically in response to economic and social stress. The development of modern cooperative organizations is rooted in the response to the Industrial Revolution in England during the late 18th and early 19th centuries *(7)*. What is now often regarded as the prototype of the modern cooperative, the Rochdale Equitable Pioneers Society, was formed in 1844 as a group of 28 men working as weavers in English cotton mills *(8)*. The group developed a set of principles based on the values of self-help, self-responsibility, democracy, equality, equity and solidarity, that are still commonly used to guide cooperatives today *(9)*. Cooperatives exist in many industries, including agriculture, insurance, retail, housing, banking/credit unions, and others. In the U.S. alone, there are over 29,000 active cooperatives with 350 million cooperative memberships and over $650 billion in total revenues *(10)*.

Some cooperatives have emerged in the transportation industry, mainly in the form of taxi cooperatives. The oldest taxi cooperative in the U.S. still operating today is Union Cab of Madison, Wisconsin, which formed in 1979 after two strikes against a traditional taxi service. Union Cab now has 260 workers and $6.7 million in annual revenue *(11)*. As of May 2015, there were 930 workers in the U.S. employed at worker cooperative taxi companies, with more than 800 additional workers in mid-2016 after the successful launch of Green Taxi in Denver, Colorado *(11)*. However, traditional taxi companies and ridesourcing services command a far larger overall share of the U.S. on-demand transportation market compared to cooperative organizations. Ridesourcing's large market share is due to many factors, including the low barriers of entry for drivers, high driver turnover, the absence of restrictions on the supply of ridesourcing vehicles, and the ease of use of ridesourcing apps and streamlined payment.

Mostly small-scale at present, a number of platform cooperatives have emerged in recent years with hopes of bringing more equitable ownership and governance to digital sharing platforms. Some examples of platform cooperatives include: Fairmondo, a German digital cooperative marketplace where sellers who own the platform connect with potential buyers; Stocksy, a stock photo website with nearly 1,000 artists and a revenue of over $10 million in 2016 *(12)*; and Loconomics, a San Francisco-based group launching a worker-

owned platform for freelancing professionals *(13)*. Other than taxi cooperatives, there exist a number of shared mobility platform cooperatives, including: Modo, a member-owned carsharing organization in British Columbia, Canada operating since 1997 with more than 20,000 members; La'Zooz, a carpooling platform based in Israel; and Tapazz, a Belgian P2P carsharing organization *(14)*.

Although there exist successful platform cooperatives in some types of shared mobility, AC Austin is one of the only decentralized organizations functioning at a meaningful scale as an on-demand ridesourcing service, at present. In addition, AC Austin's decentralized and informal operational and governance structure make it unique compared to more organized taxi cooperatives and most platform cooperatives. In this sense, AC Austin also aligns with the emerging movement of decentralized organizations, which often use or plan to use blockchain technologies to enable disintermediated transactions or operations. Blockchain allows for the execution of transactions and smart contracts without intermediaries through cryptography and incentivization mechanisms to create a mutually agreed-upon record of transactions *(15)*. AC has its own intentions to incorporate blockchain technology and cryptocurrency payment into its platform, although the details are unclear at present *(16)*.

There are many nascent efforts exploring the use of blockchain and distributed ledger technology in shared mobility applications. These include: MOBI, a consortium of companies, governments, and NGOs working on use cases and standards for blockchain in the mobility industry *(17)*; Helbiz, which plans to use its own cryptocurrency to enable P2P carsharing *(18)*; and VV Share, a proposed blockchain-based ridesourcing app backed by a former execute of China's Didi *(19)*, among many others. In addition, there are a growing number of efforts focusing on using blockchain technology to enable multi-modal trip aggregator platforms, such as: Mobio, a Lithuanian startup developing a decentralized open source protocol to integrate multiple mobility providers *(20)*; and IoMob, a blockchain-based system under development that aims to help mobility services scale by handling payments, customer registration, and reputation management *(21)*, among others pursuing similar projects. However, none of these aforementioned blockchain mobility efforts are operating at a significant scale, at present.

