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Innovation at Uber: The Launch of Express POOL

The mood was tense in a conference room at Uber's headquarters in March 2018. For the past several months, the San Francisco-based ride-sharing company had been testing a new product called Express POOL (Express). Express offered a reduced price to riders willing to carpool, walk a short distance to/from their pick-up and drop-off points, and wait for two minutes before being matched to a driver.

The Express product was similar to POOL, except that it offered a cheaper ride in exchange for **walking** and **waiting to be matched**. When a rider requested Express, the Uber app asked her to wait for up to two minutes while the back-end algorithm assessed potential matches given the pick-up and drop-off locations of nearby riders. The app then matched that rider to others heading in the same direction and instructed her to walk to a designated pick-up point to meet her ride. Longer initial wait times enabled the app to make more efficient matches, ensuring that the car was at full seating capacity for as much of the trip as possible and making it financially feasible to sell trips at even lower prices. Riders' tolerance for waiting, however, was finite, and the company recognized the need to balance efficiency with rider experience.

Since concluding pilots in Boston and San Francisco, Uber's data scientists had been running experiments in these two cities to test a number of improvements to Express. Express had been conceived with a maximum two-minute wait time, but by early March, the results of an experiment looking at Boston riders' reactions to waiting five minutes had just come in. Duncan Gilchrist, head of data science for Uber's rider pricing and marketplace experimentation teams, had called a meeting to discuss the results. "The Boston experiment shows mixed results," began Gilchrist. "Longer wait times increase cancellation rates, but reduce our costs per ride."

Gilchrist waited as his colleagues considered how these results might impact the ongoing rollout of Express. Most pressing, just two weeks earlier, Uber had begun a new experiment (launch experiment) in 12 U.S. cities. In this experiment, Uber had launched Express in six "treatment" cities and held constant six additional "control" cities for comparison. The data science team had placed a five-week moratorium on changes to these 12 markets. This freeze was meant to allow one week for the markets to stabilize and then four weeks for data collection, data which Uber used to evaluate the impact of the new Express product on market equilibrium and company profits. Now, armed with data from the Boston experiment about the impact of longer wait times on costs, Uber needed to decide whether to

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overrule the five-week moratorium and increase wait times from two to five minutes in the six treatment cities midway through the launch experiment.

Ronak Trivedi, senior product manager for shared rides, listened with interest as Gilchrist explained more. Trivedi was focused on cancellation rates. “The fact that cancellation rates increased is a sign that customers *hate* waiting,” he said. “We should keep waiting times to a maximum of two minutes.” At the other end of the table, product manager Miraj Rahematpura had been typing numbers on his laptop. Looking up, he said, “But the reduction in costs per ride is huge. That would more than offset the increase in cancellations. We should increase wait times in our six treatment cities immediately.” “I understand both your points,” replied Gilchrist, “but these results are from just a few neighborhoods in Boston. We have no way to validate them for other cities. Besides, properly collecting baseline data from the 12-city experiment is important to inform future improvements to Express, so we must wait five weeks before changing the product.” Everyone looked to Ethan Stock, director of product management for shared rides, for a decision. “Well Ethan,” said Rahematpura, “can we increase wait times in the treatment group of our 12-city experiment?”

Uber and The Ride-Sharing Industry

Uber was founded in 2009 by serial entrepreneurs Travis Kalanick and Garrett Camp as an on-demand luxury car service targeted at executives in Silicon Valley. The company connected riders to unoccupied private black cars.¹ In mid-2012, to target a larger customer base, Uber introduced a new product, UberX, which was roughly 35% cheaper than the company’s luxury car offerings.² UberX allowed any licensed driver over the age of 21 with a car in good condition to drive for Uber. Potential drivers were required to submit to a background check and a review of their driving record and car registration. Uber provided insurance coverage for its driver-partners (i.e., Uber’s term for drivers) while they drove for the company. Driver-partners could work as much or as little as they wished.

Throughout the 2010s, Uber grew quickly, expanding into international markets and adding new products. Uber tended to launch products as soon as was feasibly possible, reflecting a maxim applied to several disruptive technology companies: “move fast and break things.” As Gilchrist explained, “Uber has this culture of being very experimentally driven. We tend to put a minimum viable product in the market and then iterate based on what we learn.”

By 2018, some 75 million riders and 3 million driver-partners used the Uber platform.³ On any given day, Uber drivers completed 15 million trips in 600 cities across 65 countries.⁴ The company had raised \$21 billion across several funding rounds and was valued at \$62 billion, making it the most valuable startup in the world.^{5,6} Because it was a private company, information about Uber’s financials was relatively sparse. Observers generally believed that Uber operated at a loss, but that its financial performance varied widely between cities. In some of its more mature markets, the company was thought to be profitable.⁷

Uber was a first-mover in the growing ride-sharing industry. By 2018, a number of other U.S.-based ride-share companies had emerged, such as Lyft and Wingz, along with global players, most notably the Chinese company Didi Chuxing Technology Co. (Didi) and Singapore-based Grab. All offered some variation of ride-sharing, which could be broadly defined as an on-demand service that connected idling independent drivers to waiting passengers for a fee. The service was powered by point-to-point software and GPS mapping installed on riders’ and drivers’ smartphones.

Despite the growth of ride-sharing platforms, access to these services remained concentrated in urban areas. Where these services were available, the ride-sharing industry was highly competitive.

Low switching costs between service providers permitted both riders and drivers to utilize multiple platforms with ease.⁸ To gain market share, companies had aggressively lowered rider fares and offered large bonuses for new drivers. Of U.S.-based companies, however, Uber remained the market leader, claiming 77% of the domestic market.⁹

Uber's Platform and Product Offerings

By early 2018, Uber offered eight ride-hailing products: Express and UberPOOL (cheaper, carpool options), UberX, UberXL, and UberSELECT (the company's core economy offerings), and UberBLACK, UberSUV, and UberLUX (premium, more expensive options).¹⁰ (**Exhibit 2** describes each product type.) Product availability varied by city.

To request a ride, users opened the app and entered their desired drop-off point. The app then prompted users to choose their preferred product. In some cities, the app also listed the projected fare and the anticipated arrival time. Once users requested the ride, the app matched them with an available driver and, if a carpool option was selected, with other riders. The app showed riders their driver's name and the license plate number for identification purposes, as well as the driver's customer rating, which ranged from 1 (the lowest rating) to 5 (the highest). Once matched, the rider could monitor the driver's movements in real time. While on their journey, riders could follow the trip's progress on a map. After the ride, the app prompted the rider to rate the driver. Uber charged the rider's credit card. Riders had the option to tip their drivers and leave comments. (**Exhibit 3** shows the rider app.)

On the driver's side, when a ride request came in, the app pinged nearby eligible drivers one at a time. Uber's driver-partners could either accept the request, passively reject it—meaning they failed to accept the ride within a 15-second window—or actively refuse a rider. If the driver accepted the ride, he or she picked up the passenger and then followed the directions in the app to the destination. Upon completing the ride, the app prompted drivers to rate passengers. Additional features on the driver app included a “heat map,” indicating areas with high demand, as well as an earnings icon that showed the driver's pay.¹¹ (**Exhibit 4** shows the driver app.)

Riders' fares varied by product type, but were generally based on the trip's length and distance. Drivers were paid a base fare for each ride as well as a set amount per mile and per minute (**Exhibit 5** shows a typical driver's earnings breakdown). Uber kept 25% of a trip's gross fare.¹² While some media outlets reported that Lyft and Uber drivers' take-home pay was exceedingly low,¹³ Uber's own research pegged its driver-partners' median earnings between \$15 and \$30 per hour (see **Exhibit 6** for estimated driver earnings disaggregated by the number of hours driven).¹⁴ The company used dynamic pricing, charging higher “surge” prices when demand outpaced supply. For example, if a surge rate of 1.8x went into effect for a given neighborhood, a normal \$10 fare would be \$18 until demand and supply recalibrated.¹⁵

In addition to its core ride-sharing products, Uber had expanded into other verticals, such as Uber EATS, a food delivery service, and Uber Freight, a service that notified trucking companies of freight awaiting transport. Uber was also working toward advancing autonomous vehicle technology.¹⁶

Organizational Structure

Uber's San Francisco-based product teams were organized into three key verticals: rider, driver, and marketplace. The rider vertical was responsible for the rider-facing app, rider recruitment and customer service. The driver vertical handled analogous tasks for drivers. The marketplace vertical maintained an overarching view of the health of all Uber products, monitored substitution patterns between products, and developed the systems and technologies behind pricing and vehicle matching.

In addition to these verticals, Uber also had a central operations team and individual city teams that ensured smooth product launches and alerted engineers and product teams of issues.

Within the three verticals, staff performed a number of functions, including product management, engineering, data science, product operations, design, and marketing. Product managers shepherded the product development and improvement process, considering the perspectives of all stakeholders. Engineers and data scientists developed the technology behind Uber's products and evaluated improvements to its algorithms. Product operations specialists liaised with technical teams and city operations teams to ensure product-market fit. Designers curated the look and feel of Uber's website and rider- and driver-facing mobile apps. Finally, marketing teams created advertising and marketing campaigns to ensure consistent product messaging. (**Exhibit 7** provides an organizational chart.)

Product operations specialist Bradford Church clarified the role of product operations. "Global teams need local feedback to refine products," he said. "We work closely with city teams to collect information and feed it back to the engineering teams. A good example is how we integrate with airports. Engineering teams might only be familiar with how a couple of airports work, so, without product operations, they might build a product feature that works well at the San Francisco airport but does not work for the vastly different airport setups around the world."

Uber's product development process involved teams staffed with representatives from four functions: a product manager, a data scientist, a designer, and an engineer. "Engineers are practical, designers are aspirational, and data scientists are tactical," Trivedi said. "The product manager takes multiple perspectives into account and helps make decisions." Typically, teams designed a minimum viable product and then invited others within the company to examine it and tell the team what aspects to cut and which to add. "The process is painful," said Trivedi, "but necessary."

Engineering manager Danny Guo believed that for the most part, Uber employees maintained collegial relationships, even across functions. "There is a level of trust between product managers and engineers here," he said. "Engineering tends to be very technology-driven, which means that we do not always consider the way that products will perform in the real world. Product managers and operations specialists give us that perspective, which helps us build pragmatic products."

Innovation at Uber

Innovation at Uber spanned a spectrum with regard to the degree of product change involved. At one end of the spectrum, Uber made continuous incremental improvements to its core products. As Guo said, "We are constantly iterating. Software only lasts for about 18 months here." Next, Uber identified and developed new ride products, such as Express, that were optimized for a different set of customer preferences (e.g., for price-sensitive customers who did not mind waiting and walking). Finally, Uber placed bets on riskier ideas, based upon fundamental changes to its business model and technology (e.g., Uber EATS and autonomous vehicles).

To understand riders' experiences, Uber ran rider surveys and looked at proxy data for rider satisfaction (e.g., ride re-requests, driver ratings) in the app itself. With drivers, the company gathered information more directly, through interviews and other interactions. Uber also followed online forums frequented by its driver-partners to gauge their satisfaction. Hamid Nazerzadeh, a staff data scientist in Uber's marketplace optimization team, said, "We are especially sensitive to drivers' feedback because they are such important partners for us."

A key element of Uber's innovation strategy was its substantial investment in data science. Of the 200 employees staffing the company's marketplace vertical, for instance, 60 were data scientists; these

individuals typically held doctoral degrees in data science and related disciplines from a top-ranked school. (See **Exhibit 8** for the proportion of data scientists employed by Uber as compared to its peer companies.) Uber employees believed that the use of data science at the company was relatively advanced. As Gilchrist noted, “Generally, data scientists at Uber have a fair amount of influence. That’s because the types of problems we’re solving require us to focus on a combination of algorithms, user experience, and scale.” As senior data scientist Connan Snider added, “Uber is unique. A lot of places are engineer-driven because they are dealing with straightforward production problems. But we are sorting through very complex issues that require data scientists to understand and evaluate how users interact with our technology. We start by adjusting algorithms manually, and then build systems to update automatically based on what we learn about demand and supply. For example, we recalibrate many of the parameters in our dynamic pricing algorithms on a weekly basis.”

Uber ran different types of experiments to improve its products, depending on the type of improvements to be tested. Among those most commonly used were user-level A/B experiments, switchbacks, and synthetic controls.

User-level A/B Standard, user-level A/B experiments compared the behavior of app users to test the effects of platform decisions. For example, say Uber wanted to understand how differences in product placement within the app affected riders’ propensity to select one product type over another. In a standard A/B experiment, the platform would randomly allocate riders into either the “treatment” group or the “control” group. When users in the control group opened their app, they would see the standard app design. Users in the treatment group, by contrast, would see the newly proposed product placement on the app. After some time, Uber would compare the frequency with which riders selected one product type over another in the treatment versus the control group to estimate the degree of change in behavior induced by the different app design.

