CAPSTONE FINAL REPORT
Throughput and Demand Analysis Consulting Study for Joe's Pizza Ann Arbor

Mika Benezer
Julia Gallagher
Halle Mohr
Rachel Russell
24 April 2023
Winter Semester 2023

TABLE OF CONTENTS

I. Introduction

Problem Statement/Abstract

Since its grand opening in the fall of 2019, Joe's Pizza in Ann Arbor, Michigan has far from lagged behind its flagship location in New York City, New York. Their stable customer demand keeps business extremely profitable across all days during the week, with surges occurring during the final hours of service typically. However, they struggle to reach operational excellence in one main component - long order times resulting from their notoriously extensive line that often accumulates to the central campus Diag, resulting in higher than expected customer loss, subsequent potential revenue loss, and cold students, U-M staff members, and Ann Arbor residents who are just trying to grab and enjoy a slice or whole pie at the end of their day.

The purpose of this capstone is to provide tangible solutions and recommendations for Joe's Pizza on their bottleneck wait times in their Ann Arbor shop, in addition to operational excellence best practices for new facility design layouts and continuous improvement across all brick and mortar locations.

Business Case, Current KPIs, and Key Variables

Joe's Pizza makes close to a thousand pies a day in their small Ann Arbor store alone, thus requiring much efficient operations from their sourcing and supply, all the way to their customer-facing point of sales system. While the back end of their production, as well as their daily demand forecasting, are both robust and efficient, they experience a large bottleneck when customer surges occur typically from 8 pm to 2 am mostly on nights from Thursday to Sunday. The result is not only customer dissatisfaction, but also customers being lost when wait times can exceed up to one hour just for a simple slice order. This customer loss financially impacts the business, as estimated in later analysis to be anywhere from 50 to 100 customers lost on a busy night, providing an extremely large potential revenue loss.

To drive the best and most informative results, we decided to establish KPIs to track where these variables will change or improve upon recommendations being made, as detailed in Table 2 below.

Table 1. Key Performance Indicators

Key Performance Indicator	**Purpose**
Revenue	Joe's top-line is of most importance to highlight their performance, as we make changes to the system, in order to justify these changes the overall revenue per day must significantly increase.
Customers Lost	Since the long line results in customer loss, tracking customer loss with simulated layout changes will inform the overall productive minimization made.
Customer Wait Time - Main Queue	Customer wait times are important to track in order to minimize the total changes in wait per customer.
Cash Register Utilization	Tracking old resources being utilized are important too when adding new resources because utilization of all of these should not be so low that we experience waste issues while incurring higher costs.

Project Scope

The project is limited to examining the business operations of Joe's Ann Arbor location. We will be suggesting best operational practices for their new locations, but not requesting data from other existing locations. Below in Table 2 details the activities for the project that were in scope and out of scope.

Table 2. Activities In-Scope and Out-of-Scope

In-Scope	Out-of-Scope
Analyze current state of Ann Arbor store	Analyze new POS call service system for orders
Recommend techniques related to facility layout, system tracking, and new machinery	Recommend specified new marketing strategies for any new implementation
Build demand profile	Physically impose the recommended changes
Analyze daily revenue estimate	Analyze costs and overall profitability

II. Outline of Questions and Problems Addressed

Upon meeting with the Joe's Pizza Ann Arbor client representative, Pete Levin, we conducted several interviews for the findings and solutions discovery process, in addition to detailed and specific data requests to inform the input design side of the ProModel simulations. Listed below displays what questions were asked during these interviews about their current situation, bottleneck discovery, and previous methods deployed to attempt to solve their key sales, operational, supply, demand, and processing issues. From these questions, we deduced that the largest bottleneck of the business in their day-to-day operations systems.

A. What is your biggest challenge to the business? (is it Sales, e-commerce vs. in person sales management, digital system tracking, labor/workforce retention, hiring/training/onboarding process, operations, maintenance/machine upkeep, marketing efforts, being the only distant location from the flagships, profitability)
B. What's one or two large initiatives that would drastically improve your business or make you happier if they were worked on over the next few months?
C. Sales-related Questions
    1. E-commerce vs. in person sales proportion and the issues they are experiencing, perhaps if it's a large discrepancy or if it's more about increasing lead time issues or tracking of first come first serve orders
    2. Data on the proportion and # of item types sold on a typical basis - which are more popular? What do you have trouble selling? Are you losing money on any of these product types? Are you looking to increase profits/revenue by introducing a new product or set of products that we could help you process, map, and launch?
    3. How do your catering/event sales compare to individual in store and e-commerce sales?
D. Operations-related Questions
    1. How do you keep track of your inventory?
    2. Do you ever have any waste? What is the average $ lost from this waste?
    3. What happens when you have extra finished goods once service is over? What is the average $ lost from this waste?
    4. Do you wish you had a bigger space to work and sell?
E. Supply-related Questions
    1. How are your suppliers and contracts?
    2. Do you have quality or service time issues with certain ones?
    3. Do you nearshore or offshore ingredients? Which ones?
    4. Do you wish certain ingredients from suppliers were cheaper, if so which ones? Which ones would you be willing to renegotiate with/look into new suppliers?
F. Processing/Queue-related Questions
    1. What's your biggest bottleneck in the pizza making process? (e.g. labor shortage during service, one machine specifically, the way they batch, one ingredient specifically that they always run out of, etc.)
    2. Overhead and other incurred costs

3. What are some of the highest recurring costs of your business aside from what goes directly into the products? (e.g. electricity, water, training, power FOR CERTAIN machines, rent, cleaning materials, etc.)
4. What are your wait times on an average day like? On a busy day? On a slower day?
5. What percentage of customers would you say are lost from not wanting to wait in line? Does this increase in the winter (seasonality aspect)?
6. What are your largest constraints to making this better? Staffing, physical space, pizzas produced per unit of time, etc.
7. How long is the wait time on a busy night?
8. How long is the wait time during the day, on average?
9. How have you tried minimizing wait time?
10. What is the biggest cause of long lines?
11. How much business is lost due to too long of wait times? (in $ value and # customers)
12. Does the wait time tend to be longer for customers who went through digital e-commerce platforms, in-person sales, or catering orders?
13. How much resources/time are you willing to dedicate to solve and implement a solution to this problem?

G. Marketing and Demand-related Questions
1. Digital vs. tangible marketing efforts they've done and its success (ROIM)
2. What their most effective/ineffective marketing efforts in the past have been
3. The customer base for them that is the most ideal
4. Any new marketing efforts that they would like to see
5. Any partnerships or joint ventures they'd like to do

III. Methods

Data Collection

Our team collected data in multiple stages and through a variety of methods. We began our data collection by interviewing Pete Levin, and asking him a series of questions about Joe's Pizza operations, as discussed above. Following our conversation with Pete, we collected the following customer data in an hourly broken down Excel sheet from Pete in November 2022:

- Order count and item count of the following categories per hour of the day:
    - Pies
    - Slices
    - Soda
    - Extras
- Total order count and item count at the revenue center (cashier)

We also received information on hours of operation each day, which is outlined below:

Mon 11am - 12am, Tues - Sat 11am - 3am, Sun 12pm - 2am.

However, since Joe's is primarily interested in improving operations on busy days, we chose to model after the Tues-Sat hours (16 total hours).

