

The Augmented Shopping Experience with Intuitive Intelligence and Machine Learning

By

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### Abstract

Computer algorithms are increasingly being used to predict people's preferences and make recommendations. Data is being collected like never before, through advancing technologies and enhanced data scraping techniques. Here, we will look at a connection of data from a person's personal closet and shopping habits, combined with their social and business calendar to make predictive recommendations to users on their next purchase. Data exists in each person's shopping habits and personal wardrobes. If this data is collected, extracted and combined then connected with recommender systems the outcome would have an effect on the way a consumer shops. By extracting existing data from clothing already in a person's closet, combining it with personal preferences such as cost, quality and style and connecting it to a person's social calendar- the shopping experience could be forever changed. By using Artificial Intelligence and recommender systems, accurate suggestions could be made to users before they even knew they needed a new article of clothing. Using data to predict when a person would be likely to purchase something and or recommending purchases based on a set of like parameters would enhance the users shopping experience.



### Acknowledgments

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### Overview

Our society has entered an age in which data-driven decisions are more important than ever before. Businesses succeed or fail in today's modern world based on their ability to collect, analyze, and make decisions with their data. Using different predictive analysis tools, artificial intelligence (AI), and machine learning, businesses can also make predictions using their data. This same concept applies to a consumer shopping experience, allowing end users to provide real and accurate data regarding shopping habits, their personal style and size, and their personal calendars with events or activities. Bridging the gap between end-user data and its connection to the retailers by inserting artificial intelligence is a real possibility, and it opens up a whole new shopping experience. Using the right data and artificial intelligence, technology could generate customized and realistic recommendations to users for their shopping needs.

Artificial intelligence (AI) refers to machines that respond to stimulation consistently. The AI allows the machine to have human-like judgment, decision-making, and intention. AI allows computers to make decisions that normally require a human level of expertise. Artificial-intelligence algorithms are complex mathematical equations that use multiple variables typically connected to real-time data, and use them to predict or make decisions.

Machine learning is an application of artificial intelligence that provides systems the ability to automatically learn and improve from experience, without a software developer modifying system code. Machine learning relies heavily on the concept that a computer can access data and use it to self-discover and learn for itself. The process of machine learning begins with a system observing data or inputs (Expert Systems, 2017). The machine looks for patterns between the inputs and outputs and uses this information to make better decisions in the future. The primary goal of machine learning is to allow the system to learn automatically without human intervention.

**More Data, Better Answers.** To better understand the uses of machine learning, consider some of the instances of applying machine learning. At Disney World, guests

use a MagicBand that acts as room key, tickets, and payment. It also collects information about where the guests park their car and recommends experiences based on information about the places the guests eat and shop. Progressive Insurance uses telematics to track its customers' driving habits and history. They use this data to predict the likelihood of a driver to get into an accident and to customize policies for the driver. Starbucks uses machine learning to remember a customer's favorite drink and what time of day it is usually ordered. Machine learning and the extraction of data to improve a user's life are all around us. Recommender systems can make predictions from the data they collect, giving technology the power to help make decisions for its users (Kumar, 2016).

**Uses of Machine Learning.** Recommender systems share some clear advantages over human recommenders. Recommender systems use complex mathematical algorithms to perform consistently and quickly. Machine-learning algorithms find natural patterns in human-computer interaction and the data with which they interact (Walsh and Golbeck, 2010). The machine generates insight and helps the user to make better decisions and predictions, and navigate daily life. Machine learning is now seen in almost every consumer's day. From music applications, to medical diagnoses, to stock trading and online dating, machine learning and recommender systems are everywhere (Francis, 2009). Facebook recommends people you may know, Pinterest recommends other recipes you might like to try, and Netflix recommends your weekend binge—all uses of machine learning. When Netflix recommends a movie and you watch it, Netflix's algorithm is reinforced, confirming that it calculated its prediction correctly. If you do not watch a movie or rate it poorly, Netflix's algorithm is fed additional information to help strengthen or redirect its predictive power in the future.

**Popular Machine-Learning Methods.** Machine-learning methods vary; however, there are two main methods: Supervised Learning and Unsupervised Learning. Supervised machine learning can apply what has been learned in the past to a new data set, using predetermined examples to predict future events related to that new data. Unsupervised learning finds hidden patterns or intrinsic structures in data when the

information used to train is neither trained nor labeled. It is used to draw inferences from data sets consisting of input data without labeled responses.

**Intuitive Intelligence.** Intuitive intelligence lives past the boundaries of science and analytics. It begins to bridge the gap between reality and a human imagination (Francis, 2009). Intuitive intelligence is the idea that through machine learning, a computer could know what you wanted, needed, or desired even before you do. By using the machine-learning techniques discussed previously and combining machine learning with the proper data, a computer can address a user's needs before the user is even aware of them. Machine learning's goal is to continue to define and develop the concept of intuitive intelligence. The meaning of intuition is everything a human does without thinking about it, such as breathing, controlling muscle movement, or generating speech. With machine learning, technology can be trained to read our needs. Think about how much less work humans could do and how much more they could rely on technology. (Anderson, 2007)

### **Tech in the Works**

The Fashion Industry has taken the first step and has transitioned to being digital-centric. Most retailers have put the Web first and set up an appealing and easy-to-use online presence. (Kumar, 2016)

Technology plays a large role in the consumer fashion industry. In the past several years, it has changed the way the consumer interacts with fashion, shopping, and retail purchases. Inspiration sites, such as Instagram and Pinterest, allow the users to go seamlessly from idea to purchase.

Currently, multiple companies focus on the same goal—an augmented shopping experience. The range of tech varies, and the functionality of each application is different. However, each is playing a major role in the development of our shopping data and what can happen when you collect, analyze, and make decisions based on this data.

**Amazon Look.** Amazon Echo Look focuses on capturing style. Using voice commands, users can direct the Echo to take a photo of them. Echo Look is designed with a focus on personal style. It will take a full-length photo or a six-second video, so that the

user can see the outfit from every angle. These photos and videos are then categorized and saved to create the user's digital closet (Tillman, 2018). Echo Look allows the users to tag the outfits with metadata, creating different collections, seasons, and coordination. This allows the users to categorize their closet by color, season, style, or occasion.

**Applications.** Applications like ClosetSpace, Stylebook, and GlamOutfit are also leading the market to digital closet space. Each of these applications varies in functionality, but each collects photos and metadata on wardrobe and allows the users to categorize their closets accordingly (Quihuiz, 2017). Some of these applications feature the ability to create a suitcase, allowing a user to plan digitally for a vacation. Once the closet is collected in the application, the user can start putting outfits together for a planned vacation or trip. Once the user has "filled the suitcase," the outfits can be shared with others who might be traveling together. This allows groups of friends to see what other items their friends are packing for the trip, to coordinate or plan around.

**Visual Search: Find Me Something Similar.** Computer vision as a technology is used by large retail stores such as Macy's, Nordstrom, and Target. Visual search uses key indicators of an item to search for other like items. For example, if a user searches "size small, cotton black dress" on Nordstrom's website, the visual search will suggest other items that are similar or that will match that article of clothing. Computer vision and visual search concern artificial intelligence being able to extract information from images. The easier that is for a computer, the easier it will be for retailers to suggest other options to match or go with articles of clothing.

**Visual Fitting Rooms.** Items being returned after a consumer orders them online is an issue with which online retailers battle. Tools that allow users to try on items digitally will be a big trend in the future of online shopping. Using virtual reality and 3D body scanners, tools will be able to compare a consumer's body size to the item being considered for purchase. Creating an avatar of oneself to then virtually try on outfits before purchasing will be a common tool (Kumar, 2016).

**Wearable Technology.** Wearable technology is becoming more common, with the Apple watch leading the way. We can expect the fashion industry to continue to look at how tech can intertwine with fashion. Wearable technology helps track information based on location, temperature, and motion, truly becoming an extension of oneself.

### **Visualizing Data**

Data can be visualized using many tools and services. For this research, the tool Qlik was chosen to visualize the data. Qlik is a data-visualization tool designed to help find patterns and connections within data sets. By having these connections and building a data model, the data can be quickly “sliced and diced” to show different perspectives on the data. When data sets are large, it is hard for the human brain to sort through all the data and find the connections and patterns. By using a data visualization tool like Qlik the data connect and patterns are created quickly and accurately in the back end, so the user can view the data in a more palatable way. Using a holistic view of the data, then filtering on their different attributes, a user can quickly analyze and find trends in the data. All the data collected for this research were combined and connected within QLIK for analysis.

Once the data were exposed to QLIK, I was able to make tables, pie charts, and key performance indicators to view the data. Below is an example of one of the dashboards I created with the data collected (Figure 1).

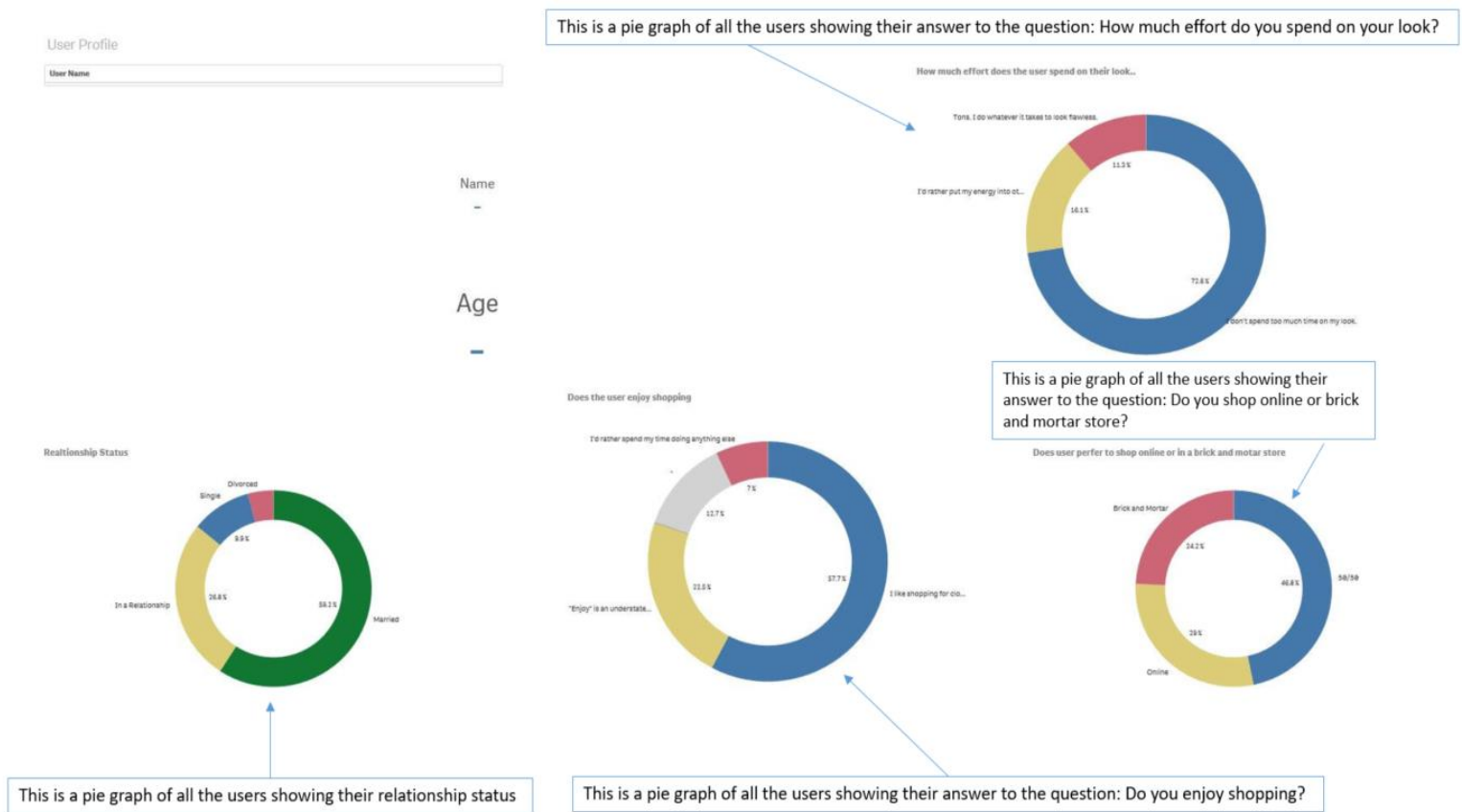


Figure 1. User Dashboard made with Qlik.

After looking at the data collected, I was able to develop three use cases through which to take each of the user's data. These dashboards allowed seeing the data from different perspectives.

- Use Case 1 Dashboard—The User has an upcoming vacation planned.
- Use Case 2 Dashboard—The User needs a new pair of jeans.
- Use Case 3 Dashboard—The User has a formal event in the upcoming month.

“Use Case 1—The User has an upcoming vacation planned” dashboard is explained (Figure 2).

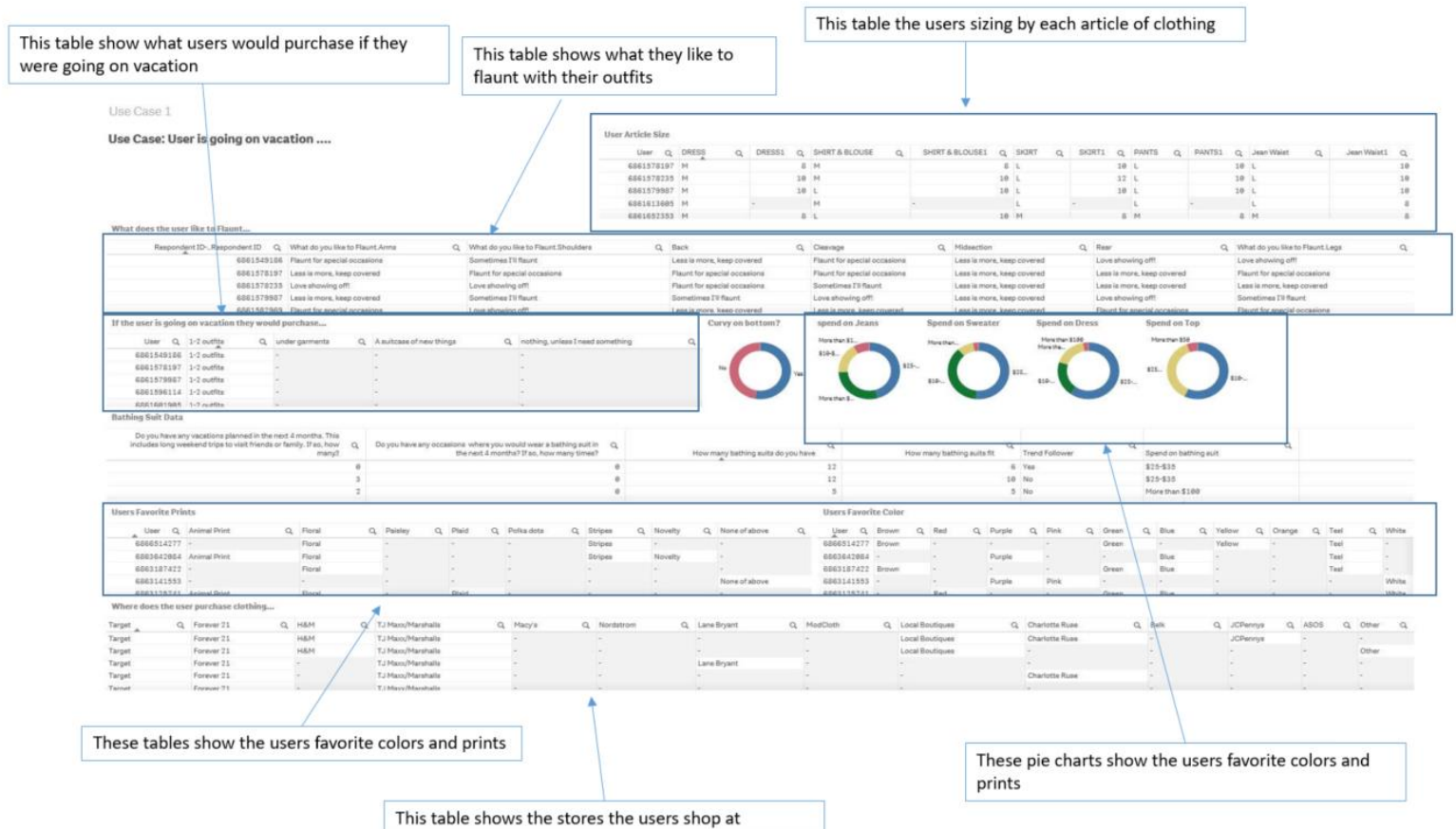


Figure 2. Explanation of Use Case 1 Dashboard.



