# Designing the Future of Personal Fashion

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## ABSTRACT

Advances in computer vision and machine learning are changing the way people dress, and buy clothes. Given the vast space of fashion problems, where can data-driven technologies provide the most value? To understand consumer pain points and opportunities for technological interventions, this paper presents the results from two independent need-finding studies that explore the gold-standard of personalized shopping: interacting with a personal stylist. Through interviews with five personal stylists, we study the range of problems they address and their in-person processes for working with clients. In a separate study, we investigate how styling experiences map to online settings by building and releasing a chatbot that connects users to one-on-one sessions with a stylist, acquiring more than 70 organic users in three weeks. These conversations reveal that in-person and online styling sessions share similar goals, but online sessions often involve smaller problems that can be resolved more quickly. Based on these explorations, we propose future personalized, online interactions that address consumer trust and uncertainty, and discuss opportunities for automation.

## ACM Classification Keywords

H.5.2 Information Interfaces and Presentation: Interaction styles, natural language; I.2.11 Distributed Artificial Intelligence: Intelligent agents

## Author Keywords

Conversational agents; chatbots; fashion; need-finding

## INTRODUCTION

Advances in computer vision and machine learning are changing the way people interface with fashion. With Amazon's Echo Look, users can take a selfie to have their outfit rated [39]. Intel's Magic Mirror allows consumers to virtually try on clothes [36]. Companies like Stitch Fix use data-driven models to curate a personalized selection of clothing every month and deliver it to your door [42]. Data-driven technologies can enable a host of new *personalized* fashion experiences, but what are the few, essential interactions that will define the next-generation of fashion ecommerce systems?



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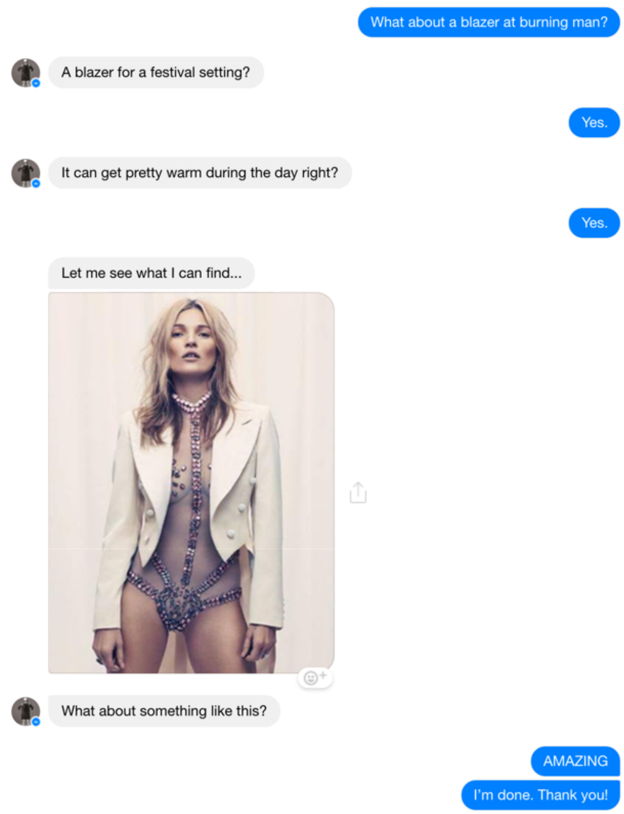


**Figure 1:** A conversation between a user looking for fashion advice and a stylist enabled by PSBot, a Facebook Messenger chatbot that we built and deployed to study personal styling interactions in online settings.

Past research has explored how to design for fashion applications that focus on body [6, 25], in-home [43], and in-store [4, 5, 33] interactions. To design the future of personal fashion, we look to the gold-standard of shopping experiences: interacting with personal stylists in both in-person and online settings.

High-end stylists offer *in-person* consultations for curating wardrobes and creating outfits. Consumers who can afford these services have better shopping experiences: they enjoy both functional benefits — quicker, easier selection — and symbolic benefits — greater confidence in the results [41].

Retailers also often offer *free* personal stylist services both in-store and online to help customers find available items that meet their needs [8].

This paper presents the results from two independent need-finding studies that explore *in-person* and *online* stylist interactions. In the first study, we interviewed five personal stylists that offer *in-person* wardrobe and image consultations. In a separate second study, we study *online* styling interactions by building and deploying a chatbot — PSBot — that connects users to one-on-one sessions with a stylist. We released PSBot for three weeks, and collected 88 organic styling conversations with 73 unique users (Figure 1).

We observe that styling sessions in both settings address similar consumer goals; however, online conversations often tackle self-contained, smaller problems that can be solved in minutes rather than hours or days. In-person consultations afford inferential data gathering, whereas in online conversations, stylists have to explicitly ask about a user's physical appearance and style preferences to make more personalized recommendations. On the other hand, it is easier for an online stylist to quickly explore the space of options with a client through visual examples and adapt recommendations to changing requirements.

Based on these two studies, we propose design recommendations for future data-driven fashion systems: navigating user *uncertainty* by asking the right questions and showing visual examples, increasing user *confidence* by explaining solutions, and establishing *trust* by providing critical feedback — not only recommending items that users would like, but discouraging them from making bad decisions. Finally, we discuss how data-driven models can automate these capabilities to scale personal fashion.

## STUDY 1: IN-PERSON STYLING SESSIONS

To understand the scope of in-person, high-end fashion services, we interviewed five personal stylists. We recruited them from fashion-centered US cities — New York, Los Angeles, Chicago, and San Francisco — through direct contact, generating leads based on alumni networks and Instagram. The stylists interviewed were all female and worked in ready-to-wear fashion, with diverse clients (men and women, middle to high income, in a variety of life stages). While some stylists had specialties (e.g., women over 50), most described styling sessions with a variety of different types of clients.

Interviews were conducted by the first author, using a semi-structured format focusing on ten key questions (Table 1). Interviews typically lasted 30 minutes. Interviews were analyzed by the first author using an iterative open coding approach; from five interviews consistent themes emerged.

All stylists agreed that fashion is "*super, super, super personalized*" (S4):

> *It gets down to like [...] I had a client who hates green, for no reason, and it's a fabulous color. I need to know what fabric allergies they have. Do they abhor ruffles because they had a bad experience in second grade?* (S4)

| | |
|---|---|
| 1 | When you begin with a new user, how do you prepare for a meeting? |
| 2 | Where do you typically meet your clients? Why do you choose that environment? |
| 3 | How does a meeting with a client typically go? |
| 4 | How personalized do you think style advice needs to be? Do you need a lot of specifics or do you find you give out similar advice again and again? |
| 5 | Is there any information you wish you could have about your clients, that would help give better style advice? |
| 6 | What are some typical goals that clients have? What are people trying to accomplish in an appointment, or over the long term? |
| 7 | Do you find that users want to use your meetings to learn about fashion or to solve an immediate problem? |
| 8 | How do you say no (i.e., give critical feedback)? |
| 9 | How do you follow up? Do you initiate or wait for the client to get in touch again? |
| 10 | How does technology fit into your personal stylist work now & how has that changed? |

**Table 1:** Interview questions for personal stylists focusing on the range of problems they address and their processes.