We also received the following data regarding cooking pizzas:

- Average time to make a whole pizza: 45 seconds to 1.5 minutes to stretch the dough/make the pizza (depending on who's making it), 5 minutes in the oven when its slow, 6-7 minutes when its busy
- Average time to reheat a slice: 30 seconds roughly (a little longer for Caprese and Sicilian slice)
- Number of ovens: 2 double stack Bakers Pride ovens
- Oven capacity: 3 pies per deck, or 6-8 slices per deck

Pete also described the number of workers utilized in each area of operation in order of least busy to most busy days:

- Slow day front of house personnel: Either 2 pizza makers + 1 cashier or 3 pizza makers (one of which helps as a cashier)
- Slow day back of house personnel: 2
- Slow day delivery personnel: 1
- Busy day front of house personnel: 3 pizza makers, 1 counter person, 1 expo person, 1 cashier, 1 phone order taker
    - SUPER busy days would have 4 pizza makers in addition to the others
- Busy day back of house personnel: 4 + dishwasher
- Busy day delivery personnel: 4-6

In February 2023, we also received the following additional data from Pete, which allowed us to create the ProModel simulation of Joe's Pizza:

- Order data for an entire week (as opposed to an hourly spreadsheet which we received in November)
- Number of people who can place an order at once at the counter: person working the counter can take usually up to 4 orders at a time, but the person on the register however can only cash out one at a time
- Estimate on the distribution of number of slices people order at a time: on average just under 2 slices at a time
- Estimate on the distribution of number of full pies people order at a time: on average one pie per person but there is no clear number on this

Our final method of data collection was observation and conversations with in-store workers. Since there were several other metrics that needed to be incorporated into our model (such as the time it takes to place an order, time it takes to pay at the cashier, and average line length that instigates customer loss), we chose to observe operations on 2 busy days throughout the winter and note average customer behavior. We also spoke with our client representative at Joe's, Pete Levin, along with several workers to gather their insights on what the average customer behaviors are as well. This helped us gather more specific information to use as inputs to our model in the form of user distributions and customer process logic (*see model assumptions and inputs section*).

Demand Profiling

After receiving requested data from Joe's, we analyzed and graphed out their demand over two consecutive weeks of data, highlighting the demand by hour. This robust demand profile displayed an extremely consistent daily demand, with heightened surges typically happening from Thursdays to Saturdays, typically from 8 pm to 2 am. Figure 1. shows the typically weekly sales based on the item category. From the consistency in the data we were able to determine that demand forecasting will provide us the least amount of insights and recommendations for change because of its stability and predictability.

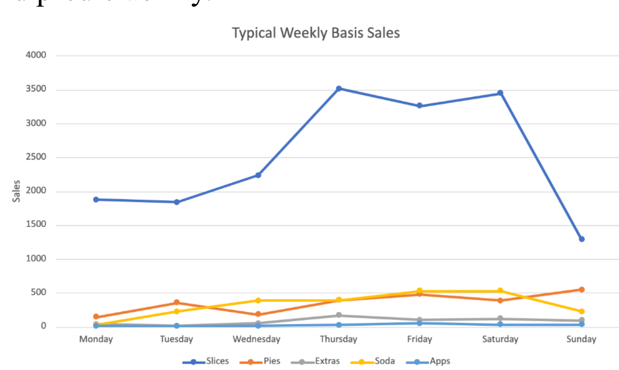

Figure 1. Typical Weekly Sales of Joe's Differentiated Between Items

ProModel Simulations

When speaking with our client, we became aware that there are several components of typical operations that they are unable to observe or measure. Namely, the number of customers lost and effect of facility and operational improvements on overall throughput, wait times, and revenue. To assist Joe's with this issue, we created three ProModel simulations that allow a visual representation of these facets. We created three models, each with a different purpose served. The first model represents the current flow of operations at the storefront. The second model incorporates the added component of an outdoor digital ordering kiosk that is available to customers who are placing orders for a full pizza. The third and final model utilizes a pick-up window for customers who order at the kiosk or who order online through a third-party source (GoPuff, Uber Eats, DoorDash, the Joe's Pizza mobile application or website). This order window can be used whether the customer orders a full pie or slices of pizza. Each of these models and the assumptions made in their creation are detailed in the subsequent sections.

Each model has the following elements:

<u>Entities</u>:
1. Order Here Customer
2. Pizza
3. Slice

<u>Resources</u>:
1. Cook (4)
2. Cashier (1)

<u>Locations</u>:
1. Customer Queue (queue for customers entering the store before ordering)
2. Order Counter
3. Cash Register Queue
4. Cash Register
5. Beverage Fridge
6. Wait Area (where a customer waits to receive their order)
7. Indoor Dining
8. Outdoor Dining
9. Inventory (where infinite supply of pizza/slices are stored)
10. Oven Queue
11. Dummy Queue (where items are routed when oven capacity is met)
12. Oven

<u>Additional Elements Present in Kiosk Model</u>:

1. Kiosk Queue
2. Kiosk
3. Entry Queue (for routing percentages of pizza orders to the kiosk or inside)

<u>Additional Elements Present in Ordering Window Model</u>:

1. Order Window Worker Resource (1) *and only 3 cooks*
2. Entry Queue (for transitioning percentages of orders to online orders)
3. Order Window
4. Pickup Wait Area
5. Online Order (to represent a customer ordering online and triggering the order to send to the oven)

Model-wide Assumptions and Inputs

Since the complete replication of operations in any service-oriented industry is nearly impossible, several assumptions had to be made to create the most realistic representation of operations. Many of these were made in conjunction with our client and by using our data collected, others were educated assumptions made by in-store observation. These are as follows:

Customer Habits:

- Customer arrivals follow the pattern of one specific day (the hourly data provided to us by Joe's)
- Customers will purchase a beverage with a 0.15 probability
- All customers will attempt to eat inside
- If indoor seating is at capacity, they will eat outside with a 0.2 probability, the rest will exit the system
- Customers will always pay before receiving their order (and will proceed to the wait area where they can be joined by their order)
- For simplicity sake and lack of additional data, we are only modeling customers who order at the storefront
- Customer Loss in each model:
    - <u>Baseline</u>: If the Customer Queue is longer than 30 people, a customer will exit the system before ordering
    - <u>Kiosk and Order Window</u>: Follows the following logic:

```
If Order_Type = 2 Then { //pizza
    If CONTENTS(Kiosk_Queue) > 10 Then {
        If CONTENTS(Customer_Queue)  + Contents(Cash_Register_Queue) < 15 Then{
            Route 1
        }
        Else{
            Route 3
        }
    }
    Else{
        Route 2
    }
}
```

Figure 2. Logic for Customer Entry Behavior

Staffing:

- In the baseline and kiosk models, there are 4 cooks and 1 cashier
- In the model with online ordering, there are only 3 cooks, 1 online order pickup worker, and 1 cashier
- Employee breaks are negligible and usually taken when no customers are in-store, so no downtime was included

Pizza Preparation:

- There is infinite inventory (*this assumption was able to be made since we found through interviews with Joe's Pizza that inventory never proves to be an issue, even on busy nights*)
- The time taken to prepare and cook a pizza is uniformly distributed with a mean of 7.125 minutes and half range of 1.375 minutes (*calculation made by taking the average and upper/lower bounds of the data given to us in the data collection section of the report*)
- Slices take 30 seconds to heat up

Ordering Times:

- It takes an average of ⅓ of a minute to place an order at the order counter (*measured by observation and modeled as E(0.333) min*)
- It takes an average of 30 seconds to get a beverage from the beverage fridge (*measured by observation and modeled as E(0.5) min*)
- It takes an average of 45 seconds to pay at the cash register (*measured by observation and modeled as E(0.75) min*)