Switchbacks “Switchbacks” were another type of study design used to evaluate the effects of a product tweak on some outcome variable of interest. Say, for example, that Uber wanted to test an improved algorithm for matching riders to drivers. In a switchback experiment, the data science team would expose all riders and drivers in a given market to Uber’s standard matching algorithm for a 160-minute period. During the subsequent 160-minute period, riders and drivers would be exposed to the revised matching algorithm. There would be an odd number of switches per day, ensuring that if a Monday evening rush hour was in the treatment group in the first week, it would be in the control group the following day and the next Monday. Uber would continue to switch back and forth for a two-week period, and compare differences in efficiency and customer satisfaction metrics between the two groups. “We try to keep our switchbacks as clean as possible,” explained Gilchrist. “The problem is that we can only really run one at a time in a city to prevent them from interacting with each other.”

Synthetic control experiments These experiments attempted to create treatment and control cities to study the effects of a product tweak on a set of city-level outcomes. Synthetic control experiments randomized treatment and control at the city level, and despite their name, were not an application of the statistical synthetic control method.¹⁷ For instance, if Uber wanted to understand how a new rider app affected market demand, the company would roll out the new app in a random set of treatment cities and measure total requests and cancellation rates in those cities. Uber would then study the same outcome variables in a group of similar cities that remained unexposed to the new rider app. Because these experiments assigned all riders and drivers within a city to either the treatment or the control group, they allowed the company’s data scientists to evaluate how product tweaks affected city-level outcomes. However, noted Nazerzadeh, “With synthetic controls, in order to detect any changes, they need to be fairly significant – usually 5% or higher – but lots of our experiments generate effects of smaller magnitudes.”

Uber teams ran several experiments simultaneously. As product operations specialist Jane Lee noted, “At any given time, we have teams experimenting with rider-side and driver-side features, and other teams making smaller product tweaks, all within a finite number of cities. So, figuring out how to launch new products and test their effects without interfering with other experiments is challenging,” Nazerzadeh added, “For Uber, the problem is that it is easy to run out of cities in which to experiment.”

Gilchrist had been tasked with keeping track of these experiments and helping teams accurately interpret their results. “In general, it is very hard to measure the effects of our product tweaks because there are a lot of external factors to take into account,” he explained. “There are also network effects to consider. In the past, Uber had a bit of a ‘wild, wild West’ approach to experimentation. Teams were presenting results that overstated effects, so when I came on board in mid-2017, there was a general consensus that we needed to have more trustworthy experimentation.”

To impose more order on the experimentation process, Gilchrist and his team developed a process called the Marketplace Change Protocol (MCP) for scheduling major experiments. (Major experiments were defined as those that could have a significant impact on products other than the target.) During a weekly steering committee meeting, teams hoping to run a major experiment gave presentations explaining the goals and risks of the proposed experiment. Uber’s head of product and head of engineering made the final decision about which experiments would move forward. Smaller experiments, like user-level A/B, were not subject to the same review; hence teams could still implement and run these experiments on their own.

As the importance of data science had grown at Uber, so had its role in driving innovation across the business. Trivedi noted, “It’s not just measuring the results of small experiments. Some big ideas can come out of our own observations around travel patterns supplemented with rapid experimentation. For example, three years ago, we noticed that lots of people were traveling along similar routes at similar times. That’s one of the observations that led to UberPOOL.”

Shared Rides: Launching UberPOOL

In 2014, Uber launched UberPOOL (POOL), its first shared rides product, which offered a discounted fare to riders willing to carpool with other passengers. POOL was still a door-to-door pick-up and drop-off service, with no walking required. Uber hoped that this option would generate higher “seat utilization” — a key metric of interest for the shared rides team — thereby increasing the company’s overall ridership and boosting earnings per ride. POOL drivers were paid based on ride time, distance, and surge rates. In addition, they received a rider pick-up fee of between \$0.50 and \$1.00 for each additional passenger in the car.¹⁸ This meant that if two separate passengers were both going from point A to point B, a driver taking both passengers would be paid between \$0.50 and \$1.00 more than a driver taking only one passenger. Media outlets estimated that passengers’ fares on a POOL trip were roughly half those of an UberX trip.¹⁹

Initially, to generate interest in POOL, the Uber app asked UberX riders to push a button called “I’m Feeling Lucky” if they were willing to share the car with a co-rider in exchange for a price cut. If the app located a suitable co-rider, the UberX became a POOL, and the original passenger’s fare was cut in half. If the app found no compatible co-rider, the original passenger took a normal UberX and paid the UberX fare. “We thought the ‘I’m Feeling Lucky’ option would be popular,” explained Trivedi, “but people gravitated toward paying a bit more for an uninterrupted journey. You just never know what will happen in the market until you release a product. Optimizing toward your assumptions is foolish.” Uber soon switched to modeling the probability of matching. If the app predicted that riders on a given

route would be matched with others, it offered the reduced POOL fare upfront. Riders who chose POOL then paid this discounted fare regardless of whether they matched with a co-rider.

To identify co-riders for POOL trips, Uber used a “greedy algorithm.” Essentially, all POOL rides began as UberX trips. Once on the trip, the algorithm constantly looked for other passengers to add to the trip. If it located a rider whose pick-up and drop-off locations were within certain parameters relating to the original passenger’s route, it directed the driver to pick up the new rider. The algorithm permitted POOL drivers to pick up multiple additional riders, either until the car hit its seating capacity (i.e., three passengers) or the driver had completed 95% of a given rider’s trip.

In many markets, adoption of POOL was growing at a faster rate than UberX. While Uber was pleased with rider uptake, the greedy algorithm system posed challenges for both riders and drivers. POOL riders, for instance, tended to react negatively to the loops and detours necessary to pick-up and drop-off co-riders, especially if they required the driver to backtrack. Drivers worried that POOL might leave them vulnerable to poor reviews due to factors beyond their control. Moreover, the product’s capacity to match co-riders was not as efficient as it could be, with about half of all POOL trips left unmatched. As a result, by the end of 2016, POOL was still unprofitable.

Express POOL Project

In early 2017, Peter Deng, head of Uber’s rider vertical, began advocating for the company to rethink its shared rides strategy. He believed that products like POOL would drive Uber’s future growth, but that they needed to be far more efficient to reach their potential. Several Uber executives bought into Deng’s vision, and the company made improving the efficiency of shared rides an organizational priority. In July 2017, the company’s leadership created a joint task force between the shared rides team and the marketplace team, and asked that they make a series of improvements to shared rides. Deng placed director of product Stock in charge of the task force.

Stock explained, “The merged team comprised product managers and operations specialists, engineers, and data scientists, who all had different perspectives. They had to make hard trade-offs between rider experience and cost efficiency. Products like POOL need to be high-quality, because if they aren’t, people won’t take them, but they also have to increase our earnings. In an ideal world, these objectives would be complementary, but they often conflict.”

Stock noted that his role was primarily to set up the structures and processes to enable the merged team to make good decisions. “I really relied on the team to come up with the details,” he said. “I asked them to create specific metrics to quantify a positive trip experience, rather than relying on vague feelings.” The team identified metrics for measuring rider experience. These included, for example, opt-in rates (i.e., the percentage of total riders who requested a shared ride) and rider cancellation rates. To measure cost efficiency, the team looked at the number of occupied seats per minute and per mile; the ideal scenario was three riders to one driver (i.e., the maximum seating capacity) for as much of the trip as possible. The more riders on a shared trip, the more revenue that Uber earned.²⁰

By August 2017, the team had adopted two key strategies for improving shared rides. They would ask riders to: 1) wait up to two minutes while the algorithm matched them to co-riders, and 2) walk a short distance to/from their pick-up and drop-off points. If done well, this would result in fewer detours and better matches. Uber had already tested walking and waiting in a few key markets. In New York City, for instance, the company in 2016 launched HOP, a product requiring riders to walk to a fixed pick-up point. Custom-built for this market, it accounted for the city’s many one-way streets. Trivedi, who had been deeply involved in the launch of this product, noted, “We put HOP in the

market, and riders loved it. They intuitively knew that it made more sense to meet their driver at the correct side of an intersection. Riders started rating drivers more highly. Drivers' lives got easier too because they no longer had to circle around a city block to pick up passengers. That resulted in better rider ratings. Everyone was happier." Uber had also tested waiting in Chicago and San Francisco by offering riders the option to wait a few minutes to be matched to a ride in exchange for a discount.

August 2017: Adapting the JIT Algorithm to Express

Once the team had settled on adding walking and waiting to shared rides, Uber's leadership asked engineering manager Guo to lead a "tiger team," or a group of ten engineers, to build a new algorithm for rider matching. As Rahematpura summarized, "The customer learnings from HOP carried over, but the software technology did not because it was custom-built for New York City." Whereas POOL's greedy algorithm matched ride requests on a first-come, first-served basis, this new system would use a two-minute window to batch all requests and active rides to jointly find the optimal allocation of passengers to drivers. Stock explained, "By having riders wait to be matched upfront, we exponentially expand the number of possible overall matches because there are hundreds of ride requests coming onto the platform in that timeframe. This allows our system to find highly compatible riders at massive scale, providing both efficiency and quality."

To build this new algorithm, the tiger team adapted an existing system called "Just In Time" (JIT), which had been built six months earlier to improve the driver dispatch process for UberX. Rather than matching rides one by one, the JIT system delayed driver dispatch a few seconds, during which Uber looked at all ride requests across product types and matched a driver to that UberX requester as efficiently as possible. In early 2017, Uber had tested the new JIT driver dispatch system with Uber EATS's food delivery service. As Guo quipped, the company felt comfortable testing the new software on food delivery because "sandwiches don't have feelings." The tiger team would need to extend the batching time window and adapt the JIT system to accommodate co-rider matching and walking.

One early debate was whether pick-up points should be fixed prior to matching, as they were for the HOP product, or whether they should be determined by the new algorithm. "We discussed this issue at length," recalled Trivedi. Dynamism ultimately won over customer preference for fixed pick-up points. As Trivedi said, "In the end, I understood that our efficiency gains will stem from our ability to be as flexible as possible." In lieu of fixed pick-up points, the team decided to select and tag a series of "corners" as possible pick-up points for a given area (see **Exhibit 9**). Once the rider was matched with others, the app directed her to walk to the most convenient corner for pick-up, as determined by the location of her co-riders and driver. Product operations specialists worked with city teams and Uber's engineering teams to refine corners, ensuring that they did not place riders in danger or ask them to complete impossible tasks, such as fording a river to reach the pick-up point.

Stock's team debated whether to simply add walking and waiting to the existing POOL product or to create a new shared rides product. Ultimately, they chose to launch a new product called Express. Stock explained, "We were concerned that if we told people who were used to POOL that they now had to walk and wait, we would be perceived as insensitive to safety and accessibility concerns. We wanted people who were used to POOL to still have that option." In markets without POOL, however, Uber could make Express the default POOL product. For example, UberPOOL in Australia, launched in early 2018, was actually the Express product.

It took Guo and the tiger team two months to develop the additional JIT software required for Express. Their development plan included two milestones: version 0 (v0) which accommodated walking and matched riders and drivers within a fixed waiting time, and v1, which added flexible waiting. In the latter, a rider was guaranteed to wait up to the maximum waiting time, but if the

algorithm found a good match beforehand, she would be immediately notified about her driver and pick-up location. "Throughout this process," said senior data scientist Lior Seeman, "we had discussions with the shared rides product team, refining the corners and making sure we had all the details right." Within a few weeks, the team had built a basic, bare-bones prototype of the Express product. They continued to refine the prototype until they had built the Express code base.

September 2017: Simulations and "Trip Parties"

Starting from September 2017, the team began to run simulations mimicking how Express would work in the market as a function of different matching parameters. To do so, the team cloned Uber's historical POOL requests and simulated the matches that would occur under different Express scenarios, for example with longer or shorter waiting times. "In just two hours per simulation, we could see the details of all Express matches that would have occurred in a two-week period," said Rahematpura. The team then reviewed these matches together in meetings, called "trip parties."

These meetings served more than one purpose. Their primary goal was to establish a set of parameters that would dictate Express matching, based on the results of the simulations. The team would focus on simulated trips to evaluate how varying waiting and walking parameters influenced rider experience and efficiency. An equally important goal of the trip parties was to provide a forum for different stakeholders to discuss the experience/efficiency trade-offs. By the end of the trip parties there was broad agreement about the matching parameters for Express. Maximum waiting time was set at two minutes.

Pricing

While they were confident about the waiting and walking parameters they had established, the Express team remained unsure if riders would buy into the service. "This was a completely new product for us," said Stock. "In meetings, people would say, 'The magic of Uber is that it's an on-demand, door-to-door service, and Express is neither.'"