Some noted that there are general fashion design principles:

> *There are certain basic ideas or principles that apply... For body types, for example, if you're styling someone who is a triangle shape [...] there's certain style advice you would give that would be universal.* (S5)

In general, however, stylists thought that fashion is highly personal, requiring a great deal of explicit and inferred data — a person's body shape, skin color, budget, and color and style preferences — to make recommendations.

This viewpoint pervades their processes. Although stylists address a range of needs, from transitioning a client's entire wardrobe after a major life change (i.e., re-entering the workforce) to creating new outfits with existing pieces, they still require similar, intense onboarding appointments to gather user data.

Meetings with stylists typically fell into three categories: initial introductory meetings, home "wardrobe" appointments, and in-store shopping experiences. In the introductory and home meetings, stylists had a number of ways they sought to understand users' styles and needs, both in order to determine if it was a good match but also to provide good, personalized advice. Through these initial interactions, stylists try to establish a basis of trust that they can build on over a longer-term relationship.

### Explicit and Inferential Information Gathering

The onboarding process actually begins even before the first meeting. While the stylists themselves rarely prepared for an initial meeting, several had clients complete "*homework*" (S3): "*I do have a list of probably like 10-15 questions*" that "*get very specific*" about style, budget, and size (S1). These questions covered a client's physical attributes such as height, weight, eye and hair color, but also included questions like "*what is your favorite color,*" "*describe the attributes of that color,*" and whether the "*attributes of that color are also how you see (or wish to see) yourself*" (S5).

One stylist noted that this "*eventually leads to refining words that define their style*" that can be used to frame the rest of their advice (S5), while another framed it as "*I'm trying to get a little bit of sense of who they are and what their life entails*" (S3). This process not only helps the stylist better understand their client's style, but also helps with self-reflection: "*A lot of people, honestly, haven't delved into their psyche [...] haven't even thought about themselves*" (S4).

Stylists did not entirely rely on self-reported answers since they are not always accurate. They also inferred relevant personal information using clients' homes, current closets, and other features in their life. Inferential processeses were particularly common for understanding body shape and coloring, which clients have trouble getting right. While stylists asked about these features in their questionnaires, they still verify: "*I peek at what sizes they're actually buying, because sometimes when they tell me what size they are, that's actually not correct*" (S3). One stylist noted that while she occasionally does initial meetings over the phone, "*it's a lot better when I can actually meet them in person because I actually take photos of them*" (S1). Another said "*one piece of information that would be really helpful is a standardized good picture [...] so I could see what her figure is*" (S3).

There are also some questions stylists don't want to ask explicitly, and instead use clients' homes or existing wardrobes to infer information:

> *First things first, driving up to the house, I'm like this is a 10,000 square foot, six-plus million dollar mansion, so [...] I can already predict brands that were going to be in her closet. Going in, looking at the color palette [...] she's totally neutral [...] with a lot of very modern art, minimalism, very clean, very organized. Just from that 30 second glance around, I can predict what her closet is going to be like* (S4).

In some cases, stylists used this inferential approach to avoid asking awkward questions directly:

> *I do not ask what their income is. I can kind of just gather. Plus do they have kids? Where is their money going? Do they travel a lot? Is it a single guy? I gather all of those pieces of information, but I don't ask them* (S1).

In others, stylists used people's homes and current wardrobes to understand their fashion style because it is hard for people to express their style preferences concretely. One stylist reported that clients "*can say 'oh I'm a bohemian style' but let's talk about the words – what does that mean to you?*" (S5). Using the client's existing wardrobe or home as a proxy can help, as:

> *Most of my clients have a sense of their style [...] a lot of people will have it in their interiors, but not in their wardrobe. I think a lot of people actually are afraid to stand out, a lot of people just try to dress like everybody else, and they're honestly afraid to take a risk* (S4).

**Wardrobe Assessment**

A lot of a personal stylist's work revolves around managing a client's wardrobe. After the introductory meeting, stylists often schedule a wardrobe appointment. One stylist even said, "*I won't shop with a client until I work in their closet*" (S4).

These wardrobe appointments are typically intense, lasting several hours; it can often take multiple meetings to completely go through a client's wardrobe: "*you can spend a couple hours and make good progress, but usually it requires more appointments*" (S5). After initially establishing the client's goals and preferences, stylists have clients go through each item in their closet and decide whether or not to keep it:

> *We can get in there and just go through section by section and have them pull out clothes, and we say, 'Keeping your style words in mind – is this going to work?' And start trying things on. Things that don't fit have to go; things that are damaged beyond repair, we pull out* (S5).

This process can be extreme. As one stylist said, "*When I go into their closet, I will get rid of over half of what they own. It's very shocking to people, because most people wear 10/15% of their clothes*" (S4). One noted,

> *Clients generally know what looks good, but also generally have plenty of things that don't. So maybe half their closet will be things that are the right shape, the right colors, and look okay on them* (S3).

Once they know the items that fit, are in good repair, and match the client's goals, they can "*help them take a fresh look at their closet, see what they can do, working with what they have*" (S5). One stylist noted, "*That very day, that I'm in their closet, they end up with some new way to wear things for Monday*" (S3). Future shopping trips will often reference the wardrobe sessions:

> *We'll do wardrobe styling, and I see the gaps in their closet, of what they need, where they need a staple. And then I put together a shopping a list* (S1).

While most of their appointments are intense and last several hours, stylists did mention some lightweight interactions they support. One noted that "*my really wealthy ones will use me all the time*" (S4) to pack for trips, select outfits for dates, and so on. Some clients send spur-of-the-moment texts, asking for help:

> *I keep pictures in my phone, so even if I'm out of state and they're like 'what should I wear tonight?' I'll just peek through their outfits and text them a picture and say, 'how about this one?'* (S4)

**Importance of Trust**

Many stylists see establishing trust as one of the most important features of a personal stylist relationship because the client relies on the stylist to make good choices for them:

> *The women who have their shit together – they know where to shop, they've got it all figured out – in general, I really don't work with women like that. My clientele are*

*really just searching for someone who's an expert in this area, someone they can trust* (S1).

Stylists saw the importance of it even in the smaller aspects of their interactions. For example, during a wardrobe appointment, clients may start by getting dressed in the bathroom, but quickly shift to getting dressed right in the same room:

> *It's honestly building a very personal, trusting relationship. Because most of these clients are in their underwear with me most of the time. How much more vulnerable can you be? It's truly just really building up that trust and confidence in each other. And if it's not there, I'll refer them to another stylist that might be a better fit* (S4).

Indeed, stylists noted that this extended beyond giving style advice, "*Oh yeah, when people are in their underwear with you, they tell you about their marriages, divorces, their kids' problems. They tell you everything*" (S4).

