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Restaurant Analytics: Emerging Practice and Research Opportunities

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Abstract

Smart technologies and increased data availability enable restaurateurs to gather more information about customers and their behavior. These data can be combined with data from other sources to make a wide range of strategic and operational restaurant decisions, and can therefore generate tremendous value for restaurants and their customers. This study focuses on discussing the most promising research opportunities in restaurant operations that leverage data analytics. In particular, we focus on specific research questions across restaurant decision domains such as location, reservation and table management, queue management, menu design and engineering, and multi-channel order management. For each research question, we motivate its practical and theoretical relevance, identify data sources, propose a methodological approach for analysis, and discuss actionable insights for practitioners. As a result, this paper aims to highlight data analytics opportunities for restaurateurs and inspire researchers to contribute in this domain.

Keywords— Business Analytics, Restaurant Operations, Service Operations, Big Data, Data-Driven Optimization, Data-Driven Decisions

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1 Introduction

The advent of "smart" technologies and the corresponding increase in data availability has provided businesses across the board with new ways of improving their operations (Guha and Kumar 2018). The competitive restaurant sector, a near $800 billion industry in the U.S. (National Restaurant Association 2021), has also been substantially affected by the rise of new technologies (e.g., reservation, Point of Sale (POS) and feedback systems), the platform economy, and the role of social media, which has enabled restaurateurs to gather information about customers and their behavior. This information can be leveraged to improve operations and enhance restaurant performance (Jargon 2018).

For example, customer data can be collected when customers use the internet to search and select a restaurant, make a reservation, while waiting to be seated, and when ordering and paying (e.g., through digital table-management and self-service technology). Customers may also generate data after their dining experience when posting online ratings, reviews, and photos. These large quantities of data, in combination with the advancement of analytic tools and computing technology, can generate tremendous value for

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restaurants. The recent increase in demand for carry-out and meal deliveries has accelerated the adoption of technological solutions and has given rise to new business models (e.g., cloud kitchens, seat-less restaurants purely focused on delivery), which provide numerous opportunities for data collection and analytics.

At the same time, while it is becoming increasingly necessary to reap the benefits of data availability to keep up with the competition, the topic has received limited attention from a practical and academic perspective. To identify to what extent business analytics has already found a place in the academic literature on restaurants, we conducted a compact content analysis of the literature using Web of Science. As an initial step, we used the search term "restaurant" to obtain an overview of all literature focused on restaurants between 1990 and 2020. We excluded conference proceedings and papers from the "emerging citations index", which only captures data since 2015. The resulting search yields 11,958 publications, with a strong upward trend throughout the full time horizon between 1990 (37 publications) and 2020 (1,183 publications). As shown in Table 1, these publications are scattered across a wide variety of domains. The categories of business and management are traditionally the most prominent domains for business analytics applications, but together only account for 1,610 publications (about 13 percent of the total).

Table 1: Publications by Web of Science category (top 20) between 1990-2020, keyword "restaurant*"

Web of Science Category	**# of publications**	**percent of total (11,958)**
Public Environmental Occupational Health	2,053	17.2%
Hospitality Leisure Sport Tourism	1,386	11.6%
Food Science Technology	1,072	9.0%
Management	1,010	8.4%
Nutrition Dietetics	979	8.2%
Environmental Sciences	897	7.5%
Business	600	5.0%
Economics	526	4.4%
Medicine General Internal	460	3.8%
Sociology	352	2.9%
Substance Abuse	312	2.6%
Environmental Studies	297	2.5%
Biotechnology Applied Microbiology	286	2.4%
Computer Science Information Systems	261	2.2%
Engineering Environmental	259	2.2%
Infectious Diseases	214	1.8%
Architecture	198	1.7%
Information Science Library Science	179	1.5%
Computer Science Artificial Intelligence	178	1.5%

However, analytics applications in the restaurant domain are likely to be present in several other categories as well. In the subsequent identification of the publication trend in restaurant analytics, we therefore do not exclude any categories. To identify this trend, we used the search term "restaurant* analytic*". This yielded 212 publications. In the 1990s and 2000s publications on restaurant analytics only emerged sporadically. They started to increase after 2010 (Figure 1), and more than 40 percent of all publications on the topic were published in 2018-2020. This is in line with the grown popularity of research involving applications of data analytics in Operations Management (OM), driven primarily by the increasing availability of richer data but also by methodological advances in statistics, machine learning, and optimization fields (Mišić and Perakis 2020). The term, (data) analytics, itself has also evolved in scope during the past decades, from a focus on descriptive analyses towards more predictive and prescriptive analytics techniques. The current publication is the first academic article that provides an overview of the field of restaurant analytics in particular, and outlines concrete research opportunities with high practical and theoretical relevance.

More specifically, this manuscript focuses on how restaurateurs can capitalize on analytics when making strategic and operational business decisions, and how researchers can support these decisions through new cutting–edge research avenues. We first identify the systems and technologies available to collect data in

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Figure 1: Publication trend in restaurant operations & analytics

the restaurant domain (Section 2). We then propose and discuss six carefully selected research questions with high practical relevance and theoretical premise (Section 3). We do not attempt to provide a fully comprehensive overview of the field and its research potential, but provide concrete opportunities spanning a variety of established and emerging restaurant decision areas (for a broader overview of restaurant management domains and research opportunities, see Thompson 2010). Our choices were motivated by extensive talks with industry practitioners and review of restaurant operations literature, combined with the potential of new data and methodologies to provide novel and actionable insights. Finally, we discuss the implications and risks of data ownership in Section 4, and provide some closing thoughts in Section 5.

2 Restaurant technologies and data availability

The service industry has been transformed by the vast increase in data availability and the tools to capitalize on these data (Cohen 2018). While restaurants have not been at the forefront of these developments, the role of technology in the restaurant business has now become too big to ignore. Restaurant technologies play a critical role in fulfilling restaurant orders from multiple order platforms, and restaurants have become a place where customers often expect an immersive experience in addition to their meal. Technologies are changing the way restaurants operate, and these transformations are helping restaurants to meet customer expectations. The importance of technologies has grown even more against the backdrop of COVID-19, with safe and viable restaurant operations heavily depending on innovative technological solutions. In this section, we first describe the process workflow from the perspective of a customer journey and then specify the technologies that enable the processes (as displayed in Figure 2). We discuss the potential data captured by the systems and how these data elements can be integrated to answer significant research questions.

To begin, customers discover restaurants spontaneously, through word-of-mouth, or via third-party platforms (e.g., Zomato, Yelp, and TheFork). Subsequently, customers arrive at the restaurant through one of the four order streams: 1) Carry-out, 2) Dine-in (reservation), 3) Dine-in (walk-in), or 4) Home deliveries. Together, these four streams represent a wide variety of possible restaurant operations. For instance, the reservation and walk-in streams in Figure 2 represent the process in a full-service restaurant, whereas the carry-out stream is more applicable to a quick service restaurant setting. Likewise, the home delivery stream could correspond to the processes enabled by online delivery platforms. The core element among all restaurant technologies is the POS system, also known as the billing system. The POS application can run on a stand-alone desktop or on a cloud server. Orders from any of the four channels interact with the POS.

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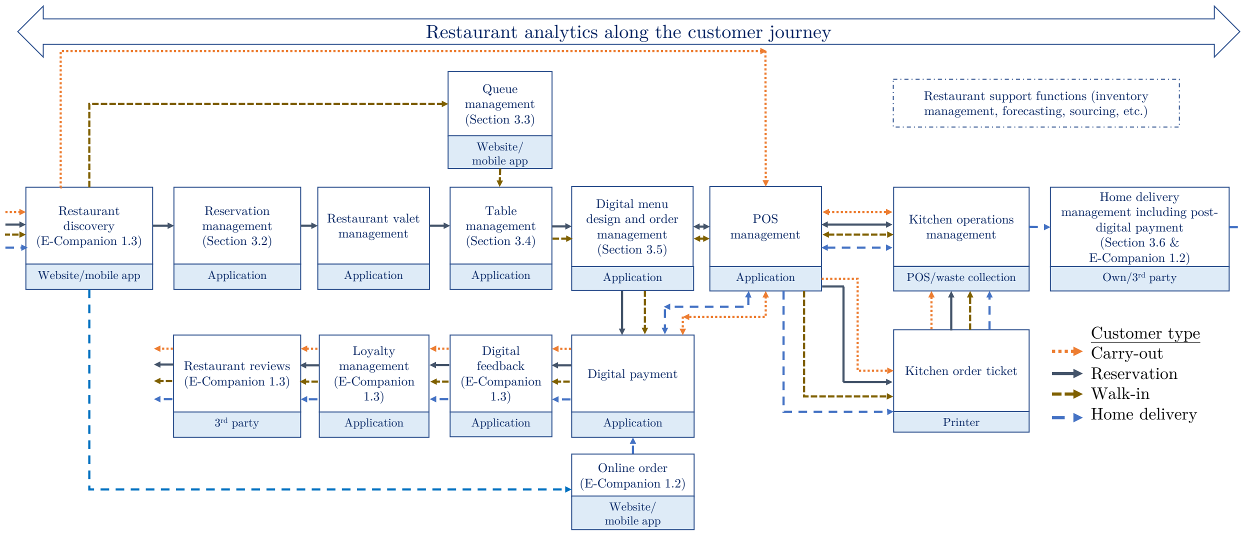

Figure 2: Integration of restaurant technologies and data sources (shaded) along the customer journey. POS is the central unit that interacts with the frontroom (dining area) and backroom (kitchen).

If customers arrive with a reservation, the customer reservation information (e.g., customer name, phone number, group size, and seating preference) is already available in the reservation management system. Upon arrival, customers interact with the valet staff and are assigned to a table. At the table, the menu (physically or digitally, through phone or tablet) is available. Digital menus provide the opportunity for novel ways to interact with customers. For example, using a smartphone, customers can scan a QR code to retrieve the restaurant menu. Digital menus can be updated in real time and used to offer menu personalization or deals based on customer preferences or restaurant inventory levels. Customers place the order either with the waitstaff, using a tablet provided by the restaurant, or on their own phone. In all cases, the order enters the POS system, which relays it to the kitchen staff via a kitchen order ticket (KOT). A KOT is simply the order that a customer places. The POS system prints a ticket or shows the order to the kitchen staff via a kitchen display system (KDS). Each item on the menu is linked to a recipe, which includes information on the amount of each ingredient used in preparing the dish. Once the orders are placed via the POS, the POS interacts with the kitchen operations management system, which links the orders with the raw material requisition, and monitors raw material wastage during dish preparations. After dining, customers can pay using digital payment gateways and also give feedback (e.g., using a tablet). When customers leave, the dine-in process is completed. The event timestamps provide valuable information on the time spent by the customer during various parts of their journey. After dining, customers may also post reviews on third-party websites, to which restaurateurs can respond. In addition, there are applications to support restaurant operations such as procurement of raw ingredients and packaging material, and forecasting demand.