One major uncertainty regarded Express pricing. While the simulations had mimicked actual historical POOL rides, they had not included price points. To assess riders' willingness to wait and walk at different price points, the company sent a segment of its riders conjoint surveys—a type of questionnaire that measured consumers' sensitivity to different variables. Based on the surveys' results, Uber built a calculator that aimed to predict pricing thresholds based on walking and waiting parameters. As Church recalled, "The survey gave us a helpful floor and ceiling for pricing. Most people simply will not wait 15 minutes for a ride, even if prices are far cheaper."

To help refine its pricing, the company also looked at demand curves previously estimated for the POOL product, which quantified rider sensitivity to price changes. As Church said, "We wanted to launch a product that did not lose money, while still allowing us to offer a lower price." While pricing would be dynamic, Uber decided that Express would always be at least 20% cheaper than POOL. "But," said Lee, "if that's only a \$0.50 difference, that probably isn't enough to persuade people to take Express and deal with waiting and walking, so in some cases the discounts are deeper." Thus, Uber also planned to adjust the prices for the POOL product in order to make Express attractive. "We are still determining what the substitution patterns are," said Snider. "Then we will revise accordingly."

November 2017: Boston and San Francisco Pilots

By November, the merged team believed that it was ready to release the Express product into test markets. "It was still only half as good as we wanted it to be," said Church, "but we knew we needed

to get it into the market to see riders' reactions." Thus, in early November, Uber launched Express in select neighborhoods of Boston and San Francisco. The company chose these cities because they were competitive, dense markets. "We had 'home curb advantage' in San Francisco," explained Lee. "If something went wrong, we knew that we could address it fairly quickly." Boston's heavy student population was also a consideration. Launching in just a few neighborhoods would confine the effects of any negative repercussions to smaller geographies, and provide an opportunity to test the algorithm for bugs, since many Uber employees would use the new product in San Francisco.

When riders clicked on the Express product in their Uber app for the first time, a box popped up that read, "Walk a little, Save a lot," and offered a primer on Express. For drivers, the product was quite similar to POOL, so there was less need for driver education. According to Seeman, "The limited launches went well. Nothing was a huge surprise. We learned small things. For example, riders really care about not getting dropped off 100 feet before their door just to make the ride one minute shorter."

In December, Uber expanded the product to all of Boston and San Francisco. Express was well-received in San Francisco. "We saw an increase in volume and cost savings, with no degradation of marketplace metrics around user experience," said Lee. Reception in Boston, however, was more lukewarm. "Weather was certainly a factor influencing adoption," said Seeman. "We launched in the winter, and people likely did not want to walk and wait in the cold."

February 2018: 12-City Synthetic Control Experiment (Launch Experiment)

On February 19, 2018, after seeing that the Express product had not caused any major problems in Boston and San Francisco, Uber launched a synthetic control experiment (launch experiment) in 12 U.S. cities. The company launched Express in six treatment cities and held constant a set of six control cities. In the six treatment cities, riders were made to wait up to two minutes before being matched to a driver.

As was the case in Boston and San Francisco, all of the 12 cities already offered the POOL product prior to the experiment. In preparation for launch, the company ran advertisements and sent emails to all its users in the treatment markets. Following the launch, Uber began monitoring the effects of Express on these markets, as compared with the control cities. As was standard practice, the company placed a five-week freeze on experimental changes to all 12 of these cities to enable data scientists to interpret any market changes as cleanly as possible.

The Wait Time Debate

To evaluate riders' willingness to wait, in mid-February the Express product team launched an experiment in Boston (**Exhibit 10** provides a timeline of all the experiments discussed). By that point, the Express product – with two-minute waiting – had been available in Boston and San Francisco for three months, allowing ample time for the markets to stabilize after the addition of a new product.

To evaluate the effects of longer wait times, the team set up a switchback experiment in Boston. Every 160 minutes, the matching algorithm switched between letting riders wait up to two (control group) and five minutes (treatment group) before being matched to a particular driver. After two weeks, the data scientists analyzed the experiment results. The data indicated that Uber's costs per ride decreased with longer wait times, but there were differences in how rush and non-rush hours were affected. Because the longer wait times resulted in more efficient matches, seating capacity was better utilized, thus making lower prices profitable. (**Exhibit 11** provides a snapshot of the experiment data.)

This was the information that Gilchrist was conveying to his colleagues at the meeting in early March. Gilchrist and his colleagues now needed to decide whether to overrule the 5-week freeze in the launch experiment and increase the wait time from two to five minutes in the six treatment cities. Trivedi emphasized the negative effects of longer wait times on customer experience, while Rahematpura pushed for an immediate increase of waiting times given the economic benefit.

Gilchrist, while sympathetic to the product managers' views, reiterated the importance of continuous data collection after a product launch. "We only get one shot for clean data collection," he said. "The data from the launch experiment will inform all future product improvements to Express." Seeman agreed with Gilchrist, adding, "Say we go ahead and increase wait times to five minutes across all six treatment cities midway through the launch experiment. If, in three months, we find that Express is performing poorly, we won't be able to say with certainty whether this is due to defects with Express or because people in those markets are reacting poorly to the increased wait times." Rahematpura, who had been running numbers, interjected: "According to some back-of-the-envelope calculations, by not increasing wait times now, we stand to lose \$1.6 million in the six treatment cities. That might outweigh the data collection concerns." Everyone looked to Stock for a decision.

Exhibit 1 Selected Data, Uber vs. Competitors, 2018

Company	Founded	Primary Market	# of Trips in 2017	# of Drivers	# of Riders	Last Valuation (in \$bn)	\$ Raised
Uber	2009	U.S.	4 billion	3 million	75 million	62	\$21 billion
Lyft	2012	U.S.	375 million	1.4 million	23 million	15	\$4.1 billion
Didi Chuxing	2012	China	7.4 billion	21 million	450 million	56	~\$19 billion
Ola	2010	India	6 million/wk (2016)	1 million	-----	7	~\$3 billion
Grab*	2012	Singapore	1 billion total (as of 2017)	2 million	68+ million	6+	\$4.1 billion
Go-Jek	2010	Indonesia	-----	900,000	15 million/week	~5	~\$2.1 billion
Taxify	2013	Europe	-----	500,000	10 million	~1	\$177 million
Yandex**	2011	Russia	285 million	-----	-----	3.7 (w/ Uber co-ownership)	
Careem	2012	Middle East	-----	560,000	14 million	1.2	\$572 million

Source: Casewriter, compiled from: Uber, "Company Info," 2018, <https://ubr.to/2xIGJJK>; Jillian D'Onfro and Josh Lipton, "Uber Posts Big Sales Jump in First Quarter and Boosts Valuation to \$62 Billion," CNBC, May 23, 2018, <https://cnb.cx/2LsID7N>; Megan Rose Dickey and Ingrid Lunden, "Uber's Raising up to \$600M in a Secondary Round at \$62B Valuation, Q1 Sales Grew to \$2.5B," TechCrunch, May 23, 2018, <https://tcn.ch/2KJvYwv>; "Lyft Raises New Capital and Continues Momentum," Lyft (blog), June 27, 2018, <https://lft.to/2IKNzCG>; "Our 2017 in Review," Lyft (blog), January 16, 2018, <https://lft.to/2Nk0mzq>; Dara Kerr, Lyft Grows Gangbusters in 2017, Bringing Competition to Uber," Cnet, January 16, 2018, <https://cnet.co/2lQkgpf>; Xiaochun Zhao, "Losing \$300M in 2017, Didi Chuxing Wants to Turn a Profit in 2018 amid Fierce Competition," Kr Asia, April 3, 2018, <https://bit.ly/2z64UWY>; Johana Bhuiyan, "China Ride-Hail Giant Didi Chuxing Has Raised \$4 Billion," Recode, December 20, 2017, <https://bit.ly/2BJddpA>; Xinhua, "Didi Completes 7.43 Bln Rides in 2017," January 8, 2018, <https://bit.ly/2z61UtS>; "Ola," Crunchbase, <https://bit.ly/2MGmuCP>; Arjun Kharpal, "Uber's Biggest Rival in India Just Got \$1.1 Billion from Tencent, SoftBank, Valuing Company around \$7 Billion," CNBC, October 11, 2017, <https://cnb.cx/2hAS9rj>; Anaya Bhattacharya, "As Uber Sputters, Ola Is Really Stepping on the Gas in India," Quartz, February 15, 2018, <https://bit.ly/2EvFQHq>; Sayan Chakraborty, "Ola, Uber See Rides Rise Fourfold in 2016: Report," LiveMint, February 17, 2017, <https://bit.ly/2Krn4YJ>; Swashwati Shankar, "Undeterred by High Attrition Rate, Ola and Uber Banking on Drivers in Their 20s," The Economic Times, June 1, 2017, <https://bit.ly/2tOGHzn>; "Billion Dollar Unicorns: Grab Becomes the Most Valuable Startup in Southeast Asia," One Million by One Million Blog, December 8, 2017, <https://bit.ly/2z5RDxI>; "You're One in a Billion," Grab (blog), November 6, 2017, <https://bit.ly/2j5Mu0Z>; Jon Russell, "Go-Jek Buys Three Startups to Advance Its Mobile Payment Business," TechCrunch, December 15, 2017, <https://tcn.ch/2BLuAlt>; "GO-JEK," Crunchbase, <https://bit.ly/2rk0yag>; Anshuman Daga, "Indonesia's Go-Jek Raises \$1.5 Billion as Ride-Hailing Market Heats Up: Sources," Reuters, February 26, 2018, <https://reut.rs/2F5QGUC>; Crunchbase, "Taxify," not dated, <https://bit.ly/2NkqIL9>; Jon Russell, "Uber's European Rival Taxify Raises \$175M Led by Daimler at a \$1B Valuation," TechCrunch, May 30, 2018, <https://tcn.ch/2J09giY>; Frank DiPietro, "Yandex.Taxi Is Just One Example of the Sprawling Empire Yandex Is Building in Russia," The Motley Fool, July 26, 2017, <https://bit.ly/2KFaf9a>; Ingrid Lunden, "Uber Rival Careem Closes \$500M Raise at \$1B+Valuation as Daimler Steps In," TechCrunch, June 15, 2017, <https://tcn.ch/2t4kwml>; "Careem," Crunchbase, <https://www.crunchbase.com/organization/careem#section-locked-charts>; Megan Rose Dickey, "Ride-Hailing App Careem Reveals Data Breach Affecting 14 Million People," TechCrunch, April 23, 2018, <https://techcrunch.com/2018/04/23/careem-data-breach/>; all accessed June 2018.

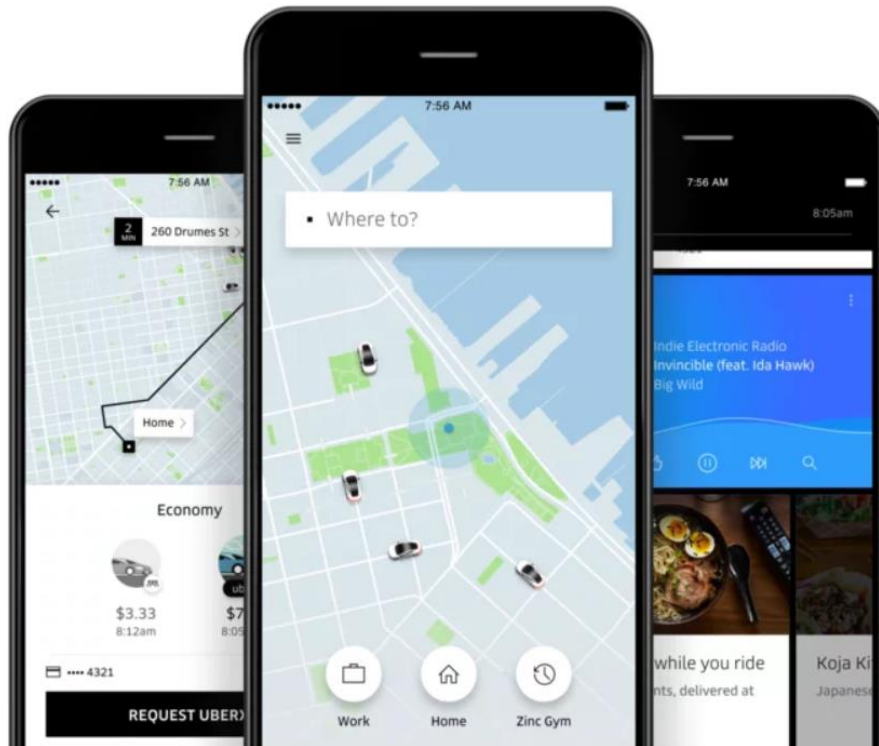
Note: * These numbers are from late 2017, prior to Uber taking an ownership stake in Grab.