To establish this trust, the stylists used humor ("*I do, literally say, I'm like a doctor, I've seen every possible size and shape*" (S3)), but focused primarily on being genuine and unbiased. By genuine and unbiased, they typically meant they focused on the client's satisfaction and weren't influenced by external factors like money:

> *I mean I think a lot of that is just being very genuine in your approach. If you go to a Neimans' or a Nordstrom, I have had clients say that to me, they just feel like they want to sell them whatever it is they have on the floor. I think my approach is different in that I really want them to love it, I want them to feel good about it. I want them to look in their closet and think 'I'm excited to wear this' [...] So I think trust just comes from being unbiased and really genuine and wanting them to feel good, whether they buy anything or not* (S1).

This focus on being unbiased and separating the personal styling advice from purchasing was very important:

> *I think there's an advantage of working with a wardrobe consultant versus an in-store personal shopper. Because they are paid a commission on what they sell, I don't always feel their interests are the best for the customer, there's a built-in bias. So I try to stay neutral. Because it doesn't matter to me, personally, where we find that item they need* (S5).

This goal of being genuinely focused on the client's happiness led to stylists rejecting items they felt were good choices:

> *I don't like talking them into things that I think they won't wear... I can tell by body language and facial expressions when a client has something on, whether (even though I think it's great) she won't actually pull it off the shelf. And I'll say to her, 'I love that on you but I can tell this is not something you're going to get up and look for'* (S3).

A second way of establishing trust with clients is by saying 'no.' Disagreeing with clients is a way of establishing that you truly have their best interests at heart. Stylists encountered this frequently; one stylist noted that when going through clients' closets "*some get a little argumentative...*" (S3). When clients disagree, stylists have a few strategies, but the primary strategy is reminding the client of the stylists' expertise:

> *One thing I find myself saying a lot is 'I'm so judgemental, aren't I?' and then they'll come back, 'but that's why I'm paying you!' So trying to remind them, that yes, they are paying for this. I'm so choosey and I want you to be too. They like when you're not just placating them, what's the point of that?* (S4)

Another common strategy for saying 'no' nicely is setting a high bar initially. One stylist asks her clients to try on their favorite outfit "*because it usually looks best. And that gives me a bar to surpass*" (S3). Then the stylist can frame any choice in terms of how good the client could possibly look:

> *Well I think a phrase I often use is, 'I think we can do better than this,' and I can tell them why. I can say, 'This isn't the spot you're wanting to emphasize on your body.' People are with you, because they want that feedback. That's why they hired you, you know, to give them honest feedback. So they're usually very receptive to that.* (S5)

## CUIS, CHATBOTS, AND CONVERSATIONAL AGENTS

The goal of the first study was to understand the nature of high-end, personalized fashion services and the needs of their clientele. Since many retailers offer free online stylist services to help consumers, we wanted to also study the types of fashion problems people bring up in online settings. To capture and analyze online styling interactions, we developed and deployed a chatbot service that connects users seeking fashion advice with stylists.

Chatbots are simple interactive systems accessed through a conversational user interface (CUI). CUIs allow users to interact with natural language (speech or text) in text messaging, instant messaging, and command line apps. CUIs can support interactions with another human, with an intelligent agent, or with a bot (simple software program) [34].

Researchers and companies are exploring diverse ways in which chatbots can provide value in different domains. Recent work examines using crowd-powered chatbots as personal assistants [22]. Although general natural language understanding has not been solved, domain specific chatbots that can schedule meetings [35], provide weather reports [14], and even surface historical documents [23] successfully leverage automated (intelligent) conversational agents. They, however, still face challenges, especially around how the agent's personality influences interactions [24].

Fashion-focused chatbots have received a great deal of industry attention in recent years. Several brands have developed chatbots that help users get feedback [2], shop their websites [18], and even buy items directly from runway shows [37]. In addition, more general chatbots have been developed to help users learn about trends, search for items across retailers, and see outfit suggestions [38].

While chatbots are finished products in their own right, they also make effective *proxy systems* — lightweight prototypes that can be drastically different in form and function from the

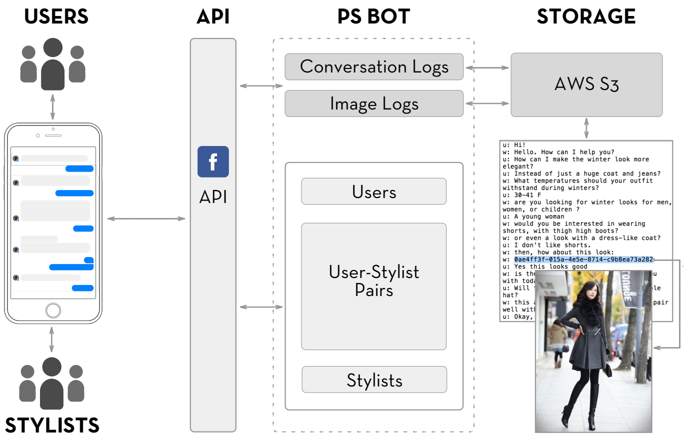


**Figure 2:** PSBot system architecture: users and stylists have conversations via a Facebook Messenger chatbot. PSBot tracks users, stylists, and user-stylist pairs. Conversations, including images, are permanently stored.

final product — which can be used for early validation of data-driven interactions. In addition to scaffolding implementation and testing, chatbots afford *staged automation* [20]. Initially, they can be backed by humans instead of computational systems, and wizard-of-oz experiments can be run to understand which pain points and types of system interventions elicit the greatest user engagement [30]. After — and only after — determining that an interaction is *useful*, researchers can the invest time and resources into building and testing data-driven models to support it, shortcutting wasted engineering effort on products and services that are technically impressive but lack product-market fit.

Conducting needfinding with chatbots using a wizard-of-oz approach is also important because users often misunderstand chatbot capabilities and their expectations can be "dramatically out of step" with system capabilities [27, 28].

## PSBOT : THE PERSONAL STYLIST CHATBOT

To understand common fashion problems addressed in online settings, we conducted a need-finding study by developing a Facebook Messenger bot — PSBot — that offers people one-on-one sessions with stylists. Facebook messenger bots afford private conversations similar to those one might have with a stylist on a retailer's website. The platform's popularity also helps in advertising and reaching target users. Moreover, it has a well-supported development environment that has built-in support for capabilities such as image sharing.

### Interaction Design

When a user first messages PSBot to start a styling session, it responds with two automated messages. It first asks, "I'm getting ready — can you describe what you'd like help with?" After a user responds to this first question, PSBot follows up with a second message, "Happy to help with that! Anything else you'd like to add?" This initial interaction serves three purposes. First, the user receives confirmation that the bot is online and working since they at least received two messages. Second, it allows us to collect data for every user that tries the bot even if they decide not to wait for an available stylist. Third, by pushing these initial responses to available stylists, we can help them prepare before diving into a conversation. If all stylists are busy with other users, PSBot adds new users to a waiting queue and gives frequent updates notifying them of their place in the queue. Once an available stylist claims a user, they communicate directly with each other.