Walk-in customers follow a similar process, except that the table is not reserved apriori. Carry-out orders typically interact with the POS directly and the customer may wait to receive the packaged food items. Home delivery orders also interact with the POS and kitchen. However, for these orders a greater emphasis is placed on the last-mile food delivery process. Usually a third-party platform application (e.g., Uber Eats) is integrated with the POS for delivery orders.

Matching restaurant capacity with the (estimated) total demand is crucial for the success of a restaurant. A typical restaurant is characterized by two main areas: a frontroom dining area, and a backroom kitchen

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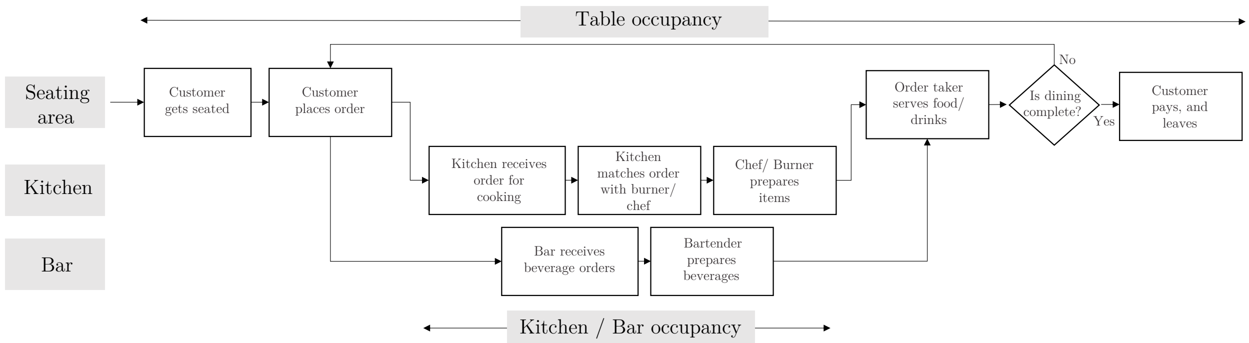

Figure 3: Interaction between (frontroom) seating area and (backroom) kitchen and bar area

area. In many restaurants drinks are also an important driver of profitability, and some have a dedicated bar for mixing and serving drinks (e.g., cocktails, soft drinks). Restaurant performance in terms of throughput capacity and customer turnaround time depends on the interactions among multiple resources in the dining, bar and the kitchen area such as tables, order takers, kitchen burners, chefs and bar staff. Further, tactical and operational choices such as menu length, dish complexity, and customer behavior can affect restaurant's throughput capacity. Due to complex interactions between the various demand streams and the dining and the kitchen/bar resources, an integrated analysis of the restaurant is key to estimate the overall capacity. As Figure 3 shows, bottlenecks can emerge in the both the dining area and the kitchen/bar. Variations in demand across order channels can create additional challenges, as different order types require a different set of unique and shared resources. For example, dine-in orders require runner and/or waitstaff capacity, whereas online orders require packaging capacity. Hence, understanding the effect of multiple order types, such as carry-out, reservations, walk-in, and home delivery orders, on the resource capacity is of vital importance. From the point of view of a restaurateur, an understanding of the dine-in capacity can help to decide the menu, the number of tables, and the maximum number of reservations to accept.

Restaurateurs can obtain data on customer location preferences, menu choices, seating preferences, arrival time preferences (in case of reservation), and dining duration by using customer-centric event timestamps obtained from POS systems and integrated platforms used in restaurants. For example, a restaurant that operates multiple franchisees in a city can learn the preferred outlet location of a customer during the week versus weekend. This is only possible as the customer can now be tracked using a unique identifier such as a phone number or a loyalty identification number. Restaurant discovery platforms and customer relationship (loyalty) management software capture the customer preferences over a large number of visits. Table 2 shows an overview of possible data sources in restaurants, and the types of data typically available from these sources. For example, visit recency refers to the time between the last visit and current time, loyalty points refers to the earned points provided by the restaurant against the sales value, redemption frequency refers to the number of times loyalty points has been used to make the payment, and redemption quantity refers to the number of loyalty points that has been used to make the payment. Software packages or online platforms that capture these data typically enable restaurateurs to obtain an overview of some basic restaurant statistics and manage profitability. For example, through a dashboard, restaurateurs can usually observe a breakdown of sales per day, hour, and table, as well as the top selling items.

Apart from the system-generated data captured during various phases of a customer journey, data from external sources can also be used. For example, economic indicators can provide early indicators on cus-

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tomers' willingness to spend, and weather and traffic data can provide better real-time (and forecasted) estimates of restaurant demand and food delivery times.

In the next section (Section 3), we discuss various restaurant applications of analytics across a number of decision areas by identifying concrete, data–driven research questions.

Table 2: Examples of available restaurant data per data source

Valet management	Reservation system	POS system	Feedback system	Loyalty program	Kitchen system
Car type	Visit number	Order type	Customer feedback	Loyalty points	Current quantity
Billing to valet time	Visit recency	Order items	Birthday	Redemption frequency	Reordering point
	Visit day and time	Order value	Gender	Redemption quantity	Recipes
	Visits per outlet	Discount	Age		Preparation time
	Waiting time	Table types			Wastage source
	Seating time	Table count			Wastage quantity
	Group size				

3 Data-driven restaurant research opportunities

In this section, we elaborate on the practical and theoretical relevance of six proposed research questions, by providing specific business examples and reviewing the past literature. We then point to specifically relevant data sources and propose a methodological approach (and an initial model when applicable) for addressing each question. Last, we discuss potential managerial implications and actionable insights for relevant stakeholders. For example, understanding the competition and customer profiles through a combination of restaurant discovery applications and publicly available data can help restaurateurs in deciding the location of a new restaurant (Section 3.1). Using the data from the reservation system, restaurateurs can analyze reservation behavior such as last minute cancellations or no-show and inform reservation limits and customer prioritization policies (Section 3.2). Understanding the effect of waiting time on customers and staff, and actively managing queues accordingly, can be used as a tool to increase restaurant profitability (Section 3.3). Transaction data, customer characteristics and labor data can be capitalized to better assign incoming customers to available tables/waitstaff (Section 3.4) and provide dynamic and personalized menu item recommendations (Section 3.5). Last, we discuss how the emergence of new order channels (such as online platforms) poses new challenges to restaurant capacity management and propose an integrated approach for managing the different order streams (Section 3.6). Besides the specific research questions that we discuss in-depth in the main manuscript, we highlight several additional opportunities for applying analytics in a variety of emerging restaurant decision areas in the E-Companion. The E-companion also includes a summary table with an accessible overview of the research questions identified in the manuscript, and their connection to the relevant OM literature.

3.1 How can competitive intelligence inform the long-term restaurant location decision?

3.1.1 The restaurant location decision in research and practice

Restaurant location is a highly significant determinant of restaurant performance and survival (Parsa et al. 2005, 2011). For example, Park and Khan (2006) conclude that location is the primary factor predicting the success or failure of franchise restaurants. Further, personalizing customer needs such as restaurant menu choices is heavily based on the site location. Several factors affect the suitability of a restaurant location. For example, population density, real-estate prices, access to user-friendly parking facilities, traffic conditions

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around the vicinity of the restaurant, visibility (presence on Google Maps or other GPS maps), and competition density are crucial factors impacting the restaurant location decision. It may seem that restaurant location decision is static in nature and mostly based on spatial demand-driven attributes. However, the temporal dimensions may also be crucial in deciding the location, as location characteristics can change over time. A location that would not be earmarked as a dense area 10 years ago may be considered competitively dense 10 years later, due to shifts in demographics and newly developed neighborhoods.

To assess the potential of a new store location, data analytics tools are already widely adopted in practice. For example, Starbucks leverages data from its in-house mapping and business intelligence platform, Atlas, to assess potential store sites. Atlas provides Starbucks with data about socio-demographics and amenities near the potential store location such as consumer demographics, competitors, population density, income levels, car traffic patterns, public transport stops and the types of other stores (Wheeler 2014). With statistical modeling tools, Starbucks is able to estimate the foot traffic and average customer spend of a given location, thereby enabling Starbucks to determine the business viability and make an informed location choice. Likewise, competitors of Starbucks such as Dunkin' Donuts also use data analytics tools to determine potential store locations based on demographics, the presence of competitors and traffic trends. These applications of location intelligence can inspire a new stream of research on dynamic modeling of competitive restaurant site locations, against the backdrop of publicly available data.

In terms of academic research, studies on optimizing site location are mostly found in the context of retail stores. The literature on the location decision in these sectors is relevant, as the determinants for the restaurant location decision partly overlap with those for retail stores. The early versions of gravity models were applied to the retail store location screening problems (see Rogers 1987) where the models forecasted the turnover of a new store based on a simultaneous consideration of factors such as store size (including the size of competitors), distance, and population distribution and density. Today the site selection literature is quite rich and location models allow for simultaneously identifying multiple site locations subject to customer service level requirements. The models are broadly classified into four categories: 1) Covering problems, 2) P-center problems, 3) P-median problems, and 4) Fixed charge problems (Owen and Daskin 1998). These models can use demand estimates from statistical demand forecasting models and prescribe the optimal location(s) for a restaurant subject to certain constraints (e.g., distance). Often new site locations are decided using such static optimization frameworks, where the objective is to open minimum number of restaurants from a given potential set of locations such that the demand regions are within accessible distance and costs are minimized (a classical set covering problem). Other constraints such as minimum distance from competitors can also be added to the model. However, estimating the new demand with opening of a new facility is challenging, because exact competitor demand information is unknown. Furthermore, the models do not account for future competitive entry or exit of the incumbents. Hence, the most profitable location may also be most vulnerable to new entrants, and potential new site locations may no longer be profitable in the long term.