Below, “Use Case 2—The User needs a new pair of jeans” is explained (Figure 3).

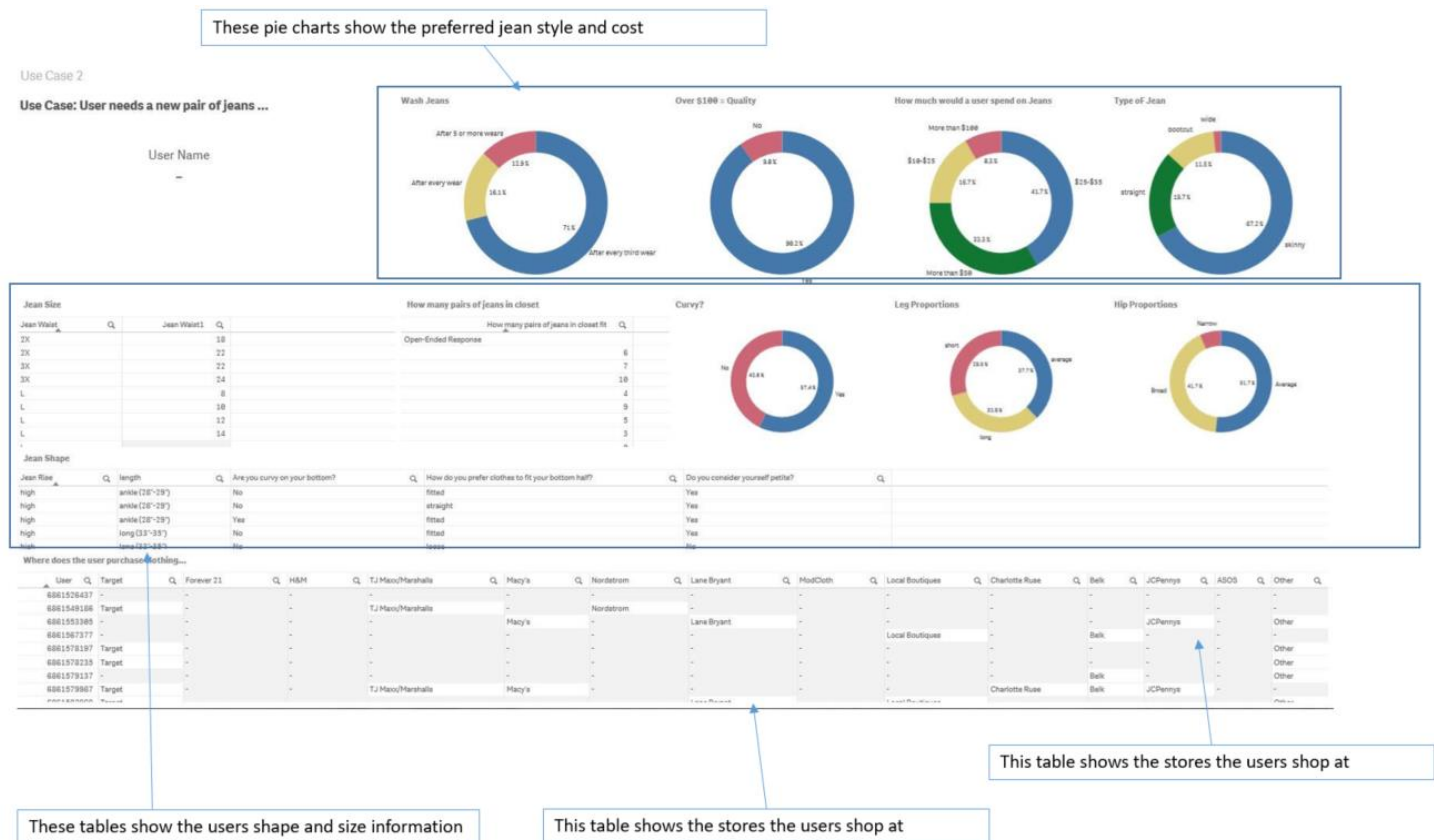
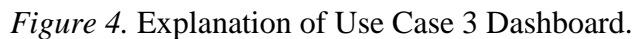


Figure 3. Explanation of Use Case 2 Dashboard.



The goal for the end users is that they enjoy the solutions experience from beginning to end and feel that they would include this in their daily lives. Ease of use will be paramount for the user's adoption of this process and new way of shopping. Data

capture will be a difficult piece of the experience, as this is where users must self-report information they might not want to; yet, it is critical, in order for the rest of the experience to be successful. The end goal for the users is for the shopping experience to be more enjoyable, customized, and time saving. The end goal for the machine learning solution is for the data collection to be detailed enough to predict favorable selections to the end users.

### **Background**

With consumers shopping across so many different platforms and devices, retailers must be committed to connecting with their consumers online and offline. Offering personalized offers and messages will be key to purchasing power (Wallace, 2019). The average household spends \$1,803 annually, according to the Bureau of Labor Statistics 2017 Consumer Expenditure Survey. That amounts to about \$150 per month.

A recent study surveyed over 1,000 U.S. consumers to assess their online shopping and buying habits. The company said the “results show that 96 percent of Americans are shopping online, spending an average of five hours per week making online purchases and allocating an average of 36 percent of their shopping budgets to e-commerce”(Wallace, 2019). Below are some impactful statistics on today’s shopping experience, captured from this survey.

- 51% of Americans prefer to shop online;
- 96% of Americans have made an online purchase in their life, 80% in the past month alone;
- 67% of Millennials and 56% of Gen Xers prefer to shop on online rather than in-store;
- Millennials and Gen Xers spend six hours per week shopping online;

- 49% cite not being able to touch, feel or try a product as one of their least favorite aspects of online shopping.

The retail industry and the way consumers shop is continually evolving. For storefronts, traffic and sales are declining. The market continues to see new applications, more mobile usage, and savvier uses of data to create personalized shopping experiences. Retailers must continually rethink ways to create customizable experiences for the user, especially when there is no in-store interaction.

## Methods Section

### User Analysis and Demographics

The solution's targeted user population is vast. It targets anyone who is interested in shopping but has a busy lifestyle. The solution is built to expand to different price points, styles, shopping habits, and retailers. It is not gender specific; however, for testing purposes, I did choose to narrow the demographic to just women. The solution's concept is to help users fill their fashion needs quickly and easily. Whether a user wants to use the solution only for a planned vacation or for all shopping needs, it is expandable.

### Personas

#### Rachel Jones



*“Work hard, play hard and looking my best at both. I feel that what I wear represents how I feel inside and I need to look confident and on my game at all times. Hiring an actual personal shopper is outside my comfort zone but I feel like that’s the type of service I need. Someone to help me plan my outfits, order me replacement items, and suggest new styles that will actually work for me.”*

Rachel is a 34-year-old lawyer working in Manhattan. She works long hours but also has an active social life. Her motto is “work hard, play hard,” and she wants to look her best for both. Rachel wants to stay current with

*Figure 5. Rachel Jones Persona. (Styleoholic, 2019)*

her fashion whether it’s for the courtroom or the next girls trip to the islands. She has a hard time finding the time for online shopping and definitely does not have the time shop in a brick-and-mortar store. She has tried personal shopping but feels like she is left disappointed by the selections (Figure 5).



Figure 6. Zoey Adams Persona. (Addy, 2019)

### Zoey Adams

*“I + to rely heavily on my roommates and friends to help me with my fashion choices, but now that I live on the opposite coast that’s not a real time option. I finally made it to Hollywood, now I need to say one step ahead of the trends and keep current.”*

Zoey followed her dreams of working with the stars. She always dreamt of working in Los Angeles, brushing shoulders with celebrities. She is 26, a personal assistant to an up-and-coming star and needs to look and feel her best. Zoey has a busy schedule, including a lot of traveling. Since she is new to Los Angeles, with most of

her friends and family living on the East Coast, she wishes she could get fashion advice when it’s convenient for her. Zoey wants to stay trendy, but on a budget (Figure 6).



Figure 7. CeCe Johnson Persona. (Klein, 2010)

### CeCe Johnson

*“My husband and I attend a lot of functions where I am photographed, it is a lot of pressure! I enjoy the occasions much more when I feel I look my best. I don’t mind all eyes on me as long as I am feeling confident.”*

CeCe is a 44-year-old wife to a Fortune 500 CEO. She attends a lot of philanthropy fundraisers, events at her children’s school, and many dinner parties and galas with her husband. She needs to look and feel her best with little time to get to a store to shop. Since her husband is a high-profile figure, she is often photographed and does not like to wear the same

outfit twice. CeCe needs outfits that fit her age, the occasion, and the season. She has tried personal shoppers and enjoyed the experience (Figure 7).

### **Wizard of Oz Testing**

The Wizard of Oz testing technique allows technology that has not been developed to be tested and evaluated by using a human to generate the response. This method is used when the concept does not yet exist but is too close to the prototype state to develop. The “wizard,” who is a human, observes the user’s actions behind the scenes during the testing and simulates what the technology would do in real-time. The wizard helps to generate the system’s response to the user. Wizard of Oz testing helps to gather actual human responses about nonexistent interactions. It allows the user to test the interaction of a prototype before building a functional model. It also provides a unique insight into the user’s actions, gained from interacting with the user during the evaluation. (The Usability Body of Knowledge, 2012)

### **Research**

The research was limited to female participants to create a smaller sample size. A survey was created and participants were invited through Facebook to participate in the survey. The idea is that by collecting the right data about users’ shopping habits and historical data held within their closet, a user agent could start making intelligent shopping recommendations for the user. Users who are familiar with services such as Stitchfix or Threadbox are familiar with similar strategies. Each of these services collects information about the user and makes intelligent guesses, depending on their data. However, what these user agents are not doing is considering the users’ entire ecosystem (Figure 8).

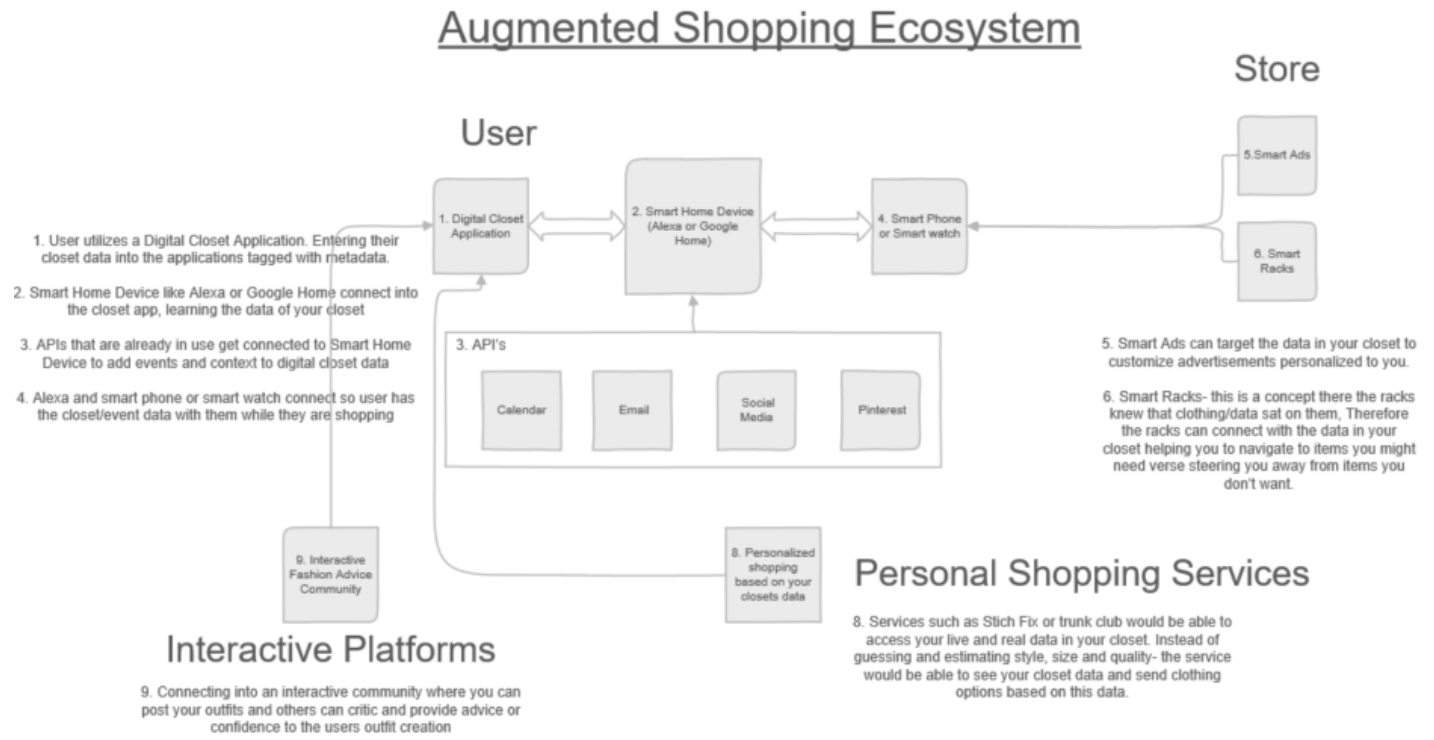


Figure 8. Information architecture of the augmented shopping ecosystem.

A user has a plethora of data that is relevant to her shopping habits. Event calendars, online social presence, and her financial data are all relevant to a person's shopping habits. Furthermore, the data that a user holds within her already-established clothing closet might be more beneficial for determining shopping habits than the data a survey could collect. For instance, a woman might self-report an inaccurate pant size on a survey, but if the technology had the actual and real data within this woman's closet, a user agent could more easily shop for her. The reality is that a person's closets are filled with a tremendous amount of data that not one store or brand owns. How this data is captured and interconnected with other data to make shopping easier and choices more intuitive for the user is part of this solution. If an AI had a person's social calendar, self-



reported purchase data, financial data, and raw data from her own closets, could an AI predict and suggest her next purchase?