There has been very little academic research on the topic of blockchain in shared mobility applications. The few studies on the topic typically review companies and potential use cases, like digital identity, supply chain efficiency, usage-based tolling or taxes, as well as shared mobility systems and automated vehicles (AVs), among other potential uses *(22, 23, 24)*. However, no studies that we are aware of evaluate the real-world operational qualities and implications of decentralized shared mobility organizations, which is the key focus of this article.

There also exist gaps in the literature regarding the operations of more prevalent commercial ridesourcing operations. While there is some publicly available research on the time of day, day of week, trip distance, and trip purpose profiles typical of ridesourcing services *(25, 26, 27)* there is little to no coverage on other critical functions of ridesourcing networks like when or why ride requests succeed versus fail. Some of the only publicly released information on trip request completion comes from Uber's publicly subsidized pilot operations in the small city of Innisfil, Canada, where only 75% of trip requests were completed in November and December 2018 *(28)*. It should be noted that this rate is most likely much higher in large cities where ridesourcing more commonly operates and driver supply is larger and trip demand is higher. This hesitance to share operational data is likely because these data are considered sensitive trade secrets by commercial ridesourcing companies. These companies may believe that releasing these data could harm their reputation or market position if shared with competitors or public agencies. For these reasons,

the major U.S.-based ridesourcing companies rarely share certain types of data with other entities or the public. In this sense, AC Austin's operations through a Facebook group offer the unprecedented opportunity to study certain service metrics of ridesourcing operations, such as ride request failure and when and why it occurs.

In this paper, we focus on a decentralized ridesourcing service, AC Austin, which links community drivers with those requesting rides, deliveries, or other services through a membership-based Facebook group. We examine their scale in Austin and assess various operational aspects like request type, pre-scheduled rides, response and wait times, request success rate, and reasons for failed requests. We also explore operational metrics unique to the group's decentralized platform cooperative operating model, like helper and moderator assistance and multiple driver responses per request.

METHODOLOGY

This paper uses operational data collected from AC Austin's Facebook group over the span of three weeks between April 16th and May 7th, 2018. We recorded trip-level attributes of every request over the three weeks and corresponding driver, helper, or moderator responses to these requests. These attributes were manually scraped from the AC Austin Facebook group page itself. Recorded attributes include: member identifiers, date and time of requests, time elapsed before driver or helper/moderator responses, proposed wait time by drivers, driver selection (if multiple drivers responded), special non-ride requests like deliveries, whether the ride was pre-scheduled or not, and payment type used (if specified). We also recorded whether or not the request succeeded and if not, what the given reason was for request failure (no drivers, requester unresponsive, request canceled, etc.). The operational data over three weeks included 3,123 requests from 906 unique requesters, averaging 149 public requests per day. There were 90 unique drivers responding to requests during this time period. Approximately 25% of posted requests over the three weeks were deleted for unknown reasons. While we could still record when the deleted request occurred, we could not assess driver responses or matching success rates of these deleted posts, due to missing information.

Study Limitations

A main limitation of our methodology is that we only collected data from requests posted to AC Austin's Facebook group. According to sources familiar with the group, a substantial number of requests occur through direct messaging to potential drivers. Because these requests are never posted publicly on the Facebook group, we had no way to record these requests. Therefore, the total volumes in our study are likely an underestimate of the actual activity of the group over the study timespan.

Another limitation is that we were not able to analyze spatial data related to trip requests. Although origin and destination are often specified by the requester, these data are not collected in a standardized format and thus require extensive data cleaning. For this reason, associated metrics like trip distances and overall vehicle miles traveled were not assessed in this study.

A final limitation is that because we only analyze activity data and not other sources like survey data, we do not gain insights related to trip purpose, mode substitution, vehicle ownership impacts, reasons for using AC instead of commercial ridesourcing services, and member demographics. We hope to explore spatial and survey-based metrics in subsequent studies.