Revenue:

- Pizzas are each \$26 (*the average price of all pizza types*)
- Slices are each \$4 (*the average price of all slice types*)
- Beverages are each \$2.50, and a customer will only purchase one per order

Capacities

- Indoor dining has a capacity of 15 people
- Outdoor dining has infinite capacity
- The oven can fit a total of 12 full pies (if only pies), and 24 slices (if only slices)
    - This was modeled as a variable "Num_In_Oven", and each pizza took up one "spot", while slices took up two "spots"
    - The variable monitored capacities in logic statements, so the actual oven location has infinite capacity
- All queues have infinite capacity
- 4 cooks can take an order at a time, so the order counter has capacity of 4
- The cash register has a single capacity since only one customer can pay at once
- 3 customers can be at the beverage fridge at a time
- 1 person can order at the kiosk at a time

In addition to these assumptions, several insights were taken from our data collection and put in the model as inputs. The first is **customer arrival times**. This was modeled as an arrival cycle, where we used the data contained in the spreadsheet containing total orders at each hour of the day on a busy day (November 10, 2022). The table below shows this data entered into the "Order Here Customer" arrival for the 'quantity each' column:

Table 3. Customer Arrival Cycle

Hour	Total in-person orders
11am to 12pm	59
12 to 1	70
1 to 2	60
2 to 3	56
3 to 4	49
4 to 5	66
5 to 6	70
6 to 7	72
7 to 8	66
8 to 9	64
9 to 10	58
10 to 11	84
11pm to 12am	61
12 to 1	125

1 to 2	115
2 to 3	110

This arrival cycle allowed our model to replicate the pattern of customer arrivals that occurs in real life, sending approximately the totals shown for each hour into the system. Although the total number of customers will vary in each replication, the pattern or distribution of the arrivals will remain consistent with the data collected from an observed day.

There are also several **user distributions** that influenced our model. The first is the distribution for order types. This was derived by taking the spreadsheet containing specific order items ordered each day throughout a week (February 6 - 12, 2023). We calculated the percentage of orders that were slices and whole pies, normalized by the number of customers entering the system in the entire day and averaged it throughout the week to obtain the following ratios for the "Order_Type_Distr" attribute assigned to each customer:

Table 4: Order Type User Distribution

Percentage	Value
77.7	1
22.3	2

If a customer receives a value of 1, they are a slice order. If they have the value of 2, they are a pizza order. Additional user distributions were made and assigned to these customers to determine the number of slices or pizzas they are purchasing. As mentioned in the data collection section, we were provided with an average number of slices purchased by a customer (which is a little under 2 slices at a time). However, when using this as an exponentially distributed value in the simulation, the results turned out to be vastly different from real life when we conducted our data verification and validation. Therefore, we needed to develop a user distribution by speaking with Joe's pizza workers and creating an educated assumption. Through this, we were able to generate a rough breakdown of the number of slices ordered per person. The breakdown is show in two tables below, where the percentages of customers who order each integer number of slices are demonstrated:

Table 5. Number of Slices Ordered

Percentage	Value
30	1
60	2
10	3

This user distribution shows that, on average, 30% of slice order customers will order 1 slice, 60% will order 2, and 10% will order 3.

Table 6. Number of Pizzas Ordered

Percentage	Value
80	1
20	2

This user distribution shows that, on average, 80% of pizza order customers will order 1 pizza and 80% will order 2.

Next, we also incorporated **logic for wait times** throughout the ordering operations. The wait time for ordering at the order counter and paying at the cash register were modeled as the average time gathered through observations, and inputted in the model as this value exponentially distributed. The time it takes for a pizza or slice to be prepared and cooked was modeled as described in the assumptions portion of this report.

Finally, logic for the resource usage was implemented to model the use of Cooks and Cashiers in daily operations. This will be discussed in the next section when the overall process flow is described.

These inputs were incorporated into all three models. In the following sections, the additional processing and inputs for each individual model will be discussed.

Simulation One: Current Situation

The first model we created was a representation of current operations at Joe's Pizza's storefront in Ann Arbor. Our goal for this model was to understand operations more fully and identify any bottlenecks, both ones demonstrated to us by Pete and unanticipated. A view of the layout in Promodel is shown below:

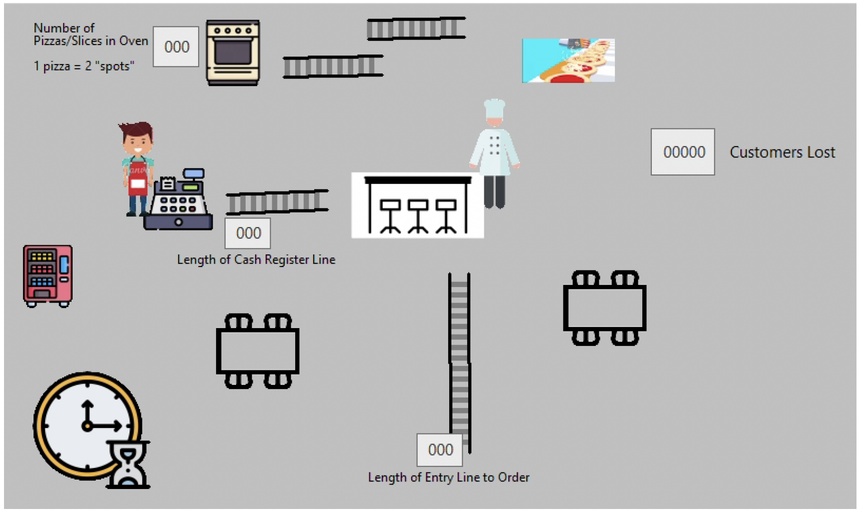

Figure 2: Layout of Baseline Model

The model contains 2 different processes: one for customers and another for orders (slices and pizzas). The overall process flow of a customer is described below:

First, a customer enters the system by joining the Customer Queue. From there, they are routed to the order counter (or exit the system subject to the customer loss logic described in the assumptions section). When they arrive at the order counter, they are assigned an order type attribute using the Order Type Distribution. If they receive the order type of 1 (slice order), they are then assigned an attribute for the number of slices they order based on Table 3. Otherwise, the customer is a pizza order and they are assigned the attribute of number of pizzas ordered based on Table 4. At this time, a cook is obtained using a “Get” statement and the customer places their order which triggers that number of slices or pizzas to be sent from the inventory to the oven for preparation.

After a customer places their order, the cook is “Freed” and the customer proceeds either to the cash register queue or the beverage fridge with the probabilities mentioned in the assumptions. Once at the cash register, a cashier is obtained using a “Get Statement” and the customer pays for their order using the following logic:

```
Get 1 Cashier
Wait E(.75) min //time it takes to pay
If Order_Type = 1 Then{ //ordered slices
    Inc Revenue_from_slices, Number_of_Slices * 4
    Inc Total_Revenue, Number_of_Slices * 4
}
Else{ //ordered full pie
    Inc Revenue_from_pizza, Number_of_Pizzas * 26
    Inc Total_Revenue, Number_of_Pizzas * 26
}

Free 1 Cashier
```

Figure 3: Customer Order Payment Logic

Next, they move to the wait area where they are joined with their order as soon as it is ready with a "Join" statement. Finally, they proceed to dining indoors, outdoors, or exiting the system following the probabilities mentioned in the assumptions.