### **Participants**

The first step in testing the solution was to reach out to potential participants for the testing. I first worked with a group of 150 women from all different social, cultural, and financial backgrounds and explained what this concept and testing was trying to accomplish. I created a Facebook page explaining my goal and concept for research then invited friends and asked friends to repost and repost until it went “viral”. Once I had a large population of women to survey, I randomly selected 150 of them. I asked all 150 women to take the initial survey. Sixty-eight women, ranging from 24 to 68 years old, completed the survey, and the mean age of these women was 34 years old. After these 68 women completed a survey, I asked them to complete an additional survey with true data from their closet. This survey was conducted by dividing the women into three categories, depending on their desire to shop. Forty-five women, ranging in age from 24 to 68, completed this survey. I asked these women to complete one last survey about their calendar. Listing social, business, family, travel, and work functions they would be attending over the next six months, 23 of these women completed this survey. I randomly selected 8 users for the Wizard of Oz testing, ranging in age from 26 to 59, with a mean age of 37 years.

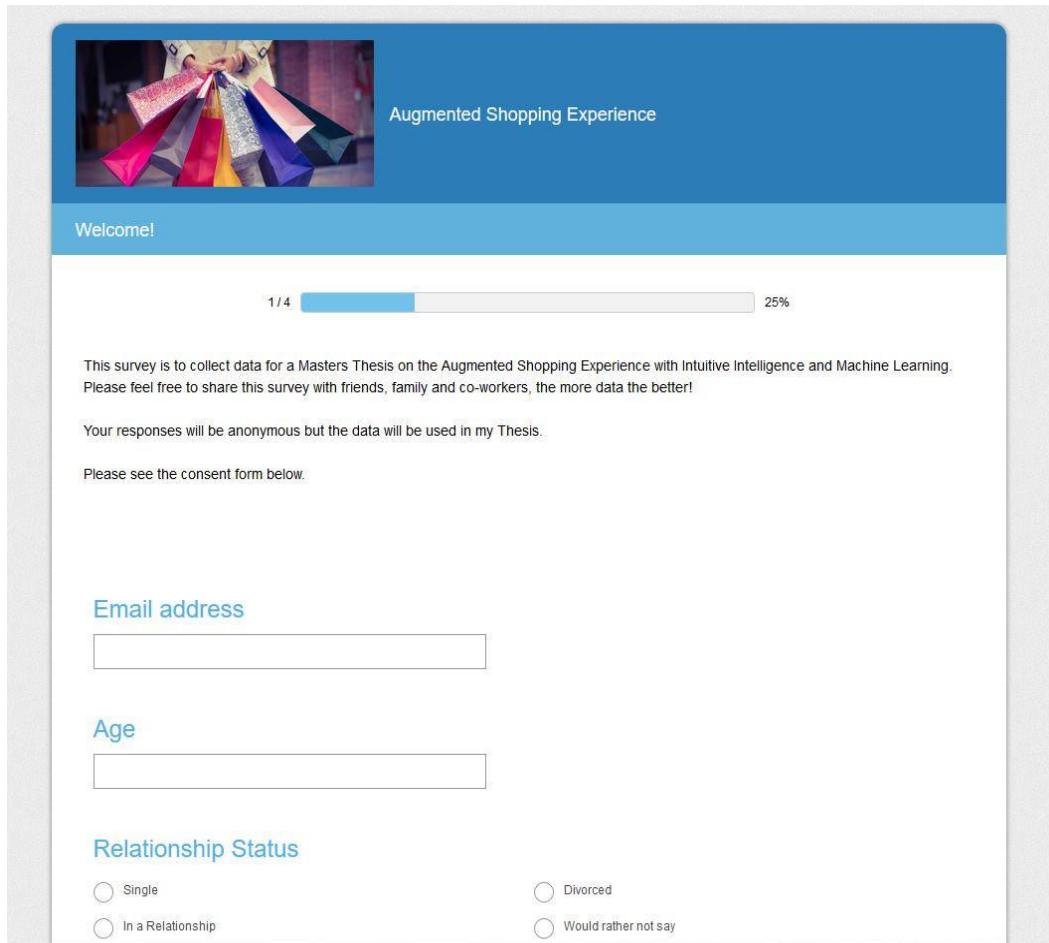
### **Data Collection**

The survey was done using Survey Monkey, Web-based application for survey-design, data collection and reporting. The survey sought to collect information that would be useful for making future predictions. Asking the right questions and collecting the right type of data are critical to the ability to make informed decisions and create outputs for users. Something I considered often when creating the survey was how likely a user would be to answer the question honestly. Trying to make the surveys fun for the user was also a challenge; if the user is enjoying filling out the survey, the likelihood of truthful responses is higher. I did group the questions in what I thought was the easiest to

understand and most logical way to ask the questions. I tried to make as many of the answers as possible “drop-downs,” essentially multiple-choice options. If choices are structured as a drop-down, the user must think less and is more likely to complete the question. The surveys were also mobile friendly, in that they could be completed on a phone or a tablet.

Once the data was collected, I compiled it into a data-visualization tool. I used the Qlik visualization tool, with which I was most familiar. This tool helps to quickly filter large data sets and represents my Artificial Intelligence platform. I walked eight selected users through a customized test, using their data. Each test was to see if the output generated strictly off the data input would be successful, where “success” was measured by the user liking or indicating she would purchase the output received.

**Augmented Shopping Experience Survey.** The survey below demonstrates the look and feel of the survey sent to the users. The idea was to create a clean and easy-to-follow survey that took the users less the 10 minutes to complete (Figure 9).



The image shows a screenshot of a web-based survey titled "Augmented Shopping Experience". At the top left, there is a small image of several colorful shopping bags. The title "Augmented Shopping Experience" is displayed in white text on a blue background. Below the title, a light blue banner says "Welcome!". A progress bar indicates "1 / 4" completed, with a blue segment representing 25% of the survey. The main content area is white and contains the following text: "This survey is to collect data for a Masters Thesis on the Augmented Shopping Experience with Intuitive Intelligence and Machine Learning. Please feel free to share this survey with friends, family and co-workers, the more data the better!". Below this, it states: "Your responses will be anonymous but the data will be used in my Thesis." and "Please see the consent form below.". The survey form includes three sections: "Email address" with a text input field, "Age" with a text input field, and "Relationship Status" with four radio button options: "Single", "In a Relationship", "Divorced", and "Would rather not say".

Figure 9. Augmented Shopping Experience Survey.

**Shopping Experience Survey Questions.** Below are some of the questions that resided on the initial survey sent to all participants. The rest can be found in the appendix.

- Do you enjoy shopping?
- Is your closet color coordinated?
- How many times would you be photographed in the same outfit?
- How often would you wear a pair of white pants before its time for a new pair?
- Fabrics to avoid...
- Do you consider yourself a trend follower?

- How often do you dress for the following occasions?
- Do you shop online or brick-and-mortar store more often?
- Favorite colors to wear
- Where do you typically purchase clothes from?
- Do you like to experiment with new styles?
- How much effort do you spend on your look?

**Personal Closet Data Survey Questions.** Two weeks later the users were asked to fill out the “Shopping Experience” survey. The idea was to stagger the surveys so that a user did not necessarily feel pressure to align this survey with what she had filled out in the “Shopping Experience” survey. Below are some of the questions that resided on this survey, and the rest of the questions can be found in the appendix.

- How many formal dresses do you have in your current closet?
- How many of your formal dresses fit you currently?
- How many bathing suits do you have in your closet?
- How many of your bathing suits fit you currently?

**Social Calendar Survey Questions.** At the same time as filling out the Personal Closet Data, the users filled out a survey related to their social calendars. Below are some of the questions that resided on this survey, and the rest of the questions can be found in the appendix.

- Do you have on your calendar or do you anticipate having any formal events in the next four months?
- Do you have any vacations planned in the next four months? This includes long weekend trips to visit friends or family. If so, how many?

Three surveys' worth of data were collected from over 100 users. These surveys served a key role in the research by supporting predictive analysis (Figure 10).

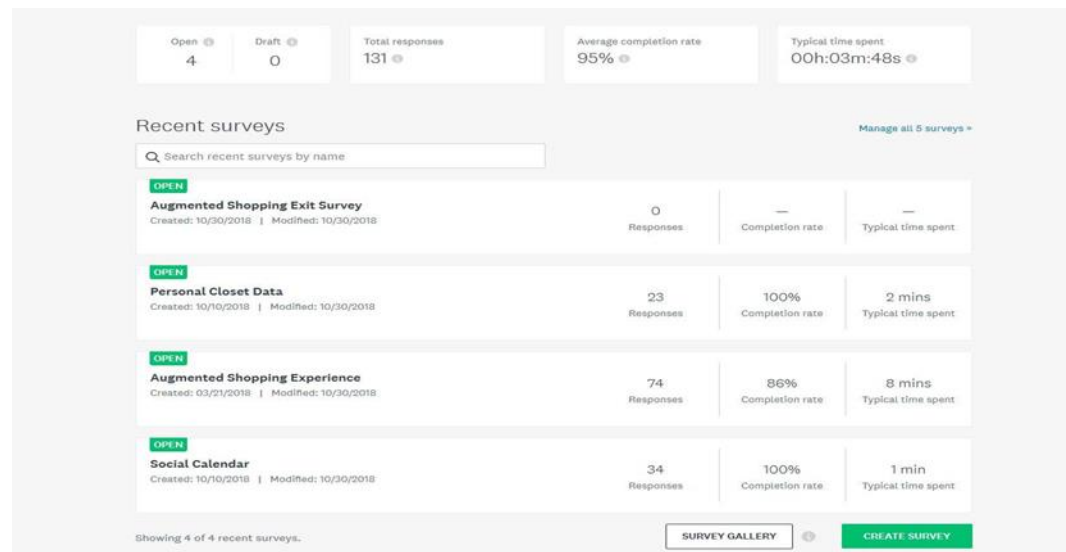
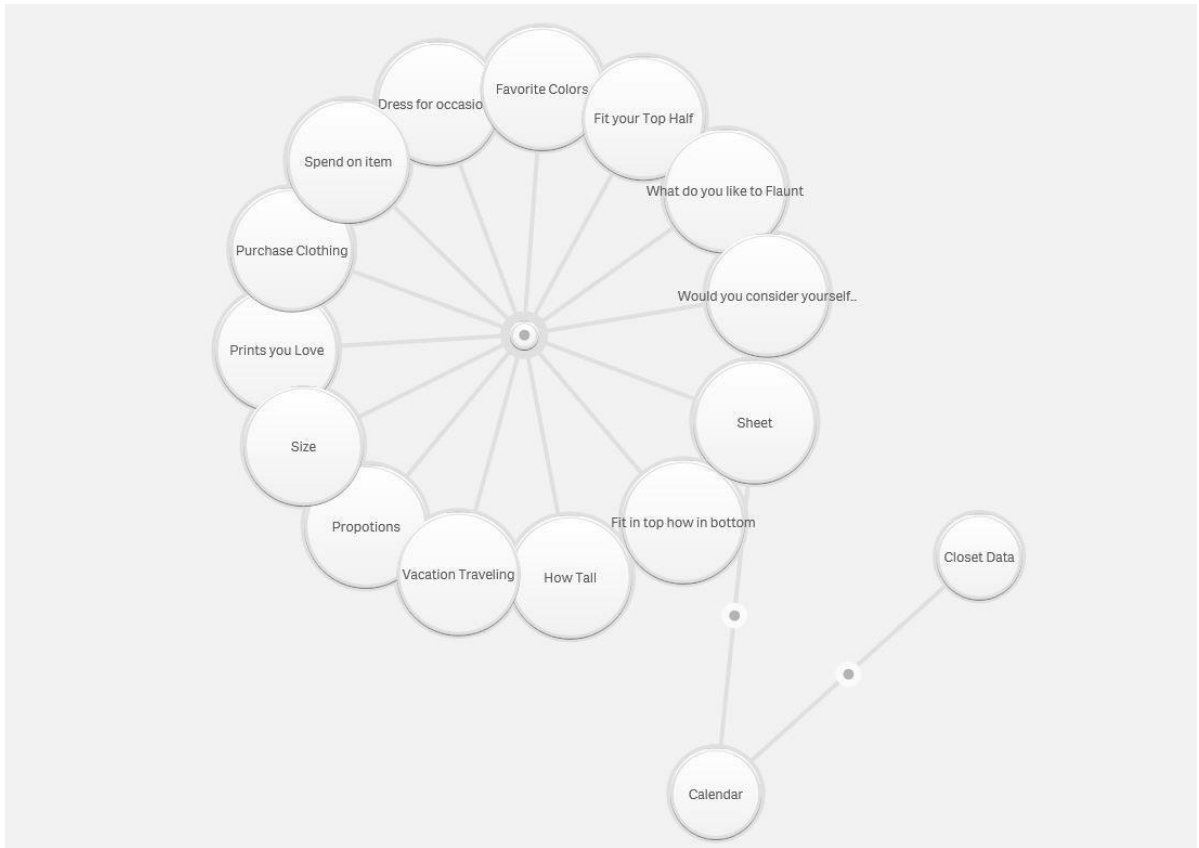


Figure 10. Augmented Shopping Experience Survey Results.

**Data Visualized.** The visualization tool, Qlik, used the users' email address as a unique identifier, connecting each user's set of three surveys together. Below is the data model the QLIK created to connect all the data (Figure 11).



*Figure 11.* Augmented Shopping Experience Data Model.

By linking together each of the data pieces in the data visualization, the computer can easily digest large amounts of data and supply the AI with the right information to make informed decisions. Once I had all the data in the tool, I began making dashboards.

**General Data Dashboards.** I created a User Profile Dashboard (Figure 12). The User Profile is a combined data set of all the users.

The data explored in this dashboard is as follows:

- How much effort does the user spend on their look?
- Relationship Status

- Does the user enjoy shopping?
- Does the user prefer to shop online or in brick-and-mortar?

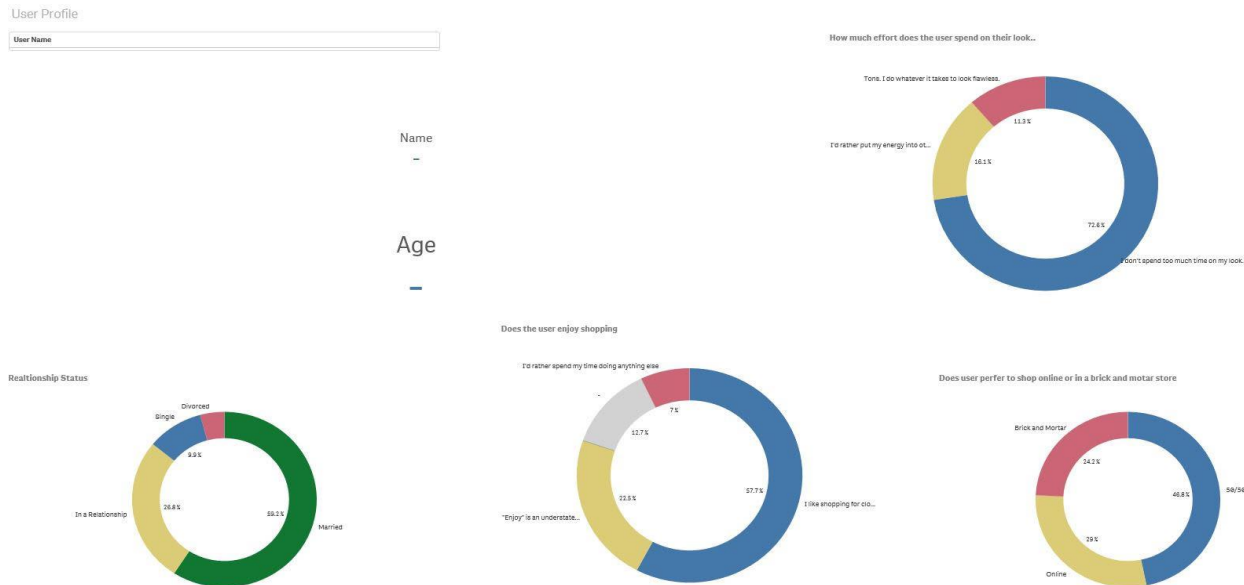


Figure 12. User Profile Dashboard.