RESULTS

As part of our results discussion, we highlight three key areas of our analysis, including: 1) the number of participants and requests, 2) request types, and 3) operational effectiveness.

Number of Participants and Requests
In our analysis, we aggregated participant and request data over the three-week study span in order to better understand the scale and basic request patterns of the group. Over the three weeks, there were 906 unique requesters who made 3,123 cumulative requests served by 90 unique drivers. There are also helpers or moderators, who are those who comment on a request post in order to aid in the matching process, either with tags to a driver they think may be active or to "bump" the post back up to the top of the page for greater visibility. Although there are only nine official moderators (as designated on the Facebook page), we found there were 99 unique helpers over the three-week period. However, two of the helpers (who also happen to be official moderators) accounted for 63% of all help posts.

During the three weeks, the average requester completed just over three successful ride or other requests, while the average driver gave slightly more than 20 rides. Similar to other digital platforms, we also find that a relatively small portion of participants make up the majority of activity in the group. While there are over 900 requesters, we find that just 92 requesters (about 10%) made up more than half of all requests. Similarly, 16 drivers (about 18%) gave more than half of the all rides on the platform during our study period.

Requests by Day of Week and Time of Day
As expected, there are a greater portion of requests made on some days of the week than others. Saturday is the most active day, with 188 requests, on average, over the three weeks. Friday and Sunday also contain larger amounts of requests, at 165 and 178, respectively, showing that Fridays and weekends receive a larger portion of requests than the average weekday. Tuesdays through Thursdays experience lower request rates than other days of the week, ranging from 113 to 129 requests, on average.

Requests also fluctuate depending on the time of day. As shown in Figure 1, the majority of public requests are made between 2pm and 4am, with slight peaks from 2pm to 7pm, and 10 pm to 3am. Morning and early afternoon requests are less prevalent on the platform. This pattern of higher request rates during the late afternoon, evening, and early AM time periods may due to the popularity of certain trip types on the network, like commuting home from work or going to and from restaurants/bars. More research is needed to more deeply assess trip purposes on the AC Austin platform.

FIGURE 1 Request Time of Day Distribution
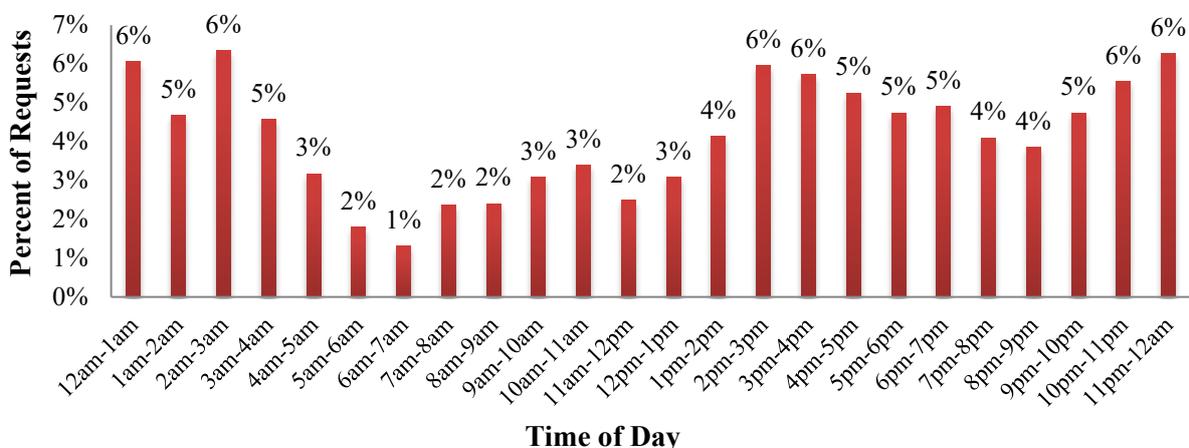
To summarize, a greater portion of requests on the AC Austin platform are made on Fridays and weekends, and during the late afternoon, evening, and early AM time periods.