** Yandex is now combined with Uber in some regions. These numbers are from June 2017, just prior to the Uber deal.

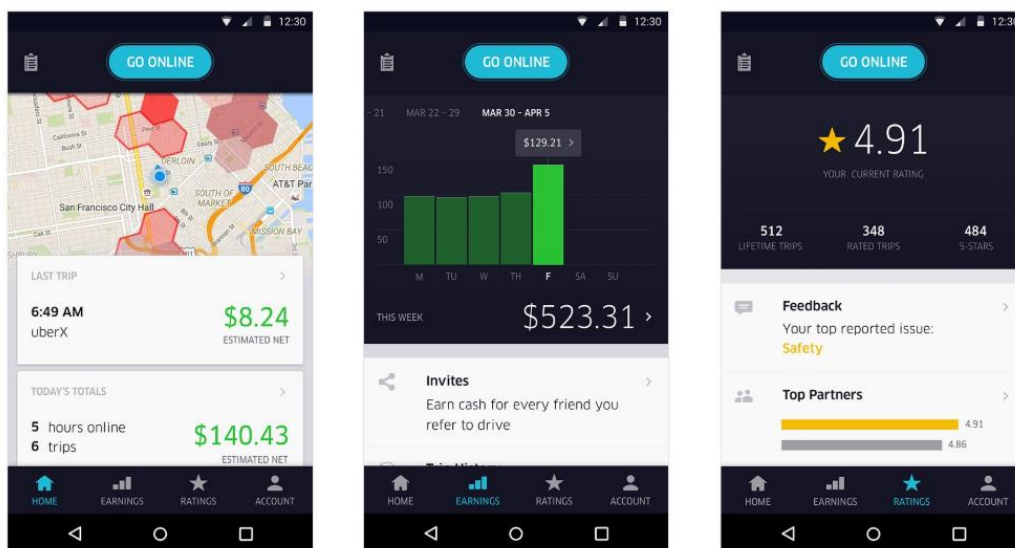
Exhibit 2 Uber Product Types, 2018

	Type	Launched	Description
Carpool Options	Express	2018	Matches riders going in the same direction; Requires riders to walk to/from their pick-up and drop-off points and wait a few minutes to be matched
	Pool	2014	Matches riders going in the same direction; Offers door-to-door rides with no walking or waiting
Economy Options	UberX	2012	Provides private, affordable rides for 1 to 4 people; Uber's core economy product
	UberXL	2014	Provides private, affordable rides for up to 6 people
	UberSelect	2015	Provides private rides for 1 to 4 people with a driver who has been consistently highly rated
Premium Options	UberBLACK	2010	Uber's original ride option; Provides private rides in high-end black cars with professional drivers for 1 to 4 people
	UberSUV	2015	Provides private rides in luxury SUVs for up to 6 people
	UberLUX	2014	Uber's most luxurious option; Provides private rides in high-end cars for 1 to 4 people

Source: Casewriter, compiled from: Uber, "Ride," 2018, <https://www.uber.com/ride/>, accessed June 2018.

Exhibit 3 Uber's Rider-Facing App, 2016

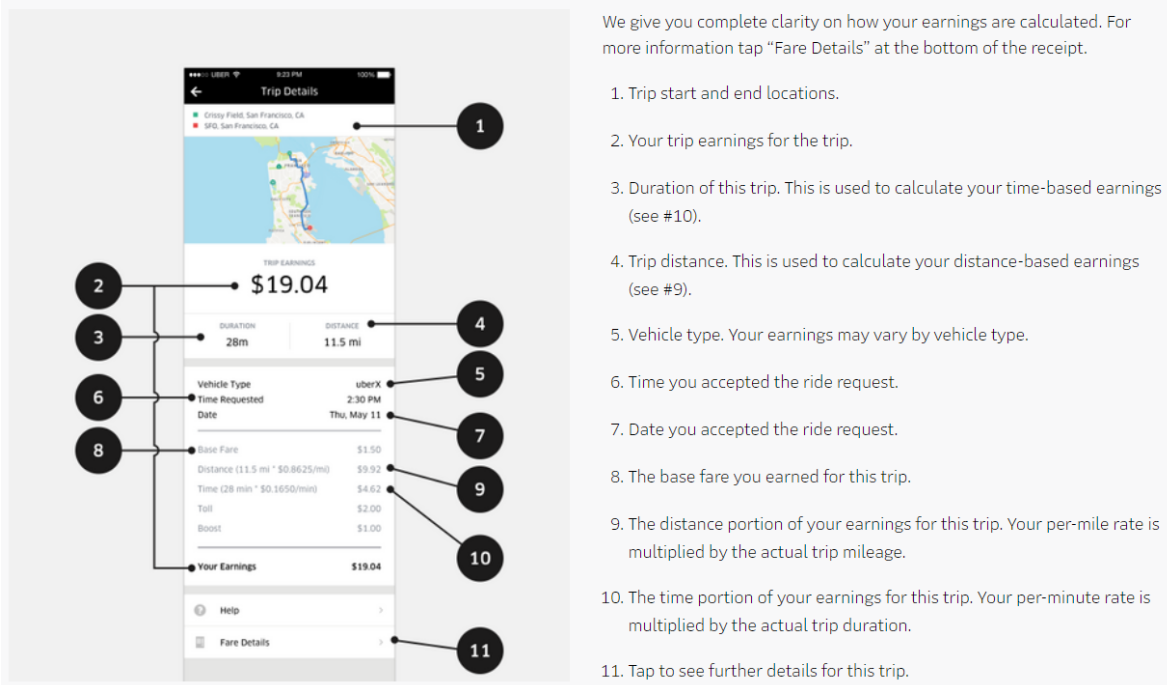
Source: Company documents.

Exhibit 4 Uber's Driver-Facing App, 2015

Source: Company documents.

Exhibit 5 Driver's Earnings Breakdown in Uber App

In the app



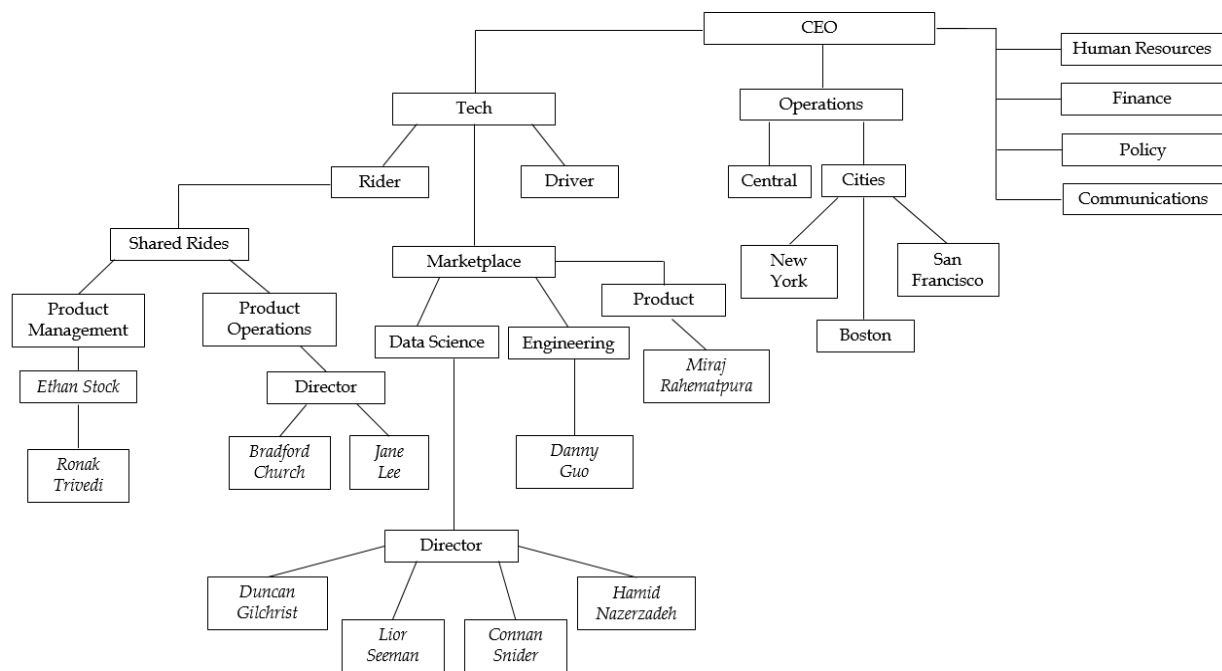
Source: Uber, "Trip Details," 2018, <https://www.uber.com/drive/resources/earnings-trip-details/>, accessed June 2018.

Exhibit 6 Median Hourly Earnings per UberX Driver, by Number of Hours Worked Weekly, 2014

	1 to 15 hours/week		16 to 34 hours/week		35 to 49 hours/week		Over 50 hours/week	
	% of drivers	Earnings/hr	% of drivers	Earnings/hr	% of drivers	Earnings/hr	% of drivers	Earnings/hr
Bos	58%	\$19.25	30%	\$20.41	9%	\$20.78	4%	\$20.48
Chi	56%	\$15.60	31%	\$16.12	9%	\$16.21	4%	\$16.03
DC	53%	\$16.61	31%	\$17.46	10%	\$17.70	6%	\$17.41
LA	59%	\$16.37	29%	\$17.07	8%	\$17.07	4%	\$16.97
NY	42%	\$26.03	35%	\$28.47	16%	\$29.65	7%	\$29.61
SF	53%	\$23.74	34%	\$25.51	10%	\$25.36	3%	\$25.36

Source: Jonathan Hall and Alan Krueger, "An Analysis of the Labor Market for Uber's Driver-Partners in the United States," *Uber*, January 22, 2015, p. 18, https://s3.amazonaws.com/uber-static/comms/PDF/Uber_Driver-Partners_Hall_Krueger_2015.pdf, accessed June 2018.

Note: Bos = Boston; Chi = Chicago; DC = Washington, DC; LA = Los Angeles; NY = New York City; SF = San Francisco.

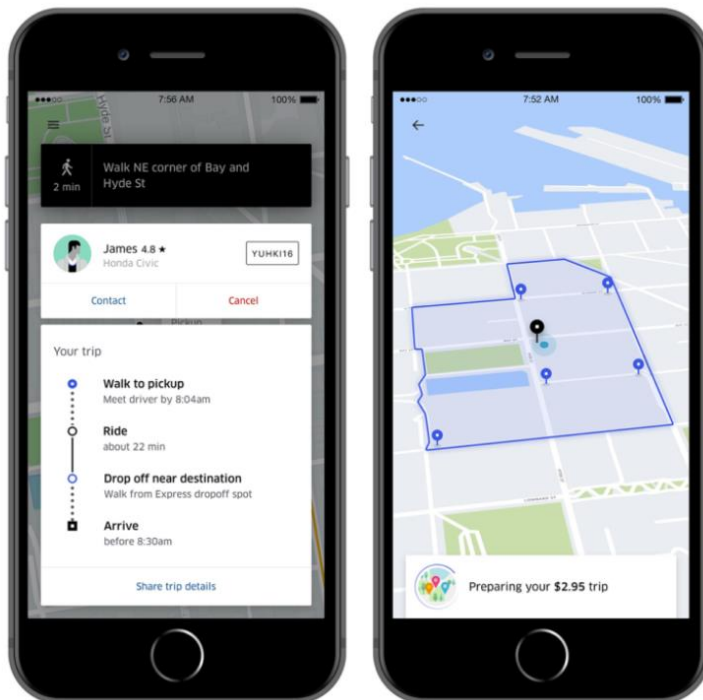
Exhibit 7 Uber's Organizational Chart, March 2018

Source: Company documents.

Exhibit 8 Ratio of Data Scientists Employees at Major Tech Companies, July 2018

	Approximate Total Employees	Share of Data Scientists
Facebook	30,000	4.5%
Airbnb	8,000	2.7%
Uber	16,000	2.4%
Netflix	5,000	1.8%
Instacart	2,000	1.0%
Lyft	14,000	0.9%
HomeAway	6,000	0.7%
Google	83,000	0.7%
Amazon	195,000	0.5%
Apple	155,000	0.5%
Upwork	33,000	0.3%
Rover	2,500	0.1%

Source: Casewriter, compiled from LinkedIn, accessed June 2018.

Exhibit 9 Uber's Express POOL User Interface

Source: Company documents.

Note: The circled area in the second picture indicates the “corner” selected for this particular area. Each of the pins is a potential pick-up point.

Exhibit 10 Timeline of Events

Date	Event
2014	Uber launches Uber POOL
2017	Uber begins re-thinking shared rides strategy to increase profitability
September 2017	Uber begins simulations on the Express POOL concept
November 2017	Uber launches pilots of Express POOL in San Francisco and Boston
February 19, 2018	Uber launches a 5-week-long synthetic control experiment to test Express POOL. The experiment has six treatment cities (Denver, Los Angeles, Miami, Philadelphia, San Diego, and Washington DC) with Express POOL and 2-minute wait time, and six control cities.
March 6, 2018	Results of the switchback experiment in Boston are available. The switchback experiment compared 2- versus 5-minute wait times.

