The Ensemble-Building Challenge for Fashion Recommendation:

Investigation of In-home Practices and Assessment of Garment Combinations

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Fashion is a domain that poses new and interesting challenges for recommender systems. While most recommendation problems seek a single-point solution (e.g. a product the user will purchase), individual garments must function within a wardrobe system, and must ultimately be matched with other garments to build an outfit. The outfit-building challenge is poorly understood in academic literature and professional practice. Here, we present data from two sources: subjective self-reports from consumers about their outfit-building practices, and assessments (by expert and crowd-sourced assessors) of computer-generated outfit combinations pulled from a real-world wardrobe. Results illuminate the objectives and obstacles of consumers in the daily dressing decision, and support the complexity of building combinations from a large set of individual garments.

CCS CONCEPTS •Information systems~Information retrieval~Retrieval tasks and goals~Recommender systems•Human-centered computing~Human computer interaction (HCI)~HCI design and evaluation methods~User models

Additional Keywords and Phrases: Fashion recommendation, clothing recommendation, consumer behavior, wardrobe management, dressing behavior

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1 INTRODUCTION

"What am I going to wear?" is a question faced daily by a large portion of the world's population. For some, the answer is simple and direct, and for others it requires a complex, resource-constrained decision-making process. Guy, Green, and Banim [3] describe this process as the "wardrobe moment", a daily mini-crisis in which the individual's wardrobe management techniques are put into play in a time-restricted problem-solving challenge.

The motivations that influence consumption patterns and garment choices in shopping contexts are well-characterized in the clothing and retail literature [10,15] but little is known about the functional management of those garments at home or the influence of system management on consumption. Management of such a complex system is a non-trivial task involving many inter-related variables [7]. Because of the many constraints on cognitive resources during the wardrobe moment, users are likely to employ decision-making heuristics such as satisficing strategies (ceasing search at a "good enough" solution) or availability heuristics and be influenced by cue order (prioritization of garments seen first.) They are also likely to be subject to the size constraints of working memory (generally agreed to be seven +/- two items [8].) These factors lead to the reinforcement of a smaller number of items that may consequently become disproportionately utilized, while other garments fall into disuse. This is supported by our prior work with small numbers of participants [2,13], which show as little as 5% of the wardrobe in regular use.

The challenge of assembling an outfit from component garments is relatively under-studied. Approaches like collaborative filtering based on user and garment attributes [5,6], classification of "good" (human-generated) from "bad" (artificially created) outfits [11], and discovery of item compatibility across types [12] have been implemented toward the goal of developing methods of effectively building ensembles. However, these approaches often represent an outfit by only one top and one bottom (neglecting more complex outfits) and are based collections of garments from online marketplaces or social networks rather than actual wardrobes. The home wardrobe is a collection curated for the most part by one individual, which may offer some coherence to the components. However, while outfit-building from online repositories may be an exercise in creative exploration (assembling an interesting whole from relatively unlimited resources), managing the home wardrobe is far more resource-constrained, and relies more heavily on combination and re-combination of existing elements. Understanding the parameters and scope of that task is vital to the success of an in-home wardrobe decision-making assistant. Here, we explore the in-home problem from two angles: first, by investigating the challenges, values, and strategies of individual decision-makers in order to better understand how individuals are currently experiencing and managing the complexity of the dressing decision. Second, we form outfits from permutations of garments in a real individual wardrobe, and assess the resulting outfits for wearability in order to better understand the full scope of the decision's complexity.

2 IN-HOME OUTFIT BUILDING STRATEGIES

2.1 Methods

To explore the strategies currently used by individuals to choose clothing daily, we conducted an online survey of 194 respondents which is the basis of the bulk of the results presented here. The survey was conducted with participants recruited from Amazon Mechanical Turk, filtered for location (USA only). Respondents were paid $0.50 each for their participation. Participants ranged in age from 18 to 63, 128 were female, and 66 were male. Participants in all instruments used here were assigned a score indicating their position on the consumer spectrum according to a distribution originally described by Rodgers [9] that identifies 5 groups of consumers: fashion innovators, fashion opinion leaders, mass-market consumers, late fashion followers, and fashion isolates and laggards. Consumers on the innovative end of the scale are more likely to make choices based on a desire to differentiate themselves from others, while consumers on the lagging end of the scale are more likely to seek conformity with their social group [1]. To calculate consumer spectrum score, we used a set of nine five-point Likert scale questions derived from [4] and [1], assigning points on an inverse scale for self-reported behaviors relating to level of creativity in dress, adoption of new fashion trends, and influence on others' fashion consumption behaviors, for a total spectrum of possible scores from nine (laggard) to 45 (innovator). The consumer-spectrum distributions of our survey participants are depicted in Figure 1.