Request Types
In this section, we focus on special request types that occur on the network. Although ride requests are the most common, making up 92% of all public requests during the three weeks, the remaining portion of requests are for deliveries or other purposes. The 8% of non-ride requests are most commonly for goods delivery purposes, with 51% for food delivery, 8% for alcohol delivery, and 22% for other goods delivery. In addition, 13% of non-ride requests are for moving help (furniture items or all-day moving help), 5% of these requests are for car help (to jump an engine, unlock a car, etc.), and 2% are for other requests. This portion of non-ride requests is notable because it shows how flexible and easily customizable special requests are on the AC Austin platform, likely due to the functional simplicity of the platform itself. Large commercial ridesourcing companies around the world have entirely different platforms for their food delivery services (e.g., Uber Eats, GrabFood, and others) because their ride-specific platforms are more rigidly built to serve rides only. In addition, commercial ridesourcing companies do not offer moving and car help, which typically require using different types of platforms altogether (like TaskRabbit and others). In this way, the simplicity of the platform and the decentralized nature of operations enable a wider range of request types under the same common platform.

Pre-scheduled rides are also common on the platform, comprising 19% of all public requests. Although most pre-scheduled requests are made only a few hours in advance, some requesters book rides for a day or more in advance. Pre-scheduled requests are slightly more common in the morning and early afternoon time periods and may reflect riders scheduling commute trips to work. Pre-scheduled ride functionality was only adopted by the major ridesourcing companies in the U.S. within the last two years *(29)* and is another feature that is enabled by the platform's simplicity.

The AC Austin platform also allows for a diverse range of payment types, and some requesters specify their preferred payment type when posting a request. Thirty-nine percent of public requests over the three weeks specified preferred payment types, with 93% of those specifying cash as a preferred payment type. Venmo, credit card, debit card, PayPal, and Facebook Pay were also specified as payment types, among others.

Operational Effectiveness
In this section, we cover the operational effectiveness of the AC Austin platform by exploring driver and helper response times to requests, total wait times, and the matching success rates of requests based on various factors. Because AC Austin does not have a centralized operator (like many taxi companies) or algorithms (like most commercial ridesourcing companies) that match requesters with drivers, the network relies on drivers identifying and responding to requests themselves and on helpers and moderators to aid in the matching process by identifying potential drivers or calling additional attention to requests (also known as "bumping"). Overall, 96% of requests received some form of attention from a driver, helper, or moderator. Eighty percent of all requests were successfully matched with a driver. The success rate is lower for non-ride requests (66%) and slightly higher for ride requests (81%) and pre-scheduled requests (84%). We discuss request matching success factors and reasons for failed requests in more detail later within this section.

Request Response Metrics
The responsiveness of drivers and wait times for requests are major factors contributing to successful matching and to the success of the AC Austin platform, in general. Typically, drivers will respond to ride requests with an estimated time of arrival (ETA) based on the location of the requester. A unique feature of this type of decentralized platform is that

multiple drivers often respond to a single request and the requester then chooses which driver he or she prefers. While the majority of requests have just one driver responding, at 66% of all requests, 21% of requests have two drivers responding, and 5% of requests have three or more drivers responding. Eight percent of requests do not receive a driver response. This equates to 1.24 drivers, on average, per request over the three weeks. This is one of the most unique features of the AC Austin network compared to commercial ridesourcing platforms, which do not allow riders to choose their driver but rather automatically provide matches based on their proprietary algorithms.