After analyzing the data, three Use Cases were developed. I created dashboards to easily look at the data pertaining to the Use Cases.

- Use Case 1—The User has an upcoming vacation planned.
- Use Case 2—The User needs a new pair of jeans.
- Use Case 3—The User has a formal event in the upcoming month.

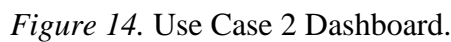
**Use Case 1 Dashboard—The User has an upcoming vacation planned.** This dashboard shows all collected data pertaining to decisions a user might need to consider when going on vacation. It shows sizing, style, stores, and price points at which a user may want to spend on clothing for an upcoming vacation. By creating this dashboard, the data can easily be “sliced and diced” to support making informed decisions or recommendations to the users (Figure 13).



- User's size by article of clothing
- What does the user like to flaunt?
- If the user were going on vacation they would purchase?
- Bathing suit size and how many owned
- User's spend data per article
- User favorite prints
- Where does the user purchase clothing?
- User's favorite colors

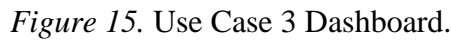
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- Wash of jeans
- Measure of user's idea of "quality"
- How much would a user spend on jeans
- Type of jeans a user wears
- Jean size
- Jean fit
- Where does the user shop?

This dashboard is tailored to show data for users who were attending a formal event in the upcoming month. The data on this dashboard is tailored to making predictions on formal wear a user might like or purchase. The formal-wear data on this dashboard helps to make decisions regarding user's style, cut, what they want to show or hide, price point, and stores at which they would shop to show off (Figure 15).



- How formal-wear fits on a user
- Arm and waist proportions
- How much for a user to spend on formal wear?
- Size of formal wear
- How many photos would someone take in the same formal wear
- Places a user shops for formal wear

## Findings Section

### Data Findings

Once the data was collected and I had created the dashboards, I started to act as the user agent and “slice and dice” the data to look at it from different perspectives. I quickly began to find trends.

### Target Use Case

I decided to look at all data pertaining to users who shop at Target. Fifty-three percent (34 out of 68 users) of the users from whom I collected data shop at Target (Figure 16).

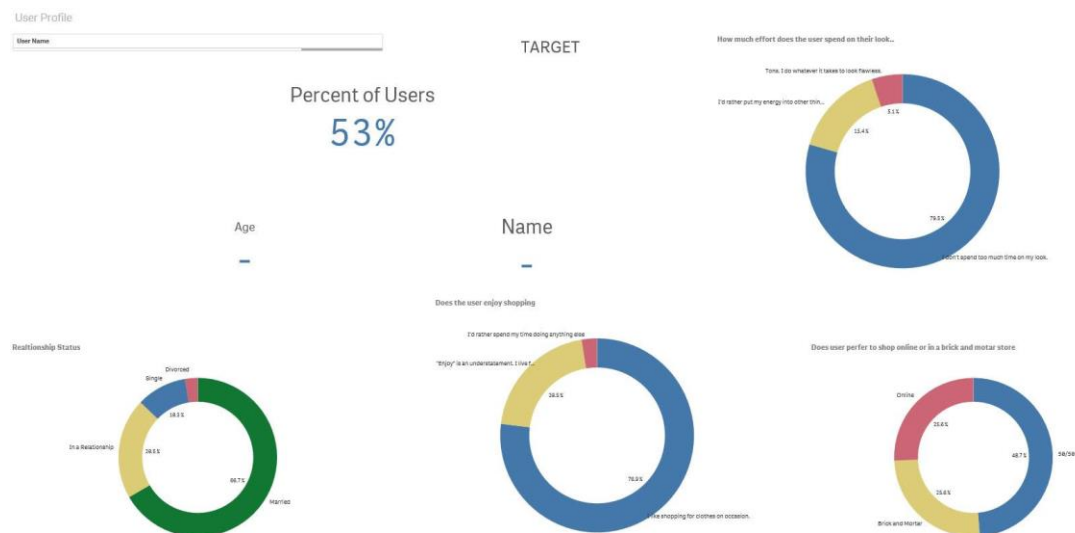


Figure 16. Target General Profile.

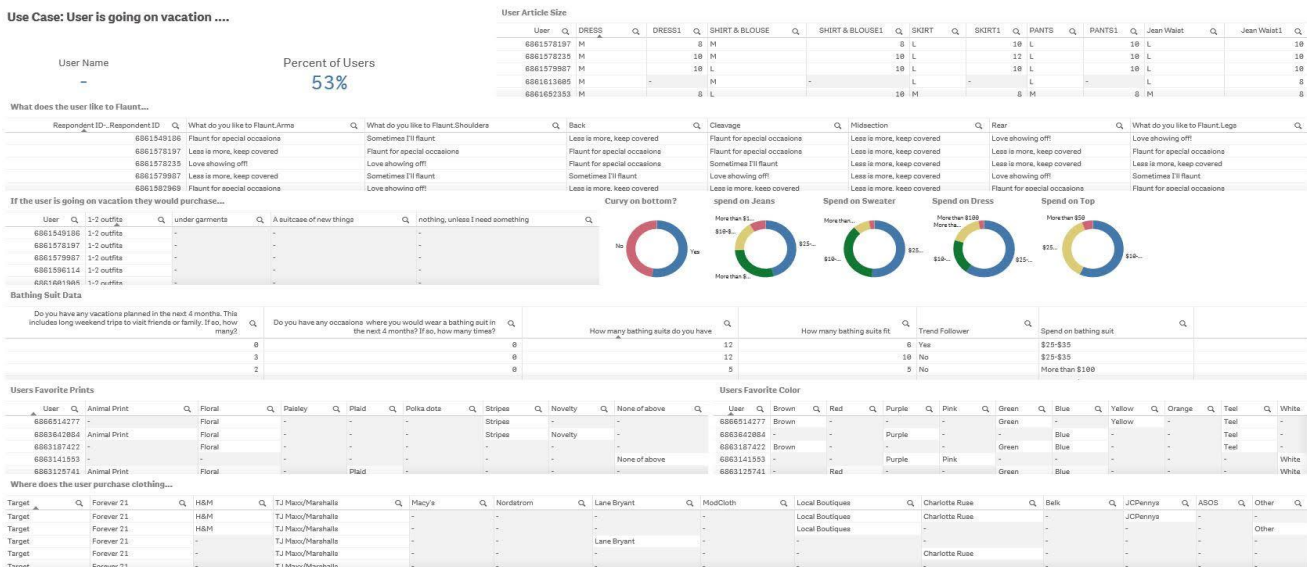
Once I began to look at the users who shop at Target, I decided to run the Target data through Use Case 2, since many of the users who shop at Target also purchase one or two outfits when they go on vacation.

**Use Case 2—User Is Going on Vacation.** Out of the 53% of users who shop at Target, 36% (12 out of 34 users) of those users said that they would purchase one or two outfits if

they were going on a vacation. This data is very critical because it shows that Target could start to market purchasing new outfits to their customers who are going on vacation. Once we understand that the majority of Target shoppers are willing to purchase one or two outfits before going on vacation, Target could use the rest of the

Use Case 1

Use Case: User is going on vacation ....



shopper's data to make informed recommendations regarding price point, style, and colors (Figure 17).

Figure 17. Target Use Case 2 Profile.

By only using the data provided in the surveys, I acted as the AI and was able to quickly filter through the data and see that 36% of the users who shop at Target would purchase one or two outfits if they were going on vacation. This could be an incredible gain for Target, not only as a convenience to the shoppers but also a potentially huge increase in sales for Target (Figure 18).



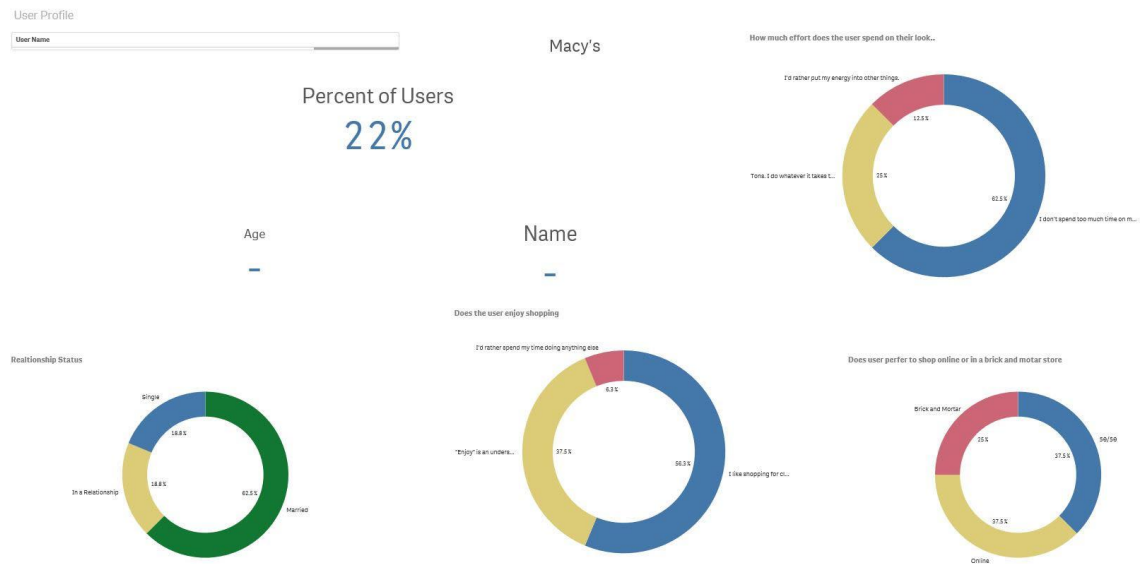


Figure 19. Macy's General Profile.

Twenty-two percent is not a particularly interesting number. However, acting as the AI and looking at the data collected on the users who shop at Macy's, I could see a direct connection between users who shopped at Macy's and users who would be wearing formal wear in the upcoming months. Out of the 22% of users who shopped at Macy's, 30% (4 out of 12 users) had formal events in the upcoming month (Figure 20).

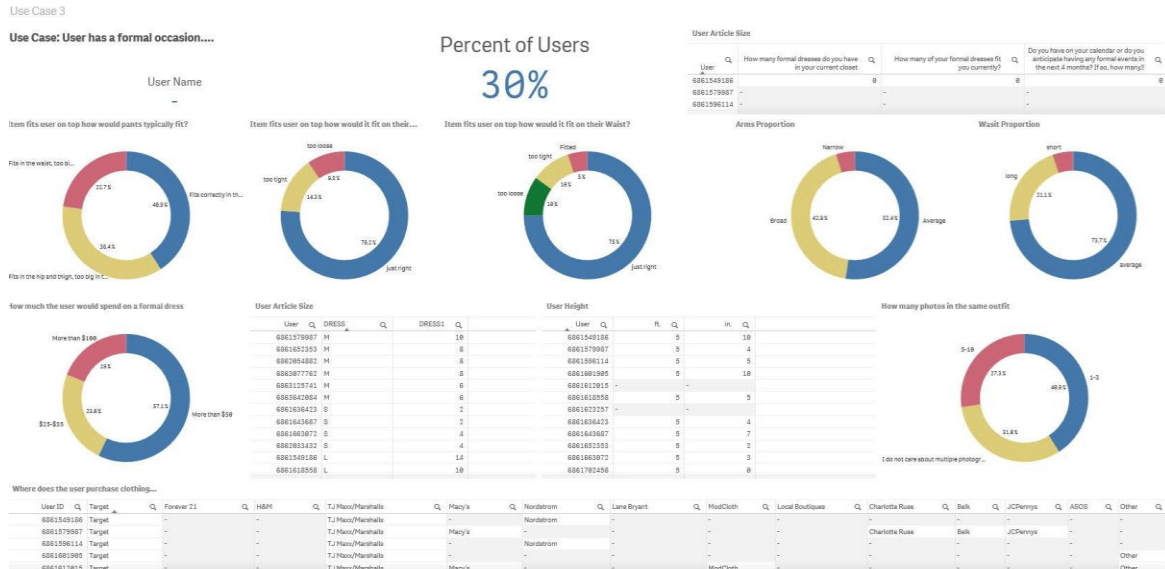


Figure 20. Macys Profile with Use Case 3.

By looking at this data, Macy's could quickly market to the 30% of Macy's shoppers who have a potential formal-dress need in the upcoming month. By using the rest of the data, Macy's could easily market to users considering their preferred size, style, cut, and price point of formal wear. Forty-six percent (5 out of 12 users) of users who are shopping for a formal dress at Macy's would pay more than \$50.00 for their dress, while 31% of users shopping for a formal dress at Macy's would pay more than \$100.00 for a dress. This is critical information for an AI system to consider when making recommendations to the user for a formal dress from Macy's (Figure 21).

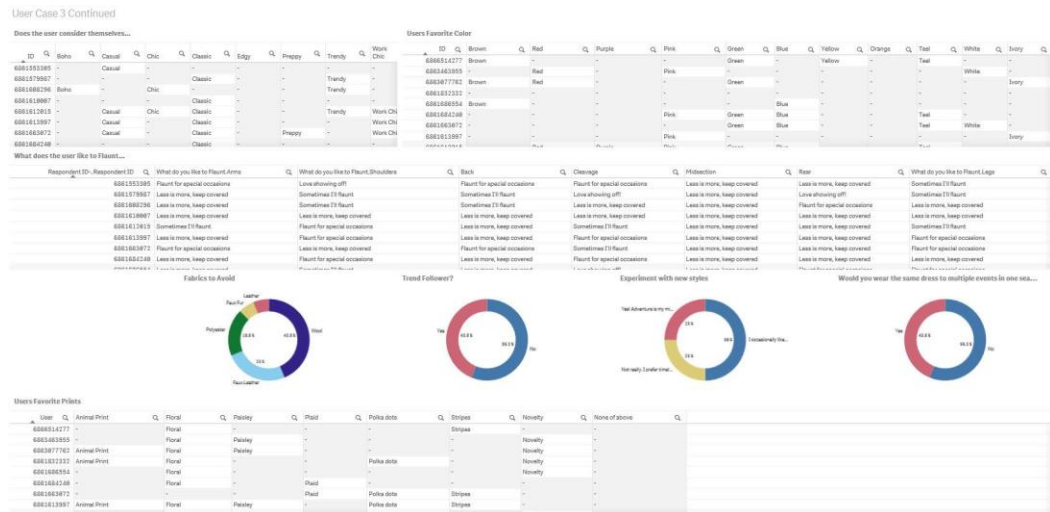


Figure 21. Macys Profile with Use Case 3, continued.

## Implementing the Testing

Once the data was captured to show how a machine could combine the data to make informed decisions and recommendations, I used the data and acted as the AI to make predictions for a select group of the users. Below are the eight users with whom I tested, using Wizard of Oz techniques to conduct the testing. Once the data was combined, I acted as the Artificial Intelligence to make recommendations to the user. All names were changed for the research.

Below I will outline the testing material structure and explain the dashboards, prior to viewing the test results.