Source: Casewriter.

Exhibit 11 Snapshots of the Data Dictionary and Data from the Boston Switchback Experiment

Data Dictionary		
Variable	Type	Definition
city_id	String	Location where the experiment took place. In the data it is always equal to "Boston."
period_start	Date	Start date and time for the 160-minute time period of the current observation.
wait_time	String	This variable takes on two possible values: "2 mins" if the matching algorithm let riders wait up to 2 minutes during the current time period; "5 mins" if the matching algorithm let riders wait up to 5 minutes during the current time period.
treat	Boolean	This variable takes on two possible values: "TRUE" if wait_time equals "5 mins"; "FALSE" if wait_time equals "2 mins".
commute	Boolean	This variable takes on two possible values: "TRUE" if the time period happens during rush hours (7-9:40AM or 3-5:40PM), "FALSE" otherwise.
trips_pool	Numeric	Total number of POOL trips completed in the current time period. Each matched ride request is a separate trip.
trips_express	Numeric	Total number of Express POOL trips completed in the current time period. Each matched ride request is a separate trip.
rider_cancellations	Numeric	Total number of requested trips that were cancelled by the rider in the current time period.
total_driver_payout	Numeric	Total dollars paid to drivers for trips completed in the current time period. This is equal to Uber's total costs for matching trips in the current time period.
total_matches	Numeric	Number of completed trips during the current time period that were paired with at least another rider for part of the trip. Each matched ride request is a separate trip, so two separate riders matched together would count as two matches.
total_double_matches	Numeric	Number of completed trips during the current time period that were paired with at least two other riders for part of the trip. Each matched ride request is a separate trip, so three separate riders matched together would count as three double matches.

Snapshot of Boston Switchback Dataset

city_id	period_start	wait_time	treat	commute	trips_pool	trips_express	rider_cancellations	total_driver_payout	total_matches	total_double_matches
Boston	2/19/2018 7:00	2 mins	FALSE	TRUE	1415	3245	256	34458.41163	3372	1476
Boston	2/19/2018 9:40	5 mins	TRUE	FALSE	1461	2363	203	29764.34982	2288	1275
Boston	2/19/2018 12:20	2 mins	FALSE	FALSE	1362	2184	118	27437.36736	2283	962
Boston	2/19/2018 15:00	5 mins	TRUE	TRUE	1984	3584	355	44995.45299	4035	2021
Boston	2/19/2018 17:40	2 mins	FALSE	FALSE	1371	2580	181	27583.9553	2200	979
Boston	2/19/2018 20:20	5 mins	TRUE	FALSE	1401	2022	135	23888.11085	2066	1062
Boston	2/19/2018 23:00	2 mins	FALSE	FALSE	1216	2543	103	29642.90567	2600	1406
Boston	2/20/2018 1:40	5 mins	TRUE	FALSE	1691	2018	150	25794.86992	1918	1281
Boston	2/20/2018 4:20	2 mins	FALSE	FALSE	1248	2481	131	23238.94629	2623	1059
Boston	2/20/2018 7:00	5 mins	TRUE	TRUE	1815	2539	284	34047.4739	2624	1565
Boston	2/20/2018 9:40	2 mins	FALSE	FALSE	1594	2773	166	28053.3648	2723	855
Boston	2/20/2018 12:20	5 mins	TRUE	FALSE	1629	2380	185	25964.4189	2477	1322
Boston	2/20/2018 15:00	2 mins	FALSE	TRUE	1640	3290	236	39912.40151	3777	1969
Boston	2/20/2018 17:40	5 mins	TRUE	FALSE	1173	1891	144	22029.73431	1893	998
Boston	2/20/2018 20:20	2 mins	FALSE	FALSE	1853	2305	159	33299.09273	2234	1145
Boston	2/20/2018 23:00	5 mins	TRUE	FALSE	1145	2419	182	25062.18271	2214	1104
Boston	2/21/2018 1:40	2 mins	FALSE	FALSE	1490	1949	125	25419.06091	1904	1120
Boston	2/21/2018 4:20	5 mins	TRUE	FALSE	1560	2309	180	25104.44488	2125	990
Boston	2/21/2018 7:00	2 mins	FALSE	TRUE	1916	3469	245	44871.10585	3575	1809
Boston	2/21/2018 9:40	5 mins	TRUE	FALSE	1664	2320	183	27626.13599	2344	1309
Boston	2/21/2018 12:20	2 mins	FALSE	FALSE	1039	3188	168	29259.93547	3045	1607

Source: Casewriters.

Note: This snapshot is provided as a case supplement. Note that the instructor may choose to assign the case without the data supplement.

Endnotes

¹ Moon, "Uber: Changing the Way the World Moves," p. 2.

² Alexia Tsotsis, "Uber Opens Up Platform to Non-Limo Vehicles with 'Uber X,' Service Will Be 35% Less Expensive," *TechCrunch*, July 2, 2012, <https://techcrunch.com/2012/07/01/uber-opens-up-platform-to-non-limo-vehicles-with-uber-x-service-will-be-35-less-expensive/>, accessed June 2018.

³ Uber, "Company Info," *Uber*, 2018, <https://www.uber.com/newsroom/company-info/>, accessed June 2018.

⁴ Uber, "Company Info."

⁵ Jillian D'Onfro and Josh Lipton, "Uber Posts Big Sales Jump in First Quarter and Boosts Valuation to \$62 Billion," *CNBC*, May 23, 2018, <https://www.cnbc.com/2018/05/23/uber-q1-financial-data-increased-sales-valuation-with-new-tender-offer.html>, accessed June 2018.

⁶ As reported by: Megan Rose Dickey and Ingrid Lunden, "Uber's Raising up to \$600M in a Secondary Round at \$62B Valuation, Q1 Sales Grew to \$2.5B," *TechCrunch*, May 23, 2018, <https://techcrunch.com/2018/05/23/uber-q1-2018/>, accessed June 2018.

⁷ Moon, "Uber: Changing the Way the World Moves," p. 3.

⁸ Miranda Katz, "This App Lets Drivers Juggle Competing Uber and Lyft Rides," *Wired*, February 15, 2018, <https://www.wired.com/story/this-app-lets-drivers-juggle-competing-uber-and-lyft-rides/>, accessed June 2018.

⁹ Leslie Hook, "Can Uber Ever Make Money?" *Financial Times*, June 23, 2017, <https://www.ft.com/content/09278d4e-579a-11e7-80b6-9bfa4c1f83d2>, accessed June 2018.

¹⁰ Uber, "Ride," 2018, <https://www.uber.com/ride/>, accessed June 2018.

¹¹ Moon, "Uber: Changing the Way the World Moves," p. 4.

¹² Stephen Antczak, "11 Things to Know before Becoming an Uber or Lyft Driver," *Forbes*, April 23, 2017, <https://www.forbes.com/sites/nextavenue/2017/04/23/11-things-to-know-before-becoming-an-uber-or-lyft-driver/#503d71fd6579>, accessed June 2018.

¹³ Noah Smith, "Uber Better Not Be the Future of Work," *Bloomberg*, March 8, 2018, <https://www.bloomberg.com/view/articles/2018-03-08/uber-drivers-earn-pay-that-s-just-above-the-poverty-line>, accessed June 2018.

¹⁴ Jonathan Hall and Alan Krueger, "An Analysis of the Labor Market for Uber's Driver-Partners in the United States," *Uber*, January 22, 2015, p. 18, https://s3.amazonaws.com/uber-static/comms/PDF/Uber_Driver-Partners_Hall_Kreuger_2015.pdf, accessed 2018.

¹⁵ Uber, "How Surge Pricing Works," 2018, <https://www.uber.com/drive/partner-app/how-surge-works/>, accessed June 2018.

¹⁶ Eric Newcomer, "Uber, Daimler Strike Partnership for Self-Driving Vehicles," *Bloomberg*, January 31, 2017, <https://www.bloomberg.com/news/articles/2017-01-31/uber-daimler-strike-partnership-for-self-driving-vehicles>, accessed 2018.

¹⁷ Wikipedia, "Synthetic Control Method," https://en.wikipedia.org/wiki/Synthetic_control_method, accessed June 2018.

¹⁸ Johana Bhuiyan, "Uber Drivers Will Get a Flat Fee for Every New Pick Up on Rides," *Recode*, September 26, 2017, <https://www.recode.net/2017/9/26/16365904/uber-drivers-pool-driver-improvement>, accessed June 2018.

¹⁹ "From Zero to Seventy (Billion)," *The Economist*, September 3, 2016, <https://www.economist.com/briefing/2016/09/03/from-zero-to-seventy-billion>, accessed June 2018.

²⁰ Johana Bhuiyan, "Uber's new 'Express Pool' is all about getting more riders to share rides," *Recode*, February 21, 2018, <https://www.vox.com/2018/2/21/17032598/uber-express-pool-transit-bus-cheaper>, accessed February 2020.



CUSTOMER ANALYTICS AT BIGBASKET – PRODUCT RECOMMENDATIONS

**PAUL ABRAHAM, MANARANJAN PRADHAN, LAKSHMINARAYANAN,
GANESH IYER, AND U DINESH KUMAR**

Paul Abraham, Manaranjan Pradhan, Lakshminarayanan, Ganesh Iyer and U Dinesh Kumar, Professor of DS&IS, prepared this case for class discussion. This case is not intended to serve as an endorsement, source of primary data, or to show effective or inefficient handling of decision or business processes.

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Customer Analytics at Bigbasket – Product Recommendations



We need to continuously improve the shopping experience of our customers. With more and more customers choosing mobile handsets to place order, browsing the entire merchandise is challenging, we need innovative ideas to make Bigbasket customer friendly.

Hari Menon, CEO and Co-founder of Bigbasket.com

Pramod Jajoo, the chief technology officer (CTO) at Bigbasket gulped down coffee, picked up his bag and mobile, ran down the stairs and hurried towards his car to leave for the airport. While he sat in the car, his phone rang and it was Sangeetha Puneekar his friend from college. Sangeetha worked in an advertising agency and had recently moved to Bangalore from Nagpur with her family. After exchanging pleasantries, Sangeetha shared her recent experience of shopping at Bigbasket.com for her groceries. Pramod was very pleased to learn that his friend was part of his customer base. Soon, the conversation turned to an interesting idea when Sangeetha shared her difficulty in placing orders using her mobile since she was not getting time in her office to use her computer to place orders owing to work pressure. She usually placed orders while traveling home in the bus. She also told Pramod that she purchased from Bigbasket.com twice in the previous week since she forgot to order a few items the first time.

During the conversation, Sangeetha introduced Pramod to two significant pain areas faced by customers based on her personal shopping experience. Sangeetha said:

At first, every time a customer logs into Bigbasket.com, they have to go through a sea of products to select the ones they need to purchase though they have a small set of regular items to purchase. Many a time, I place orders from my mobile while returning from office in the evening. Searching for the products in a small handset is painful. It invariably takes me about 20 to 30 minutes to place an order at Bigbasket.com.

Pramod shared this conversation with his team at Bigbasket.com the next day. He said to his team:

It is common that many customers forget grocery items and there are apps such as “out of milk” that helps customers with their shopping list. We as a technology team should create a solution that will assist customers with shopping list and avoid customers placing frequent orders due to their forgetfulness. Often, I tend to forget items and end up walking to the nearby store to get the forgotten item.

His team agreed that they had an opportunity to improve the shopping experience of their customers. Pramod also highlighted the fact that customers forgetting items had a significant financial impact. They may place another order at Bigbasket.com for forgotten items, which in effect meant that the logistics team at Bigbasket.com, would be making two trips to the same place possibly within a few hours, which in turn would incur additional cost for the company in terms of the supply chain cost; or the customer may choose to buy the forgotten item from a store close to his/her residence and may buy other products also from the shop resulting in lesser basket size in the future for Bigbasket.com from that customer.

The technology team at Bigbasket.com held several brainstorming sessions and simultaneously continued its research to find the most appropriate solution to the problem Sangeetha shared with Pramod, especially while placing an order on mobile handsets. In one of their follow-up meetings in May 2015, Pramod said:

E-commerce companies such as Amazon and Flipkart use product recommendations. In fact, I read in a book that Amazon earned 35% of the revenue through its product recommendations. I think we need to find a solution to our customer problems using predictive analytics. What we are trying to do is to predict what a customer is likely to buy in the future and whether the customer may have forgotten an item.

There was a consensus among the team members that they should generate an analytics solution to the problem that they were trying to solve.

BIGBASKET.COM – THE ONLINE GROCERY RETAILER

Bigbasket.com was India's largest online grocery and food store established in 2011 by a group of entrepreneurs Hari Menon, Vipul Parekh, V S Ramesh, V S Sudhakar, and Abhinay Choudhari. In 2016, Bigbasket sold more than 18,000 products and 1,000 brands operating across 12 Indian cities.