In addition to the customer process flow, the pizza and slice preparation process occurs in the following manner:

When a customer places their order at the order counter, it triggers a "Send" operation of a certain amount of pizzas or slices (depending on the order type and number of items) from the Inventory to the Oven Queue. At this point, the number of items in the oven is checked by routing a pizza into the oven if the "Num_In_Oven" variable is less than or equal to 23, and a slice into the oven if the variable is less than or equal to 22. Since the oven capacity is 42 slices or 12 pizzas, if a slice enters the oven the "Num_In_Oven" is increased by 1, and if a pizza enters the oven it is increased by 2. Otherwise, if the oven is full the pizza or slice is sent to a dummy queue, where it will be routed back to the oven queue with a priority one level higher than the new items entering the oven queue (so that the items in the dummy queue pre-empt the new order items entering the oven queue). After waiting for the order preparation and cooking duration characterized by the times outlined in the assumptions, the "Num_In_Oven" variable is decreased the appropriate amount and the pizza or slice is joined to the corresponding customer using an "If Join" rule.

Throughout the process, several variables and attributes were used for analysis purposes. Aside from the attributes associated with each customer's order type and number of items ordered, we also included attributes for customer wait time start and finish. These were noted when a customer placed an order at the order counter and then when they were joined with their order in the wait area using the Clock() function, which uses a timestamp in the simulation to note the occurrence. When the order finished attribute is assigned at the wait area location, the wait time start attribute is subtracted from it (to get the total wait time for that customer). This value is checked against a variable called "Max_[Slice/Pizza]_Wait_Time" (order type is checked with an "If" statement, and then the corresponding variable of Slice or Pizza is analyzed). If the order finished attribute is greater than the current maximum wait time value for the pizza or slice order, it is re-assigned to that variable to keep a running maximum wait time. We also included and tracked variables for line length in all of the queues and revenue from pizzas, slices, beverages, and all items.

This helped us see clearly where the bottlenecks in their operations lie. More specifically, it allowed us to present to Joe's exactly at what times of the day, at what moments in a customer's in-store experience, and the quantitative effect these bottlenecks have on their revenue, throughput, wait times, and customer satisfaction (measured by customers lost in a day).

Simulation Two: Potential Recommendation - Ordering Kiosk Implementation

Simulation two added a new element to their operations - namely a digital ordering kiosk stationed outside their storefront location in Ann Arbor. This kiosk is for the use of customers who are ordering a full pie. It allows these customers to avoid waiting in the main line (the customer queue that all slice ordering customers enter).

The translation to Promodel consisted of building upon the baseline model. The three main changes are as follows:

1. All customers enter an "Entry Queue" where they are routed to the traditional queue ("Customer Queue") or to the kiosk queue ("Kiosk Queue"). The percentage of customers who are ordering a full pie that are routed to the kiosk queue depends on a macro that is varied using scenario analysis. We chose to vary this percentage from 0% (all pizza customers enter the original queue and kiosk utilization is nonexistent) to 100% (all pizza order customers place orders at the kiosk), varying by 25% increments.
2. After ordering and paying at the kiosk (an estimated 1.5 minutes), customers go directly to the wait area to be joined by their order that was sent to the oven in the same way it gets sent when an order is placed inside the store.
3. A "Max_Kiosk_Wait_Time" variable was added to understand the difference between this and the normal pizza or slice wait time inside the store. It was implemented using the same logic as mentioned in the baseline model section and was helpful in our data analysis.

The photo below shows the setup in Promodel, with the objects on the right being the kiosk and the queue to order at the kiosk.

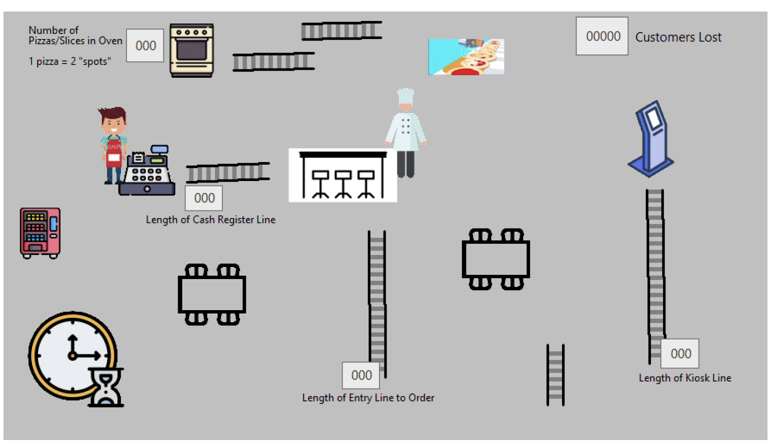

Figure 4: Layout of Kiosk Model

All else remains the same as the baseline model.

Simulation Three: Potential Recommendation - Physical Ordering Window Implementation

For this model, we wanted to understand the impact a new window for order pick-up has on in-store operations and wait time. Additionally, we wanted to understand if Joe's should put more effort into their mobile application and online ordering options to pair with this implementation. We decided to model this by taking a percentage of the customers who, in the other two models, would order in-store and representing them as online orders. This way, we could see if an increase in utilization of online ordering platforms in tandem with a pick-up window would be beneficial for the storefront.

This model is similar to the baseline and yet again builds upon its elements and process flow. Instead of routing all customers to the queue indoors, customers are routed to the "Online Order" location based off of a probability that is set by a macro and varied by scenario analysis. The scenarios are as follows:

1. All customers order inside (no online)
2. 50% of pizza orders are online orders, 50% of slice orders are online orders
3. 25% of pizza orders are online orders, 25% of slice orders are online orders
4. 25% of pizza orders are online orders, 15% of slice orders are online orders
5. 15% of pizza orders are online orders, 25% of slice orders are online orders
6. 10% of pizza orders are online orders, 10% of slice orders are online orders
7. 10% of pizza orders are online orders, 5% of slice orders are online orders
8. 5% of pizza orders are online orders, 5% of slice orders are online orders

The process for a customer who is routed to the "Online Order" location is that they 'place an order' at this location, representing a mobile order from the Joe's pizza app. It triggers their order to be sent to the oven. They are then sent to a separate "Pickup Wait Area" and are then sent to the "Order Window" location to collect their order (an estimated 2 minute duration), as they would if this was implemented at Joe's. Variables that tracked the number of online orders for both pizzas and slices was also added. The overall layout is shown below.

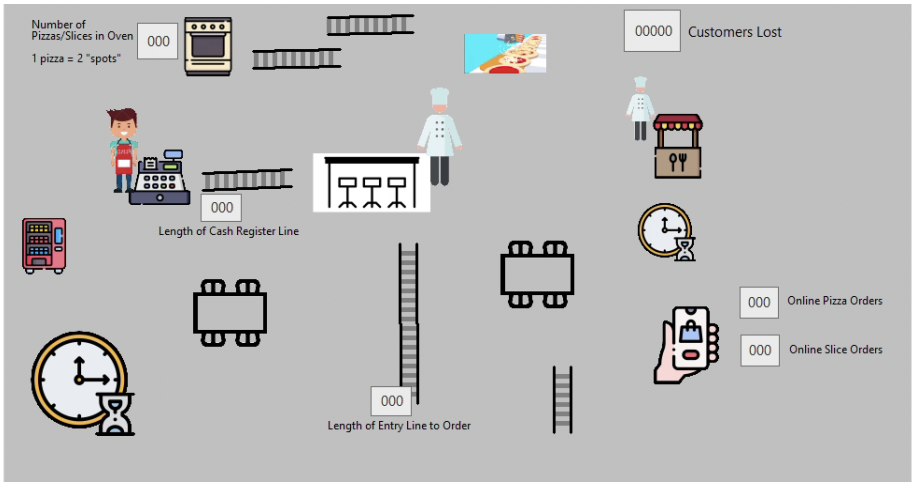

Figure 5: Layout of Ordering Window Model

The issue with this model is that it is hard to estimate when a pickup customer will come to get their order. We cannot reasonably estimate this human behavior, so we chose to omit that from our model and just have these customers move through the system without waiting. Although this is a large flaw in this model, we still were able to drive important conclusions about the effect of online order conversion rates and its effect on customer wait time, revenue, and customer loss. These results will be discussed in the results section of this paper.