Understanding the competition at a potential location site is crucial towards assessing a site's economic viability. For example, Thomadsen (2007) developed computational game-theoretic models to study the location choice of two competitive restaurant chains, Burger King and McDonald's. Using empirical demand data, their analysis reveals that Burger King and McDonald's should pursue different location strategies. In particular, Burger King, as the weaker player in the competition, should try to locate far away from McDonald's to create its own unique customer base. In contrast to classical facility location models, competitive facility location models have also been developed. These models account for spatial interactions among

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facilities, compete for a share of fixed demand and customer utility. Customer utility can be increased by, for example, locating the facility closer to the customer, or enhancing facility design features (e.g., size, appearance, accessibility, layout, or product variety). Most competitive location models are still optimization formulations that are solved as a bi-level mixed integer program (for example, see Beresnev and Melnikov 2018). Consider a set of potential locations and a set of potential customers. Each facility can be opened by a leader or a follower. Both parties sequentially open their facilities at potential locations. The customers have a free choice option i.e., given any two opened facilities, any customer may choose their preferred option. Both the leader (company) and follower (company) try to maximize profit, which is determined as a sum of fixed costs (with a minus sign) associated with opening the facilities and the income derived from serving the assigned customers.

Further, empirical models are used to identify the drivers for a successful site location such as site characteristics (e.g., hotel size, and hotel function) and site attributes (e.g., accessibility, agglomeration, and environment). For example, using bootstrapping techniques and data from a large hotel chain, Biemer and Kimes (1991) propose a statistical technique to determine an ideal decision rule, which can predict the success of a site location. However, studies on leveraging data in prescribing the optimal location for a new restaurant is scarce.

This does not mean that relevant data is not available for restaurants. Restaurants can leverage publicly available data and use analytics to estimate demand, model demand substitution in the presence of competitors, and use the demand estimates to take informed location decisions. For example, Geographic Information Systems (GIS), which are computerized systems used for the storage, retrieval, mapping, and analysis of geographic data, provide an efficient decision-making support system for the selection of viable sites for new sites by accounting for spatial demand considerations. Against the backdrop of fast-growing data availability, we particularly identify data-driven prescriptive models as most promising approach to tackle the competitive restaurant location selection problem in the future.

3.1.2 Relevant data

Nowadays, several publicly available data in categories such as demographics and location, boast many opportunities for analytics, especially when combined with restaurant-specific data (see Table 3). These data sources help to estimate the potential demand (market of a new restaurant), as well as the current market of existing restaurants. The Census Bureau is a good source of demographic-related attributes. Likewise, Google Maps offers rich information on location attributes. For example, the Google Maps API offers both static data about potential sites (e.g., latitude and longitude information), and dynamic image and count data (e.g., on the type of amenities present in a particular location). The type and quantity of amenities other than restaurants, such as shopping malls, parks, community centres, swimming pools, hospitals, health club facilities, party rooms, or theaters near a potential restaurant site could be a good indicator of latent demand. These data sources could be more accurate in comparison to traditional census data, which are collected at a much lower frequency. In such cases, satellite images that capture the number of households with emitting light sources can provide better estimates of population size and density per region. Static information on neighborhood demographics (e.g., employment ratio and household size) also provides an indication about the probable success of the restaurant. Traffic and search data from discovery platforms also provide information about potential demand and competition around the potential site.

3.1.3 Methodologies and models

Competitive facility location problems are generally modeled as a bi-level optimization formulation, and customer preferences are assumed to be known and used as input to the model. While such preferences

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Table 3: Relevant data sources for location analytics (see also Talluri and Tekin 2021)

Category	Relevant constructs	Possible data source(s)	Details
Demographics	Population	Census Bureau (of a specific country)	To determine the population in a zip code
	Household size		To determine the distribution of household sizes
	Age		To determine the age distribution
	Working population		To obtain working population estimate
	Income		To obtain income distribution
Location	Type and count of amenities	Google Maps	To obtain type and count of amenities
	Zip code	Google Maps	To fetch zip code of a potential site
	Rent ($/sq ft)	Yellow Pages	To estimate rent per square feet at a location
	Latitude, Longitude	Google Maps	To determine latitude and longitude at a location
Restaurants	Capacity	Municipality	To determine the current capacity of restaurants
	Size (sq ft)	Municipality	To determine the current size of restaurants
	Reservation	Reservation System (e.g., OpenTable, Sapaad)	To fetch the booking information at restaurants
	Occupancy	Google Maps	To estimate the level of traffic at a restaurant
	Reviews	Websites (e.g., Yelp, Zomato, Zagat, Google Reviews)	To determine rating distribution, also text

can be estimated using surveys, survey outcomes are likely to suffer from sampling bias and generalizability issues, and the resulting location decisions may not be profitable.

In traditional facility location models, demand information is known. For example, the inventory to be fulfilled from a warehouse to the retail stores is known. However, in competitive facility location models, the demand information of competing restaurants is often unavailable, and the evolution of demand after opening a new restaurant is unknown. Hence, the demand estimation problem is a challenge.

In such cases, relevant public data can be used to estimate restaurant demand at a potential new location. For instance, information about customer traffic at competitors, competitor review ratings, macro economic indicators, population density, can shed light on the viability of prospective restaurant locations. Several demand estimation models such as Linear Regression, Lasso, and other AI/ML estimation tools can be deployed for this purpose. Once the demand is estimated, optimization models such as dynamic programs can be developed to understand the impact of a new entrant on the long-term profitability of the incumbents.

To model the long-term profitability of a restaurant (e.g. over a time horizon of 20 years or more), demand models should also capture both demand loss (due to new entrants in the same segment at the location) and demand gains (due to incumbents exiting the market). A more advanced approach to capture the impact of market exit of competitors is to model the exit probability over time of every relevant competitor individually. For example, a Logit model based on review ratings during a period, the number of competitors in the same segment, price, traffic levels, and macroeconomic indicators could estimate the probability of a restaurant exiting the market per month or year. A more parsimonious (and less data-intensive) approach would be to model the aggregate count of exiting competitors using Poisson or Negative Binomial regression models. Similar regression models can be used to model the number of new restaurants entering the market. Both restaurant entry and exit estimates can be leveraged to forecast future restaurant demand at a specific location. Note that the business cycles can significantly affect consumer expenditure and restaurant demand. Hence, using restaurant demand estimates longitudinally in a dynamic program framework is required to offer a rich understanding of restaurant lifetime profitability at a location.

Talluri and Tekin (2021) propose a two-stage (estimation and optimization) approach to the restaurant location problem. First, they model the ratings as a function of demographics, features, and unobservable latent factors (e.g., taste and quality). Then, they model demand for the establishment as a function of the obtained ratings and the location of the facility, and use a multinomial logit (MNL) to estimate the customer choice to select a restaurant. In the second stage, they use a location attraction function to estimate the probability of a restaurant entering or exiting the market, and obtain the optimal restaurant location using

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an integer programming (IP) formulation. In the IP formulation, the competitive entry and exit decisions are captured using an equilibrium framework. This approach is promising, especially if these models can be extended to reevaluate demand at different points in time, and to account for the economic cycles.

Overall, using demographics, social media data, and reviews to predict demand based on specific restaurant characteristics (e.g., cuisine, price) offers promising insights for practitioners and provides a fruitful context for future research explorations.

3.1.4 Actionable insights

The importance of the restaurant location decision is evident, as the choice for a location affects the long-term profitability of a business. Restaurateurs can use location intelligence data to estimate the success probability or potential payback period and learn how menu correlation with incumbents affects the success potential for a new site. Likewise, restaurateurs can analyze how the distance from existing competitors affects demand. They can also identify the points in time at which they need to revisit the concept, seating capacity, or kitchen capacity to stay relevant and counter the evolution of potential competition. The approach can be extended to inform decisions on setting up cloud kitchens (also known as dark or ghost kitchens). Such cloud kitchens typically offer speedy home delivery of food from a larger assortment of brands. Hence, accounting for the distance of the kitchen from potential customers is essential to positively affect demand and long-term profitability. Similar two-stage models can also be used to address the location decision in other sectors such as retail or the hotel industry.

3.2 How should incoming restaurant reservations be managed?

3.2.1 Restaurant reservation management in research and practice

Although the effectiveness of restaurant reservations is currently under debate in practice and in academia (Alexandrov and Lariviere 2012, Sietsema 2014), restaurateurs still widely use reservations to facilitate kitchen and staff planning, and customers reserve to avoid excessive waiting time. However, the use of more advanced reservation management processes in restaurants has been far less developed than in other sectors, such as the hotel and airline industries. Restaurateurs typically simply accept reservations until the available capacity is filled, and overbooking practices are rare in the restaurant domain. As a result, last-minute customer cancellations and no-shows often result in spoiled capacity. Since making a reservation is usually free of charge for the customer, no-shows can be extremely costly for the restaurant and make the difference between operating profitably or at a loss (Winterman 2021). Upscale restaurants commonly try to reduce no-shows by reconfirming customer reservations through a phone call, text message, or email. Some restaurants have even addressed the no-show problem by charging their customers a nonrefundable deposit, which is typically subtracted from the final bill once they visit (The Independent 2020). These measures may lead to fewer no-shows, but can also cause confusion and increase the barriers for customers to reserve.

Consequently, restaurateurs need to make a well-informed decision about what proportion of restaurant capacity should be allocated to reserving customers. This problem is somewhat similar to the fare class protection airlines face (Subramanian et al. 1999). Companies essentially face a newsvendor tradeoff between protecting too much capacity (resulting in spoiled, unused seats) or too little capacity (resulting in revenue spill). Airlines continuously evaluate and update their protection thresholds based on the available capacity and latest demand forecasts (Li et al. 2014). Restaurants typically use a simpler rule and allocate a fixed share of capacity to reserving customers. Because of the high costs involved with cancellations and especially no-

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shows, the literature also includes studies on whether accepting reservations is beneficial at all. Alexandrov and Lariviere (2012) show that reservations should be allowed if competition is strong and if customer no-shows are negligible. Oh and Su (2018) employ a different, game-theoretic approach. They propagate the use of reservation deposits and propose that restaurateurs should apply price discrimination between walk-in customers and reserving customers. Furthermore, they conclude that the reservable proportion of restaurant capacity should be smaller if the market size of the restaurant is bigger. If accepting reservations, restaurateurs have to decide on whether to directly assign these reservations to a specific table, or to pool reservations. The latter approach is more efficient, but also more complex to implement (Thompson and Kwortnik 2008).