Online grocery market in India has been small, but a rapidly growing segment. According to “*The Retailer*” Ernst and Young's publication in consumer products and retail sector, during July–September 2015, India was among the top-10 food and grocery markets in the world, with an estimated size of INR 22.5 trillion (approximately USD 350 billion¹). The market has grown at 10–12% CAGR between 2010 and 2015, with food and grocery being the largest segment, accounting for close to 60% in 2015 alone. Despite this staggering figure within the segment specified, the presence of organized players has been still very low at less than 5%. One of the emerging trends in food and grocery retailing has been online grocery stores. The size of online grocery retailing market in India was estimated to be around INR 40 billion (approximately USD 0.6 billion) in 2015, which is less than 1% of the overall food and grocery sales. According to Ernst and Young report in 2015, the online grocery retailing market was growing at a rapid pace of more than 35% CAGR,² with a market penetration estimated to be at 2.3%.

According to Ernst and Young³, there is no clear winner in terms of which business model works best with online grocery retailing. Several players, following different models, have entered the online grocery market in India. According to USDA report 12⁴, online grocers increased from 14 in 2013 to 44 as of September 2014. In 2015, pure-play online grocery retailers were at the forefront of the boom in grocery e-commerce. These companies built large warehouses and distribution centers outside major cities and owned fleets of GPS-enabled vehicles in order to serve online demand. In 2015, Bigbasket, LocalBanya, PepperTap, Grofers, EkStop, and ZopNow were the main players leading this space.

¹ Source: [http://www.ey.com/Publication/vwLUAssets/EY-the-retailer-july-september-2015/\\$FILE/EY-the-retailer-july-september-2015.pdf](http://www.ey.com/Publication/vwLUAssets/EY-the-retailer-july-september-2015/$FILE/EY-the-retailer-july-september-2015.pdf)

² Ibid

³ Ibid

⁴ Rise of online grocery retail. GAIN report number IN4079

In 2015, Bigbasket.com hired the Bollywood star Shah Rukh Khan as their brand ambassador and released promotional material (**Exhibit 1**). Bigbasket.com had a customer base of greater than 3,50,000 with an order growth rate of 30% every month.

CUSTOMER ANALYTICS AT BIGBASKET

Bigbasket.com was the first online store in India. The unique selling proportion (USP) of Bigbasket.com was customer convenience, especially in cities such as Bangalore, where travel time could be high even for short trips owing to traffic congestions. Adding to this, the internet penetration in Tier 2 cities was low and many could access internet only through smart phones. Pramod said:

We estimated that about 30% of our customers place orders through smart phones. Unlike other e-commerce companies such as Amazon, Bigbasket customers place order for several products, sometimes as high as 80 in one order depending on their purchase frequency. A few customers buy all their groceries once a week and there are customers who would place order once a month. When the basket size is high, using smart phones to place order is challenging.

However, compared to e-commerce companies such as Amazon, customers at Bigbasket.com bought the same product repeatedly since these were daily use items such as vegetables, bakery and dairy products and branded foods. Pramod and his team thought that using the purchase behavior of a customer, they could predict the products a customer was likely to purchase in the future. Thus, the idea for “Smart Basket” emerged, which was created for each individual customer on basis of what he/she was likely to purchase when logged into the Bigbasket.com system.

It was possible that customers could forget to buy items, especially when they did not use the “Smart Basket” option. Thus, the idea for the “Did you forget?” feature was conceived, providing product recommendation to the customer while checking-out, based on the purchase history of a particular customer.

The “Did you forget?” use case is a unique problem to solve; the input to derive the recommendation looks primarily at the items in the basket and the customer’s purchase history. It does not look at buying history or patterns for other similar customer profiles. The problem statement is specific to the situation where the customer has already filled the basket and is ready to check-out.

DECISION MAKING AND ANALYTICAL SOLUTION

Bigbasket.Com had access to all the point of sale data. It had a list of registered customers along with their purchase history, which served as an input to building a recommendation algorithm. Data structure and results of data exploration are provided in **Exhibit 2**. Both the “Smart Basket” and “Did you forget?” features are essentially product recommendations. There were many recommendation algorithms

Customer Analytics at Bigbasket – Product Recommendations



such as collaborative filtering for recommending a set of products to the customers. E-commerce companies such as Amazon, Flipkart, and Netflix greatly benefited by using advanced algorithms for designing recommender systems. However, the problem faced by Bigbasket.com was significantly different from other e-commerce companies. The team led by Pramod started exploring various ways in which the “Smart Basket” and “Did you forget?” features could be built and improvised upon.

Exhibit 1

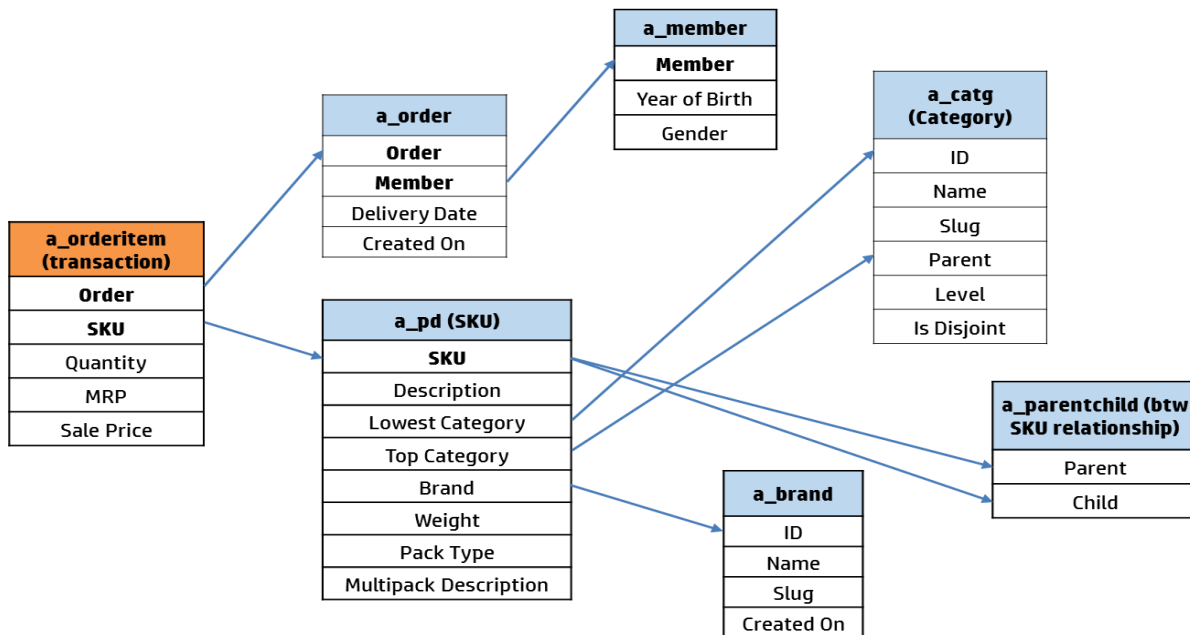
Bigbasket.com Brand Ambassador Bollywood Superstar Shah Rukh Khan



Source: Bigbasket.com

Exhibit 2

Entity relationship diagram showing how data is collected and stored by the online retailer



Source: Based on data received from Bigbasket.com

ENHANCING VISITOR EXPERIENCE AT ISKCON USING TEXT ANALYTICS

R VINODHINI, S R VIGNESHWARAN AND U DINESH KUMAR

R Vinodhini, S. R Vigneshwaran and U Dinesh Kumar, Professor of Decision Sciences, prepared this case for class discussion. This case is not intended to serve as an endorsement, source of primary data, or to show effective or inefficient handling of decision or business processes.

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It was 6 am on Sunday, 2 September 2018. It was a typical monsoon day in Bangalore with the chilly breeze and light drizzle. The International Society for Krishna Consciousness (ISKCON) temple, Bangalore was crowded with devotees, visitors, and curious minds. Vignesh a research student at the Indian Institute of Science, Bangalore was at the Higher Taste restaurant inside ISKCON premises, waiting for his favorite Vedic coffee. While waiting for the coffee, Vignesh started observing the crowd and began to wonder what motivated these people to visit ISKCON on a drizzly Sunday morning. Until that day, Vignesh believed that ISKCON was a worship place of Sri Radha Krishna. However, looking at the mission statement of ISKCON on the walls of the restaurant, Vignesh realized ISKCON was much more than a place of worship. Mission statement of ISKCON:

“We are trying to give human society an opportunity for a life of happiness, good health, peace of mind and all good qualities through God consciousness.”

While sipping the coffee, Vignesh began to reflect on how a temple could give a life of good health. To understand the philosophy behind ISKCON and how it enabled visitors to lead a happy and healthy life, Vignesh decided to meet Karuna Keshava Das, the youth guide at ISKCON.

After greeting each other, Karuna said:

“We believe that for someone to be happy and peaceful, the foremost necessity for sustenance – food – should be met. A hungry man is an angry man. ISKCON is trying to bring happiness by satiating the hunger of millions of people across the world. The first charitable initiative of ISKCON was the Unlimited Food for Education program which has now grown to become the world's largest NGO-run mid-day meal program serving wholesome school lunch to over 1.76 million children in 14,314 schools across India.”

Karuna also fondly remembered how Steve Jobs quoted his affiliation with the Hare Krishna Movement during his commencement address at Stanford University in 2005.

“I didn't have a dorm room, so I slept on the floor in friends' rooms. I returned coke bottles for the 5¢ deposits to buy food with. And I would walk the 7 miles across town every Sunday night to get one good meal a week at the Hare Krishna temple. I loved it.”

Vignesh, a passionate data researcher, noticed that feedback forms were distributed to the visitors and was keen to understand how ISKCON was using the data that they collected. Karuna Kesava Das said:

“You should meet Janarthanan Balasubramanian, Division Head, Information Technology and Online Communications at ISKCON. His team collects a lot of data and you can probably help us analyze the data and tell us what you find.”

The following day Vignesh met Janarthanan Balasubramanian, and discussed about how ISKCON was collecting data and how Vignesh could help to derive insights from the data. Janarthanan told Vignesh that

while they gather data from various sources, they did not find potential use of data that was collected and stored. ISKCON was keen to analyze the feedback/reviews from visitors and devotees.

Janarthanan elaborated that while ISKCON, Bangalore had footfall from various regions across India and abroad, the feedback form (**Exhibit 1**) used by them was not enough to get a proper picture about visitors' experience at the temple. Very few visitors filled the feedback forms placed at various points inside the temple premises. Moreover, with the increasing use of social media, many people preferred to share their experiences in social media platforms such as Trip Advisor, Facebook, and Google. ISKCON wanted to use the data from social media to understand the areas of improvement.

Janarthanan said:

“It is essential for us to reach out to people and for people to be in touch with us. To understand what visitors are talking about us on various social media, we have a data team that collects comments/reviews across these platforms manually, every day. Our team also collects the offline reviews from the feedback forms placed in different areas of the temple. We do not have enough manpower to analyze the data and take quick measures to improve devotee's experience at ISKCON. We are trying to explore how analytics can help us improve our services to the visitors.”

ABOUT ISKCON

The International Society for Krishna Consciousness (ISKCON), also known as the Hare Krishna movement, was founded by His Divine Grace A. C. Bhaktivedanta Swami Prabhupada in New York City in 1966. In 1965, he traveled to the United States with the ambition to start the worldwide Hare Krishna movement. In the next 11 years, he established more than 100 centers, temples, vegetarian restaurants, and farm communities, Vedic schools, the Bhaktivedanta Book Trust, and initiated various community projects.

Many eminent researchers and historians have extensively studied ISKCON and the books by Srila Prabhupada. Diana Eck, Professor of Comparative Religion and Indian Studies at Harvard University, describes¹ the movement as “a tradition that commands a respected place in the religious life of humankind.” In the 1980s, Dr. A. L. Basham, one of the world's authorities on Indian history and culture, wrote about ISKCON:²

“It arose out of next to nothing, in less than twenty years and has become known all over the West. This, I feel, is a sign of the times and an important fact in the history of the Western world.”

Around 1984, devotees from across the world took initiatives to open ISKCON centers in different parts of India. In 1987, ISKCON started its operations in Bangalore from a rented house. Later in 1997, the temple

¹ Source: <http://www.iskcon.org/what-is-iskcon/>

² Ibid

and cultural complex was inaugurated by the then President of India, Shankar Dayal Sharma. ISKCON, Bangalore has since become one of the largest ISKCON temples in the world.

ACTIVITIES OF ISKCON

ISKCON, Bangalore is not just a religious institution. It has been a charitable society involved in a lot of social work and has initiated several self-sustained groups that work towards improving the physical, mental, emotional, and intellectual well-being of human life³.