For all requests, the average time elapsed between request post and first response by a driver, helper, or moderator (which we refer to as "response time") is 5.2 minutes. For real-time ride requests (i.e., not pre-scheduled or non-ride requests), the average response time of the first responding driver is 5.5 minutes and the average lowest posted total wait time (response time plus ETA) is 14.8 minutes. We remove pre-scheduled and non-ride requests from response and wait time analyses due to incomplete ETAs for non-ride requests and longer response times for pre-scheduled requests since some do not require immediate responses because they are booked in advance. These response and total wait time metrics vary depending on the time of day. Figure 2 shows the average first response time (by a driver, helper, or moderator), the average first driver response time, and the average lowest posted total wait time by hour of the day, for all real-time ride requests. We find that the lowest average response and total wait times occur during 8pm to 10pm and 1am to 4am. These two timespans exhibit response and wait time metrics that perform better than the overall averages. For both the 8pm-10pm and 1am-4am time periods, the average first response times are all under 4 minutes, the average first driver response times are under 5 minutes (with the exception of 4am), and the average total wait times are all under 14 minutes. This pattern may be due to the relatively greater number of requests occurring during this timeframe and the larger supply of potential drivers. This also suggests that the AC Austin network may be especially effective at serving certain trip types, like rides to restaurants/bars (8pm-10pm) and from restaurants/bars (1am-4am), although more research is needed to fully investigate trip purposes. Average response and wait times are highest during the early morning after 5am and are about average or slightly higher than the overall average times during the afternoon.

FIGURE 2 Average First Response and Total Wait Times by Hour of Day
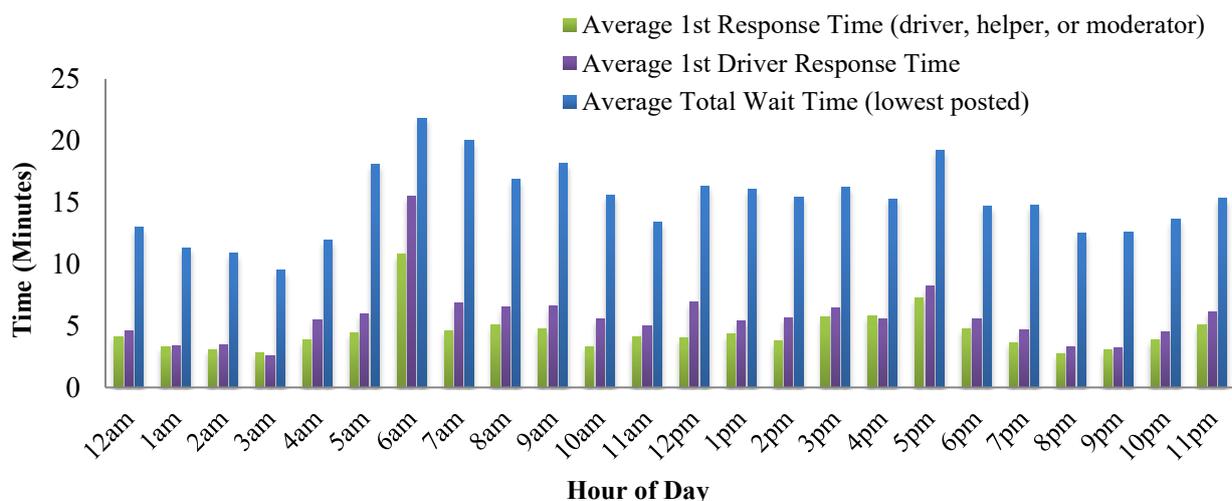
Although there exists very little publicly available information regarding wait times of commercial ridesourcing services, the average wait times on the AC Austin network are likely

higher than the wait times of Uber and Lyft in Austin due to the larger scale of operations and algorithmic matching. Next, we explore how response and wait times affect matching success.

Matching Success Factors
The time it takes for drivers, helpers, or moderators to respond to requests and for drivers to arrive at the requester's location are key operational factors that influence whether a request is successfully completed or not. In this section, we analyze how first responder times, driver response times, and total wait times affect matching success rates. We also assess reasons for unsuccessful requests.

Twenty percent of total requests on the AC Austin platform over the three study weeks were not successful. In order to better understand why some requests fail, we classified failed requests into five categories based on rider, helper, and moderator comments to the request. Half of the failed requests were due to the requester, with 2% being cancelled, 27% being resolved somehow (got a ride from a driver off-platform, from a friend, or from another ridesourcing service), and 22% having no follow-up response after drivers responded. On the other hand, 30% of failed requests were due to no drivers responding to the request. About 20% of these failed requests had an unclear outcome based on missing information in the comment thread of the request. It is possible that some of these requests we classified as failed were ultimately resolved through off-platform direct messaging. For this reason, our success rate over the three weeks likely reflects a conservative estimate of the overall matching success rate. These results show that while some requests fail due to a lack of any driver response, a greater portion fail due to factors from the requester's side.