Another relevant approach in the context of no-shows, capacity limitations, and spoilage is to allocate more than 100 percent of restaurant capacity to reserving customers. Overbooking is still highly uncommon in the restaurant domain, but could be considered in the context of increased data availability and increasing costs associated with no-shows and late cancellations (Tse and Poon 2017). The line between success and failure in restaurant overbooking is very thin, and effective applications lean heavily on data availability and analytics. To identify if and how restaurant overbooking can be employed in a specific situation, restaurateurs should be aware of the direct consequences in terms of capacity spillage and spoilage, and identify the acceptance and reaction of customers encountering these practices (Roy and de Vries 2020).

If restaurants accept reservations, they can consider various priority sequencing rules. Restaurateurs typically have to choose directly between accepting or rejecting a reserving customer. This makes it complex to determine the consequences of rejecting a customer group when capacity is still available, and restaurateurs might perceive it as too risky to reject a customer in favor of a potential customer with a higher value. In addition, restaurateurs might simply not possess sufficient information on the potential value of customer groups, and therefore only rarely deviate from first-come-first-serve (FCFS) protocols. Party size is the most obvious customer characteristic that can be used to determine priority rules, and could be profitable especially for smaller restaurants (Thompson 2011).

Overall, reservation management remains a vital issue for almost every restaurant and a domain that can benefit substantially from data-driven insights. The next level in restaurant reservation management can be reached if dynamic customer-specific data can be used to accurately derive expectations about the potential behavior and value of each customer. These expectations can enable restaurants to minimize no-shows and use customer reservations to their advantage, facilitating only the most committed customers.

3.2.2 Relevant data

The importance of reservation management applications and booking systems has increased during the past years as they typically provide customers with an accessible and almost effortless way to compare restaurants and reserve tables. These systems typically also collect a rich set of data related to the characteristics of reservations and reserving customers. Large players in the restaurant reservation management domain include OpenTable, Resy, Inresto, and TheFork. These companies capitalize on customer data to provide their customers with insights that are often directly relevant for operations. At present, the reservation system can typically be integrated with the POS to obtain a combination between pre-visit customer and reservation information and detailed ordering data collected during the visit. This combination allows restaurateurs to estimate the expected value of a reserving customer and use this expected value to inform reservation acceptance and prioritization policies (Kimes and Beard 2013). Table 4 presents an overview of reservation-related data that can be collected through reservation platforms and POS systems.

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Table 4: Relevant reservation data and data sources

Relevant constructs	Possible data source(s)	Details
Customer characteristics	Reservation platform	Demographic details about customers
Reservation channel	Reservation platform	Channel and source of incoming reservation
Time at which customer reserves	Reservation platform	Timestamp of when reservation was made
Location at which customer reserves	Reservation platform	Precise (GPS) or approximate location of reservation
Time of desired reservation	Reservation platform	Time at which customer intends to visit
Party size	Reservation platform	Number of people in party
Customer status	Reservation platform	Does the customer show up, cancel, or show up?
Past visits	Reservation platform/POS	Number of past visits
Past spending	Reservation platform/POS	Spending (per person) during past visits
Dining preferences	Reservation platform/POS	Preferred orders, allergy information, etc.
Server	Reservation platform/POS	Employee in charge of serving the table

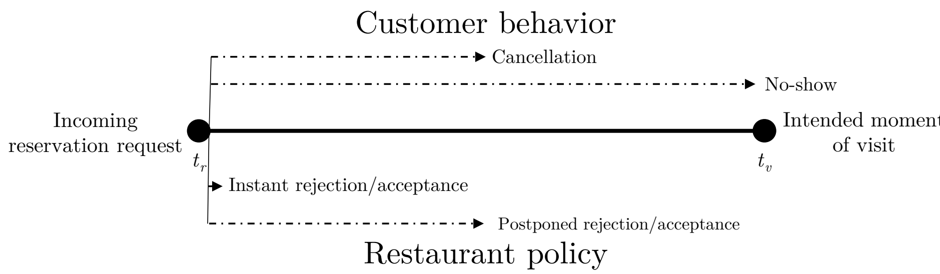

Figure 4: Reservation evolution process: what can happen to an incoming reservation?

3.2.3 Methodologies and models

Incoming restaurant reservations do not necessarily result in seated, revenue-generating restaurant visits. This discrepancy can be caused by customer actions, but also influenced by restaurant policy. Figure 4 shows a variety of possible trajectories of incoming reservations. When a customer tries to make a reservation, the restaurateur can directly choose to accept or reject this reservation. This decision is typically based on the available capacity in the reserved slot at that moment. Alternatively, restaurant policy could be to accumulate a batch of reservations during a period of time and subsequently choose which reservation requests to accept based on specific criteria. Researchers can develop new models focused on predicting customer behavior to inform the decision to accept or reject a reservation. The existing research on restaurant reservation management also emphasizes the potential value of possessing relevant and real-time data on customer behavior and market conditions in informing reservation policies (Thompson 2010). These data are not always straightforward to interpret, and the predictors of no-show and cancellation behavior might differ substantially in different stages of the reservation horizon (Romero Morales and Wang 2010). For example, a reservation that is made very far in advance is still subject to substantial uncertainty until the day of the planned visit, but might also signal that a customer is very committed to the reservation.

Typical reservation management models (such as the models presented in Thompson 2015) use an integer programming approach to maximize revenue, while assuming a known reservation demand and inflexible but perfectly reliable customers. Due to richness of available data in the reservation management domain more advanced models can now relax these assumptions to better match the situation in practice. Along these lines, several specific steps can be taken to reach the next generation of data-driven reservation management models:

1. *Dynamic no-show/cancellation probability* – More advanced reservation management models can use historical data per time-slot, customer characteristics, and past customer behavior to statically assign a

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no-show and cancellation probability to an incoming reservation request, and use this to directly inform the reservation acceptance decision. At the same time, the no-show/cancellation probability of reserving customers is conditional on the time since the reservation was made, the time until the reserved slot, and potential exogenous events that have occurred in the meantime. Dynamically updating these probabilities based on a continuous analysis of the available customer and restaurant data can improve the reservation acceptance policy and lead to a better match between restaurant capacity and arriving customers. These analyses can be performed using dynamic discrete choice or logistic regression models or even machine learning algorithms such as XGBoost (see Antonio et al. 2019 for a similar application in the hotel industry).

2. *Response to deposits, rejection, and overbooking* – Researchers can also focus on the implications of charging reservation deposits to address the problem of no-shows and cancellations. Little is known about the potential deterring effect of such deposits on the resulting stream of incoming customers and their behavior during the restaurant visit. Similarly, the impact of overbooking or rejecting a customer with a reservation request is largely unknown. Customers could give up, try to reserve again for another time slot, or shift their demand to another restaurant. This decision is likely to differ among customer groups with different characteristics and requirements. The methods recommended in step 1 also apply to this domain, as empirically unraveling these relationships and generating models with high predictive power allow us to estimate how current reservation policies affect future demand streams.

3. *Timing flexibility* – Restaurant reservation models are typically based on the assumption that customers demand to reserve at a specific, inflexible time (Thompson 2019). In reality, customers typically are somewhat flexible in their time slots. Restaurant reservation platforms such as Resy and OpenTable capture this flexibility by pro-actively presenting a list of available dining times to customers. Alternatively, reservation systems can present customers with a list of potential alternatives only after informing them that their preferred slot is unavailable. To truly steer demand towards less popular slots, the next step would be to strategically present available options based on the time of reservation and customer characteristics (such as the no-show/cancellation probability discussed before). These policies can be designed and tested sequentially using online controlled experiments and A/B tests (Kohavi and Longbotham 2017), methods commonly employed in marketing research and practice.

3.2.4 Actionable insights

These approaches towards improving restaurant reservation management practices should result in benefits for restaurant operations across the board. The most obvious consequence is increased restaurant capacity utilization by more accurately forecasting customers' no show and cancellation probabilities. If these forecasts are updated dynamically, restaurateurs can make well-informed real-time decisions about the number of reservations that should be accepted. Insights into the response of customers to restaurant policies can further inform these decisions. For example, if a restaurateur can accurately estimate the (negative) value of overbooking a specific customer, restaurant overbooking practices might suddenly become much more feasible. Airlines frequently use auctions to bump customers who accept the lowest amount of money in exchange for their seat. Data-driven insights into which restaurant customers do not mind being overbooked could facilitate similar practices without auction, by simply offering these customers a form of compensation (e.g., vouchers for later visits or alternative locations) if no seats are available.

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While overbooking practices do not necessarily appear customer-friendly, the combination of a compensation plan and more customers being able to have dinner should result in an aggregate consumer surplus. In addition, if a customer-specific reservation price can be determined, it also becomes possible to assign customers with lower reservation prices to off-peak slots.

3.3 How can managing waiting time affect restaurant performance?

3.3.1 Restaurant waiting time management in research and practice

All restaurants that accept walk-in customers face queues if the arrival rate of customers exceeds the restaurant's service rate during certain time intervals. A survey among 8,500 restaurant managers in the U.S. revealed that about 93 percent of the surveyed restaurants experienced queues, with an average length of approximately ten parties who face a mean wait of 23 minutes (LRS 2013). Also after being seated, customers may experience (virtual) queues before ordering, after ordering, and when wanting to pay. Simultaneously, the impact of these waits on restaurant operations and performance is typically not clear. Queuing dynamics differ among various restaurant segments but affect revenue across the board. For instance, carry-out fast food restaurants can typically directly influence the customer throughput rate by changing the kitchen capacity, the speed at which food is prepared, and the time required to process the payment. This gives them a direct lever to influence customer throughput, demand, and resulting profitability (Allon et al. 2011). These dynamics are more complex in sit-down restaurants, where customers typically have some discretion in choosing how long they occupy the table and seats assigned to them. Although increasing the service speed and pushing customers to vacate tables faster can increase restaurant capacity, customer experience and future demand might be affected by these practices.

Consequently, queue management in restaurants involves considering a broader array of metrics and effects than myopically balancing the arrival rate and service rate alone. For example, being the result of an imbalance between the arrival and service rate, queues can also carry a signaling value that can affect the arrival rate. Based on queue length, potential customers can decide if they want to join a queue. The absence of a queue does not necessarily send a positive signal in this context. The so called "empty restaurant syndrome" describes the phenomenon that if a restaurant is (nearly) empty, new customers may be hesitant to come because they conclude that the restaurant offers poor food and service. Theoretically, a (short) queue can therefore be desirable to attract more customers. This phenomenon has been empirically validated by Raz and Ert (2008), who established that especially for restaurants focused on tourists, customers seem to prefer longer queues. Giebelhausen et al. (2011) and Kremer and Debo (2016) confirmed this finding in a lab setting, demonstrating that queues can have a positive impact on uninformed customers in particular. Ryan et al. (2018) highlight the importance of identifying a potential tipping point, at which the potential positive impact of queues turns negative. The perceived remaining queue length can also still carry a signaling value to customers after they have joined a queue. This remaining wait can be influenced by service providers through delay announcements. In multiple contexts, Allon and Bassamboo (2011) and Yu et al. (2017, 2018, 2020, 2021) show that the timing, accuracy, and granularity of these announcements can affect waiting costs and customer behavior.