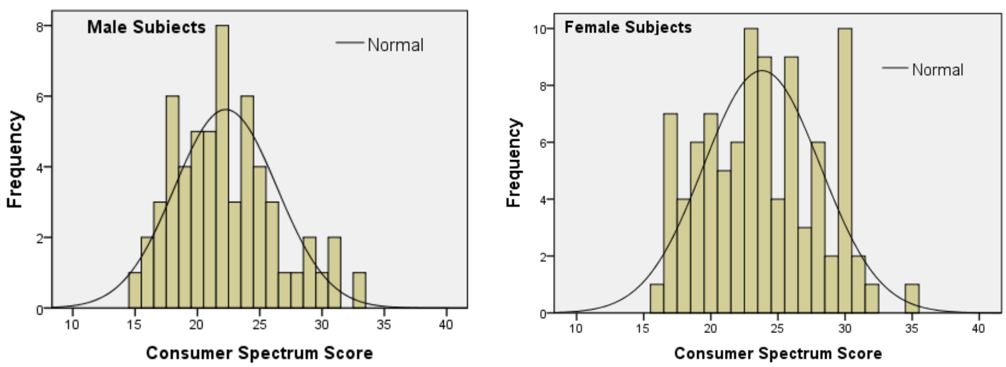

Figure 1: Distribution of respondents in terms of calculated Consumer Spectrum Score

The survey covered variables related to the wardrobe moment in five categories, as developed using the preliminary pilot surveys and interviews. The objective of this survey was to investigate the critical variables of dressing and the wardrobe moment that had emerged from our preliminary work. The five categories of questions included were: (1) Perceived wardrobe size and use; (2) Values and objectives in dressing; (3) Constraints of the wardrobe moment; (4) Variables at play in the dressing decision; (5) Outfit-building strategies.

2.2 Results and Discussion

2.2.1 The Wardrobe System

The survey respondents were asked to estimate the size of their "working wardrobe", defined as "the overall number of garments you would wear to work/school or your regular daytime activity". Participants were directed to include only tops, bottoms, dresses, and jackets in their estimates, excluding hosiery, undergarments, outerwear, accessories, etc. Participants who did not have a regular daytime activity or who wore a uniform to work were asked to discontinue the survey. Participants reported average working wardrobe sizes of 25.49 garments (male, SD=22.08) and 36.72 garments (female, SD=40.78). When asked to estimate more specifically by reporting numbers of garments in sub-categories (tops, bottoms, and dresses), these averages rose slightly to 27.89 (SD=21.05) for male participants and 42.10 (SD=42.31) for female participants. We saw no strong relationships between wardrobe size and consumer spectrum score for men or for women. This finding contrasts with earlier studies such as Workman and Johnson [14] who found significant differences between fashion innovators and fashion followers in need for variety. However, notably such prior work has assessed self-perceptions and desires in dressing, and has not related these theoretical perspectives with empirical assessment of wardrobe contents.

Survey respondents estimated the percent of their wardrobe in "regular use" (defined as garments worn once per month or more) at 63.00% for female participants (SD=30.41) and 57.92% for male participants (SD=34.8).

These results show a vast spectrum of system complexity for the wardrobe across the population. Using a very simplistic combinometrics calculation, a woman's wardrobe of the average size reported by survey respondents (13 bottoms, 24 tops, and five dresses), assuming half of the tops can be worn under the other half, could amount to 1,877 outfits (13*12*12+5). However, some real wardrobes may be far larger and more complex. A wardrobe of the average size reported in [2] (50 bottoms, 159 tops, and 36 dresses) could amount to 316,036 outfits (50*79*80+36).

2.2.2 Objectives in Dressing

Behind the question of the utility of an in-home wardrobe recommender system is the question of what the user aims to achieve in dressing. What implicit values should the system be designed to support? Toward this end, we asked our survey respondents to rate on a five-point Likert scale the level to which 12 value statements were true for them. The results for the statements as described below are summarized in Figure 2.

1. I want to look my best or improve the way I look
2. I want to make use of everything I own and waste as little as possible
3. I want to look trendy and keep up with current fashion
4. I want to have fun putting together outfits, be creative, and express myself
5. I want to fit in and look appropriate every day
6. I want to dress to flatter my body
7. I want to reduce my consumption of clothing
8. I want to be comfortable (physically) in my clothes every day
9. I want to look unique and different in the way I dress
10. I want to get dressed as quickly as possible
11. I want to spend less money on clothing
12. I want to do laundry less often

As Figure 2 shows, the overall most important objectives for female participants were comfort and dressing to flatter the body. Comfort was the clear leader for men as well, followed by a desire to dress quickly. Of secondary interest for both men and women were looking good and wasting as little as possible in the wardrobe. Fitting in and looking appropriate was of fairly strong interest to both genders, but this factor was stronger than looking good/decreasing waste for men.