Akshaya Patra has been an initiative to provide mid-day meals for schools in rural India where most of the children are underprivileged and undernourished⁴. The Cultural Education Services (CES) wing of ISKCON worked with children to enhance values and life skills through cultural activities. Krishnashraya, a home-based spiritual rejuvenation program, was conducted at various locations in the city of Bengaluru to inculcate the principle of devotion and volunteering among people. Friends of Lord Krishna (FOLK) was a Youth Empowerment Club aimed at guiding younger generation to a happy life. The program also catalyzed the youth culture by designing rich avenues in art, theatre, science, philosophy, and so on⁵. Senior devotees of ISKCON organized pilgrimage trips to various holy places in India. The organization was also involved in protecting cows (goshala), nitya annadana (food distribution for temple visitors and pilgrims) and organizing harinama kirtanas and bhajans (musical programs where the devotees sang the holy names of Lord Krishna).

OVERVIEW OF IT AT ISKCON

The primary responsibility of the IT department at ISKCON was to design, deploy, maintain, and support the ISKCON information technology infrastructure in an efficient, productive, and secure environment. The IT function at ISKCON could be broadly classified into four sections namely: Governance, Infrastructure, Application, and Online Presence. The Governance team was responsible for ensuring that the IT infrastructure was planned and deployed to achieve the strategies and objectives of the organization. The infrastructure team was responsible for supporting the end user computing infrastructure and to set up and maintain the data center and network infrastructure. The application team was involved in enterprise implementation and in developing, maintaining, and supporting various business applications used by ISKCON. The online presence team created and maintained websites and social media accounts for creating awareness on various activities of ISKCON.

PROBLEM AT HAND

The online presence team at ISKCON collected the visitor feedback from various social media channels to see how this feedback could help the organization improve its services to the visitors. The primary problem at hand for Janarthanan was to reduce the existing manual effort for his team. In 2018, three resources (staffs) were involved in collecting the reviews from social platforms such as TripAdvisor, Google Plus,

³ Source: ISKCON website: <https://www.iskconbangalore.org/our-objectives/>

⁴ Source: Akshaya Patra Website: <https://www.akshayapatra.org/>

⁵ Source: FOL website: <https://www.folknet.in/about-us/>

and Facebook and labeling each review into one of the four classes viz, positive, negative, neutral, and mixed. Two other resources converted the reviews from paper feedback forms/feedback registers placed at different points inside the temple, to an Excel file. The team began its day by manually collecting, labeling and collating the reviews in an Excel file⁶ (**Exhibit 2**). At the end of the day, these labeled reviews were stored in the database. At the end of the week, the total count of reviews for the four classes viz, positive, negative, neutral, and mixed was calculated to understand the overall sentiment. This was an extremely time-consuming manual process from data collection, that is, manually copy pasting the comments from social mediums to data labeling and collation.

Janarthanan wanted his team to spend time and effort on analyzing the data and working on remedial actions rather than on these mundane daily operations. He wanted to understand the issues/topics that ISKCON should work on, rather than manually classify reviews and get the count of each review type. Janarthanan felt that getting only the split of positive/negative/neutral/mixed classes was not enough to draw inferences.

Janardhan said:

“Having just the number of positive and negative reviews is not helping us much. We want to comprehend if there is any pattern in the number of positive and negative reviews. For e.g. are the negative comments higher on weekends or weekdays? Have the negative comments increased during a particular month? Are there any spikes or dips in negative sentiment? To summarize, we are looking for a timeline analysis that shows if the number of negative reviews have come down over a period of time. This analysis would help us understand if our remedial actions are actually working.”

Janarthanan pointed out another issue they encountered because of the manual process of labeling the reviews. He mentioned that each staff used their own logic to label a given review as positive/negative/neutral/mixed. The labels were thus subjective and there was a lot of overlap between the mixed and neutral classes. As a result, the classification count and sentiment label was not accurate. Another confusion with the mixed class (both positive and negative in one review) was to figure out how positive/negative a given review was and how to handle the mixed class.

Along with the aforementioned problems, Janarthanan was curious to understand if there was any way to drill-down on the sentiment classification and infer the tone of the reviewer. Vignesh gave another option that they could drill-down sentiments to emotions instead of inferring the tone, that is, if a sentiment is positive, what is the associated emotion (Joy, Peace, Surprise); and if a sentiment is negative, what is the associated emotion (Anger, Disgust, Frustration)?

Janarthanan said that his current team was not equipped with the skills and he was looking for a fully automated solution that would automatically extract the reviews from social media and label them into one of the four classes. The results would then be showcased to the management to discuss the top issues that people expressed about ISKCON and how to act upon the visitors' concern. Janarthanan concluded saying

⁶ Excel spreadsheet containing the data is provided as a supplementary material

that he was looking for an all-in-one solution that would give the sentiments, trends, emotions, and top 10 issues to be addressed.

At the end of the meeting, Vignesh was rapt and inquired as to why a charitable society like ISKCON gave so much importance to visitor feedback and had a dedicated team to investigate this.

Janarthanan elaborated:

“ISKCON’s vision is to bring more visitors to the temple and spread the message of Vedic scriptures so as to increase the awareness of Krishna consciousness among masses. We want to understand the good/bad of ISKCON from a visitor’s perspective. What we think good, might be less appealing to visitors.

For e.g. ISKCON and “food” are synonymous in people’s mind. Hence, we thought feedback would revolve around the quality of food and meal portions. On the contrary, lately, we are seeing negative reviews popping up in social media for the souvenir stalls we have in the exit pathway of the temple. We would like to reach out to people and make them understand that souvenir stalls are a means to fund our charitable activities, as we cannot rely only on donations all the time. Visitors should understand that buying from our stalls is a form of help to our charitable work. ISKCON is the only temple that provides extremely tasty, rich and hygiene free food for every person who visits the temple. Very few temples provide one free meal a day or sometimes on special occasions. We are looking to continuously improve the experience we provide to our visitors and clarify ourselves on any sort of negative sentiment from people’s minds.”

Janarthanan gave Vignesh all reviews they had manually collected from January 2015 to September 2017. The sample data is provided in **Exhibit 2** and data dictionary is provided in **Exhibit 3**.

Upon analyzing the data, Vignesh came up with few difficulties that was not elementary.

- Comments had at least two different languages apart from English.
- English reviews had a lot of spelling errors.
- Many reviews were duplicated.

Vignesh called up his friend Vinodhini, who had previously dealt with text data and detailed the problem statement. Vinodhini found another set of new problems with the data. One major problem was that the reviews were not only in English, French, and German, but also had Hinglish (Hindi language written in English). Another problem she encountered was regarding the classification labels – how do we handle the mixed and neutral classes?

The following explanation was given by ISKCON for mixed and neutral classes:

“Mixed type” is when comments are both Positive and Negative.

‘E.g. Temple is clean and well maintained, but it looks like a mall with way too many shops.’

“Neutral type” is just giving facts.

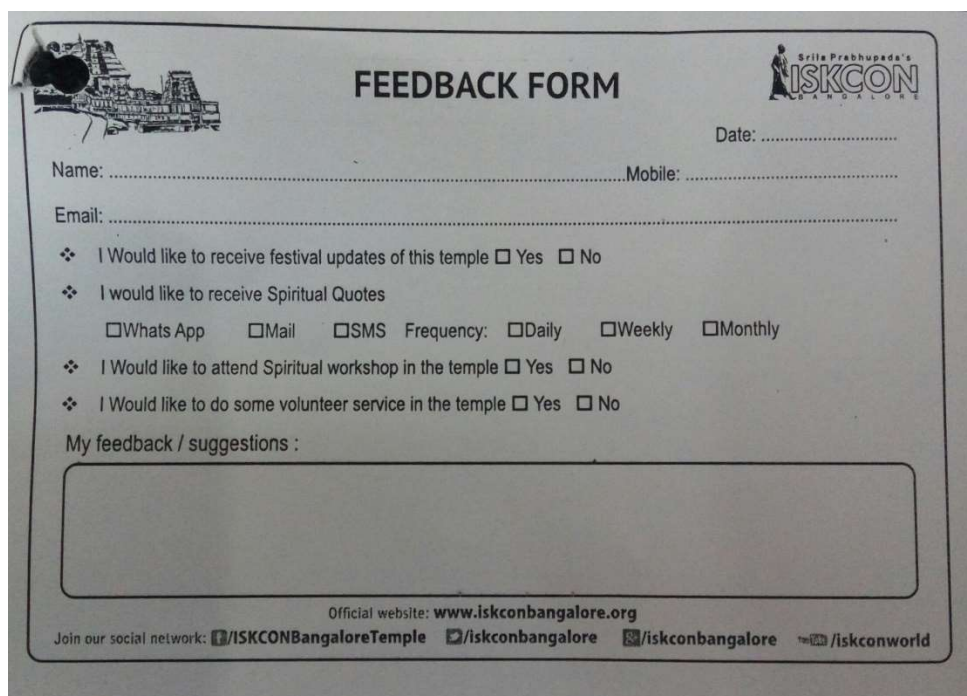
‘E.g. Temple will be opened till 12.30pm.’

After a few brainstorming sessions, Vignesh and Vinodhini identified the following decision points:

- 1) How do we reduce the manual effort and automate the current process?
- 2) How do we create a user interface (UI) that will make the entire data analysis more efficient? What open-source technologies should be used?
- 3) How do we perform a trend analysis with the given data?
- 4) How do we handle the multi-label classifications (positive, negative, neutral, mixed)? Is it necessary to have four classes? Can the mixed class be merged with either positive or negative class?
- 5) What kind of emotions would people have when they visit the temple? How do we analyze these emotions?
- 6) How do we handle Hinglish and other language comments?
- 7) What actionable items do we suggest for ISKCON based on text analytics?

Exhibit 1

Feedback Form



FEEDBACK FORM

Date:

Name: Mobile:

Email:

❖ I Would like to receive festival updates of this temple ☐ Yes ☐ No

❖ I would like to receive Spiritual Quotes

☐ Whats App ☐ Mail ☐ SMS Frequency: ☐ Daily ☐ Weekly ☐ Monthly

❖ I Would like to attend Spiritual workshop in the temple ☐ Yes ☐ No

❖ I Would like to do some volunteer service in the temple ☐ Yes ☐ No

My feedback / suggestions :

Official website: www.iskconbangalore.org

Join our social network: [/ISKCONBangaloreTemple](#) [/iskconbangalore](#) [/iskconbangalore](#) [/iskconworld](#)

Source: ISKCON

Exhibit 2

Sample Data

Review ID	Source	Reviewer	Review date	Review Subject	Text	Review rating	Review Type
1	Facebook	Hari Shanker	10/8/2017		Excellent devotional place	5	POSITIVE
2	Facebook	Dr-Harsha Vardhan Reddy	10/8/2017		Hara rama Hara krishna Huge temple. Inside it having lot of shops.	4	POSITIVE
3	Facebook	Sujit Tiwari	10/8/2017	N/A	It is very good place to get peace of mind n pray to God... Hare ram Hare ram ram Hare Hare... Hare krishna Hare krishna krishna krishna Hare Hare..... I like this very much	4	POSITIVE

Exhibit 2 (Contd.)

4	Google	Jason Zachariah	10/8/2017		I loved the architecture. But towards the end, commercialisation of the complex send a bit of bad vibe. Still, i liked the place a lot	4	MIXED
5	Google	Anand G	10/8/2017		Nice temple ... Whenever i visit, I feel very peaceful.	5	POSITIVE
6	Facebook	Anil Grover	11/8/2017		Jai mata dihare kreshna ji.....Jes jagha per parmatma ka VAAS hai..Vo jagha SAWARG se the SUNDAR hai.....AGR	4	POSITIVE
7	Trip Advisor	LizWaz	11/8/2017	Lovely temple	Worth a visit, beautiful deities, wonderful chanting and incense and prasad was offered, a delicious curried rice. Very clean and excellent gift shops.	5	POSITIVE
8	Trip Advisor	Vtvram	11/8/2017	A cultural complex	It is not a temple in the strictest term as the atmosphere of an Hindu temple is missing. It is more a picnic spot Visited May 2014	3	NEGATIVE
9	Trip Advisor	Krishna1906	11/8/2017	Pilgrimage	Divine and heavenly. Very neat and serene atmosphere. But one thing I do not agree is the forced sale of various products inside the temple. Visited June 2014	5	MIXED
10	Facebook	Yassigue Roger Fofanan	12/8/2017		Spendid temple. Tres beau a visiter et propre. Replète une image agreable a bangalore.	4	POSITIVE

Source: ISKCON

Exhibit 3

Data Dictionary for Online Reviews

Variable Name	Description
Review ID	<No description... review identifier>
Source	Social medium on which the review was posted
Review By	Reviewers name
Review date	Date of review in <dd-mm-yyyy> format
Review Subject	Title of the review
Text	Content of the review
Review rating	Rating given by the reviewer
Review Type	Labels given by ISKCON team

Source: ISKCON

LHSC MULTI-ORGAN TRANSPLANT PROGRAM: POOLING ONTARIO'S KIDNEY TRANSPLANT WAIT-LISTS

Felipe Rodrigues and Fredrik Odegaard wrote this case solely to provide material for class discussion. The authors do not intend to illustrate either effective or ineffective handling of a managerial situation. The authors may have disguised certain names and other identifying information to protect confidentiality.