Data dashboards used for testing:

- User Profile
  - This would be a tool used by the “wizard” or AI to help inform recommendations.
  - The user’s information is displayed:
    - Age



- Relationship status
- How much does the user spend on their look?
- Does the user enjoy shopping?
- Does the user shop online or at brick-and-mortar stores?

Below is an example of the User Profile (Figure 22).

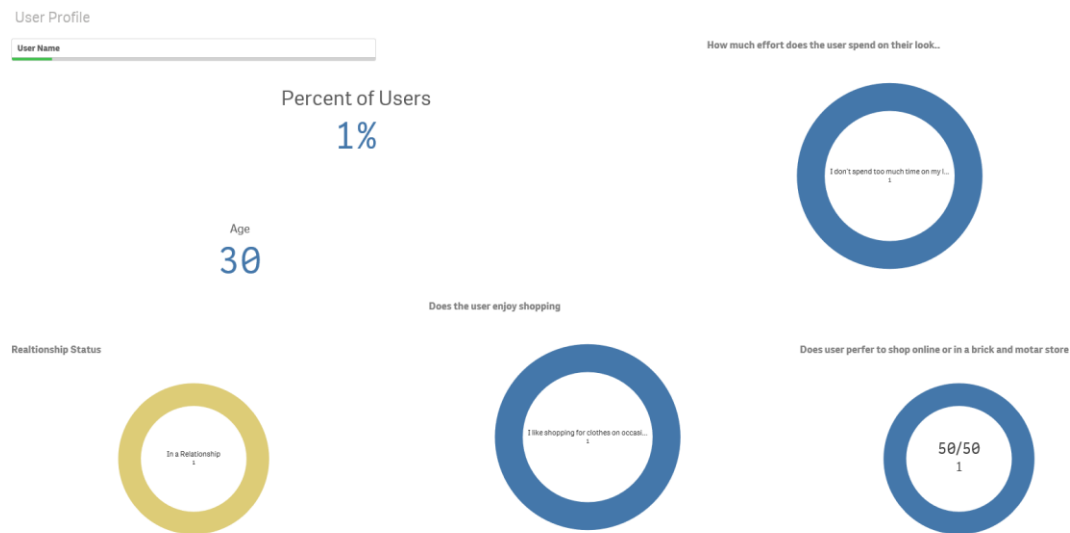


Figure 22. Example of a User Profile.

- Use Case Dashboard
  - The “wizard” or AI would use this dashboard to help inform recommendations.
  - These dashboards will vary depending on the Use Case; however, most of the data is similar:
    - Size and style of the clothing
    - How much a user is willing to spend on an article of clothing
    - Where the user shops for the clothing
    - Color and pattern of the clothing
    - Fit of the clothing

Below is an example of the Use Case Dashboard (Figure 23).

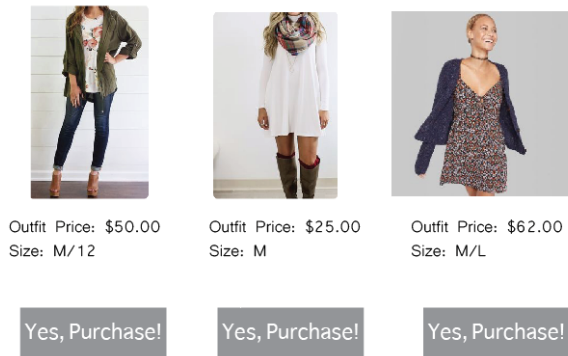


Figure 23. Example of a Use Case Dashboard.

- Output
  - This is the output the “wizard” or AI generated for the user based on the input received, sent in the form of an email or text message to phone.

Below is an example of the output (Figure 24).

*User*, I see you are going on a birthday trip to Charlotte this weekend. Need a fall inspired new outfit?



*Stores on your shopping list:*

- Nordstrom
- Target
- Forever 21

\*\* outfits do not include shoes

Figure 24. Example of an Output.

- Exit Survey Dashboard
  - The exit survey dashboard is a view of the user's exit survey. The "wizard" or AI would use this dashboard to determine success and understand the user's feelings after experiencing the entire solution.
    - Would the user use this service?
    - Would you pay for a service like this?
    - How would the user rate the overall experience?
    - Did the user find entering the data to be easy?
    - How much would the user pay for this type of service?
    - Does the user have any overall improvement comments?
    - Does the user have any overall positive comments?

Below is an example of an Exit Survey Dashboard (Figure 25).

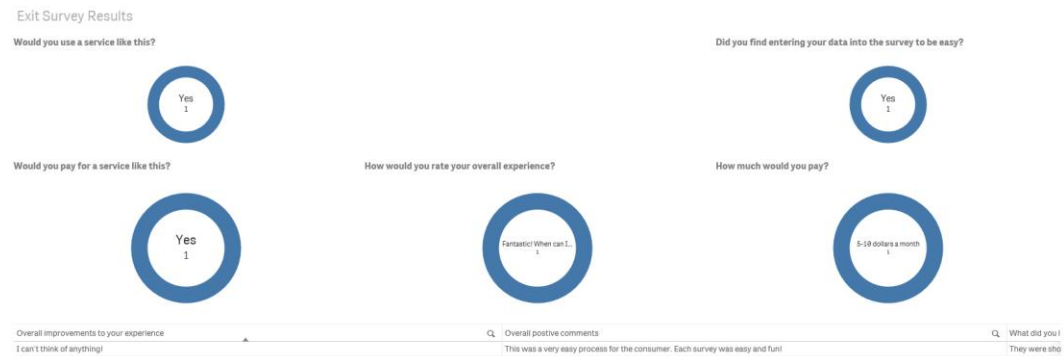


Figure 25. Example of Exit Survey Dashboard.

### **Intuitive Shopping Findings Summary**

**Completion of Survey.** Users filled out three surveys to fulfill the data requirements for this solution. The users did not mind filling out the surveys, commenting that the surveys were “painless” and “easy and quick.” Users typically do not enjoy filling out surveys with information. However, the surveys for our solution were tailored with drop-down selections, common language, and a flow that made sense to the users. The success rate was high and users commented that the experience was great.

**Loved the Recommendations.** Users really like the recommendations the AI suggested to them. Users were even surprised at times, saying “I actually looked at this dress” and “These suggestions are spot on!” The outputs were well received by each of the users. At no time did the users not like the output or say something to the effect of “I don’t like nor do I need this.”

**Where Do I Buy?** Many of the users stated that they would purchase at least one of the output’s recommended outfits. Four out of eight users stated that it would be hard to pick just one and asked if they could purchase more than one. All users selected the “Yes, Purchase” button during testing. Users also stated the pricing was accurate; not only did they like the recommendations; they thought the price points were agreeable.

**Pay for This Service.** Three out of eight users stated they would pay for this type of service. If an application existed, these users said they would pay a subscription fee to use it.

## Intuitive Shopping Findings Details

**Lauren Lewis, age 30.** Below is the User Profile for Lauren (Figure 26).

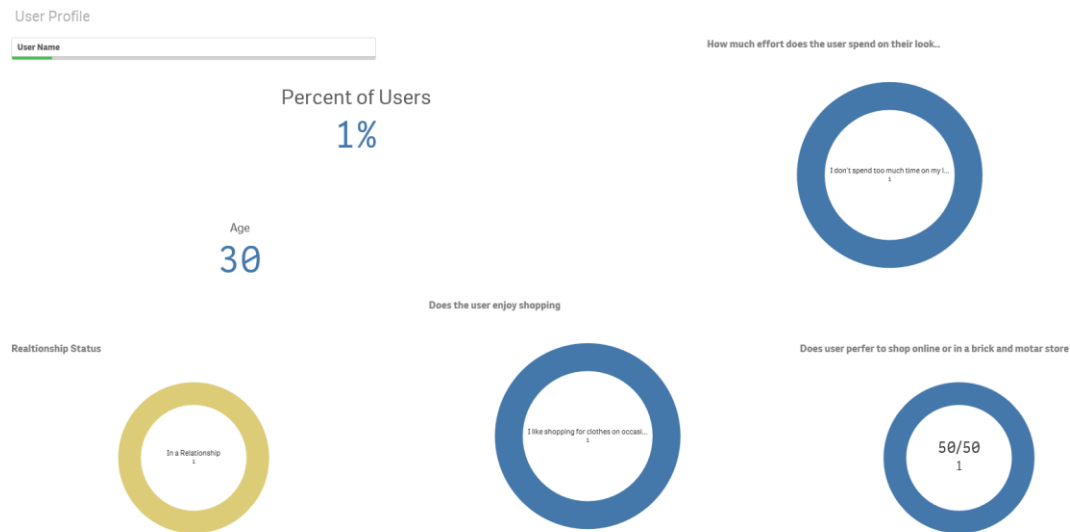


Figure 26. Lauren's User Profile.

When the closet data, personal-shopping-habits data, and financial shopping data are combined, the “wizard” can quickly give output. Based on the user's profile and data, she best fits Use Case 1—User is going on vacation (Figure 27).

# The Augmented Shopping Experience with Intuitive Intelligence and Machine Learning

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## Use Case 1

Use Case: User is going on vacation ....



Figure 27. Lauren's Use Case Dashboard.

The user scenario is that she is going on vacation this weekend, derived from her calendar data, collected on the survey, and displayed in the Use Case Dashboard. The wizard can generate output using this user data. The user receives an email five days prior to vacation that looks like the graphic below (Figure 28).

*User*, I see you are going on a birthday trip to Charlotte this weekend. Need a fall inspired new outfit?



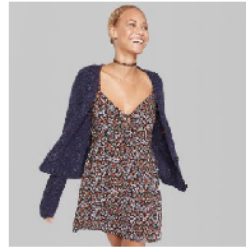
Outfit Price: \$50.00  
Size: M/12

Yes, Purchase!



Outfit Price: \$25.00  
Size: M

Yes, Purchase!



Outfit Price: \$62.00  
Size: M/L

Yes, Purchase!

*Stores on your shopping list:*

- Nordstom
- Target
- Forever 21

\*\* outfits do not include shoes

Figure 28. Email sent to Lauren.

Lauren really liked the output and said she would be very interested in these outfits for her trip. She found the experience overall positive and easy to use. Since the user is going to vacation, she thought the recommendations given to her were very spot on. The user would not pay but stated she would use the service for free. Data entry was also found to be easy and not an issue for the user, who stated that it was “Very easy to understand,” as seen in the exit survey below (Figure 29).





Figure 29. Lauren's Exit Survey.

**Sarah Brown, age 31.** Below is the User Profile for Sarah (Figure 30).

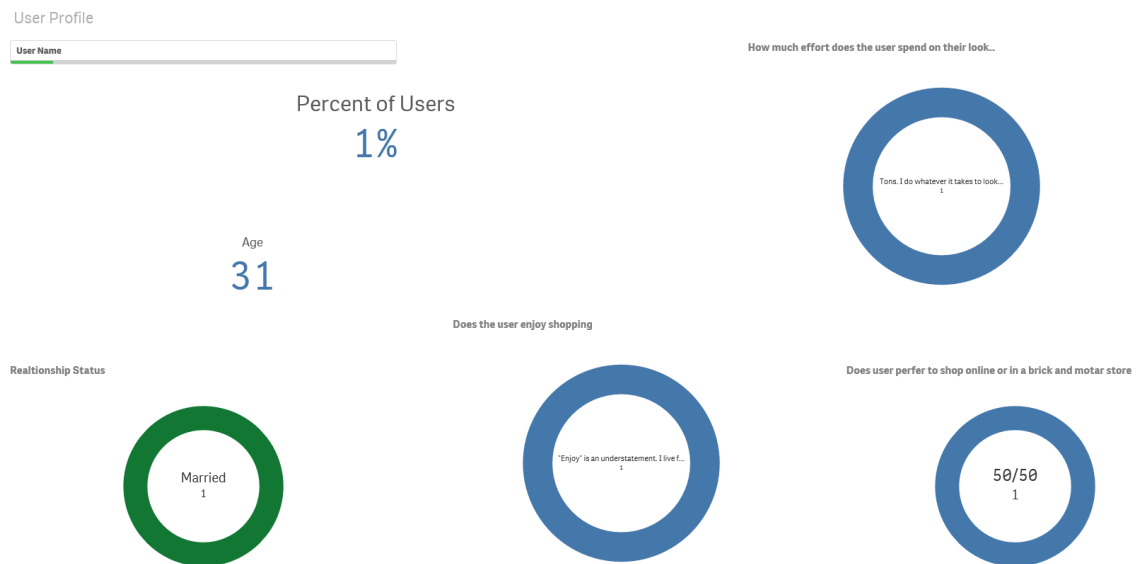


Figure 30. Sarah's User Profile.

When the closet data, personal-shopping-habits data, and financial shopping data is combined, the “wizard” can quickly give output. Based on the user’s profile and data, she best fits Use Case 3—User is going to a formal event (Figures 31 and 32).

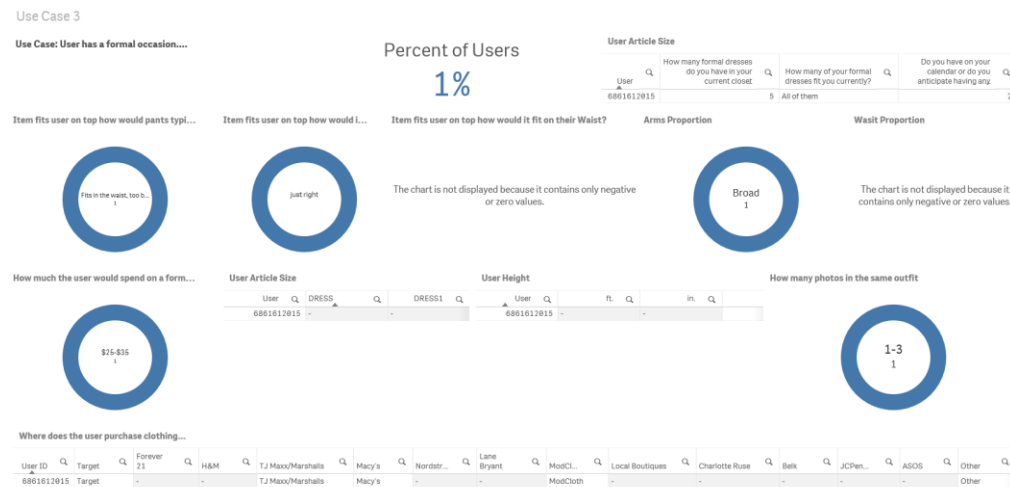


Figure 31. Sarah’s Use Case Dashboard 1.

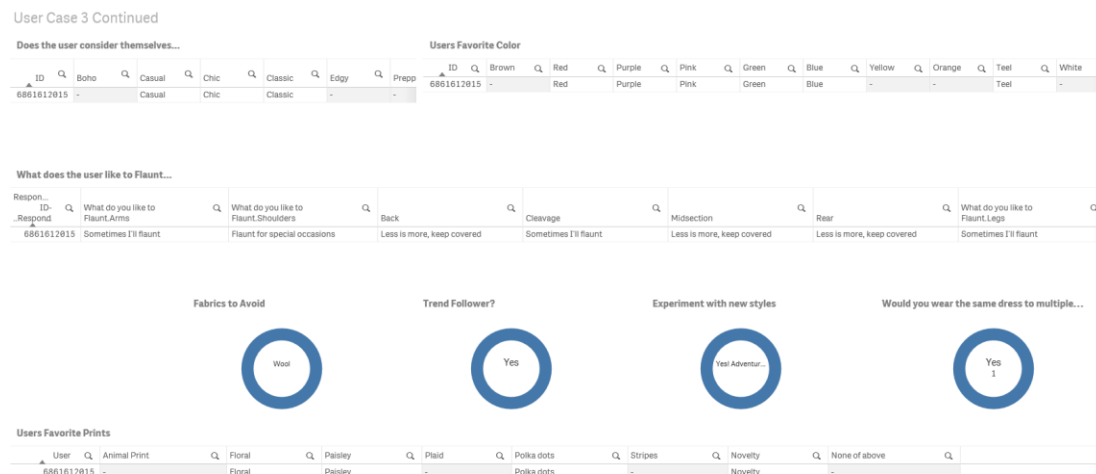


Figure 32. Sarah’s Use Case Dashboard 2.