After a stylist logs into PSBot, her status is set to "available." If there is an unclaimed user in the queue, PSBot immediately pushes the user's request to the stylist. A user request contains some personal data — name, gender, locale, and timezone — and the user's problem description. User requests are broadcast in first-in-first-out order to ensure that stylists treat all users fairly and do not prioritize easier or more interesting requests. Once a stylist claims a user, other stylists cannot be paired with that user and are shown the next user in the queue. Users often disappear after their questions are answered, so PSBot delegates the responsibility of officially ending the conversation to the stylist. Stylists log off the bot when they are unavailable to handle requests.

PSBot allows stylists and users to send text, images, and links to each other. As in Hsu et al.'s system [13], PSBot provides partial support within a broader ecosystem: if users want to purchase items, for example, they must do so outside the chatbot.

### Implementation

To support the described one-on-one interactions, we use Facebook Messenger essentially as a telephone switchboard, connecting "calls" between a user and a personal stylist using the Messenger platform. PSBot functions as the switchboard operator, tracking personal stylists accounts, user accounts, and user-stylist pairs (Figure 2).

When a user starts a conversation, their Facebook Messenger ID is added to the queue of waiting users and a user data object is created to store information like the start time of their conversation. Initially, the user's request is broadcast to all available personal stylists. When the user is claimed by a personal stylist, PSBot adds the two Facebook Messenger IDs as pairs in a lookup table. If a user or stylist's ID is in this table, messages are sent directly to the paired user.

PSBot stores conversations locally on a server until the personal stylist indicates the conversation has ended. At that point, the conversation log is saved to AWS S3, along with any images sent during the conversation. PSBot saves images with file names corresponding to randomly-generated 32-character alphanumeric strings, which are injected into the appropriate places in the conversation logs so that a conversation can be fully reconstructed afterward.

In addition to claiming users and ending conversations, stylists can indicate that an interaction has "expired." This feature is useful in instances where a user returned later to say something like "thanks" or "bye" after the conversation had been terminated — a problem also encountered in prior work [15]. This reject mechanism deletes the user request from the queue, so that other stylists will not see it and the message will not be archived.

## STUDY 2: ONLINE STYLING SESSIONS

We deployed PSBot to collect online conversations between consumers and stylists. Since the primary goal of the study was to understand the most common styling goals discussed in online settings, we did not recruit professional stylists. Instead, we recruited 10 students to serve as stylists from a college campus both directly and via referrals from existing stylists. These students were all female and self-reported prior (informal) styling experience. They staffed the the backend of PSBot for three weeks and were on-call during "office hours" (6 am – 12 am CDT) to provide advice.

To acquire users, we advertised "free fashion advice" on social media platforms and fashion-relevant blogs. At the end of three weeks, we had collected 87 conversation logs with 73 organic users: we attracted a surprisingly gender-neutral set of users (50% male) and most (90%) were from the United States. On average, conversations comprised 10 rounds of back-and-forth between users and stylists. Most centered around a single question; however, 15% of the conversations (n=13) addressed more than one problem.

We conducted an iterative open coding over the conversations' content, identifying common user goals and online interaction patterns. Conversations were analyzed by the entire research team, which after an initial coding met to discuss themes until agreement was reached.

### Styling Goals

Through qualitative coding, we identified seven categories of fashion problems. Online and in-person styling sessions involve many of the same fashion problems at different scale. For example, an online session might involve styling *one* item in a user's closet, whereas an in-person consultation would go through a client's *entire* wardrobe.

#### *Dressing for Occasions, Activities, and Seasons*

The most common user goal was getting advice on clothing for specific occasions, activities, and seasons such as dressing for a conference, a wedding, a hiking trip, or winter (n = 30). While some users were looking for particular items (e.g. warm pants), many were simply looking for inspirational photos. As one user asked, "*do you have any photos showing people actually attend[ing] a wedding*" (P3).

Some users framed their questions as "dressing for *x* but not looking *y*" (n=5). For example, one user wanted "*business casual clothing styles that aren't boring or boyish*" (P20); another user asked, "*How can I make the winter look more elegant?*" (P52). These questions indicate that many users have a core understanding of how to dress for events, activities, and seasons, but cannot reconcile it with their style aspirations. They look to stylists for help blending between what is appropriate for that context and their personal style. One of the interviewed stylists mentioned similar goals were common among her clients: wanting "*to look professional without looking really boring*" or "*professional but fun*" (S3).

#### *Matching or Styling Items*

Another common fashion problem was matching or styling clothing items together (n = 16). For example, several conversations began with a user describing something he owns — "*I have grey slacks*" (P58) — and then asking how to style it, either generally — "*What goes well with grey slacks?*" (P58) — or with other specific items — "*What about a lime shirt?*" (P58). Some users wanted to understand style rules for pairing specific items. For example, one user wanted to understand how to pair skinny pants with ankle boots: "*Are they supposed to be higher than the boots? or tucked into the boots?*" (P5).

The stylists interviewed mentioned that matching slightly off-color or off-style is often a major challenge for clients: "*If it doesn't exactly match, they don't think it goes. And yet, it may be even better if they don't quite match, either in style or colors*" (S3). Similarly, many stylists noted the phenomenon of "closet orphans," where clients "*didn't take the tags off such-and-such*" because they couldn't figure out how to wear it, but with the stylists' help, they found "*it turns out it goes with something else that they can wear*" (S3).

#### *Searching For Products*

Some users utilized PSBot as a wrapper for a search engine when shopping for specific items (e.g., boots, rain jacket, t-shirt) (n = 16). Unlike a search results gallery, a stylist communicating online provided information serially, and produced the next selection choice based on the reaction to the previous one. Working with a stylist helped users understand the underlying structure of the search space, learn the vocabulary to describe their requirements, and figure out what they want. For example, a user looking for men's dress shoes learned that there were broad subcategories such as oxfords, loafers, hush puppies, etc.

#### *Becoming Self-Reliant*

Most conversations had an educational undertone, where users were hoping to learn more generally about fashion, in addition to solving their specific problem. In some conversations (n = 13), users were explicitly trying to understand the vocabulary to do better searches, where to shop, and style rules (n = 13). Style-based questions ranged from general — "*Can I wear brown and black colors*" (P53) — to more personal — "*What colors look good on me – blue or black*" (P33).

#### *Transitioning Wardrobes*

Some users wanted help transitioning their wardrobe based on personal and environmental changes (n=8); the majority of clients who hired in-person stylists shared this same goal. For example, one user's goal was to get clothing for a new job: "*Starting a job soon – need recommendations for business casual clothing*" (P20). Others' questions were tied to dealing with changing seasons or even body shapes: "*I am trying to lose weight. What style pants look good as I change sizes?*" (P69).

#### *Minor Categories*

Looking "trendy" was only important a few users (n=4): "*Hey I'm looking for trendy fashion sneakers*" (P60). Another user asked, "*How can I make pajamas look trendy and wear them for all the daytime activities?*" (P52). For many users, trends were of secondary importance, and the goal was not to stick out. Interviewed stylists mentioned similar goals for their clients: "*my goal for them – and I tell them this specifically –*

is *'you don't have to be in style, but you shouldn't be noticeably out of style'*" (S3).