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Version: 2019-01-14

It was June 26, 2017, and Henry Rogers's first day of work at London Health Sciences Centre (LHSC) began with a surprise. Rogers had a graduate degree in Management Science and had taken the job as an analytics specialist at LHSC at the beginning of the summer. Dr. Vivian McAlister, an experienced surgeon and researcher at this internationally acclaimed hospital in Southwestern Ontario, Canada, knew that analytics could be a powerful decision tool for the health care industry. When Rogers accepted the job, McAlister knew he could put Rogers's expertise to effective use right away. McAlister invited Rogers to a meeting with Dr. Tony Jevnikar, director of the hospital's Multi-Organ Transplant Program. The meeting was about a subject Roger knew little about: kidney transplants.

"Henry, we have very little time to take a decision that could impact a lot of people's lives—a lot!" said Dr. McAlister. Saving lives was not what Henry expected on his first day. Being in unfamiliar territory made him rather nervous. He hoped he could meet McAlister's expectations.

THE MULTI-ORGAN TRANSPLANT PROGRAM MEETING

After the usual round of introductions, Jevnikar went directly to the point: "Vivian, as you know, I just got back from Toronto. I presented our current numbers to the health ministry's transplant team regarding our kidney transplant program."

"I bet they are impressed, Tony," said McAlister. "After all, we managed to keep the wait time for kidney transplantation to a little less than a year."

Rogers began to sense where this conversation was going. He knew that transplant wait-lists were a delicate issue that involved not only medical efficiency but also social fairness and politics. Waiting one year for a transplant, though, seemed like a long time.

"Yes, they are, Vivian. The big problem is, the rest of the province is not doing so well. They showed their numbers and it seems that they have been having trouble reducing their wait time to a little less than four years."

Precipitately, Rogers jumped into the conversation: “Wow, can the patients handle from one to four years for a transplant? Really?”

The looks from McAlister and Jevnikar showed that they were a little surprised by the question. After all, if Rogers was going to work at the hospital, he needed to be better acquainted with its reality. The wait time of one year was in fact a relatively good number, considering the reality of the transplantation procedure in North America.

“Henry, you are right, it is a long time. But it could be worse,” said McAlister. From the other side of the table, Jevnikar nodded approvingly.

Rogers thought it would be better to admit his lack of knowledge now than fall into a trap later. “I’m sorry for my ignorance, but can you go through the basic procedure for a kidney transplant?”

McAlister replied:

When kidney patients are diagnosed with end-stage renal disease, or ESRD, they are immediately put into dialysis treatment. Therein lies the first problem: dialysis is only supposed to be temporary. Patients take a heavy toll taking dialysis many times a week, and it is not an ideal situation for the patients, or the family, or the health care system. At the time of their diagnosis, we run some tests and we establish whether the patients are suitable for transplantation. If we find that they are, then their place is confirmed on the wait-list. Patients then take dialysis until we find a good match for a transplant. Keep in mind that not only is dialysis palliative, it is also expensive, and the survival rate adjusted for five years is less than 45 per cent. Transplants however, have a survival rate ranging from 80 to 90 per cent, depending on the type of the patient.

“So the sooner patients receive transplants, the better?” asked Henry.

Jevnikar responded:

Precisely, Henry. The demand is not so much the problem; supply is the real problem. Donors are a rare breed. Most of the organs come from what we call deceased donors. These are usually other patients who died, usually suddenly, for other reasons. We have them tested with consent of their families to see whether they can be donors of multiple organs—in this case, kidneys. We perform the surgery to extract the suitable organs and tissues, and transplant these to the patients on the wait-list. The donors are the real heroes, and we make sure to show our appreciation. You should come by to one of our donor appreciation events and see how meaningful this is for all the families involved.

McAlister agreed and, feeling he needed to explain further, said, “Kidneys have a particularity. Unlike livers, for example, we have two kidneys per donor, which helps a great deal with managing the wait-list.”

Rogers’s expression revealed that he had never thought about that fact before. He pondered how little he remembered from his high school human biology classes, and felt a bit out of place. Both doctors saw Rogers’s face at that moment of realization and glanced at each other as if saying, “This never gets old.”

McAlister continued, “We do not have enough deceased donors. And I suppose that the rest of the province is in worse shape than we are in this matter.”

“It seems the system is not stable,” Rogers said, hoping to sound knowledgeable. The result was a concerned face from both the doctors.

“What do you mean?” they asked in unison.

Rogers continued, “Well, if you have more patients arriving than donors, the queue will keep growing indefinitely.” More concerned faces, he noticed.

Jevnikar continued where McAlister had stopped, explaining, “We have many programs to help increase the number of donors, but our main alternative is living donors. Whenever new patients enter dialysis, if they or their families feel like the wait time is too long, they make an effort to find a family member willing to donate one of their kidneys.”

Jevnikar paused, then added, “And yes, you can live rather well with only one kidney,” anticipating Henry’s question. Again, the doctors glanced at each other, knowing that it was a familiar question.

McAlister added:

At the end of the day, the longer the wait time, the higher is the incentive to find a family member willing to donate. Here in London, because the wait is approximately one year, we do not rely so much on living donors. But in the rest of the province, living donors are the best way to bring the wait down. Isn’t that right, Tony?

“Does each hospital have its own wait-list?” asked Rogers.

Jevnikar replied:

No, Henry. For the sake of simplicity, let’s say that the Ontario is divided into regions. Western Ontario is attended by London, and Eastern Ontario, by Toronto. Occasionally, we share donors, but it does not happen on a consistent basis. And here is the catch. The Ministry of Health is considering the possibility of pooling the two wait-lists—in other words, merging the two independent wait-lists that we have today into one single program. We would still make the transplants in both London and Toronto, but the wait-lists would be unified and both patients and organs would be transported on a need basis.

“How does the transportation work? Does that affect the organ or the transplantation at all?” asked Rogers curiously.

Jevnikar responded:

Preferably, the organs are transported. That minimizes the hassle for the patient and the family. But you are right, the longer the organ takes to be transplanted, the higher the likelihood that it might be wasted. Unfortunately, every now and then we have a kidney that is not transplanted. This is usually due to difficulties finding a match, or either the patient or the organ does not arrive at the operating room in time. This is a problem that could increase if the wait-lists are pooled. Not to mention potentially high transportation costs. Fortunately those cases are still rare here.

“I’m a bit concerned about this merger,” said McAlister. “We have a one-year wait time, but in terms of donors, our program is roughly one-third the size of the program in Toronto. I fear that if we merge,

Toronto will have just a bit of an improvement since they are so much bigger than us, and we will increase our wait time enormously.”

“I agree, Vivian. My instincts say that our patients will be worse off, and Toronto’s patients will not even notice the change,” Jevnikar agreed, concerned. “But I guess this is the reason Henry is here, isn’t it? What can you do to help us understand the impact this merger might have?”

By now, Rogers knew this was a typical queuing problem and that, as with all things related to queues, he was very cautious: “From what you have told me so far, this situation can indeed impact the lives of many patients. One thing is for sure: I need two kinds of data to help you.” As he thought about the problem at hand, he added, “To begin with, I need the arrival dates for patients on both wait-lists. And I also need the transplant dates for those patients.”

“I am sure you can find all that in our database. We are very meticulous about details,” said McAlister.

Rogers cautiously, but excitedly, replied:

With that information, I would be able to know the rate of arrivals of the patients on the wait-lists. Also, the intervals between the transplants will give me the information I need for the service rates. Since it has not been an issue yet, I will assume that no organs are wasted and that the wait-list approximates a first-come, first-serve basis.

“Because supply and demand are so tight, I suppose you can make those assumptions,” said McAlister.

Rogers continued, “Give me a few days to get acquainted with the database, retrieve the data, and run some rough numbers, then we can meet again, say next week, and I would be able to show you a rough analysis.”

Jevnikar said:

I have to meet the Ministry of Health’s team in a couple of days. Vivian, you are coming with me to help with the clinical side. Henry, please crunch your numbers and let me know by tomorrow what you think we should do in terms of this merger. What will happen to our wait time and to the size of the wait-list? Should we pool the wait-lists? What if the number of patients increases? What if the number of donors increases?

Rogers replied nervously, “Tomorrow?”

McAlister looked at Rogers as if saying, “I told you we had very little time.”

“And by the way,” said Jevnikar, “Welcome to the team.”

BACKGROUND INFORMATION

End-stage renal disease (ESRD) was a condition in which the kidneys were permanently impaired and could no longer function normally to maintain life. Once diagnosed with ESRD, a patient had only two treatment options: dialysis, and renal replacement therapy (RRT), commonly known as a kidney transplant. Most often, ESRD was a condition caused by glomerulonephritis, diabetes, or renal vascular disease, but it could have other origins. It did not discriminate on the basis of age, gender, or race. Transplanting of kidneys, on

the other hand, had a much higher five-year survival rate, ranging between 80 and 90 per cent, depending on the population group.¹ Thus, RRT was the preferred treatment for ESRD.

From 1991 to 2010, the prevalence of ESRD in Canada had increased 77.38 per cent. Measured in rate per million population (RPMP), the prevalence of ESRD had jumped from 93.3 in 1991 to 165.5 RPMP in 2010, and was expected to keep growing. More than 39,000 Canadians had been diagnosed with ESRD, of which more than 16,000 were living with a functioning kidney transplant. The province of Ontario had Canada's largest share of ESRD patients, totalling more than 16,000. Of this total, 37 per cent were living with a functioning transplanted kidney.

Despite advancements in medicine, transplantation was not a straightforward procedure. Several difficulties were inherent in the treatment, the most notorious being the scarcity of suitable organs for donation. Low supply and high demand for organs quickly generated a longer than ideal wait-list.

In Canada, the average wait time for a kidney transplant was approximately three and a half years for the more than 3,363 patients awaiting the procedure—and the demand was growing. Since all patients on the wait-list underwent routine dialysis sessions, such long wait times resulted in a costly and lower quality of life. The long wait might also have a morbid side effect: 82 patients died in 2010 as they waited for transplantation. Patients, the medical community, and policy-makers alike considered a three-and-a-half-year wait to be far too long for such a serious condition.²

While the majority of transplanted kidneys came from deceased donors, a growing number of transplants had taken place due to living donations, meaning both donor and recipient lived with only one functioning kidney. Such hardships implied that living donors tended to be the patient's willing family members, who realized the potential threat to the patient as a result of a prolonged wait time.

Often, the living donor's decision was triggered by a higher than acceptable wait time. If the wait time was seen as acceptable, the patient underwent dialysis while waiting for an available donation from a deceased source. The longer the wait time, the more likely was the push to provide for a living donation. As expected, the wait time had a significant effect on the mix of deceased and living donations. This effect was most notable in Ontario, where close to 40 per cent of transplants were from living donors.³ By the end of 2010, the province of Ontario had 1,105 patients awaiting RRT, with new arrivals to the wait-list growing every year. Although the province was able to conduct between 450 and 550 kidney transplants each year, this might not be sufficient if demand continued to grow.

THE ANALYSIS

Rogers left the meeting feeling like he could never produce the data in time. But if he managed to show the queuing analysis for the kidney transplant wait-lists, he knew he would make the best impression. With the help of co-workers at the health information management department, he was able to compile estimates for both the patient arrivals on the wait-lists and the transplants (see Exhibit 1). As these data represented estimates, and both patient arrivals and transplants varied greatly, the data suggested considering a variation from the mean within 100 per cent to 150 per cent.

¹ Canadian Institute for Health Information, "Canadian Organ Replacement Register Annual Report: Treatment of End-Stage Organ Failure in Canada, 2001 to 2010," Ottawa: Canadian Institute for Health Information, 2012, accessed November 17, 2018, <http://ghdx.healthdata.org/record/canadian-organ-replacement-register-annual-report-treatment-end-stage-organ-failure-canada>.

² Ibid.

³ Ontario Trillium Gift of Life, accessed November 2013, www.giftoflife.on.ca/en/stats.htm#transplant10.

EXHIBIT 1: A COMPARISON OF END-STAGE RENAL DISEASE PATIENTS IN LONDON AND TORONTO

Location	Average Number of Patients per Year	Average Number of Donors (Surgeries) per Year	Estimated Coefficient of Variation* of Donors (Surgeries) per Year (Lower and Upper Bound)
London	109.025	110.047	1.0 to 1.5
Toronto	327.259	327.514	1.0 to 1.5

Note: The information has been simplified to better suit the educational purposes of the case; *Coefficient of variation: $c_v = \frac{\sigma}{1/\mu}$, or the standard deviation divided by the mean service time.

Source: Created by the case authors.