After customers have decided to join a queue, waiting is typically seen as something unpleasant. Especially in the time-sensitive fast-food sector, waiting time has proven to be a crucial factor influencing restaurant selection (Allon et al. 2011). Even so, Kumar et al. (2014) demonstrate through experience sampling and questionnaires that customers waiting for a service experience (such as a restaurant dinner) can derive

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happiness from anticipating this experience. Similarly, Ülkü et al. (2020) show with that longer waiting times could even result in more consumption. De Vries et al. (2018) use transaction data to illustrate the complex dynamics of a restaurant queuing system, which involves balancing customer reneging, their dining duration, and their return probability. From the perspective of restaurant staff behavior, queues and the associated workload have emerged as relevant predictors as well. For instance, Tan and Netessine (2014) show how workload affects server performance, and Smirnov and Huchzermeier (2020) demonstrate the impact of the load-dependent service efforts on labor planning.

Most of the existing literature on the impact of queueing in restaurants (and general service operations) uses stylized analytical models to investigate queueing dynamics. As discussed, more recent studies have focused on empirically demonstrating how individual customer or staff behavior deviates from what normative models prescribe in the presence of queues and waiting time. The next challenging step is to identify how these deviations from normative behavior jointly affect system-level behavior and outcomes (Allon and Kremer 2018). Combining these insights into accurate and robust prescriptive models is needed to derive truly meaningful insights for restaurateurs.

3.3.2 Relevant data

The increase in attention to the queueing domain and the resulting increase of queue management software solutions now offer a promising perspective to validate, improve, extend, and connect existing models using empirical insights. The quality and use of these data is essential to achieve effective queue management. Modern POS systems typically include queueing functionalities that enable restaurateurs to capture aggregate data on queue length and waiting time. Dedicated queue management systems (QMS's) such as Hellometer, Qudini, and Qless offer more fine-grained queuing data. Customer-level queueing data are typically obtained using virtual queues of customers who check in with their smartphones. In addition, detailed restaurant service speed metrics can be generated through the use of AI to monitor restaurant camera images (Noone and Coulter 2012) or WiFi positioning data (Shu et al. 2016).

Queueing practice and research has demonstrated that the behavior of (prospective) restaurant customers cannot be seen in isolation from the wait they expect (Hwang and Lambert 2009) or experience before being seated. Nevertheless, very little is known about the broader impact of this wait on customer demand. The expected wait of customers is typically difficult to identify, but publicly available estimates of waiting time on e.g., Google or Yelp can provide a proxy of customer expectations. These data together with detailed POS data could be used to obtain rich and novel insights. A general overview of constructs and data sources relevant to study the impact of restaurant queues Table 5 represents.

3.3.3 Methodologies and models

As illustrated in the research overview, complex dynamics are involved when exploring the impact of the impact of waiting time on restaurant performance. When selecting a potential restaurant, customers might use expected queues as decision criterion. Subsequently, upon arrival, they may decide to balk or join a queue after observing it. After joining, they may decide to renege if their expectations of the remaining wait exceeds their patience. Once customers are finally seated, their behavior at the table can be affected by the wait that they have experienced. Simultaneously, the kitchen staff and waitstaff serving them are likely to be affected by the queue as well and might adjust service speed and quality accordingly. These effects may in turn influence the restaurant queue and the arrival rate again. Figure 5 illustrates the complex dynamics around restaurant queues, and provides some examples of studies that explore specific relationships in this

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Table 5: Relevant queueing data and data sources

Relevant constructs	Possible data source(s)	Details
Unique customer identifier	Phone no., email, loyalty card	To track customers during restaurant visits
Customer characteristics	POS, mobile app	Demographic details about customers
Customer spending	POS	Total spending during a visit
Order details	POS	Type and quantity of items ordered
Queue length	POS, QMS	Length of queue upon arrival and during visit
Arrival waiting time	POS, QMS	Time between customer arrival and seating
Queue progression	POS, QMS	Speed of queue over time
Waiting time estimates	QMS, online sources	Informing prospective visitors about expected wait
Dining duration	POS	Time between customer seating and departure
Seated waiting time	POS	Time between ordering and order delivery
Restaurant utilization	POS	Share of restaurant capacity utilized by customers
Server identifier	POS, labor management system	To track which server handled which table/order
Server workload	POS, labor management system	Amount of work for waitstaff over time
Kitchen workload	POS, labor management system	Amount of work for kitchen over time
Kitchen preparation time	POS	Time taken by kitchen to prepare an order

domain. To truly understand these complex dynamics and achieve results that are better generalizable to practice, multiple methodologies are required to capture a wider set of interrelations. Especially the dynamics related to the staff-customer interaction in the service domain are still largely opaque. Tan and Netessine (2014) show how server workload affects customer spending and dining duration at an aggregate level. However, a more detailed perspective on the choices individual employees and customers make is still lacking. Such insights can be used to inform operating policies such as customer seating rules (see Section 3.4 for a detailed discussion).

A promising approach towards addressing how waiting time affects behavior and operating performance is to combine ML with statistical (causal) inference and multi-objective optimization. This will allow us to estimate waiting time sensitivity of individual customers and workload sensitivity of individual employees, and to use the obtained sensitivities into an optimization model to inform managerial decisions such as restaurant capacity and service policies. The broader Operations Management literature provides plenty of relevant examples of queueing policy implications that could be transferred to the restaurant domain, such as staffing policies (Koçaa et al. 2015), virtual queues (De Lange et al. 2013), delay announcements (Yu et al. 2017), and queue pooling (Zhou et al. 2021). For example, we take a closer look at how queueing interacts with the restaurant seating policy and staffing decisions in Section 3.4. Depending on the specific business objective(s) and operational levers that are considered, the focus of such an optimization model could be to maximize revenue, customer satisfaction, restaurant throughput, or a trade-off involving a combination of these objectives (e.g., minimizing dining duration while keeping customer satisfaction above a specified threshold). To causally establish the effects of waiting time, it is important to incorporate heterogeneity in customer requirements and employee reactions, and control for differences in sensitivity across different days and hours within days.

Another promising approach would be to model the restaurant as a double-ended queue. While restaurant customers face a queue if restaurant demand at a given moment exceeds restaurant capacity, a queue of waitstaff can emerge in case the service capacity exceeds the demand at a given moment. In existing studies, these two queues are typically evaluated in isolation. Combining them creates a challenge in terms of queue management, because both the customer service requirements and employee service rate can be affected by the state of the queue. For customers, a queue can affect the arrival rate, abandonment, and service duration (De Vries et al. 2018). Servers can engage in strategic behavior and adapt their service rate to avoid being assigned to arriving customers (Gopalakrishnan et al. 2016). Unlike in the traditional double-

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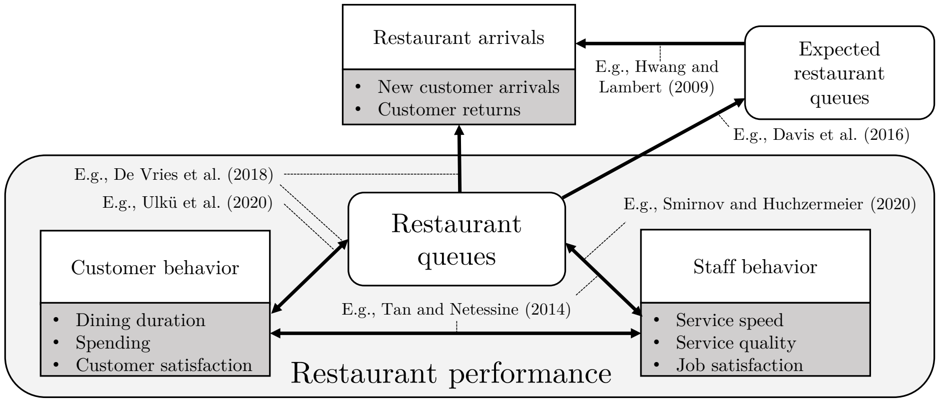

Figure 5: The complex dynamics through which queuing impacts restaurant performance

ended queueing setup where customer arrivals and service arrivals are independent, such a model should incorporate the endogenous relation between customer and server behavior. The magnitude and nature of this endogeneity first needs to be empirically explored through instrumental variable estimation, using a combination of customer-specific queueing data and transaction-level server data. A promising extension of this model would be a comparison between queues in which heterogeneous customer groups (in terms of group size, order requirements, or other factors) are pooled, and dedicated queues per customer group (see e.g., Zhou et al. 2021).

Additionally, when customer-specific queueing and transaction-level server data are both available, dynamic regression models (Davis et al. 2016) or ML can be employed to improve waiting time forecasts. Similar to the work of Ang et al. (2016) in hospital emergency waiting time forecasting, a Q-LASSO method (a mix between queueing theory and statistical learning) can be used to accurately forecast restaurant waiting times based on a combination of customer characteristics, waitstaff characteristics, and contextual factors.

3.3.4 Actionable insights

The discussed models on the impact of waiting time on restaurant performance could provide valuable input that can be used to make well-informed decisions that also have implications outside of the queueing domain (e.g., in terms of task assignment and staff scheduling). The improved decisions facilitated by these novel insights can offer value to restaurateurs, restaurant employees, and restaurant customers.

Restaurateurs: If restaurateurs have more accurate information about the impact of waiting time in their restaurant, they can use several levers to influence this impact. On a strategic level, they can focus on reducing the average waiting time by more accurately comparing the estimated value of additional restaurant capacity (including the impact of this expansion on queues) and the costs of capacity expansion. An alternative, a more tactical approach would be to use differential pricing as a mechanism to reduce the wait for customers with the highest reservation price. Such a policy could essentially enable restaurants to capture part of the value that is otherwise wasted in the customer waiting time, resulting in higher restaurant revenue. Furthermore, data-driven insights can help managers to determine under which conditions queues can be used to their advantage, either as a signaling tool or as a method to increase table turnover rates.