The user scenario is a formal event coming up, which we learned from her calendar data, collected on the survey and displayed in the Use Case Dashboard. The wizard can

generate output using this data for the user. The User walks into Macy's and receives the message below on her phone (Figure 33).

**Welcome to Macy's!**

**I see you have 2 formal  
events coming up...**

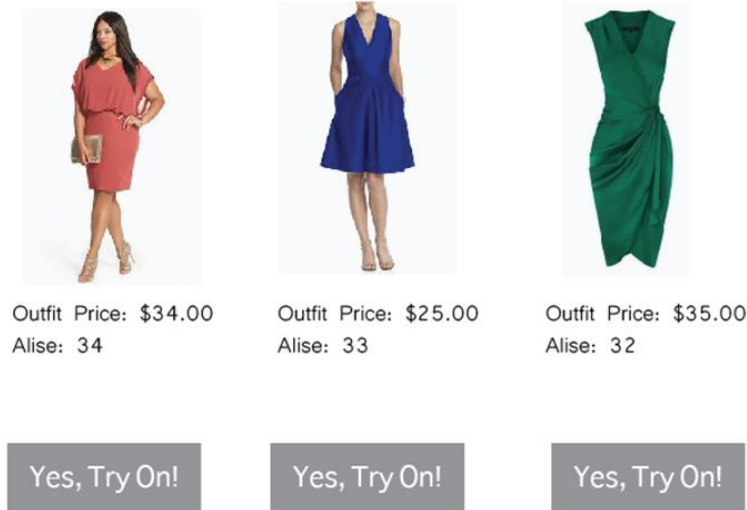
**Click here to see some  
suggestions**

**Start Shopping**

*Figure 33.* Sarah's text message received upon walking into Macy's.

User presses the "Start Shopping" button and the screen below opens up (Figure 34).

*User*, welcome to Macy's!  
I see you have 2 formal events coming up! Need  
some formal inspiration?!



*Figure 34.* Sarah's second message received about shopping in Macy's.

Sarah states that she is not particularly fond of the first dress but loves the second and third. User clicks on the "Yes, Try On!" for the second dress and receives a message asking if she needs help finding aisle 33. Sarah stated, "I love this! How can I get this?"

Sarah really liked the output, and she found the experience to be overall positive and easy to use. Sarah said she would pay for the service and also that she found the data entry was easy and not an issue for her (Figure 35).



Figure 35. Sarah's Exit Survey Dashboard.

**Charlotte Benjamin, age 26.** Below is the User Profile for Charlotte (Figure 32).

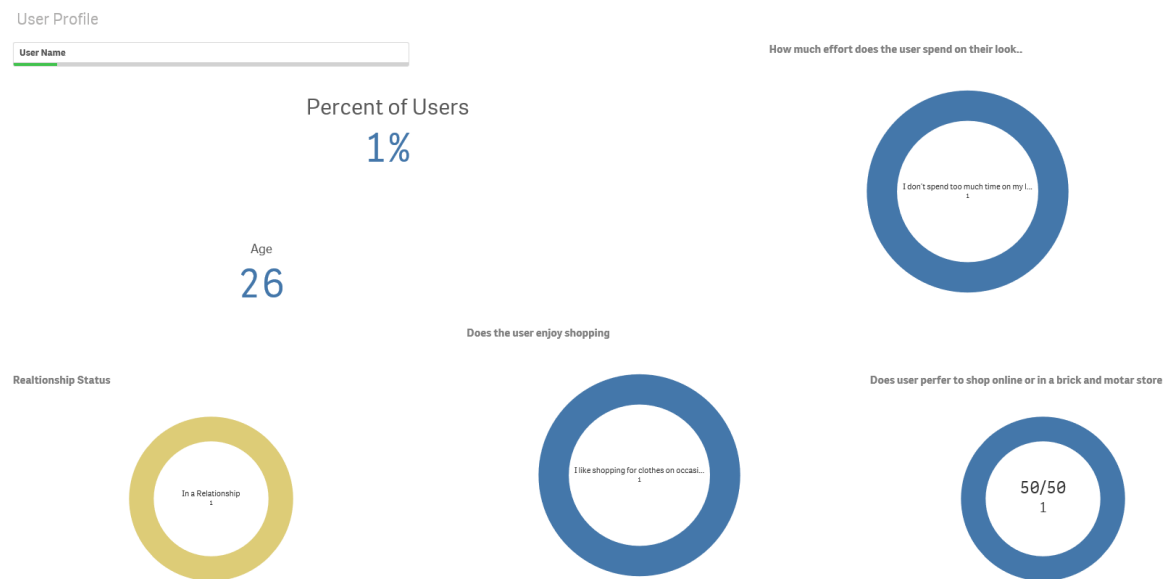


Figure 36. Charlotte's User Profile.

When the closet data, personal-shopping-habits data and financial shopping data is combined, the “wizard” can quickly give output. Based on the user's profile and data, she best fits Use Case 3—User is going to a formal event (Figures 37 and 38).

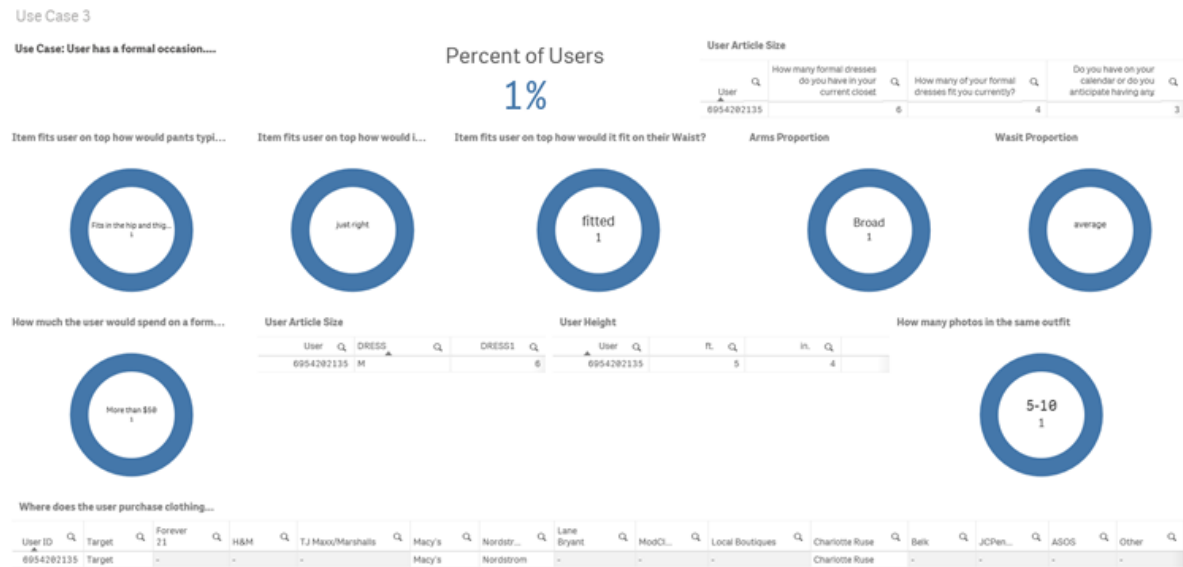


Figure 37. Charlotte's Use Case Dashboard 1.

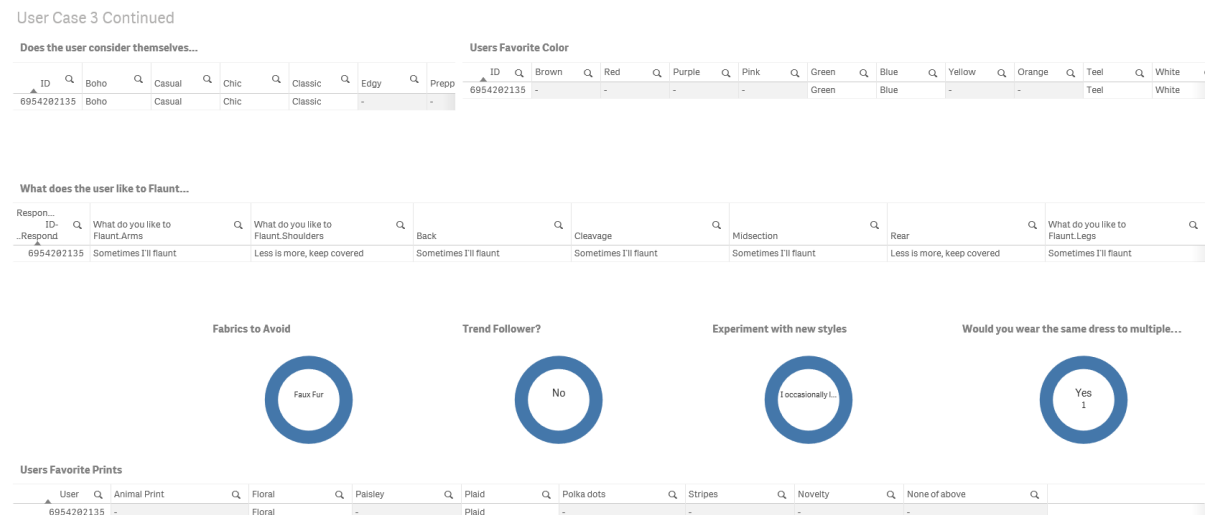


Figure 38. Charlotte's Use Case Dashboard 2.

The user's scenario is that she has a formal event coming up, which we learned from her calendar data, collected on the survey and displayed in the Use Case Dashboard. The wizard is able to generate an output using this data for Charlotte (Figure 39).

*User,* I see you have 3 formal events coming up!  
Here are some dresses and oh look- they're on sale!

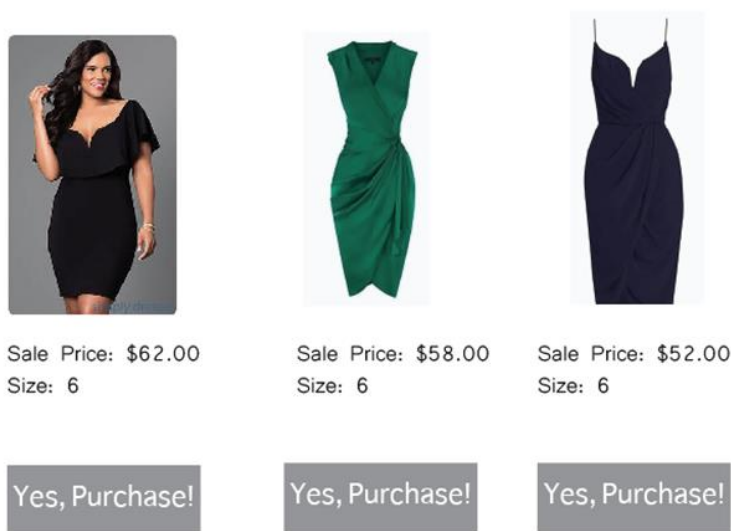


Figure 39. Email sent to Charlotte.

Charlotte was excited. "I actually looked at this dress!" "Is this really what it came up with? I love all of them," said Charlotte.

Charlotte found the experience to be overall positive and easy to use. She would pay for the service and also found data entry was easy and not an issue for the user. Charlotte stated the survey was "short and to the point" (Figure 40).



Figure 40. Charlotte's Exit Survey Dashboard.

**Jessica Feimer, age 28.** Below is a User Profile for Jessica (Figure 41).

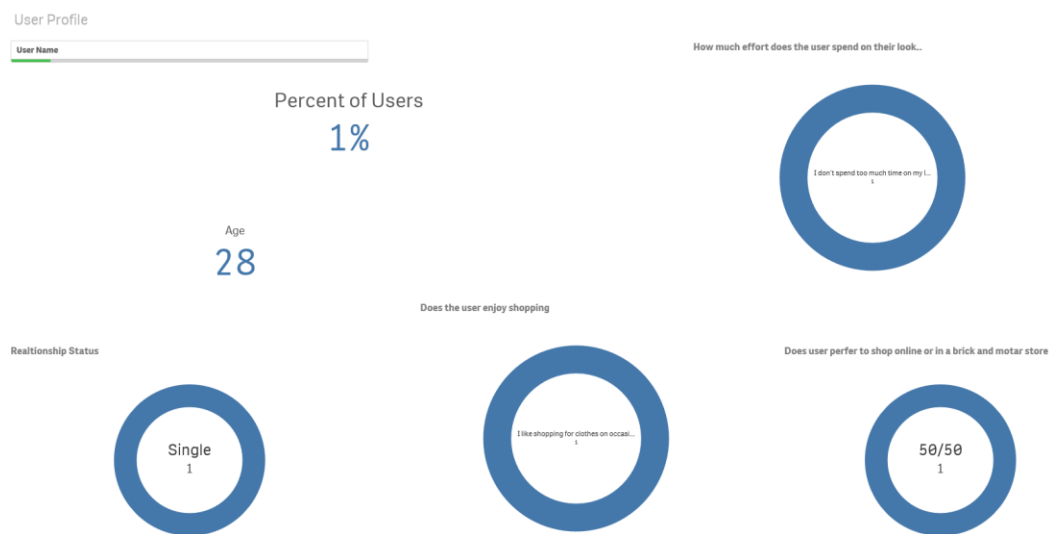


Figure 42. Jessica's User Profile.



When the closet data, personal-shopping-habits data, and financial shopping data is combined, the “wizard” can quickly give output. Based on the user’s profile and data, she best fits Use Case 1—User is going on vacation (Figure 42).

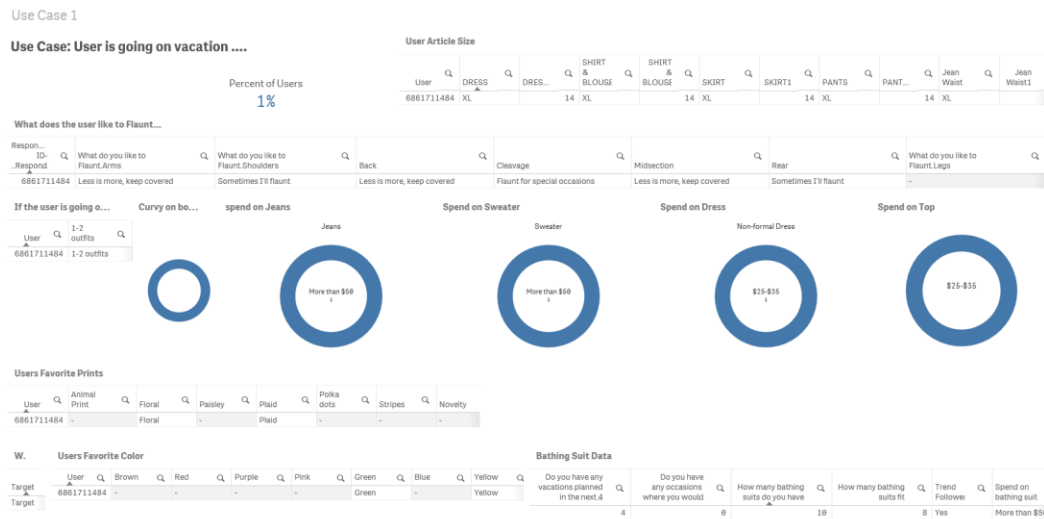


Figure 42. Jessica’s Use Case Dashboard.