Similarly, only a few conversations focused around outfit suggestions for that particular day (n = 3). One user asked for an entire outfit, "*What should I wear to college today?*" (P25); others wanted feedback on one part of their outfit. Users were willing to describe what they owned to get help with this question.

Finally, a few users wanted advice on hair, makeup and skincare (n = 4): "What sort of makeup looks good on brown skin" (P53). We suspect that this category is much bigger than the numbers suggest, since users were unsure if these topics fell under the purview of fashion. One user explicitly asked, "I was wondering whether the style elements cover fashion or even skin health or makeup tips" (P22).

### Interaction Patterns

We also coded common interaction patterns we observed between users and stylists in their conversations. While in-person styling sessions afford inferential data gathering, in an online setting, stylists have to explicitly ask questions to gather personal data. On the other hand, it is easier for an online stylist to walk a client through the space of options with illustrative visual examples and dynamically produce recommendations that adapt to users' changing requirements.

#### *Communicating with Images and Text*

Images played an important role in conversations: on average, three images were sent during a conversation, and 70% of exchanges involved at least one image. Since users seemed to "know it when they see it," stylists often presented image-text pairs to explore and refine the search space with the user.

Half of the images shown in conversations fit this visual-verbal framing, which were used to *scaffold user uncertainty* and to *explain why*. For example, one user wanted a dress for a wedding, but did not know how to describe the silhouette she preferred — a shift (i.e., a dress with clean lines, ending around the knee, and less fitted around the waist and hips than

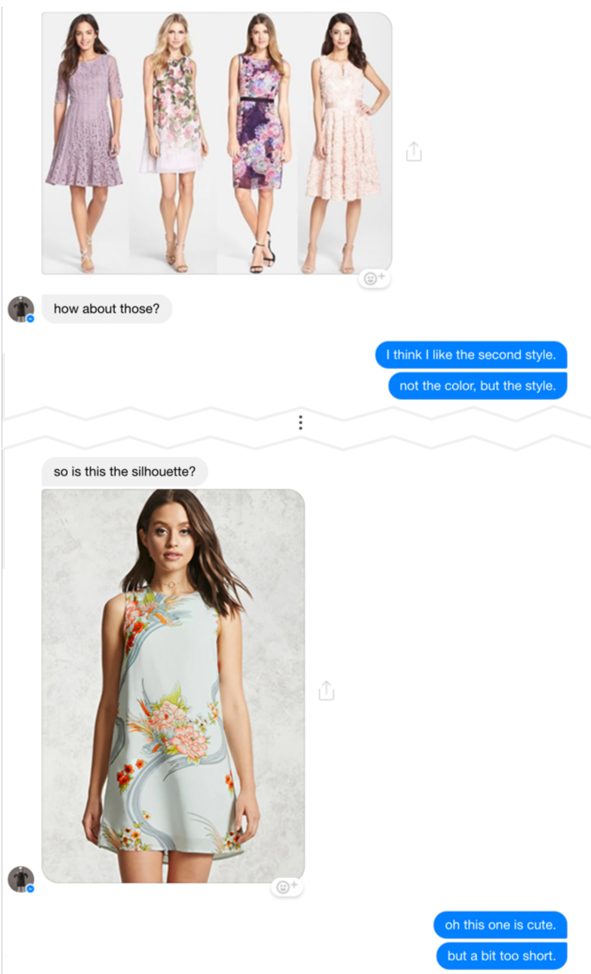


**Figure 3:** Stylists used images to help users specify what they were looking for when they lacked the specialized vocabulary of fashion. For example, here a stylist determined that the user was looking for a "shift" dress.

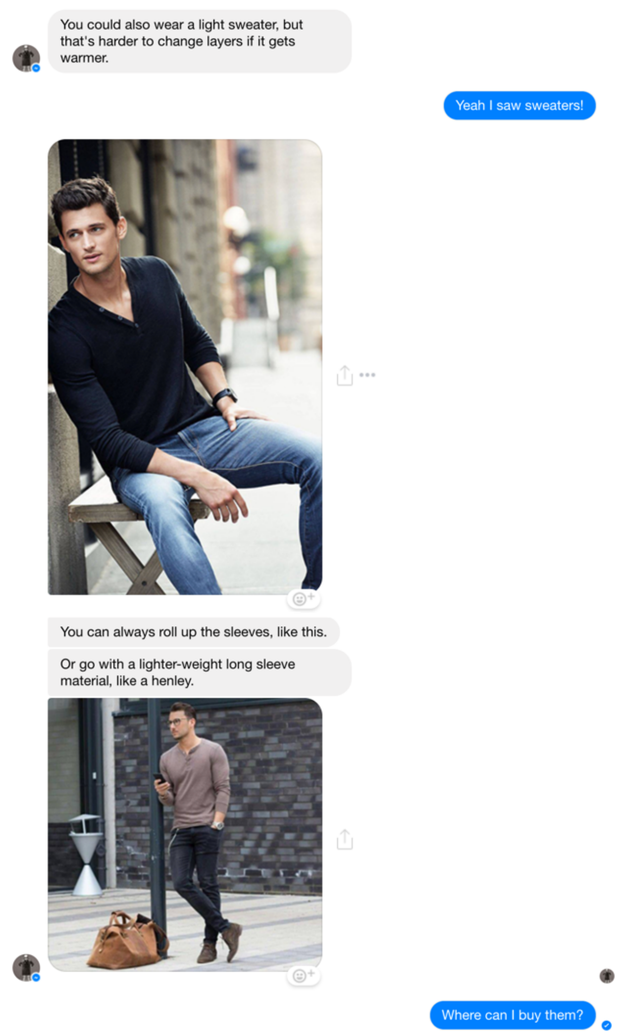


**Figure 4:** Stylists often paired images with text descriptions to communicate styling ideas.

a sheath). By iterating with images and questions, the stylist and user were able to determine what type of dress she was looking for (Figure 3). Similarly, another user looking for a spring outfit had some ideas of items he wanted to try — *"How about jeans?"* — but was not sure how to wear them (P9). The stylist paired images and text descriptions to show styling ideas and suggest new types of items (Figure 4). This example also illustrates that every detail cannot be communicated visually: through text, the stylist described the weight of a fabric, which is hard to judge just from the image.

### *Gathering Personal Data*

While many of the in-person stylists collected extensive information from clients prior to their meetings, online stylists did not spend time asking lengthy personal questions upfront. Instead, they collected additional information during the course of the conversation necessary for solving the problem at hand. Stylists frequently asked users to additonally specify desired color (n = 24), style (n = 17), budget (n = 14), print or pattern (n = 12), silhouette (n = 6), and length (n = 4). Stylists also asked for a user's location (n = 8) and skin color (n = 4).