Restaurant employees: The enhanced accuracy of queueing information and predictions can benefit restaurant employees in various ways. For example, waitstaff and kitchen staff can be informed about the required service speed in real-time. This makes it possible to flatten the peaks during their work and to arrange

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assistance or adapt service policies if queues get out of hand. Furthermore, once waitstaff possess accurate queueing information, they can use it in their interactions with customers. Inaccurate (usually underestimated) predictions of customer waiting time are a common source of customer frustration. Being able to inform customers about how long they will have to wait until they can be seated or until they receive their meal could be a key determinant of successful service interaction. This is likely to result in a more empowered and satisfied feeling for employees, and could also lead to higher tips.

Restaurant customers: If restaurants capitalize on their queueing data, customers can be accurately informed about the expected waiting time once they consider joining the queue. Ideally, the information should be updated in real-time so that they can decide whether to wait or leave. Similarly, customers are likely to be more satisfied if they know when to expect their meals after ordering.

An important side note in this domain is the fact that the effects of waiting time on restaurant performance are highly context-specific. In the fast food segment, a slightly longer wait can have a completely different impact than in a fine dining restaurant. Similar differences are also likely to exist across cultures. The influential variables are expected to be identical across contexts, but the relationships among them are likely to differ. This emphasizes the importance of developing a more comprehensive view of the effects of waiting time on restaurant performance and the context-specific moderators that influence this relationship.

3.4 How can restaurateurs match incoming customers to tables and waitstaff, while accounting for heterogeneity in behavior?

3.4.1 Restaurant table management in research and practice

Besides managing reservations (discussed in Section 3.2), table management in a restaurant involves the more strategic decision of determining the appropriate table mix, and the more operational decision of seating customers as they arrive (i.e., allocating incoming parties to tables and waitstaff). For example, a restaurateur has to decide on whether to offer the last four seater table to a walk-in party of two or whether a large party should be assigned to the waiter with the lowest workload or the one with the highest speed skills. Because customer behavior is uncertain and server heterogeneity is significant, seating policies should be flexible and seating decisions shall be made in a dynamic way, as customers walk-in or tables are freed. While these are complex, stochastic and dynamic problems, taking table management decisions effectively can be crucial to a restaurant's profitability. Table mix and flexibility significantly affects a restaurant's capacity utilization and revenue (Kimes and Thompson 2004, Thompson 2002), and speed of service can have a considerable impact on service quality and sales per check (Tan and Netessine 2014).

Past literature on restaurant table management has mainly focused on prescriptive models for determining the appropriate table mix and for allocating incoming customers to tables. For example, Kimes and Thompson (2004) use simulation to derive the optimal table mix for a large Mexican restaurant chain, Kimes and Thompson (2005) propose and evaluate several heuristics for determining the table mix, and Thompson (2002) studies whether combinable or dedicated tables lead to higher revenue. Revenue management models, largely based on queuing theory and (approximate) dynamic programming, have been proposed to optimize table configuration and at the same time dynamically make seating decisions. These models incorporate factors such as customer waiting time, congestion, fairness, and the probability of customer balking, when deciding on where to seat a customer group (see e.g., Bertsimas and Shioda 2003, Raman and Roy 2015).

However, the quality and applicability of such analytical models and corresponding management tools heavily depends on data to a) inform model assumptions about customer and server behavior, b) estimate

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model parameters, and c) empirically examine the actual behavior of decision makers in such a context (e.g., if and how they deviate from suggested solutions). POS data can be used to evaluate server performance, and inform table allocation policies (Kimes 2011). For example Tan and Netessine (2014), using a large POS dataset from a casual dining restaurant chain, find that servers increase sales effort when the workload is low, and increase speed when the workload is high. Based on this insight, they derive the optimal staffing policy in terms of workers per shift. Tan and Staats (2020) focus on the behavior of hosts when seating customers. Customers in a restaurant are traditionally seated by the host based on simple rules, such as the round–robin (RR) rule. With this rule, parties are assigned to zones in circular order in sequence of arrival and without priority. Each restaurant zone is typically serviced by different waitstaff. Using nine months of POS data and staff scheduling data from a large full service American casual restaurant chain, they find that hosts generally adjust the RR rule to prioritize waitstaff with lower workload or higher serving speed, but that they do not assign more customers to waitstaff with higher sales skills. Consequently, they show that deviating from the RR routing rule can increase revenue significantly.

Prior empirical studies in the restaurant context are scarce and have focused exclusively on aggregate server and customer behavior. However, to better match incoming customers to tables and waitstaff, restaurateurs need to understand individual server and customer behavior and how they interact under different system characteristics such as workload and waiting time (see discussion in Section 3.3). In the broader sense, the customer seating problem is similar to the customer routing decision in service operations (e.g., call centers, emergency departments), where servers possess heterogeneous skills and customers have different service needs. While this challenging problem has received extensive attention in the literature, it has been mainly examined analytically as a queuing control problem (for a review see Aksin et al. 2007). A more data-driven, empirical understanding of server and customer heterogeneity can inform the design of targeted allocation policies to maximize long-term system performance. We describe such an approach in the next subsections.

3.4.2 Relevant data

As discussed in Section 3.3, customer characteristics, transaction history, and customer-specific queuing data can be combined with transaction-level server data and server characteristics to estimate their impact on variables of interest such as customer spending, customer satisfaction, and dining duration. This section zooms in on how these insights can be used to inform the operational decision of table allocation. Table 5 presents relevant data and their sources.

3.4.3 Methodologies and models

In this section, we focus on how researchers can leverage individual-level characteristics to design targeted policies for assigning customers to tables to effectively increase both customer satisfaction and restaurant revenue. These individual-level data can refer to customers and staff. For instance, waitstaff display a wide heterogeneity in experience and abilities, and can respond differently to increased workload and fatigue during a shift. We therefore need to identify the impact of waitstaff's characteristics such as experience, zone preferences, personality traits, and skills in terms of service speed, frequency of up- and cross-selling, and service quality. As mentioned, the same outcomes are not independent of customer behavior, that may in turn depend on operational (e.g., waiting time) and personal characteristics (e.g., party size, party composition, loyalty). In such complex settings, appropriate identification strategies are needed to causally establish the effects of waiter and system characteristics (such as workload) on effort (sales / quality and speed), and

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subsequently on customer behavior (such as dining duration and spending). A two-stage estimation procedure using instrumental variables (IVs) is among the most popular techniques for causal inferences when issues of endogeneity are present (see e.g., Perdikaki et al. 2012, Tan and Netessine 2014). Using robust econometric approaches to identify the factors (and how these interact) that determine dining duration, spending, and customer satisfaction, we can subsequently incorporate these insights when modeling the allocation decision to prescribe (optimal) allocation policies or when devising heuristic methods to determine allocation policies that perform well. Simulation analysis can be used to evaluate such allocation policies and quantify their impact. For example, Mao et al. (2019) first use an IV approach to establish the effect of drivers' experience and local area knowledge on the timeliness of delivery, and the impact of early (or late) meal deliveries on future orders in a food delivery platform. Based on these findings, they develop an order assignment policy that maximizes customer's future orders taking into account customers' asymmetric reaction to early versus late deliveries and drivers' performance heterogeneity. Using simulation analysis, they compare the new assignment policy to other simpler and more intuitive ones (based on heuristics) and quantify the potential improvements with respect to the current policy. A similar approach can be adopted for the seating/assignment problem in a restaurant context. However, the identification strategy is more complex since customers' choices also affect the dining duration and spending. This adds another set of customer-specific predictors and another layer of stochasticity.

3.4.4 Actionable insights

Traditional seating rules such as the RR rule ignore waiter and customer heterogeneity. Disentangling the impact of server and customer characteristics on service speed, spending, and customer satisfaction can inform the design of more efficient seating policies under different system characteristics. For example, when the workload is high, hosts may be instructed to prioritize smaller party sizes and assign them to waitstaff with higher speed skills to increase throughput. Alternatively, hosts may assign waitstaff with more experience and skills to increase sales and customer satisfaction when customers have waited long in line to be seated. The impact of intuitive and easily implementable heuristics can be estimated using simulation and counterfactual analysis to better inform managerial decision-making. Last, understanding heterogeneity in server behavior has implications for staffing decisions in terms of the number and mix of workers in a shift. A restaurateur can mix waitstaff in a shift based on characteristics such as skills, experience, zone preferences, and flexibility to maximize operational performance.

3.5 How can restaurateurs learn about customer order preferences and design dynamic and personalized menus?

3.5.1 Restaurant menu engineering in research and practice

The menu is a fundamental choice for any restaurateur as it serves as a key marketing tool that can influence consumer choice and sales (Dayan and Bar-Hillel 2011). Menu design and engineering is a well–researched area in the restaurant revenue management domain. The current literature on restaurant menus, mainly within the domain of hospitality management, focuses on two key themes: a) menu design, dealing with topics such as the layout of menu display, item labels and descriptions, and position of menu items within a category, and b) menu analysis, focusing on systematically evaluating menu item performance, with some of the most popular classification techniques referred to as menu engineering. Menu items refer to both food items and beverages.

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Menu analysis models assess the performance of menu items, based on pre–selected criteria, focused on improving the profitability potential of the menu. Historically, menu items are segmented into four categories based on item cost/profitability and popularity criteria (Kasavana and Smith 1982, Pavesic 1983, Miller and Pavesic 1996). Initial models only accounted for direct material costs of menu items such as production and procurement costs, but later extensions employed activity-based-costing (ABC) to also assign labor and facility costs and more accurately estimated menu items' contribution margins (Raab and Mayer 2007). More recently, studies have used POS data and data-envelopment-analysis (DEA) techniques to assess the relative efficiency of menu items (Taylor et al. 2009) and menu combo sets (Fang et al. 2013). Because of their simplicity, menu engineering models are available as a module in many POS systems (e.g., Avero and Oracle). While traditional models focus on the individual menu item level, inter-dependencies within and across menu item categories may occur, both at the demand and production side. Data can be used to assess such inter-dependencies and move towards menu product portfolio models. For example, Noone and Cachia (2020) use experimentation and POS data to estimate within category menu substitution in a U.S. restaurant chain. Understanding cross–price demand elasticities can lead to better menu pricing and prioritization decisions. Online consumer-generated data are another source that can be used to infer product substitutability (and complementarity). For instance, Trevisiol et al. (2014) use reviews on Yelp across multiple restaurants, apply Natural Language Processing (NLP) and Sentiment Analysis (SA) to estimate user preferences, and employ a variation of the Apriori algorithm to detect popular menus.