As with response and wait times, matching success rates also vary based on time of day. Table 1 shows the response and matching success rates of real-time ride requests based on hour of the day. Response rates include any driver, helper, or moderator response to a request post. We find that higher response and success rates exist during the late morning and early afternoon, as requests happening between 10am and 3pm have both higher than average response and success rates. Similarly, high response and success rates exist from 6pm to 11pm as well, overlapping with the generally faster response and wait times during the evening, as shown in Figure 2. Response and success rates from 5am to 8am are the lowest, with 6am to 7am being the worst performing hour of the day with an 84% response rate and a 63% success rate, on average. These results show that although response and success rates vary throughout the day, from 63% (6am-7am) to 94% (11am-12pm), they are mostly higher than two thirds at any given time of the day.

TABLE 1 Response and Matching Success Rates by Hour of Day

| Hour of Day	Response Rate (%)	Success Rate (%)
12am-1am	98%	82%
1am-2am	100%	80%
2am-3am	97%	75%
3am-4am	95%	76%
4am-5am	98%	83%
5am-6am	93%	68%
6am-7am	84%	63%
7am-8am	96%	64%
8am-9am	100%	88%
9am-10am	100%	74%
10am-11am	100%	88%
11am-12pm	100%	94%
12pm-1pm	100%	88%
1pm-2pm	97%	82%
2pm-3pm	97%	85%
3pm-4pm	91%	83%
4pm-5pm	95%	78%
5pm-6pm	96%	78%
6pm-7pm	94%	86%
7pm-8pm	95%	84%
8pm-9pm	100%	90%
9pm-10pm	97%	91%
10pm-11pm	100%	81%
11pm-12am	95%	77%

Although time of day is an important factor in determining matching success, the response and wait times themselves more heavily impact whether a request is successfully fulfilled or not. Figure 3 shows matching success rates based on two separate response time factors, including: 1) the first response time by a driver, helper, or moderator, and 2) the first response time by a driver, in minutes. These results show significant drop-offs in matching success after certain first response and first driver response time thresholds. For first response rates, the matching success drops from 83% if the first response is within 6 to 8 minutes to 70% if the first response is within 8 to 10 minutes. The success rate drops below 50% if the first response does not occur for 20 minutes or longer. These findings show that a driver, helper, or moderator response within eight minutes makes a substantial difference as to whether a real-time request will ultimately succeed or not. However, we note that there may be other non-temporal factors that contribute to higher matching success rates as well, such as origin or destination of the request and the proximity of available drivers, among other factors.

Examining the success rates by the first driver response time, there is a steadily decreasing but still fairly high success rate from zero to 14 minutes, ranging from 94% if the first driver responds within two minutes to 81% if the first driver responds within 12 to 14 minutes. There is a large decrease in matching success rates if the first driver takes 14 minutes or longer to respond to a request, as the success rate drops from 81% (12 to 14 minutes) to

64% if the first driver responds within 14 to 16 minutes. The success rate drops below 50% at first driver response times of 25 minutes or more.

The findings displayed in Figure 3 show that matching success on the AC Austin platform is more common when requests receive a driver, helper, or moderator response within eight minutes and a driver response within 14 minutes. These response time cutoffs represent important user travel behavior factors to consider for those planning or operating on-demand transportation networks, especially platforms with decentralized operations. While these ranges of acceptable response times may be slightly unique to requesters on the AC Austin group or to travelers in Austin, they nevertheless provide important insights into factors affecting the success of decentralized ridesourcing networks.