### *Saying No (Nicely)*

Many PSBot conversations involved giving users critical feedback: those color combinations do not match, avoid certain silhouettes, that outfit might not be appropriate for an event, etc. While users were comfortable saying no bluntly — "*I don't like heels*" (P30) or "*those shoes are terrible*" (P16), — stylists used strategies to say "no" nicely. These strategies included using humor — "*Maybe for a costume party?*," — hedging — "*It's a little too colorful maybe*," — personalizing — "*I'd go with something a bit dressier*," — and providing explanations and alternatives — "*This is a more elegant look that would pair well with a beret*."

## DESIGN REQUIREMENTS FOR DATA-DRIVEN SYSTEMS

Based on the two need-finding studies, we distilled a set of recommendations for designing future data-driven fashion systems, which highlight both automation opportunities and challenges.

### Scaffolding Uncertainty with Example-Based Questioning

While most users had a general problem in mind when they engaged with PSBot, these problems were often underspecified. In many cases, users might not fully understand their own needs, they may lack the requisite vocabulary to specify the problem, or they may simply be lazy. For example, in one conversation (P4), the user initially asked for "clothes" (Figure 5). Therefore, solving fashion problems involves helping consumers define their needs and enumerate their constraints.

In online conversations, stylists navigated user uncertainty through a series of examples and questions that narrowed the user's search space. Automated agents could similarly scaffold user uncertainty: when the question is underspecified, they could probe users with relevant examples, leading to information gain that could be used to update the search space. There are several challenges that agents will have to overcome such as understanding the relevant parametric spaces for different types of problems, and recognizing when a user specifies or changes the value of a parameter explicitly or implicitly [29].

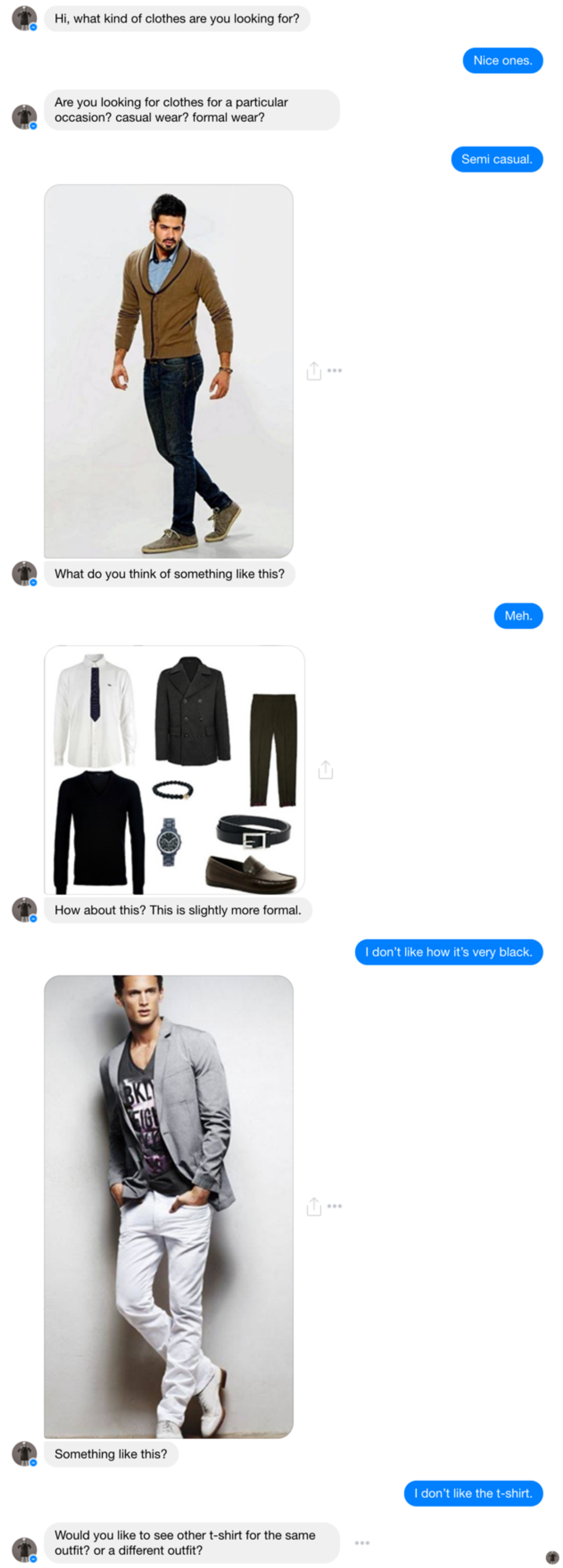


**Figure 5:** Underspecified queries were common. Online stylists used example-based questioning to resolve uncertainty and gather the information needed to provide good personal style advice.

On the other hand, data-driven models backed by sufficiently large databases are well-equipped to deal with content generation, and can provide an endless supply of relevant visual examples and corresponding questions while users figure out what they want. Consumers need not worry about taking up too much of a stylist's time or being charged by the hour: they can change their mind as often as they want until they are satisfied.

### Increasing Confidence by Explaining Why

Explaining why is a key component of every styling interaction: "*a phrase I often use is, 'I think we can do better than this,' and I can tell them why*" (S5). In online settings, PSBot was often used as a wrapper for a search engine to find a specific type of product (e.g., "rain coat"). Given the number of fashion items available today, there are often hundreds of products that belong to the same equivalence class even after filtering by average ratings and price ranges. A stylist can help users make purchasing decisions more efficiently and with *greater confidence* by offering fewer choices and *explaining why* they are the best.

In an online setting, rationales can be communicated through text, images, audio, and video. (Audio and video were not supported by PSBot.) Providing rationales is more of an embodied experience with in-person styling. A stylist can ask clients to "try it on," and offer explanations that combine visual and tactile reasoning.

In general, people know obvious rules such as "you wear coats in winter" and "black goes with everything." Both the interviews and online conversations illustrate that clients are asking hard questions — "*matching slightly off-color or off-style*" (S3) – with contradictory elements: people "*want to fit in and stand out at the same time*" (S2). Therefore, stylists cannot simply present solutions and expect that clients will understand the reasoning behind the recommendation.

As a result, data-driven models face the challenge of producing rationales to accompany their predictions. Without explanations, models trained on real, good outfit data, might appear to be generating recommendations at random to the untrained eye! In the future, conversational agents can leverage multi-modal fashion embeddings developed by AI researchers to generate textual explanations for visual recommendations and feedback [9, 12, 16, 21].

### Building Trust by Providing Unbiased, Critical Advice

In addition to increasing user confidence, explicative models also help build trust, which is a central design consideration for personal fashion interactions. Past work has shown that chatbots can perform emotional work when helping users [49]. Trust can be built through transparency and critical feedback. Today's search and recommendation engines only "push" products, and never prevent users from making bad decisions. On the other hand, stylists dissuade clients from making bad purchasing decisions all the time — that's what they are paid to do.

In both PSBot and in-person stylist interactions, being an unbiased, third-party allowed for greater trust. Unlike stylists who worked for retailers, independent stylists can care more deeply about their clients and offer better advice since they were not working on commision. Similarly, PSBot (unlike chatbots operated by brands or retailers) can offer advice that is not directly tied to purchasing: what colors look best with a user's skin tone, how to style items a user already owns, etc.