Menu design has become even more topical in the era of digital menus and digital ordering. Digital ordering allows for dynamic menu design and personalized recommendations. For example, restaurateurs can dynamically adjust their menu offerings based on operational characteristics such as current workload and ingredient availability, as well as on external data, such as weather and social events. Furthermore, the hospitality sector is increasingly adopting a customer–centric approach. Menu recommender systems allow for personalized recommendations and have the potential to further increase revenue and customer satisfaction.

While most of the existing research in the domain of menu design and engineering considers static menu item analysis and bundling for cross- and up-selling, the abundance of new data (e.g., POS data, digital menu navigation data, online consumer reviews) and the advancement of data analytics techniques provide new opportunities for dynamic menus and personalized recommendations.

3.5.2 Relevant data

Restaurateurs can capture abundant transaction data such as consumption, customer demographics, preferences, and loyalty information through the POS and reservation management systems. Customer service rating and feedback are also often captured through digital feedback systems. There has been a rise in digital ordering (through a platform's website, an app, a tablet or simply a QR code in the restaurant) in recent years, which accelerated during the during COVID-19 pandemic (as it allows contactless and hence safer order placement). Digital menus provide multimedia content and rich information such as detailed descriptions of food preparation, video materials and information about the origin of ingredients, thereby facilitating customer choice. More importantly, digital menus and digital ordering can capture richer sales data such as order item timestamps at the customer level and menu navigation patterns, and real time data about customers' browsing behavior and items already in the basket. Third-party data such as online reviews and ratings form another rich source of information regarding customer preferences. Table 6 summarizes the available data and relevant sources.

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Table 6: Relevant data for menu design and personalized recommendations

Relevant constructs	Possible data source(s)	Details
Transaction data	POS	Type and quantity of items ordered, total spending etc.
Customer journey	Ordering app	Browsing (menu categories, menu items), sequence of selected items, items in the basket
Customer service rating	Ordering app, social media	Menu item/service ratings, feedback/reviews etc
Unique customer identifier	Ordering app	Phone number, email, loyalty card
Customer characteristics	Reservation system	Demographics, preferences, and loyalty information
Kitchen workload	POS, labor management system	Amount of work for the kitchen over time

3.5.3 Methodologies and models

The menu design decision is closely related to the well-studied assortment problem, i.e., which subset of products to make available to customers to maximize the expected revenue. Most of the traditional assortment optimization literature, mainly in the retail operations domain, focuses on static assortment planning for a homogeneous population of customers (for a comprehensive literature review see Kök et al. 2015). However, recent work considers dynamic assortment decisions, heterogeneous customer segments and ultimately assortment personalization (e.g., Agrawal et al. 2019, Bernstein et al. 2019). In the restaurant domain, optimizing menu assortment and offering personalized recommendations presents new challenges compared to the online retail sector. Especially inter–dependencies during item preparation and kitchen capacity constraints that may fluctuate over time (e.g., over a day or a week) create additional complexity in this domain.

The starting point of any assortment or menu decision is understanding customer preferences, which is usually facilitated by customer segmentation. Descriptive analytics based on customer past transaction data, such as clustering analysis methods (e.g., k-means clustering and hierarchical agglomerative clustering – HAC) or latent variable models (e.g., mixture models) can be used for effective customer segmentation and targeted menu offerings for a restaurant's clientele. Furthermore, customer segmentation can help develop better demand prediction models that take into account customer heterogeneity to improve forecast accuracy. Customer preferences (in each segment) can be captured through choice models that predict how demand changes in response to the available assortment. Multinomial logit (MNL) models and their extensions have been widely used in the operations and marketing literature to estimate the purchase probability of an item given the assortment. More recent studies employ data-driven approaches to estimate nonparametric models of demand (Bernstein et al. 2019, Ho-Nguyen and Kılınç-Karzan 2021). More detailed consumer choice models (parametric and nonparametric) can now be estimated due to increasing data availability and efficient estimation techniques. Chung et al. (2019) develop an efficient approach to approximate random-utility choice models, which can be used directly in assortment optimization models. While restaurateurs capture abundant transaction and customer data, long history data may not be available for new customers or new menu items. Ho-Nguyen and Kılınç-Karzan (2021) propose a nonparametric estimation of choice models that is dynamic, based on observational data that become available over time. We propose customer microsegmentation and dynamic clustering using Bayesian data analysis (as in Bernstein et al. 2019). The goal is to dynamically aggregate information among "similar" customers, and use data beyond historical transactions (such as menu browsing and search data) to complement POS data and estimate customer purchasing probabilities (as in Farias and Li 2019).

However, as choice models become more realistic, the corresponding assortment optimization problems are computationally hard and beg for efficient solution algorithms. Aouad et al. (2021) propose an efficient dynamic programming algorithm for optimizing retail assortment for a specific type of nonparametric choice models referred to in the literature as consider-then-choose models. Others use bandit algorithms to deter-

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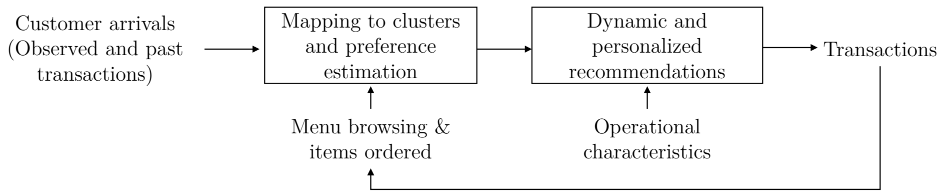

Figure 6: Data-driven learning of customer order preferences and personalized menu recommendations

mine the assortment in real time, after observing customer characteristics (Agrawal et al. 2014, Bernstein et al. 2019). We propose the application of ML methods, such as multi-armed bandits and reinforcement learning in general, to prescribe dynamic menus based on real time information about operational and customer characteristics. In the online retail sector, customer satisfaction and revenue maximization subject to inventory constraints is often the main goal for (personalized) assortment optimization (for an exception see Demirezen and Kumar 2016, who consider the impact of recommendations on demand and future inventory shortages in the context of DVD rentals). In a restaurant context, operational efficiency needs to be explicitly incorporated. Models for dynamic menu design and recommendations should capture the trade-off between customer satisfaction and item preparation requirements (i.e., kitchen efficiency) and/or available seating capacity. Models for simultaneous bundling and pricing can additionally capture the trade-off between revenue maximization and operational efficiency for prescribing personalized discounted offers (see e.g., Ettl et al. 2020, for an application in the online retail sector). Figure 6 presents a schematic representation of the proposed approach.

3.5.4 Actionable insights

The proposed approach for personalized and dynamic menu recommendations is prescriptive, aiming at optimizing an operational decision, considering customer characteristics and menu item complementary as well as operational constraints such as ingredient availability and kitchen capacity. While the main objective is to make better targeted real-time menu recommendations, such models can shed lights on the trade-offs between revenue maximization, customer satisfaction, and operational efficiency. Models for dynamic assortment can provide managerial insights at the strategic level on how to dynamically manage menu design and pricing decisions. For example, restaurateurs can dynamically update their menu bundles and offer discounts based on ingredient availability, kitchen workload, and external circumstances (such as weather and events). Furthermore, restaurateurs can offer menu bundles at a discount when the workload is high, but focus on up-selling when the workload is low. Last, a restaurateur may provide personalized recommendations based on customer characteristics but also on orders already in the kitchen and on seating capacity utilization.

3.6 How can restaurateurs manage customer order channel performance using shared resource capacities?

3.6.1 Restaurant resource capacity allocation in research and practice

Today restaurants have more than one dominant order stream. Online delivery platforms are quite popular among millennials and busy professionals who wish to receive the food at the location of their convenience. Hence, many restaurants now face an increasing proportion of online delivery orders. After placing an order,

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online customers also expect an accurate estimate of order delivery times. Capacity models can be used to provide estimates of the food delivery times to the customer location. In the case of a restaurant with multiple branches, real-time capacity estimation can help assign home delivery orders to the right restaurant. However, online platforms can have an adverse effect on restaurant margins due to high commissions, and processing online orders in the kitchen can affect preparation times of the dine-in orders. Hence, managing the shared resource capacity with several order streams is of prime importance for restaurateurs, just as it is relevant for e-retailers (Tsay and Agrawal 2004).

In terms of its history and practical value, the analysis and planning of restaurant capacity is a well established area with important implications for restaurant profitability. While capacity-related decisions have traditionally been approached as static issues, restaurants now operate in a highly dynamic environment. Customer demand across various channels interacts with restaurant resources in influencing restaurant capacity, and addressing a specific bottleneck may create unexpected effects elsewhere in the process. The increased availability of data and analytical tools to facilitate real-time, data-driven decision-making creates many novel opportunities in this domain.

The practical importance of capacity planning and analysis for restaurants is only scarcely reflected in the scientific literature. However, numerous case studies address the main questions that characterize this domain. Traditionally, process capacity analysis has been the key method to decide the capacity of the restaurant and identify the bottleneck resources (e.g., Ramdas 2003). However, process capacity analysis ignores the dynamic interactions among restaurant resources and processing time variability on customer experience. Competition for resources among demand streams can cause lengthy customer waits and significant costs. The long-term consequences of these interactions can be estimated using simulation models. Lately, both analytical and simulation tools have been developed to analyze integrated restaurant performance.

Few studies have investigated the issue of resource capacity at dine-in restaurants. Roy et al. (2016) focus on table allocation, order-taking, kitchen, and dine-in processes at a full-service dine-in restaurants using nested queuing network models. Their models capture the effect of resource capacity (in both front and back rooms) on customer wait times in the external queue. The objective is to find out whether sufficient kitchen resources (such as burners and chefs) are available to guarantee certain throughput times. This model captures the dynamic interactions between customer arrivals and restaurant resources, such as the number of tables, order takers, and chefs and burners in the kitchen.