Model Verification and Validation

We took several steps to verify and validate our model. We spoke with our client to confirm quantitative measurements of wait time, revenue in a night, and line lengths seemed reasonable based on their knowledge. We also confirmed our results with the data provided to us as mentioned in the data collection section of this report. We found all of our data to be within reasonable variation from the data estimates such as pizzas and slices sold per night and per hour and customer throughput. For instance, note the following discrepancies:

Example Data Provided by Client	**Model Output Result**	**Percent Difference**
1632 Slices Sold	1441 Slices Sold	11.7%
242 Pies Sold	257 Pies Sold	6.2%
1185 Customers Place Orders	1113 Customers Exit System	6.1%

These differences are all within the range of variations on a busy night out, confirmed by our client. Therefore, we deemed our models to be accurate representations of operations and Joe's and our recommendations as sound.

IV. Literature Review

Since we understand that the ProModel simulation portion of our project may not be a physically feasible solution for Joe's Pizza, our team outlined some other implementable solutions we brainstormed through a literature review. In order to help Joe's Pizza manage the current situation regarding wait times, our team conducted a literature review on studies done on human perception of wait times and how to incentivize people to wait in lines longer. We analyzed the following three papers: *The Psychology of Waiting in Lines, Prescription for the Waiting-in-Line Blues: Entertain, Enlighten, and Engage,* and *Psychological Time: the Case of Time and Consumer Behavior* and have outlined our findings and recommendations below.

The Psychology of Waiting in Lines

The Psychology of Waiting in Lines, by David H. Maister describes that humans are psychologically programmed to believe that the overall experience of any service or experience is lower quality if we must wait a long time for it. He outlines the First and Second Laws of Service, and constructs eight propositions on how company managers can best incentivize customers to wait longer periods of time. The First Law of Service Maister defines is S = P - E, where 'S' stands for satisfaction, 'P' for perception, and 'E' for expectation. This law implies that if you expect a certain level of service and perceive something higher than that, you will be a satisfied customer. In turn, if you expect a certain level of service and perceive something lower, you will be a disappointed customer. The Second Law of Service Maister defines is that "It's hard to plan catch-up ball", meaning if you invest in improving the perceived quality of a service, the largest payback will likely occur during the early stages.

Maister defines eight propositions on how company managers can make their customer's waiting experience as bearable and pleasant as possible. Proposition 1 states that occupied time feels shorter than unoccupied time. Some restaurants price this by handing out menus for customers to keep busy with when waiting in line to both shorten their perceived waiting time, but also shorten their physical service time as they are more likely to know what they want to order. Another tactic is to turn the waiting area into a bar, which adds revenue while lowering perceived waiting time. No matter what activity is chosen to fill time, the activity should (1) offer benefits in and of itself and (2) be related in some way to the upcoming service.

Proposition 2 states that people want to get started as soon as possible. As mentioned above, restaurant managers can practice this position by handing out menus or serving drinks to help fulfill the idea that their service has started and the restaurant has recognized the waiting customers. Another way this proposition can be implemented in restaurants is by having servers come to tables as soon as parties are served and saying something along the lines of "I'll be right with you!". This isn't as applicable to fast food services, such as Joe's Pizza, but finding ways to make the customers feel as though they are being serviced in some way during the wait can help incentivize customers to actually stay in line.

Proposition 3 states that anxiety makes waits seem longer. The anxiety Maister is associated with waiting is the fear of being forgotten. Maister states that this is reduced by making customers or clients feel as comfortable as possible, while still knowing they are being attended to. An example of this is airport lounges making flyers feel physically comfortable, while they still hear flight announcements and can know for certain they are not forgotten.

Proposition 4 states that uncertain waits are longer than known, finite waits. This means that if you are told you will be serviced "soon", you wait around and have an expectation to be served in the coming minutes. Contrarily, if you are told you are going to be serviced in 30 minutes, you won't expect to be serviced before the 30 minute period is over. There is an initial feeling of annoyance when being told a finite time, but the annoyance eventually relaxes into acceptance of the inevitability of the wait.

For Proposition 5, Maister states that unexplained waits are longer than explained waits. This proposition relates more to weather delays for taxis, plane delays, or other unexpected occurrences so it may not be as applicable as a proposition for Joe's Pizza. Proposition 6 states that unfair waits are longer than equitable waits. Maister states that the feeling that someone has cut in front of a line is very infuriating. He also mentions that queueing systems are most equitable when they are "first in, first out" (FIFO), and not prioritized in certain ways, which is already the way Joe's Pizza queues customers, as seen in the ProModel simulations. Answering phone calls while someone waits also often makes customers perceive themselves as not being treated equally, so the termination of phone orders for Joe's Pizza should likely continue but also be known and advertised for customers who do prefer to call.

Proposition 7 states that the more valuable a service, the longer a customer will wait. This is demonstrated as students are likely to wait longer for a Professor to answer questions than they are willing to wait for a Graduate Student Instructor or Instructor Assistant. Finally, Proposition 8 states that solo waits feel longer than group waits.

Prescription for the Waiting-in-Line Blues: Entertain, Enlighten, and Engage
Prescription for the Waiting-in-Line Blues: Entertain, Enlighten, and Engage, by Karen L. Katz, Blaire M. Larson, and Richard C. Larson, discusses a study conducted on customer perception of waiting in lines and proposes methods for managers to make waiting in lines more tolerable.

In November 1988, the Bank of Boston was contemplating installing two technologies which aimed to influence customers' waiting-in-line experience. The first technology was an electronic newsboard, which they named SilentRadio, installed at an off-premise ATM site and the second technology was a product created by Camtron Corporation, which utilizes "electric eyes" at the entrance and exit of a queue to estimate wait time and provide statistics for improving staffing and service levels.

Researchers tested the following hypotheses:

1. As the perception of waiting time increases, customer satisfaction decreases.
2. Increased distractions reduce the perception of waiting time, increase customer interest, and may improve customer satisfaction.
3. A wait where the length is known in advance is less stressful than an open-ended wait; having the knowledge of wait time may improve customer satisfaction.

The study was conducted in three phases. The first phase was the control phase. The second and third phases introduced variables that were hypothesized to alter the perceived waiting times and customer satisfaction. The second phase was the addition of SilentRadio technology, and the third phase was the introduction of Camtron's digital clock feature, with the removal of SilentRadio. Researchers interviewed one-third of customers after they finished their transactions at the Bank of Boston and also asked customers to rate their wait on three attributes: duration, boredom, and stress level.

The researchers found the following:

1. On average, customers waited in line for 4.2 minutes before seeing a teller.
2. On average, respondents thought they waited 5.1 minutes to see a teller.
3. On average, customers thought that 5.9 minutes was a reasonable time to wait.
4. Customers were overall very satisfied, as by the First Law of Service, S = P - E, the wait time they considered reasonable was lower than the perceived time they waited.
5. Correlations between the variables showed that as actual waiting times increased, overall customer satisfaction tended to decrease and stress levels continued to increase.
6. As actual waiting times increased, both perceived and "reasonable" waiting times increased, meaning that customers were recognizing that they were waiting longer, but were willing to do so.