The user’s scenario is that she is going on vacation this weekend, which we learned from her calendar data, collected on the survey and displayed in the Use Case Dashboard. The wizard is able to generate output using this data for the user. Jessica is leaving for vacation in a month and when she walks into Nordstrom, she receives the message below on her phone (Figure 43).

**Welcome to  
Nordstrom**

**I see you have a vacation  
coming up.. need a new  
fabulous outfit? Let us  
help you!**

**Start Shopping**

*Figure 43.* Text message received by Jessica.

User is interested and selects “Start Shopping.” The screen below appears on the user’s screen (Figure 44).

User, welcome to Nordstom!  
I see you have a vaction coming up need a new  
fall look?!



Outfit Price: \$84.00  
Size: 14/XL  
Alise: 34

Yes, Try On!



Outfit Price: \$35.00  
Size: 14/XL  
Alise: 33

Yes, Try On!



Outfit Price: \$102.00  
Size: 14/XL  
Alise: 32

Yes, Try On!

\*\* outfits do not include shoes

Figure 44. Message received by Jessica.

Jessica is elated. “I really like everything!” “If I select ‘Yes, Try On!’,” said Jessica, “is it going to show me where to find the outfit because I like that?” “Will it show me more outfits like these?” asked Jessica. She selects “Yes, Try On!” and is directed to where she can find the outfit.

Jessica found the experience to be overall positive and easy to use. She would not pay for the service and found data entry was easy and not an issue for her. Jessica stated, “The data selected clothes I am interested in and entering the data was easy” (Figure 45).

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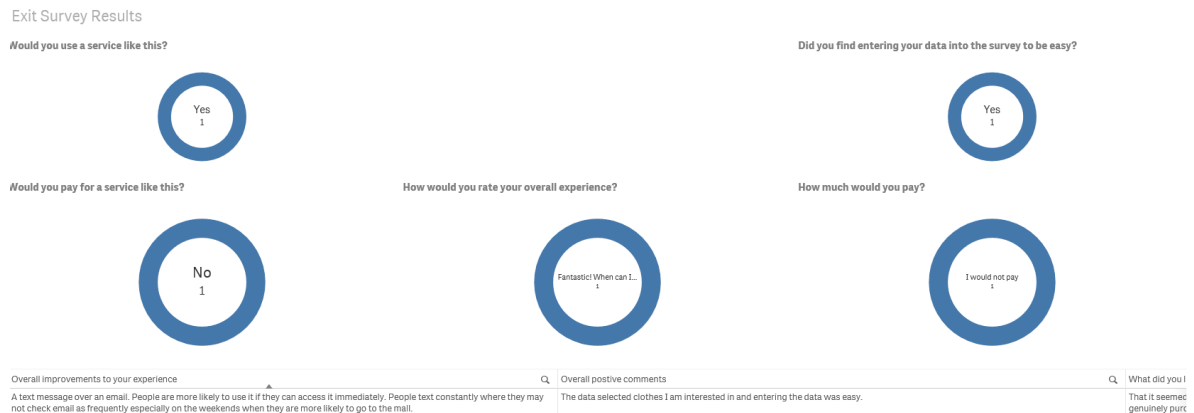


Figure 45. Jessica's Exit Survey Dashboard.

**Deb Smith, age 52.** Below is the User Profile for Deb (Figure 46).

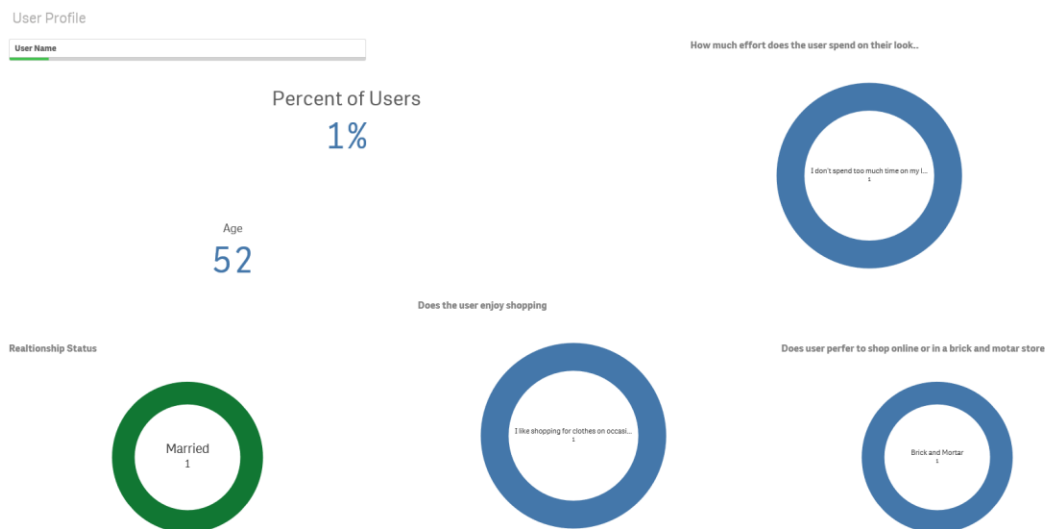


Figure 46. Deb's User Profile.

When the closet data, personal-shopping-habits data, and financial shopping data is combined, the “wizard” can quickly give output. Based on the user’s profile and data, she best fits Use Case 1—User is going on vacation (Figure 47).



Figure 47. Deb’s Use Case Dashboard.

The user scenario is that she is going on vacation in the next month, which we learned from her calendar data, collected on the survey and displayed in the Use Case Dashboard. The wizard can generate output using this data for the user. Deb walks into JC Penney’s and receives the message below on her phone (Figure 48).

*User*, welcome to JC Penney!  
I see you are going to Ireland next week want a new sweater for your trip?!



Outfit Price: \$23.00  
Size: L  
Alise: 34

Yes, Try On!



Outfit Price: \$25.00  
Size: L  
Alise: 33

Yes, Try On!



Outfit Price: \$20.00  
Size: L  
Alise: 32

Yes, Try On!

*Figure 48.* Message received by Deb.

Deb looks at the message for a bit and states, “I really like the first one and would click on the ‘Yes, Try On!’” Deb says she might try on the second two, but she really liked the first outfit.

Deb found the experience to be overall positive and easy to use. Deb would not pay for the service and found data entry was easy and not an issue for her (Figure 49).

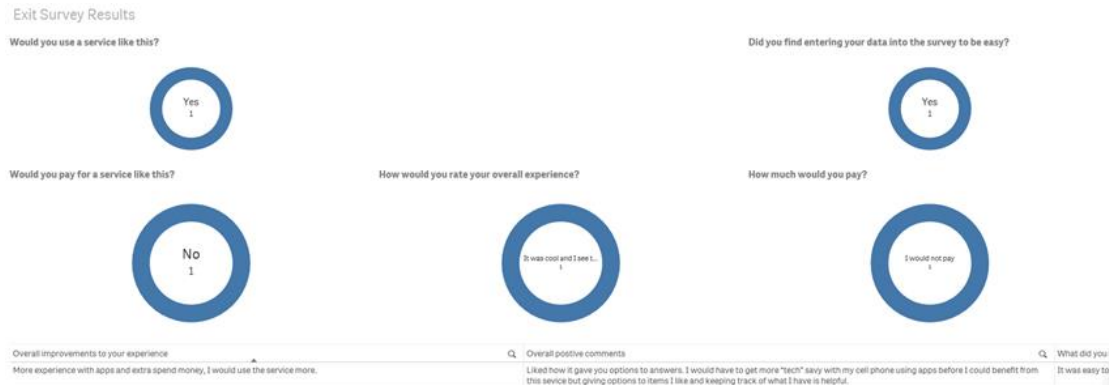


Figure 49. Deb's Exit Survey Dashboard.

**Patty Thompson, age 59.** Below is a User Profile for Patty (Figure 50).

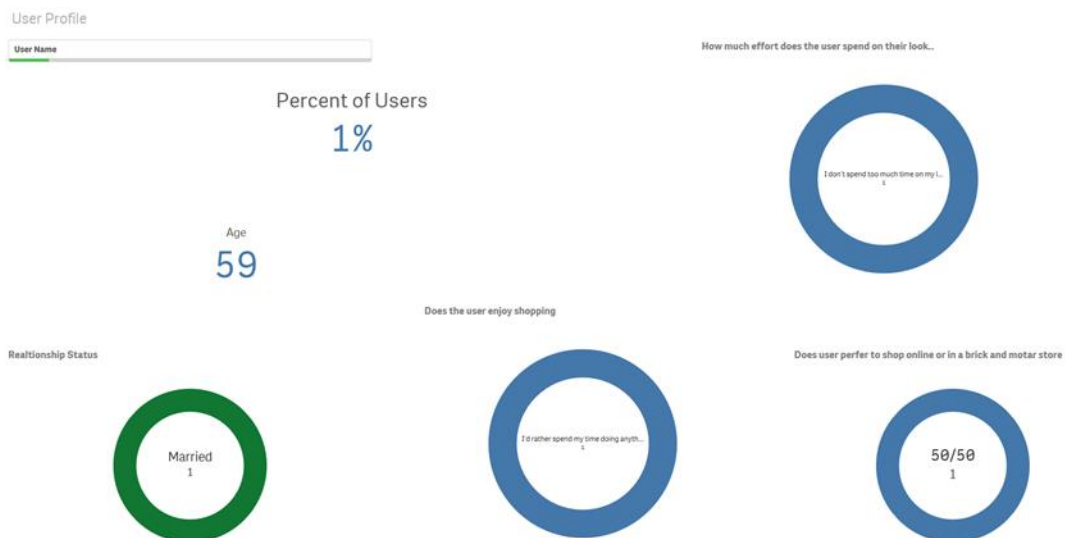


Figure 50. Patty's User Profile.

When the closet data, personal-shopping-habits data and financial shopping data are combined, the “wizard” can quickly give output. Based on the user’s profile and data, she best fits Use Case 1—User is going on vacation (Figure 51).

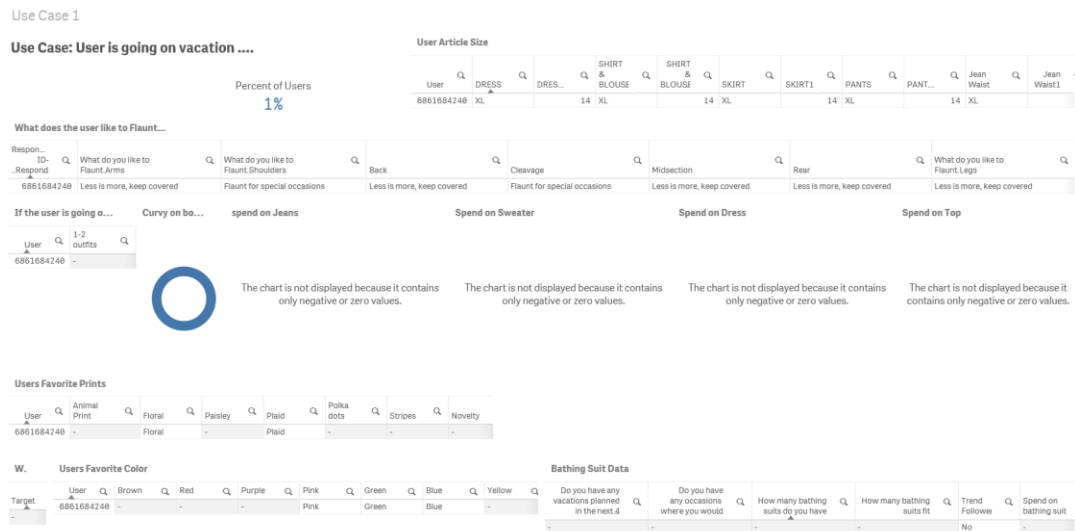


Figure 51. Patty's Use Case Dashboard.

Patty is going on vacation in two weeks, which we learned from her calendar data. She receives an email 15 days prior to vacation, which looks like the one below (Figure 52).



*User*, I see you are going to Ireland in a week!  
What a fun vacation! Need a new sweater for your  
fabulous trip?



Outfit Price: \$25.00  
Size: XL

Yes, Purchase!



Outfit Price: \$25.00  
Size: XL

Yes, Purchase!



Outfit Price: \$32.00  
Size: XL

Yes, Purchase!

*Stores on your shopping list:*

- Macys
- Lane Bryant
- TJ Maxx

\*\* outfits do not include shoes

Figure 52. Message sent to Patty.

Patty reads the email and immediately states, “How did you know? I bought something like that (pointing to the middle option) yesterday!” Patty was thrilled with the options and stated that, yes, she would use this service in the future.

Patty found the experience overall positive and easy to use. Patty would not pay for the service and found data entry was easy and not an issue for her (Figure 53).



Figure 53. Patty Exit Survey.

**Rebecca Jones, age 31.** Below is a User Profile for Rebecca (Figure 54).

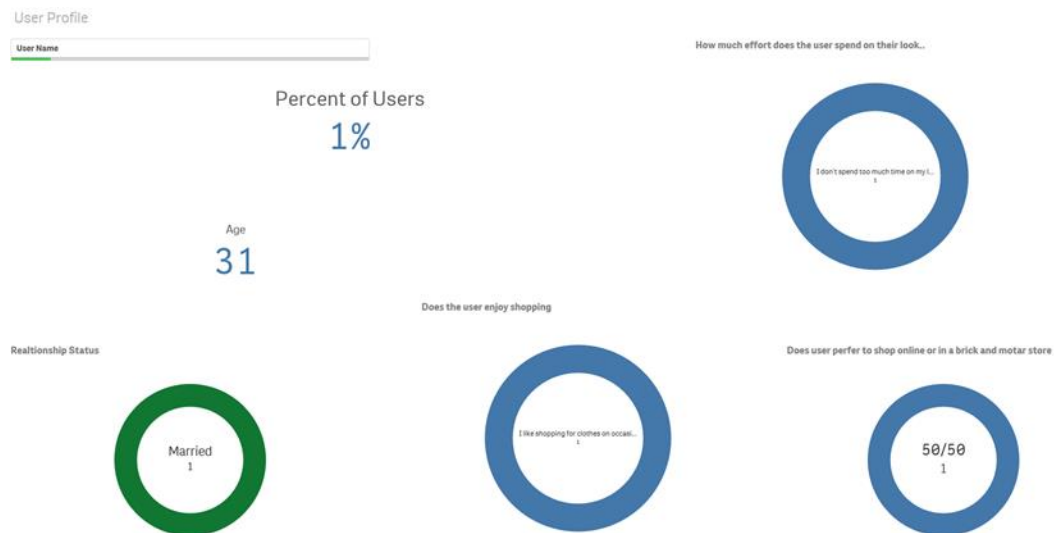


Figure 54. Rebecca's User Profile.

When the closet data, personal-shopping-habits data, and financial shopping data are combined, the “wizard” can quickly give output. Based on the user’s profile and data, she best fits Use Case number 2—User needs a new pair of jeans (Figure 55).