The effect of shared kitchen capacity on order channel performance has received little attention. In terms of seating capacity, numerous case studies underscore the importance of the restaurant seating capacity dilemma and interaction of seating capacity with kitchen or chef capacity. For example, Buell (2016) focuses on the effect of only allowing customers to take a seat after having ordered and received their food, rather than the traditional approach to let customers wait while they occupy a table. This case also discusses the dilemma of combining take out and dine-in customers in the same facility, and its effect on customer experience. Feldman et al. (2021) design contract mechanisms that account for congestion at restaurants and offers a win-win proposition for both restaurants and platforms. Traditional revenue-sharing contract may not mutually benefit both platform and the restaurant, because the platform does not consider the effect of its price on dine-in revenues. This may result in delivery menu prices being set too, thereby generating high delivery customer demand and increasing wait times for dine-in customers. Other approaches commonly used by restaurateurs to manage high traffic from online customer orders include restricting the restaurant operating times on the platform (for example, see Buell 2016), or limiting the number of online orders per time window. Studies that combine customer order data, customer characteristics (e.g., group size, dining

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duration, and menu preferences), and restaurant resource data could provide operational insights on how to better manage performance with several order streams.

3.6.2 Relevant data

Dine-in data captured using restaurant technologies in combination with the kitchen data, such as menu items and their standard preparation times, can be used to analyze restaurant capacity and estimate the effect of capacity on performance measures, such as customer wait times and resource utilization (see Table 2). Both demand and process service time estimates are key inputs to process capacity analysis models and detailed queuing network models.

The distribution of order volumes by channel and the distribution of time between two consecutive orders can be obtained from the POS system. Order data can be translated to demand per menu section, and per individual dish within each section. Restaurant technologies capture customer arrival time, seating time, ordering time, and consumption and billing time. The distribution of customer time spent at various processes can be obtained using the timestamps at various events. The processing time data can provide an estimate of resource capacity at each step of the process.

Several kinds of data are necessary to estimate the the kitchen processing capacity. The preparation time and the information on all resources used in dish preparation are required to obtain capacity estimates. It is often important to develop a family of items that share common preparation steps, resource usage, and contribution to revenue. For example, Roy et al. (2016) found that about 260 unique dishes can be found in a specific kitchen. By employing a grouping technique, akin to product family formation used in manufacturing, they reduced this to approximately 30 item groups, which were subsequently considered in their analytical model.

Other static data, such as number of tables, seating capacity, average order value, and equipment details, can be obtained from the POS system.

3.6.3 Methodologies and models

It is not clear how shared restaurant resource capacity (such as kitchen capacity) can be optimally allocated across competing order streams. Using process analysis, it is possible to analyze different proportions of order volumes from different channels, and show how the bottleneck shifts when the volume of the orders from a particular channel increases. Although standard capacity analysis can obtain rough-cut results, more advanced simulation models (e.g., MOSIMTEC 2021) can estimate the delays at the process interfaces that result due to resource interactions among the processes. Real-time models that constantly collect data on all time components can be adopted to update policy parameters such as the number of online or carry-out orders to be accepted during peak dining times.

Roy et al. (2016) develop a queuing model for integrated restaurant operations but the model only captures dine-in orders. To answer the proposed research question, it is also necessary to explicitly capture the influence of online delivery orders on the waiting times of dine-in customers. The performance estimates from the queuing network model can be adopted to control the number of online-delivery orders at a restaurant. Figure 7 illustrates a possible integrated queuing network model where dine-in customer arrivals are matched with an available table from a pool of K tables at a synchronization station. Note that the assigned table is occupied by the customer group throughout the journey in the restaurant. While the dining and payment process can be modeled as infinite sever queues, interactions with order takers can be modeled with multi-server queues. The kitchen queue can be modeled as a special load-dependent server with orders from multiple

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order channels, such as dine-in and online. The load-dependent service rates for this queue can be derived from a multi-class closed queuing network that models the kitchen processes. This queuing network forms the basis for dynamically controlling the orders from different channels using a Markov Decision Process (MDP) model.

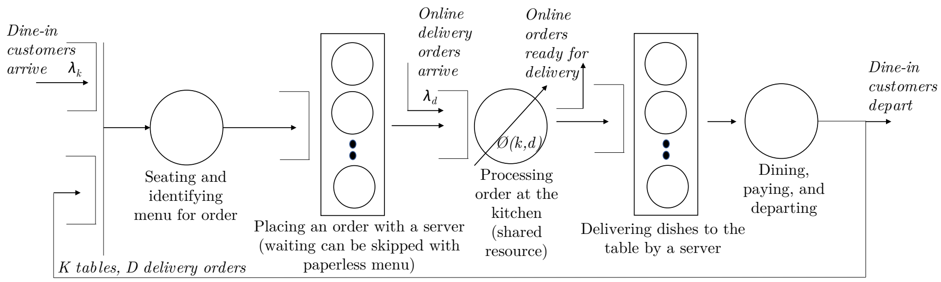

Figure 7: Example of an integrated queuing model with both dine-in and online delivery orders

This MDP framework can be used to find the optimal policy for dynamically controlling online orders (admit or reject), resulting in the lowest cost. The MDP model could be used to analyze a restaurant system that consists of a fixed number of tables, K. Dine-in customer orders arrive at a restaurant external queue with a rate of λ_k. Online orders directly arrive at the kitchen virtual queue at a rate of λ_d. The kitchen processing rates, which is influenced by the number of dine-in (k) and online delivery orders (d) at the kitchen, affect the dine-in customer order completion rates.

Now, the restaurant system dynamics can be modeled as a continuous time MDP model to reduce the long-term average costs. The cost function could consist of three components: 1) Order fulfilment cost, which is the cost of processing the orders, 2) Order delay cost, which is the cost of delay in fulfilling a dine-in order or a kitchen order, and 3) Rejection cost, which is the cost associated with rejecting online orders. The model could also use the time-varying arrival rates instead of fixed arrival rates, and could be solved using standard solution method such as policy iteration (Dhingra et al. 2018, Lamballais et al. 2022). Another research problem could be to determine the number of online orders that should be accepted every hour of operation at a given dine-in and online order arrival rates. This problem could be modeled with a multi-period integer programming formulation to minimize customer cost and restaurant staffing costs.

3.6.4 Actionable insights

Restaurateurs could use these models to decide on the timing of accepting/rejecting online orders for maximum restaurant profitability. Depending on the number of accepted orders, the restaurateur can also estimate the workload in the restaurant at specific moments in time. The exact workload requirement in the seating area and kitchen can help to further optimize the staffing levels and allocation to the front and back room. Likewise, the maximum number of acceptable orders for home delivery can help in informing the delivery capacity that the restaurant should schedule during specific days and shifts. Capacity can also be adjusted based on the demand. For example, the optimal table capacity of the restaurant can be estimated to match both seating and kitchen capacity with demand forecasts. Restaurateurs could also use this model to observe the effect of prioritizing one order type over another on order waiting costs and long term profitability.

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4 Data ownership risks

The increasing availability of data and tools that allow restaurateurs to optimize their operations based on data also comes with a risk. Platforms integrating data from various sources (e.g., customer reservations, POS systems, reviews) offer convenience, but the interests of platform owners and restaurant owners might not always be aligned (Schneider 2018). By outsourcing a large part of their interaction with customers to external platforms, restaurateurs become more dependent on those platforms. Initially collaborating with a third-party delivery app seems an attractive way to increase sales volume. However, such partnerships can often affect restaurant quality and and profitability (Buell 2016, Dunn 2018). Recent research shows that the commonly employed “one-way” revenue sharing contract between restaurants and platforms often leads to lower profitability than not offering a delivery service at all. This is because restaurateurs typically face thin margins that do not allow them to share up to 40 percent of order value with a platform. Other reasons include possible cannibalization on dine-in customers, and a deteriorating quality of dine-in service resulting from large delivery order volumes (Feldman et al. 2021).

COVID-19 related measures have exacerbated many of these issues. While synergy between the dine-in operations and third-party delivery platforms may exist under “normal” circumstances, being forced to fully rely on delivery has resulted in a non-profitable situation for many restaurateurs (Popper 2020). It is often not feasible for restaurateurs to insource the ordering and delivery process, because they also heavily rely on these same platforms for their marketing and customer acquisition. This has put independent restaurateurs in a very vulnerable position, essentially being hijacked by third-party platforms (Fil 2018). This vulnerability increases even more when restaurateurs also outsource the decision-making and control in intra-restaurant operations to platforms. While restaurateurs often lack the capacity to fully capitalize on their own data, outsourcing their data on reservations, queuing, table assignment, ordering, restaurant utilization, staffing, inventory, and payment to external platforms puts them in an extremely dependent position.

The typical discourse on data ownership focuses on privacy. However, issues such as the dependency of restaurants on platforms highlight the economic rights captured within data. So far, the market has not shown it is capable of ensuring fairness in this domain, and governments are struggling with regulatory efforts as well (Singh and Vipra 2019). If food delivery platforms follow the route of large e-commerce players such as Amazon, delivery platforms could enter the food business themselves. They have the data required to determine where to start their own cloud kitchens and could push restaurants out of the market (Singh and Vipra 2019). Several civil societies have called for enhanced regulatory efforts to limit the power of “Big Tech” (CSO 2019), but solutions are not straightforward. Singh and Vipra (2019) and Wong and Henderson (2020) propose community data ownership and co-created data commons as a way to re-balance power between the sources and controllers of data. Several examples of local, low-commission delivery initiatives created by restaurant collectives have already emerged (Bratskeir 2020). In the end, consumers and restaurateurs together have the power to invest time and effort to challenge the power of large platforms.

Besides restaurateurs that face the downsides of lacking data ownership, restaurant customers also face negative consequences of handing their data over to platforms in exchange for convenience. For example, platforms can sell restaurants customer dossiers, including detailed information on dining preferences, spending, and even demographic details such as age, address, and income (Kane 2015). It would not be new for restaurateurs to treat their best customers better, but the vast amount of data that can now be used to segment customers could come with discriminating and undesirable side-effects that should not be ignored.

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5 Closing thoughts

Due to the unprecedented growth in restaurant technologies, data analytics has permeated into the realm of restaurant operations. Restaurateurs can now obtain detailed information about their restaurant and customers. While current practice is to use data for mainly viewing descriptive statistics and dashboards, they can be harnessed for decision-making at both the strategic and operational levels. When combined with other data sources such as demographics, socio economic factors, and social media, restaurant data can provide insights about customer behavior, predict customer demand, and generate additional revenue opportunities. While gathering large volumes of data is an important step, effective data management through system integration and the use of analytical techniques to guide decisions are crucial determinants for success. Studies leveraging the data harnessed through restaurant technologies are currently still limited. However, new business models (e.g., home delivery platforms, cloud kitchens) necessitate the effective usage of data to enhance decision-making. With a large number of restaurateurs adopting technologies to engage with customers, streamline internal processes, and improve resource utilization, we hope that the current manuscript can inspire and engage practitioners and researchers towards data-driven success in the future.

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