FIGURE 3 Success Rates by First Response Time and First Driver Response Time
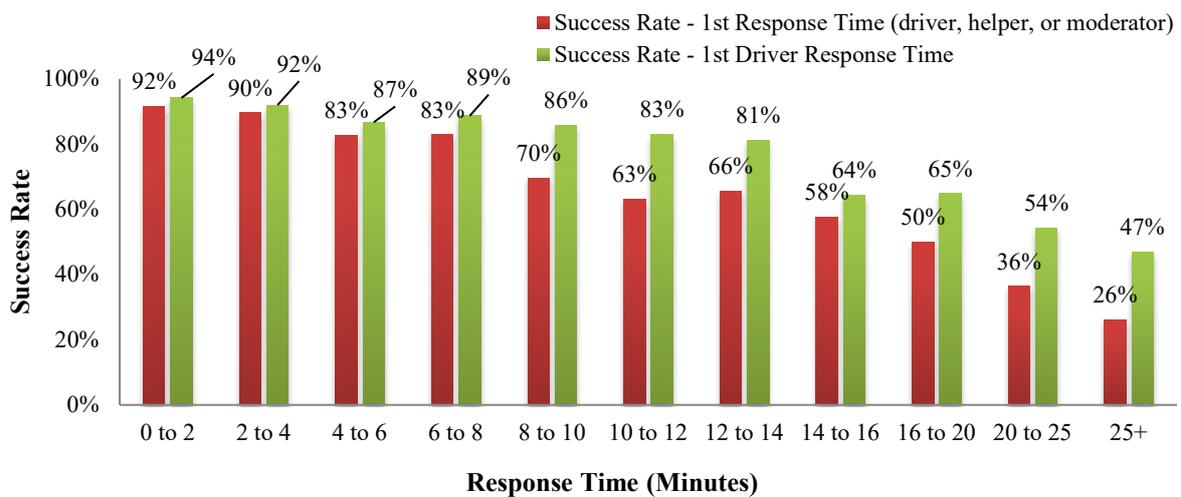
As with response times, success rates follow a similar pattern based on the total wait time of drivers, which we calculate by adding each driver's response time to their posted ETA. For these purposes, we consider the lowest total wait time of all responding drivers in the case that more than one driver responded to the request post. As displayed in Table 2, success rates are higher than the overall average (84% and higher) if the total wait time is under 24 minutes. If the total wait time is 24 minutes or more, the success rate drops to under 70%. This pattern corresponds closely with the drop-off in first driver response time success rates at about 14 minutes (Figure 3). This closely parallels the total wait time cutoff of 24 minutes since the average driver ETA is around 10 minutes. This is another finding of interest that will aid in the planning and operations of on-demand transportation networks.

TABLE 2 Success Rate by Total Wait Time

Total Wait Time (Minutes)	Success Rate (%)
0 to 4	88%
4 to 8	94%
8 to 12	94%
12 to 16	93%
16 to 20	87%
20 to 24	84%
24 to 28	68%
28 to 32	67%
32 to 45	69%
45 to 60	58%
60+	23%

Helper and Moderator Activity and Matching Success
As mentioned previously, a unique aspect of the decentralized operations of AC Austin is the involvement of helpers and moderators that aid in the matching process and organizational effectiveness of the group. While there were 99 unique helpers over the three-week study timespan, just nine individuals handled almost 90% of the help posts, with just two people accounting for 63% of these posts. Twenty-seven percent of all requests over the three weeks received some form of helper or moderator assistance. The average response time of helpers across all requests was 8.5 minutes. For real-time requests, the average response time was 7.3 minutes. There were 1.2 drivers tagged per help instance, on average. When helpers simply bumped a request to make it more visible by bringing it back to the top of the Facebook group, these were counted as zero-driver help instances.