The researchers concluded that the electronic newsboard did not significantly affect perceived waiting times, but it did make the time spent waiting more pleasant and still increased overall satisfaction with the bank's service. They found that customers looking at the newsboard tended to stand with their hands by their sides, while customers who did not see the newsboard tended to fidget or move around, indicating higher levels of anxiety and less satisfaction. The researchers were also able to conclude that the electronic clock affected perceived waiting times and overestimation of waiting times, making clock-phase respondents more satisfied as they felt that they waited less time than they actually did. They found that perceived waiting times were lower for clock-phase respondents than control-phase respondents, and that many customers liked to play "beat the clock" and felt as if they were "winning" if they spent less time waiting than the clock.

Based on the study, the authors outlined the following most important issues for our client when considering the experience from the customer's point of view:

1. Fairness: line should be first in first out, with no ability for customers who arrived after the customers ahead of them to order before.
2. Interest level: interesting things should be happening for customers to watch in line.
3. Customer attitudes: acknowledge what time pressures customers may face.
4. Environment: ensure waiting space for customers is comfortable, acknowledge if it is very hot or very cold and try to assist based on that.
5. Value of Service: if the customer can receive the same service or transaction elsewhere, find a competitive advantage in the service that would bring the customer to your shop.

Psychological Time: the Case of Time and Consumer Behavior

Psychological Time: the Case of Time and Consumer Behavior, by Jacob Hornik and Dan Zakay, discusses a conceptual framework used to show how time is linked to consumer behavior in various ways. The authors discuss that the economic household production function models make two major contributions in explaining consumer use of time: (1) they demonstrate that time is used in production (work) and consumption (leisure) and (2) consumers are constantly buying and selling time in the labor market. Hornik and Zakay state that time is linked to consumer behavior in that the satisfaction gained from products and services depend on the amount of time spent and the time at which they are consumed. They also state that time is also linked to consumer behavior as time is antecedent to and a consequence of a given purchase. This means that consumers often use time and money as substitutes or measures of valuable decisions. An example of this is the way humans may choose to pay for some form of transportation to get to work, or they may choose to walk even if it takes them more time.

As mentioned above, the authors of *Psychological Time: the Case of Time and Consumer Behavior* created a conceptual framework outlining the dynamic interactions between internal and external factors and how they influence human behaviors. The framework is comprised of the following elements:

1. Time orientation – Time orientation refers to the relative dominance of the past, present, and future in a person's thoughts. Typically, weight assigned to the past increases, weight assigned to the present varies little by age, and weight assigned to the future decreases with advancing age.
2. Time perception – Time perception is defined as the transformation of stimulus time to judgemental time. Time perception is commonly measured by presenting subjects with a task or activity and asking them to associate it with a time duration.

3. Time pressure – Time pressure can affect consumer decision making in two ways: (1) by forcing consumers to rely on their existing knowledge in their decision making and (2) by reducing the purchasing of products that consumers initially planned to buy and the frequency of unplanned purchases.
4. Time scarcity – Time scarcity increases the consumer behavior oriented towards preserving time, incentivizing customers to "buy time".
5. Individual situational factors – Positive mood is a determinant in time perception and orientation, suggesting that a marketing strategy for time-related products and services should be designed to enhance consumers' mood.
6. Situational accounts of time use, perception and orientation – Weather conditions, the presence or absence of other people, end-of-day mood at work, etc. all affect perception of time, suggesting that products and services should be made as situational-neutral as possible to avoid altercations for incidents such as bad weather.

Similar to some of the findings from the papers discussed above, the author's were able to make the following conclusions that can be linked to our client's wait time issue:

1. The more an individual tends to direct his or her consciousness to the future, the more consumption oriented the person will be.
2. If a person is engaged or distracted, their perceived time will be shorter and overall satisfaction is likely to be higher.
    a. Dull activities, such as waiting in line, usually have longer perceived times, so one way to help shorten that perceived time is to cause distractions or help disturb the time in line.

Recommendations

The findings and conclusions defined by all three papers above helped us outline the following three recommendations for Joe's Pizza with regards to incentivizing customers to wait in line for longer periods of time or in less-than-ideal weather conditions.

Flexible Queuing System

One method Joe's Pizza could use to help incentivize customers to wait in line is by implementing a more flexible queuing system. This solution would be implemented by allowing customers to receive a ticket number when they arrive at Joe's Pizza which they would order with when called on the speaker when it's their numbers turn. This would allow customers to get comfortable during their waiting times by sitting next to the outdoor heaters, grabbing a jacket during their queueing period, or allowing them the flexibility to move outside the physical line. This supports Proposition 3 discussed in *The Psychology of Waiting in Lines* as customers would have a more comfortable experience as they wait, while mitigating all the anxiety that they may be forgotten in the queuing time. This also supports Proposition 6 discussed in T*he Psychology* *of Waiting in Lines* as no customers would be physically able to cut other customers in line, ensuring the "first in, first out" method is never violated.

Expected Wait Times

Another method Joe's Pizza could implement to incentivize customers to wait in line is posting an expected wait time on the door of the store. This would warn customers who are in a rush to consider not waiting in line if the expected wait time exceeds what they are willing to wait. This idea supports Proposition 4 discussed in *The Psychology of Waiting in Lines,* which claims that uncertain waits are longer than finite waits. Customers would experience lower perceived waiting times, likely increasing their overall satisfaction. The expected wait time posted on the board of restaurants is often also an overestimation of actual wait times, making that perceived wait time even shorter.

Perks for Waiting in Longer Lines

The final method Joe's Pizza could implement to incentivize customers to wait in long lines is awarding perks for customers who wait longer than an assigned amount of time. For example, should Joe's Pizza implement the recommendation above regarding expected wait times, customers would know how long they are expected to wait for a slice or pie of pizza. If the expected wait time is over X minutes (for example, 45 minutes), Joe's Pizza would award customers a small perk, such as a side of Zingerman's Ranch or another small gift to help keep as many customers as possible in the line. This recommendation needs some exploration, as the breakeven cost of the solution may not be worthwhile for Joe's Pizza to implement depending on the revenue increase per customer compared to the revenue decrease which would be associated with giving perks to customers who wait the entire line for pizza on a busy night.

V. Results

At the end of each simulation we compared several variables and statistics related to the performance of each scenario with the main difference being the total revenue and customers lost. Figures 6, 7, 8, and 9 focus on the revenue generated from the different models based on one hypothetical day at Joe's.

Figure 6 shows the revenue differentiated by slice or pizza as well as the total revenue based on the percentage of customers that use the ordering kiosk for full pies while also being compared to the baseline revenues.

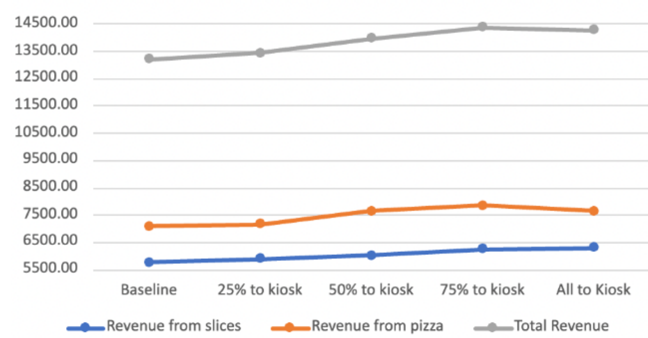

Figure 6. Revenue by Item Type and Kiosk Customers

Figure 7 shows the 95% confidence interval of total revenue by the percentage of customers that use the ordering kiosk for full pies based on 10 replications of the simulation. As seen in Figure , the highest revenue is earned when 75% of the customers use the ordering kiosk for full pies. The decrease in revenue from 75% to 100% of full pie customers is most likely due to variability. However, with multiple replications, the highest revenue is earned when all of the customers use the ordering kiosk for full pies as shown in Figure 7. The confidence intervals are wide enough to show that the decrease in revenue from 75% to 100% with one replication is insignificant.