To gain a user's trust, a conversational agent should offer both advice educating users and critical feedback preventing them from making bad decisions. While other conversational agents may encounter this situation rarely, to establish trust with users and give good advice, stylist agents will often need to say 'no.' In both online and in-person contexts, stylists have strategies for giving constructive feedback such as using humor. Linguists have extensively studied best practices around saying 'no,' in English and cross-culturally [1, 3, 19], stressing the importance of balancing clarity and politeness. Again, since data-driven models are well-equipped to generate, if an agent needs to toss out a user's idea, they can provide alternative, preferable solutions: a strategy already used by humans.

## PERSONALIZING BEYOND BEING THERE

The interviews and online conversations illustrate that fashion *is* personal. As a designer noted in a phone conversation:

> *What makes [fashion] personal, is how you take something and translate it to your own. You can give ten different women, in different subcultures, the same blazer. But they're all going to digest it in a particular way. So the punk girl might cut the sleeves off, another girl might wear it buttoned up, and another person might wear it with the collar popped, one might roll up the sleeves and wear it with jeans, another one might wear it with a mini dress, another might wear it with big, giant sweatpants. That's what's personal about fashion.* [Jay McCarroll, personal communication]

Most personal stylists try to build long-term relationships with their clients. Initially, they do an intense onboarding process so that they can offer better, personalized advice. Clients are willing to partake in this process because they are investing time and money, and potentially also want a long-term relationship. After the upfront investment of building a personal relationship, clients can more efficiently interact with the stylist for more lightweight needs like outfit ideas for an event or a wardrobe refresh.

The attractiveness of a chatbot service is precisely that it does not require a lot of time and money: people can use it to get quick solutions to fashion problems. Still, users had expectations of personalized interactions, and found it disruptive when online stylists did not provide more personalized advice or results. One user wrote, "*Do you have any non-white models?*" (P29). Others shared personal information in the context of expressing concern with offered advice: one user wrote "*I have dark skin*" (P71) when given advice that "*darker colors will make you look slimmer*."

Since users cannot "try it on" in online settings, future systems can personalize experiences by showing photos of products on people with a similar figure or skin color to help them understand whether an outfit would work for them. These systems can leverage computer vision work done in the area of extracting skin color and body shape to automatically find images and videos that contain models that most closely fit the user's profile [17, 26].

Indeed, a few users expected online stylists to make substantial inferences about their physical attributes and preferences. For example, two users started out by asking the stylist to describe their style. We hypothesize that these users believed that Facebook Messenger apps have access to more Facebook data than is provided by default. Future systems might be able to proactively estimate style preferences from users' photos posted on Facebook or other social media platforms. The Messenger platform provides stylists with basic information such as name, gender, and approximate location. Additionally, it can provide a person's profile photo, which could be useful for inferential data gathering about body type and coloring. PSBot conversations indicate that in this context, users cared more about having personalized experiences than protecting their privacy. This result is surprising given that prior work has shown that data aggregation used in displaying targeted advertisements can cause feelings of unease and revulsion [48].

Although indvidual online sessions are less personal than working closely with a high-end personal stylist, in the long-term, data-driven systems have the potential of providing higher quality personalization. By capturing several individual sessions, an online system can build up a sophisticated, personalized model of a client's physical attributes, style preferences, and existing wardrobe over time. This information can be used to power new types of data-driven interactions: systems can proactively recommend new items that allow users to create more outfits with their existing wardobe. These types of services would be low-cost and low-overhead but provide deeper and better personalization over time.

These personalized fashion interactions have the potential to revolutionize ecommerce. There is a rich understanding of the model side of fashion problems: understanding styles [7, 40, 44, 46], trends [10, 11, 47], substitutes and complements [32, 31] and how to build outfits of matching items [45, 50]. Data-driven fashion systems can leverage these models to power interactions that provide free, private, constantly-available fashion advice.

## REFERENCES


1. Kathleen Bardovi-Harlig. 1996. Pragmatics and Language Teaching: Bringing Pragmatics and Pedagogy Together. (1996).
2. Sam Blum. 2017. Amazon's Newest Feature Gives You Fashion Advice from a Real Stylist. `https://www.thrillist.com/news/nation/amazon-prime-outfit-compare-judges-your-outfits-for-you`. (2017).
3. Yuh-Fang Chang. 2009. How to say no: An analysis of cross-cultural difference and pragmatic transfer. *Language Sciences* (2009).
4. Maurice Chu, Brinda Dalal, Alan Walendowski, and Bo Begole. 2010. Countertop Responsive Mirror: Supporting Physical Retail Shopping for Sellers, Buyers and Companions. In *Proc. CHI*.
5. Paolo Cremonesi, Antonella Di Rienzo, Franca Garzotto, Luigi Oliveto, and Pietro Piazzolla. 2016. Dynamic and Interactive Lighting for Fashion Store Windows. In *Proc. CHI Extended Abstracts*.
6. Laura Devendorf, Joanne Lo, Noura Howell, Jung Lin Lee, Nan-Wei Gong, M. Emre Karagozler, Shiho Fukuhara, Ivan Poupyrev, Eric Paulos, and Kimiko Ryokai. 2016. "I Don't Want to Wear a Screen": Probing Perceptions of and Possibilities for Dynamic Displays on Clothing. In *Proc. CHI*.
7. Wei Di, Catherine Wah, Anurag Bhardwaj, Robinson Piramuthu, and Neel Sundaresan. 2013. Style Finder: fine-grained clothing style detection and retrieval. In *Proc. CVPR*.
8. Adrienne Green. 2016. The Pull of Personal Stylists in the Online-Shopping Era. `https://www.theatlantic.com/business/archive/2016/07/personal-stylist-online-shopping-era/492491/`, (2016).
9. Xintong Han, Zuxuan Wu, Phoenix X Huang, Xiao Zhang, Menglong Zhu, Yuan Li, Yang Zhao, and Larry S Davis. 2017. Automatic spatially-aware fashion concept discovery. In *Proc. ICCV*.
10. Ruining He and Julian McAuley. 2015. Ups and downs: modeling the visual evolution of fashion trends with one-class collaborative filtering. In *Proc. WWW*.
11. Shintami C Hidayati, Kai-Lung Hua, Wen-Huang Cheng, and Shih-Wei Sun. 2014. What are the fashion trends in New York?. In *Proc. MM*.
12. Wei-Lin Hsiao and Kristen Grauman. 2017. Learning the Latent "Look": Unsupervised Discovery of a Style-Coherent Embedding from Fashion Images. In *Proc. ICCV*.
13. Paris (Pei-Ting) Hsu, Jingshu Zhao, Kehan Liao, Tianyi Liu, and Chen Wang. 2017. AllergyBot: A Chatbot Technology Intervention for Young Adults with Food Allergies Dining Out. In *Proc. CHI*.
14. Kuan Huang. 2017. Poncho. `https://poncho.is/`. (2017).
15. Ting-Hao Kenneth Huang, Walter S Lasecki, Amos Azaria, and Jeffrey P Bigham. 2016. "Is there anything else I can help you with?": Challenges in Deploying an On-Demand Crowd-Powered Conversational Agent. In *Proc. HCOMP*.
16. Naoto Inoue, Edgar Simo-Serra2 Toshihiko Yamasaki, and Hiroshi Ishikawa. 2017. Multi-Label Fashion Image Classification with Minimal Human Supervision. In *Proc. CVPR*.
17. P. Kakumanu, S. Makrogiannis, and N. Bourbakis". 2007. A survey of skin-color modeling and detection methods. *Pattern Recognition* 40, 3 (2007). DOI: `http://dx.doi.org/https://doi.org/10.1016/j.patcog.2006.06.010`