The helpers and official moderators act as the decentralized network equivalent of taxi dispatchers and attempt to improve operations and matching effectiveness through bumping and tagging of requests. It is difficult to assess how the actions of moderators influence matching success due to circumstantial behavior of moderators that affects whether they post on a certain request or not. For example, requests that are resolved quickly by a driver are unlikely to receive helper attention, whereas requests that have not garnered a driver response after a long period of time could probably benefit from helper or moderator intervention. Thus, it is difficult to assess whether helper or moderator action alone improves matching success rates. However, when we consider requests that did not receive a driver response for 14 minutes or more, based on the success rate drop-off observed in Figure 3, we find slightly higher success rates among posts that received helper attention compared to those that did not. Fifty-nine percent of real-time ride requests with drivers taking 14 minutes or longer to respond that received helper attention were successful, compared with only 51% of these requests that did not receive helper attention. While this finding suggests that helpers and moderators improve the matching success of requests that do not receive immediate driver attention, more data and analysis are needed to fully assess how helper activity affects the matching success of requests.

CONCLUSION
P2P ridesourcing services like Uber and Lyft emerged in 2012 and have rapidly become an important transportation mode in cities around the world. However, there are many equity and

environmental problems that arise with commercial ridesourcing services and centralized 'sharing economy' platforms, in general. Platform cooperatives are a nascent concept beginning to emerge with roots in the cooperative and blockchain spaces. Despite their potential to transform and improve upon existing ridesourcing service models, there are very few ridesourcing platform cooperatives operating at scale, with the exception of Arcade City (AC) Austin. In addition, there is little to no research on the subject of transportation platform cooperatives.

For these reasons, we implemented a study of AC Austin to better understand this unique form of decentralized cooperative ridesourcing. We collected three weeks of continuous trip-level operational data and focused on the overall operations of the group and the factors that lead to effective pairing of requesters with drivers.

The study showed that the greatest portion of requests were made on Fridays and weekends, and during the late afternoon, evening, and early AM time periods. The AC Austin platform allows for requests other than rides, which comprised 8% of all requests over the three weeks. Most of these non-ride requests were for food or goods delivery, although a notable portion were for moving or car help, demonstrating the diversity of request types served on the platform.

The operational effectiveness analysis reveals that 96% of all requests received a response from a driver, helper, or moderator, and 80% of all requests were successfully matched with a driver. Of the 20% of requests that failed, about half were due to cancellation or resolution from the requester, 30% were due to no driver response, and 20% had an unclear reason for failure. The average time elapsed between a request post and the first response (by a driver, helper, or moderator) was 5.2 minutes, the average response time before a driver responded was 5.5 minutes, and the average total wait time was 14.8 minutes, for requests during the three-week study period. While these matching success rates and wait times likely are slightly worse than those of larger commercial ridesourcing entities in Austin, they are nonetheless quite impressive for a relatively small group without centralized operational mechanisms.

Although driver response and wait times fluctuate depending on the time of day, requester-driver matching success is more dependent on the response and wait times themselves than temporal factors alone. Through our analysis, we find that matching success on the platform is most effective when requests receive a driver, helper, or moderator response within eight minutes, a driver response within 14 minutes, and a total wait time of 24 minutes or less. Requests with response and wait times that are longer than these thresholds have disproportionately lower chances of being matched than those with response and wait times under these cutoffs. These are important behavioral insights for those planning or operating on-demand shared mobility services. They are especially relevant because most commercial ridesourcing companies do not publicly release these types of operational insights due to proprietary concerns.

Overall, our analysis of AC Austin shows that the decentralized cooperative ridesourcing model is quite effective at serving rides and other requests. The findings in this paper provide a deeper understanding of not only the operational qualities of decentralized ridesourcing but also the acceptable wait time preferences among users of ridesourcing services, more generally. Future research is needed to better understand how spatial factors affect matching and on the governance, legal, and environmental impacts of decentralized ridesourcing compared to more prevalent centralized commercial approaches.

AUTHOR CONTRIBUTION STATEMENT
The authors confirm contribution to the paper as follows: study conception and design: A. Stocker; data collection: A. Stocker, M. Takara; analysis and interpretation of results: A. Stocker, M. Takara; draft manuscript preparation: A. Stocker. All authors reviewed the results and approved the final version of the manuscript.

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