Figure 55. Rebecca's Use Case Dashboard.

The user scenario is she needs a new pair of jeans, which we learned from her data, collected on the survey and displayed in the Use Case Dashboard. Rebecca receives the email below (Figure 56).

*User*, welcome to fall! Need a new pair of Jeans? I found some deals for you!



Jean Price: \$45.00  
Size: 10

Yes, Purchase!



Jean Price: \$52.00  
Size: 10

Yes, Purchase!



Jean Price: \$32.00  
Size: 10

Yes, Purchase!

*Stores on your shopping list:*

- Macy's
- Loft
- Target

\*\* outfits only includes jeans

Figure 56. Email sent to Rebecca.

Rebecca immediately says, “I really, really like the 1st and 3rd pair and \$32.00 is a great deal.” “I have a lot of dark wash jeans but I do like the middle ones as well. The price and size are both ideal.”

Rebecca found the experience to be overall positive and easy to use. She would pay for the service and found data entry was easy and not an issue for her (Figure 57).

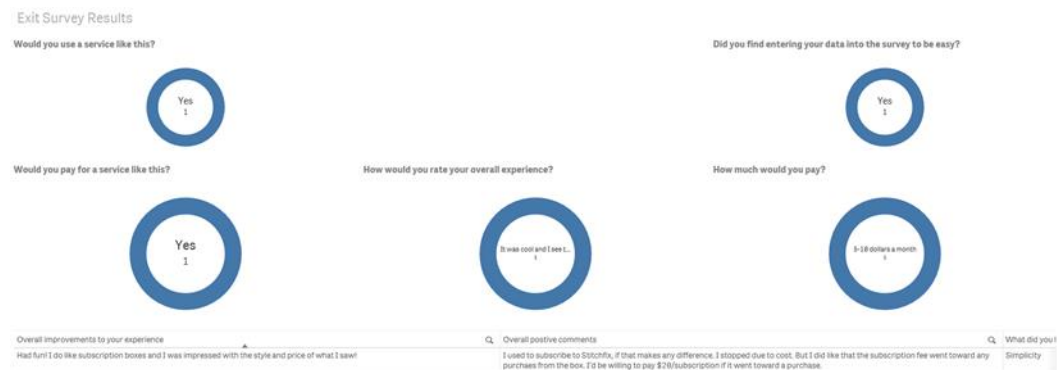


Figure 57. Rebecca's Exit Survey Dashboard.

**Michelle Bicknell, age 37.** Below is a User Profile for Michelle (Figure 58).

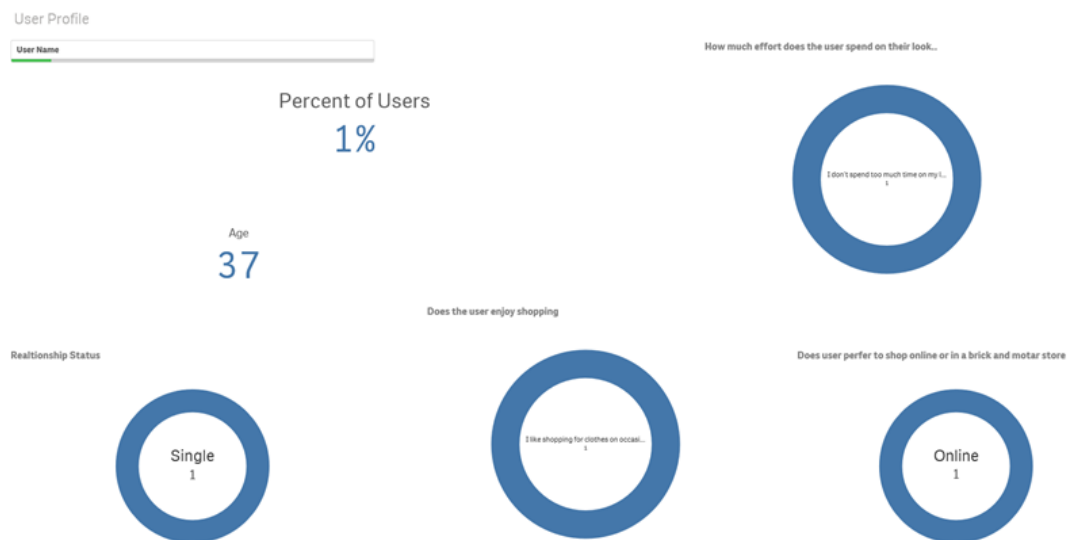


Figure 58. Michelle's User Profile.

When the closet data, personal-shopping-habits data, and financial shopping data are combined, the “wizard” can quickly give output. Based on the user’s profile and data, she best fits Use Case 2—User needs a new pair of jeans (Figure 59).



Figure 59. Michelle's Use Case Dashboard.

The user scenario is she needs a new pair of jeans, which we learned from her data, collected on the survey and displayed in the Use Case Dashboard. Michelle receives the email below (Figure 60).

*User*, welcome to fall! Need a new pair of Jeans? I found some deals for you!



Jean Price: \$25.00  
Size: 8

Yes, Purchase!



Jean Price: \$25.00  
Size: 8

Yes, Purchase!



Jean Price: \$32.00  
Size: 8

Yes, Purchase!

### *Stores on your shopping list:*

- Target
- JC Penney
- TJ Maxx

\*\* outfits only includes jeans

*Figure 60.* Message sent to Michelle.

Michelle immediately says, “Wow, this is cool.” She said, “The price point is right on, I would probably purchase the middle ones.”

Michelle found the experience to be overall positive and easy to use. She would pay for the service and found data entry easy and not an issue for her (Figure 61).



Figure 61. Michelle's Exit Survey Dashboard.



## **Contributions**

### **Themes**

After testing was complete with all the users, it was very evident that they enjoyed this experience. They were amazed to see the suggested clothing options made for them only using the data provided. Users were very impressed, and some asked if they could start using this service immediately. They said that sharing their closet data was a nonissue, and they enjoyed the process of completing the survey. More than half of the users stated they would pay for a service like this. Fifty percent (4 out of 8 users) said they would pay \$5 to \$10 a month for this service. There was not a single user who did not see the value in this type of service, and 60% (5 out of 8 users) of the users wanted to know when they could get this type of service.

Each user seemed to think that the concept was very intuitive and simple. Every user I tested said she would try on and purchase at least one of the items. Many users stated they would try on and purchase all the items. In some cases, users said, “I just was looking for an outfit like that” or “I am packing tonight, and I would have loved these suggestions a week ago.” The general consensus was that users would use a service like this. Users stated they liked the idea that this was a personal shopping experience without involving an actual person in the interaction. This is an important piece of information for retail stores to consider. Users want the personalized attention and assistance with shopping; however, they want to do it in a more introverted way. This concept is important for many reasons, but mainly for retail shops to consider spending less time and money on actual persons assisting shoppers in a retail store, and more resources on increasing the store’s ability to reach users in a personal way digitally. Though users still seem to want the assistance of a retail assistant, they want it in a different way. Furthermore, users did not seem bothered by filling out the surveys. Users commented

that filling out this information was easy and actually fun for some of them. They did not think it was burdensome or taxing (Figure 62.



Figure 62. Overall exit survey results.

With respect to a pricing model, 70% (6 out of 8 users) of the users said they would pay for the service and \$5–\$10 a month seemed to be the range the majority preferred. The service could be tiered, so that when a user pays to use it, she “unlocks” additional capability that the nonpaying user does not get.

Another pricing model could be to have the stores pay to access the data on the application. The value here is the user data. The ability to capture users’ real data and using it to make data-driven decisions and recommendations to the users is the key to the solution’s success. If retailers needed to purchase access to the data in order to align their products to it, this would be a very successful strategy.

### Future Prototype

In the future prototype, collecting all the information in one place would be important. Users filling out a survey using Survey Monkey went well for prototyping; however, for a more mature solution, a holistic application would be much more fitting.

A user-downloaded application that enabled them to complete the data collection as well as connect the application to their social calendar would be ideal. Most users capture their social events on some type of digital calendar. This would allow the AI to sort through users' events and predict their shopping needs based on events they have planned. For example, if a user has a seven-day beach vacation in the near term and only three bathing suits, the assumption an algorithm might make is that the user needs additional bathing suits. Connecting a user's calendar data and closet data will make more realistic and data driven predictions. In the future, the AI could determine the time needed for the items to be shipped to the user. If the AI can determine the lead-time needed for shipping, it can calculate that into its user recommendations.

Another important element to include would be financial data. Users can fill out a survey stating how much they would spend on items, but one way to collect this data would be to tap into the user's credit-card or debit-card records. A user may not be interested in sharing a major credit card's data with an application, but maybe a more realistic option would be to ask a user to share a certain retail store credit card with the application. That way the user feels comfortable that the data they are sharing with this application is related to retail shopping. For instance, maybe a user has a Nordstrom store credit card, they might be willing to link this credit card to this application, and then the application could compare the data the user puts into the application against their actual spending data. This would help the AI recommend more realistic and data-driven solutions to the user. It also would help collect a historical database of financial data. If the application can scan the credit card information and build records of the user's closet based on this data, the application has a more real-time idea of what articles are in the user's closet. It also allows the application to make better fashion-trend predictions pertaining to color, fabric, and patterns. For example, a user has a trip coming up and the AI knows the user will purchase one or two outfits. However, after scanning the credit card data, the AI also knows the user just bought a striped top. The AI might want to suggest either articles that would match this striped top or something completely

different. Suggesting a striped top to a user who just purchased one, might be redundant and will turn the user off to the application. A user is more likely to purchase an item to complement an already-owned piece of clothing, or something completely new, rather than purchase something similar to what they already have. The AI could send a message such as, “I see you just got a striped top and you know what would look great with this for your upcoming trip to the mountains . . . ” This is ideal for both the user and the retailer.

This should also be tested with a much larger population. I was able to test with 8 users and gain a great deal of insight; however, testing with a larger population would be more reliable. Creating a script to generate the outputs would be helpful for testing and would facilitate larger testing efforts.

### **Final Recommendations**

The final design recommendation is to focus on having a user interface that promotes ease of use for the users, a flexible predictive analytics platform that allows the user to control the variables with their ever-changing data, and a solution that continues to capture real-time data pertaining to the user. I have proven in testing that users are comfortable sharing their data and willing to input information if the output is beneficial to them. We have proven that combining social events, shopping habits, personal style, and current closet data can easily predict a shopper's next purchase, and make recommendations. Once the data elements are combined, the idea of sharing it with the user is simple and acts as a liaison between the stores and the shoppers.

Users seem comfortable and willing to share their data when it brings them reliable and smart options regarding fashion. Creating a platform to keep user data fresh and accurate is going to be key to ongoing success. Recommendations that continue to be precise and accurate will be overwhelmingly successful for the adoption of this augmented shopping experience. Most users do not want to think or be stressed out by clothing purchases. The more accurate the recommendations are regarding fit, price point, style, color, and pattern, the more likely the users are to continue to use the application.

Now more than ever, users are comfortable with sharing information about their size, figure, purchases, and style. To have an application able to collect end-user fashion data, combined with their social and business calendars and aligned with stores' retail data, is more feasible than ever before. The evolution of the shopping experience is coming and data-driven recommendations will be a part of the future.

## Conclusion

### Future Work

Consumer shopping behaviors are continuously evolving and brands must continuously adapt to meet their expectations. Emerging technologies such as voice commerce, social commerce, and augmented reality will continue to gain traction. Online shopping has become a lifestyle, growing at exponential rates. The ease of researching, purchasing, and shipping clothing with just a few clicks is very powerful. For storefronts, traffic and sales are declining, leaving retailers with little choice but to adapt to an interconnected world.

Recommended future work would entail many parts of this solution, including how to capture this information, analyze the data that is collected, build the predictive analytics that will get after the intuitive intelligence component, and continue improvements on the type of data collected. Another significant recommendation would be to test this solution on a much larger sample size. Many of my recommendations are based on a small sample size. If there were more data collected from a larger sample size, the results would only be strengthened.

**How to Capture Data.** An application for a user to input their data would be an immediate solution. However, if Amazon Alexa Look improves its ability to capture detailed data from a picture, this could be a very viable solution to pursue. Making data input easy and seamless for the user is the most important piece. Users are not going to take the time to continue to input their data if it is not easy to do. If users do not update and continue to input their data, it will become stagnant and old, which in turn will produce poor predictions. Allowing the user to input and update data frequently will be very important to this concept. An idea that might be explored would be to reach out to users weekly, asking if they purchased anything new this week and, if they have, collecting data on it what it. If users shared their location services from their phone with the application, this list could be customized and enable reaching out the user by saying, “I see you have visited Target, Macy’s, and Old Navy this week—did you purchase anything for yourself?” This way, the user does not have to think about where they

shopped; the computer does that for them. They can simply be reminded, “Oh yes, I went to Target and I purchased a white sweater, size large, and it was \$34.99.” Capturing user data in these short spurts will be critical to keep the data current and accurate.

**How to Analyze and Make Predictions.** Being able to sort through this data and make predictions is the key goal of this application. Therefore, maintaining this data warehouse and the data refresh is of utmost importance. Multiple algorithms would need to be built to create the intuitive-intelligence aspect of this application. It is important to remember that the true success of this application is to suggest realistic items that users would purchase before the user even realizes they need or want for them. This will require precise calculations of the data, as well as collecting feedback on the predictions the AI recommends. Being able to teach the AI will be beneficial for data cleansing. If a user inputs a size but starts buying clothing in a difference size, the AI will not know unless the user informs it. Therefore, the user must be able to control variables in the algorithm as their shopping habits change and grow over time. If a user loves polka dots but then has a change of heart, either the trend has changed, or the user simply changed her mind. Either way, if the application keeps suggestions polka-dot options, a user is not going to purchase anything nor will they have any interest in the application.

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### Appendix: Shopping Experience Survey Questions

Below are the questions that resided in the initial survey sent to all participants.

- Do you enjoy shopping?
- Is your closet color coordinated?
- How many times would you be photographed in the same outfit?
- How often would you wear a pair of white pants before its time for a new pair?
- Fabrics to avoid...
- Graphic Tees ?
- What do you like to flaunt? What would you rather downplay?
- Prints you love...
- Would you consider yourself....
- Would you wear the same dress to multiple events in the same season?
- If you are going on a week-long vacation do you purchase new....
- How often do you wash your jeans?
- Is your closet season coordinated?
- Do you consider yourself a trend follower?
- How often do you dress for the following occasions?
- Do you shop online or brick-and-mortar store more often?
- Favorite colors to wear
- Where do you typically purchase clothes from?
- Do you like to experiment with new styles?
- How much effort do you spend on your look?
- How tall are you?
- What sizes do you typically wear?
- How would you characterize your proportions?

- How would you characterize your proportions?
- Are you curvy on your bottom?
- How do you prefer clothes to fit your bottom half?
- Do you consider yourself petite?
- Which best describes how pants typical fit you?
- What types of jeans do you prefer?
- How do you prefer clothes to fit your top half?
- When tops fit comfortably in your bust and shoulders, how do the waist and length generally fit?
- Jean Rise
- Length?
- How much would you ideally spend on an item?
- If you had a job interview or big presentation next week, would you?
- If you spent \$100 on a pair of jeans would you consider them high quality?
- If you spent \$50.00 on a shirt would you consider it high quality?
- If you spent \$20 on a shirt would you consider it low quality?
- If you were single, and your crush asked you on a date next Friday. Would you...