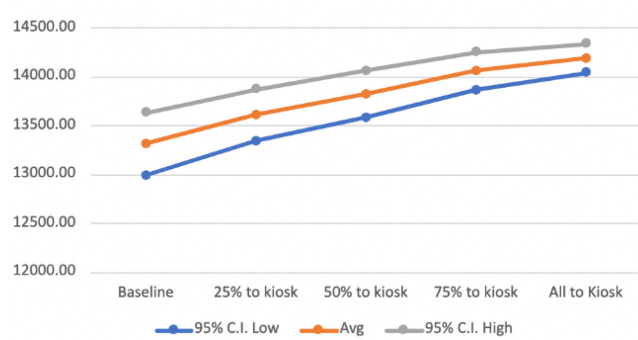

Figure 7. Total Revenue by Kiosk Customers (Confidence Intervals)

Figure 8. shows the revenue differentiated by slice or pizza as well as the total revenue based on the percentage of customers that order slices online and the percentage of customers that order pizzas online.

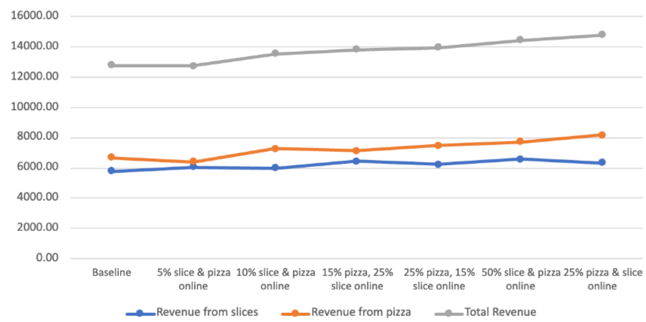

Figure 8. Revenue by Item Type and Online Order Percentages

Figure 9 shows the 95% confidence interval of total revenue by the percentage of customers that order slices online and the percentage of customers that order pizzas online. As seen in both Figure 7 and Figure 8, the highest revenue is earned when 50% of slice orders are online and 50% of pizza orders are online with the implementation of a pickup window. It could be assumed that with more online orders than 50%, there would be a further increase in revenue. However, we have to account for the likelihood that not all customers will be able to order ahead of time online. There are many customers that just walk by the restaurant and decide to order on the spot.

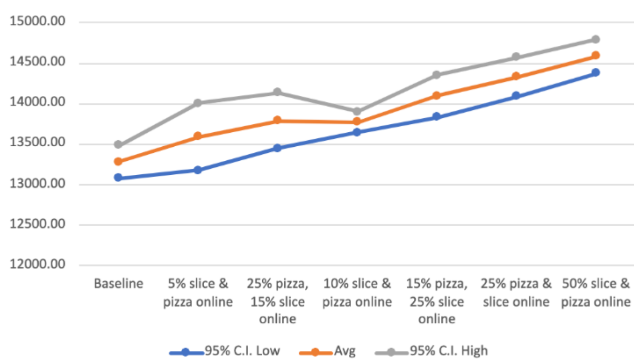

Figure 9. Total Revenue by Online Order Percentages (Confidence Intervals)

Figure 10 shows the average number of customers lost based on the percentage of customers that use the ordering kiosk for full pies while also being compared to the baseline revenues.

The revenue plots show that Joe's Pizza should encourage more customers to use the ordering kiosk as well as use online ordering ahead of time in order to increase revenue.

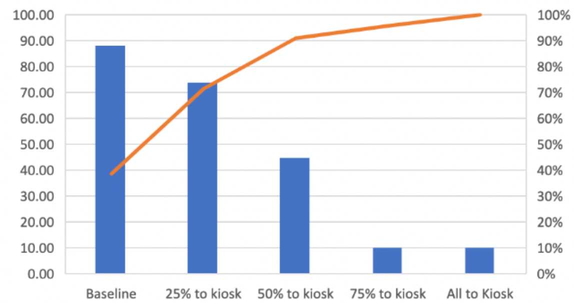

Figure 10. Pareto Chart of Average Number of Customers Lost by Kiosk Scenario

Figure 11 shows the 95% confidence interval of average number of customers lost based on 10 replications of the simulation. As seen in Figure 10, the least customers lost is when 75% of the customers use the ordering kiosk for full pies and when all of the customers use the kiosk. However, with multiple replications, the least customers lost occurs when all of the customers use the ordering kiosk for full pies as shown in Figure 11.

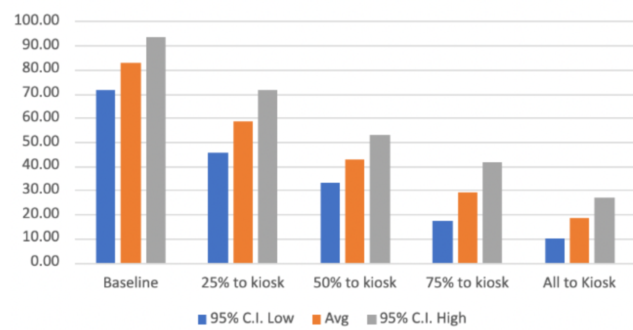

Figure 11. Pareto Chart of Avg Customers Lost by Kiosk Scenario (Confidence Intervals)

Figure 12. shows the average number of customers lost based on the percentage of customers that order slices online and the percentage of customers that order pizzas online.

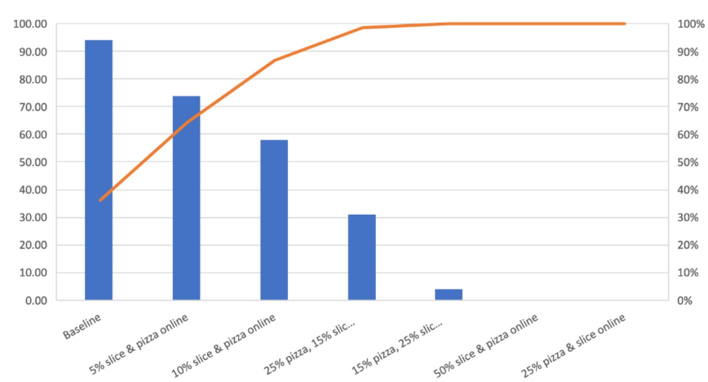

Figure 12. Pareto Chart of Average Number of Customers Lost by Online Ordering Scenario

Figure 13 shows the 95% confidence interval of average number of customers lost by the percentage of customers that order slices online and the percentage of customers that order pizzas online. As seen in Figure X, the least customers lost is when 50% of slice orders are online and 50% of pizza orders are online and when 25% of slice orders are online and 25% of pizza orders are online. However, with multiple replications, the least customers lost occurs only when 50% of slice orders are online and 50% of pizza orders are online with the implementation of a pickup window.