18. Kik. 2017. Kik Bot Shop - Fashion & Beauty. https://bots.kik.com/#/category/fashion-and-beauty. (2017).
19. Susan L Kline and Cathy Hennen Floyd. 1990. On the art of saying no: The influence of social cognitive development on messages of refusal. *Western Journal of Speech Communication* (1990).
20. Ranjitha Kumar and Kristen Vaccaro. 2017. An Experimentation Engine for Data-Driven Fashion Systems. In *Proc. AAAI Spring Symposium*.
21. Katrien Laenen, Susana Zoghbi, and Marie-Francine Moens. 2017. Cross-modal search for fashion attributes. In *Proc. KDD Workshop on Machine Learning Meets Fashion*. ACM.
22. Walter S Lasecki, Rachel Wesley, Jeffrey Nichols, Anand Kulkarni, James F Allen, and Jeffrey P Bigham. 2013. Chorus: a crowd-powered conversational assistant. In *Proc. UIST*.
23. Justin Lees. 2016. Ask me anything: AnzacLive chatbot brings WW1 hero Archie Barwick to life on Facebook Messenger. http://bit.ly/2nRxB0F. (2016).
24. Jingyi Li, Michelle X Zhou, Huahai Yang, and Gloria Mark. 2017. Confiding in and Listening to Virtual Agents: The Effect of Personality. In *Proc. IUI*.
25. Christine M. Liu and Judith S. Donath. 2006. Urbanhermes: Social Signaling with Electronic Fashion. In *Proc. CHI*.
26. Ziwei Liu, Sijie Yan, Ping Luo, Xiaogang Wang, and Xiaoou Tang. 2016. Fashion landmark detection in the wild. In *Proc. ECCV*.
27. Kiel Long, John Vines, Selina Sutton, Phillip Brooker, Tom Feltwell, Ben Kirman, Julie Barnett, and Shaun Lawson. 2017. “Could You Define That in Bot Terms"?: Requesting, Creating and Using Bots on Reddit. In *Proc. CHI*.
28. Ewa Luger and Abigail Sellen. 2016. “Like Having a Really Bad PA": The Gulf Between User Expectation and Experience of Conversational Agents. In *Proc. CHI*.
29. Shane Mac. 2017. There are a dozen ways to order a coffee. Why do dumb bots only allow one? http://bit.ly/2nDGjCn. (2017).
30. Nikolas Martelaro and Wendy Ju. 2017. WoZ Way: Enabling Real-time Remote Interaction Prototyping & Observation in On-road Vehicles. In *Proc. CSCW Companion*.
31. Julian McAuley, Rahul Pandey, and Jure Leskovec. 2015a. Inferring networks of substitutable and complementary products. In *Proc. KDD*.
32. Julian McAuley, Christopher Targett, Qinfeng Shi, and Anton van den Hengel. 2015b. Image-based recommendations on styles and substitutes. In *Proc. SIGIR*.
33. Meredith Ringel Morris, Kori Inkpen, and Gina Venolia. 2014. Remote shopping advice: enhancing in-store shopping with social technologies. In *Proc. CSCW*.
34. Dennis Mortensen. 2016. Understanding the Facebook and Microsoft Chatbot Revolution. http://bit.ly/2jvqpod. (2016).
35. Dennis R. Mortensen. 2017. X.Ai. https://x.ai/. (2017).
36. rAVe Publications (Producer). 2016. DSE 2016: Magic Mirror Is an Interactive Engagement Display Using Intel RealSense Technology. https://www.youtube.com/watch?v=AMw7Ci8FxP4. (2016).
37. Margaret Rhodes. 2016. Now You Can Buy Burberry Stuff Straight Off the Runway. https://www.wired.com/2016/09/now-can-buy-burberry-stuff-straight-off-runway/, *Wired* (2016).
38. Eitan Sharon. 2017. Mode AI. http://mode.ai/. (2017).
39. Dena Silver. 2017. Amazon’s Echo Look Is Basically a Personal Stylist. http://observer.com/2017/04/amazon-echo-look-fashion-technology/. (2017).
40. Edgar Simo-Serra and Hiroshi Ishikawa. 2016. Fashion style in 128 floats: joint ranking and classification using weak data for feature extraction. In *Proc. CVPR*.
41. Michael R. Solomon. 1987. The Wardrobe Consultant: Exploring the Role of a New Retailing Partner. *Journal of Retailing* 63 (1987).
42. Stitch Fix 2017. Stitch Fix. http://www.stitchfix.com. (2017).
43. Hitomi Tsujita, Koji Tsukada, Keisuke Kambara, and Itiro Siio. 2010. Complete fashion coordinator: a support system for capturing and selecting daily clothes with social networks. In *Proc. AVI*.
44. Kristen Vaccaro, Sunaya Shivakumar, Ziqiao Ding, Karrie Karahalios, and Ranjitha Kumar. 2016. The Elements of Fashion Style. In *Proc. UIST*.
45. Manasi Vartak and Samuel Madden. 2013. CHIC: a combination-based recommendation system. In *Proc. SIGMOD*.
46. Andreas Veit, Balazs Kovacs, Sean Bell, Julian McAuley, Kavita Bala, and Sean Belongie. 2015. Learning visual clothing style with heterogeneous dyadic co-occurrences. In *Proc. ICCV*.
47. Sirion Vittayakorn, Kota Yamaguchi, Alexander Berg, and Tamara Berg. 2015. Runway to realway: visual analysis of fashion. In *Proc. WACV*.
48. Sara Watson. 2014. Data Doppelgängers and the Uncanny Valley of Personalization. https://www.theatlantic.com/technology/archive/2014/06/data-doppelgangers-and-the-uncanny-valley-of-personalization/372780/, (2014).
49. Anbang Xu, Zhe Liu, Yufan Guo, Vibha Sinha, and Rama Akkiraju. 2017. A New Chatbot for Customer Service on Social Media. In *Proc. CHI*.
50. Lap-Fai Yu, Sai-Kit Yeung, Demetri Terzopoulos, and Tony F Chan. 2012. DressUp! outfit synthesis through automatic optimization. In *Proc. SIGGRAPH Asia*.