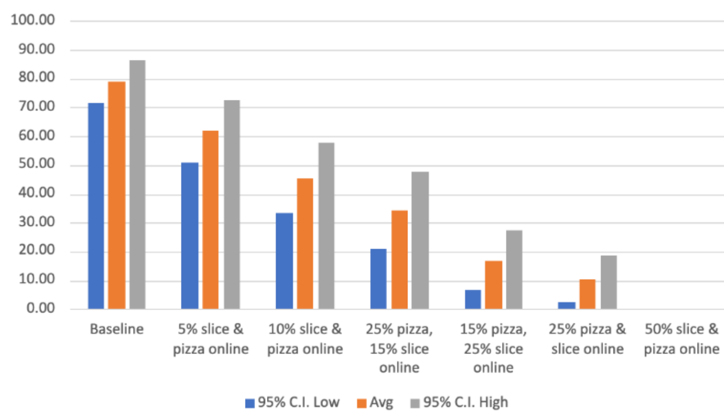

Figure 13. Pareto Chart of Avg Customers Lost by Online Ordering Scenario (Confidence Intervals)

The customer loss plots show that Joe's Pizza should encourage more customers to use the ordering kiosk as well as use online ordering ahead of time in order to lose less customers.

Figures 14 and 15 compare the results of the different simulation models together. Figure X shows the total best case revenue interval plot for each model used. For the kiosk model, 100% kiosk usage had the highest revenue with a 10.35% increase of $1,345 compared to the baseline model. The window model has the highest revenue with 50% slice orders online and 50% pizza orders online. This window implementation resulted in a 13.85% increase of $1,799 in total revenue compared to the baseline.

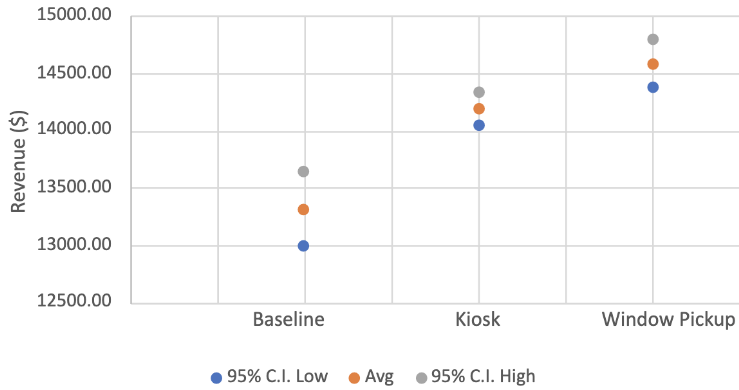

Figure 14. Total Best Case Revenue Interval Plot

Figure 15 shows the total best case customer loss for each model used. On average, about 83 customers were lost with the baseline model. For the kiosk model, 100% kiosk usage also had the lowest customers lost with roughly 19 customers lost on average which is a 71% decrease compared to the baseline. The window model had the lowest customers lost with 50% slice orders online and 50% pizza orders online with only 1 customer lost on average which is a 98% decrease compared to the baseline.

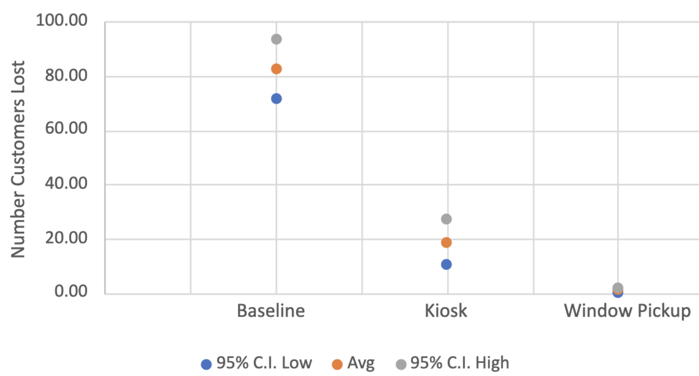

Figure 15. Total Best Case Customer Loss Interval Plot

The total best case plots show that Joe's Pizza should focus more on implementing the window pickup and encourage customers to order online ahead of time more often in order to increase revenue and decrease customers lost.

VI. Discussions and Conclusions

Recommendations for Joe's Pizza Ann Arbor

Based on our results from the Promodel simulations, we came up with 3 specific recommendations to present to Joe's Pizza. The first is the implementation of an ordering kiosk outside of Joe's Pizzas storefront location in Ann Arbor. To get the best results, Joe's should only allow customers who are ordering full pies to place an order at the kiosk and use marketing strategies to increase the adoption rate by customers since we saw the best results at 100% adoption

Based on our third simulation that analyzed the implementation of a pickup window, we found that the more that people are placing orders online and picking them up at the pickup window instead of ordering at the storefront or waiting in line to pick up an online order, the better it is for all customers regarding wait time and for Joes regarding revenue and customer loss.

Therefore, Joe's should optimize their mobile ordering app and focus efforts on increasing online orders. However, we know that creating a physical pickup window may not be feasible in their AA location. Therefore, our third recommendation for Joe's is that they should consider creating one when making future plans to open locations on other college campuses.

Recommendations for Best Operational Practices for All Joe's Pizza Storefronts

In addition to the recommendations drawn from our ProModel simulation, we have outlined the following two recommendations for Joe's Pizza to implement for their Ann Arbor location. These recommendations are drawn primarily from our literature review, where we analyzed different articles in order to understand how to incentivize customers to tolerate long lines at Joe's Pizza.

The first recommendation we make is for Joe's to implement a ticketed queuing system. A ticketed queuing system would allow for customers to be assigned a number, which would be called when it is their time to order. This would allow customers to stand by Joe's heaters while they wait in line, go grab a jacket if they live close by, or sit down on the lawn outside their storefront, which we confirmed through interviewing students would actually encourage people to wait longer durations for pizza on a cold day.

The second recommendation we make for Joe's is to post an expected wait time on their door. This is a concept supported by one of the propositions suggested in The Psychology of Waiting in Lines, which claims that uncertain waits are longer than finite waits. Customers would experience lower perceived waiting times than actual wait times, likely increasing their overall satisfaction.

From a learning standpoint for the Honors Capstone, our experience was very positive from start to finish, with a few minor obstacles in between. Our largest obstacle was gaining client buy-in, receiving timely requests on data and informational retrievals from them, and ensuring that our recommendations provided enough increase in top-line and added customer value so that the changes are meaningful enough to make. At the start of the project, finding a suitable fit for a capstone advisor who was also willing to support us was difficult. We cold emailed and asked professors in person, in which we eventually gained traction with Wallace Hopp, who was a perfect fit, as he is dually involved in the Ross School of Business and the Industrial and Operations Engineering Department. Finally, our internal group of Honors teammates collaborated extremely well and divided work based on our best suited skill sets - with Gallagher in charge of ProModel development, Russell and Mohr in charge of data analytics, demand profiling, and writing structure, and Benezer in charge of literature reviews and recommendation synthesis. Overall, we were satisfied with being able to answer Joe's questions on their bottleneck and to be able to impact the greater Ann Arbor community in a positive way before departing from our undergraduate experience at U of M. Thank you honors!

VII. References

Hornik, J., & Zakay, D. (1996). Psychological time: The case of time and consumer behavior. Time & Society, 5(3), 385-397.

Larson, R. C., Larson, B. M., & Katz, K. L. (1991). Prescription for waiting–in line blues: Entertain, enlighten and engage. Sloan Management review,(winter), 32(2), 44-55.

Maister, D. H. (1984). The psychology of waiting lines (pp. 71-78). Boston: Harvard Business School.