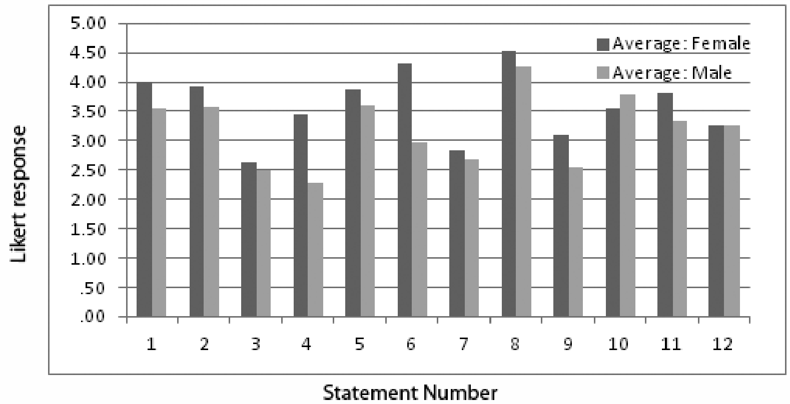

Figure 2: Male and female participants' ratings of value statements

Following current trends was of little interest to men or women, and men similarly showed even less interest in having fun/expressing themselves when putting together outfits.

Some factors showed an influence of consumer spectrum score. For instance, the value statement "I want to look unique and different in the way I dress" was more likely to be higher-rated by respondents with higher consumer spectrum scores, as shown in Figure 3.

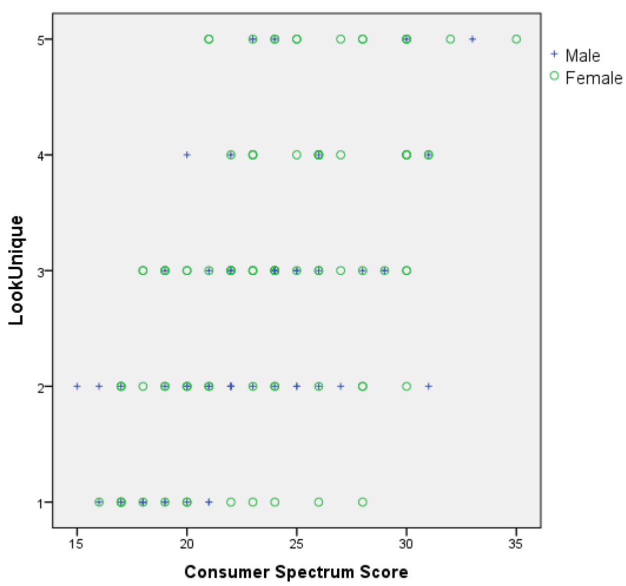

Figure 3: Influence of consumer spectrum score on importance of uniqueness in dressing

A similar effect was seen for both male and female participants in ratings of the "I want to have fun" statement, and the "I want to look better" statement, and for male participants in the "I want to flatter my body" statement. A slight negative relationship was observed for both male and female participants between consumer spectrum score and rating of the statement “I want to get dressed as quickly as possible”, as seen in Figure 4. No visible effect was seen in the other value statements.

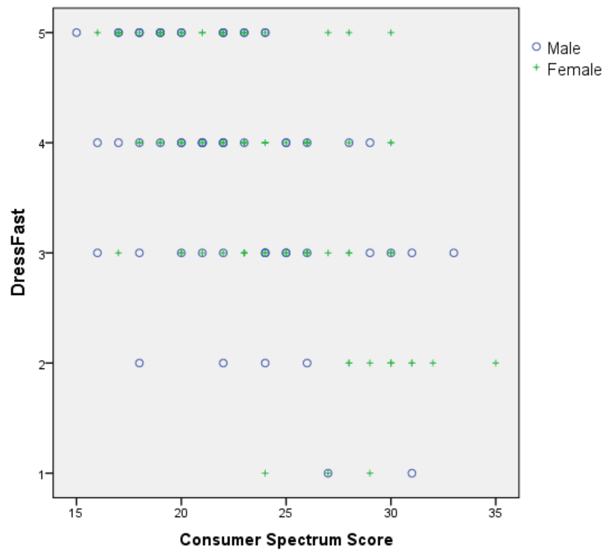

Figure 4: Influence of consumer spectrum score on importance of speed in dressing

These results imply that there are some more-universal objectives held by users across the consumer spectrum in the wardrobe moment. The objective of being comfortable is perhaps one of the more difficult to capture in a recommender system, given the lack of standardized metrics of fit and haptic preferences in clothing. Characterizing “comfort” is a complex and nuanced task. The more-universal value of looking good, however, implies that many user types would be interested in a decision-support system that augments their aesthetic abilities, or helps prescribe outfits that are likely to be aesthetically successful. An open question for the development of good recommender systems is the precise influences on aesthetic success. Women seem to be more sensitive to the role of body shape in aesthetic success of an outfit than men are, and recommendation systems should likely take body shape into account for women. Male fashion innovators seemed more sensitive to the role of body shape in dressing success, while men across the spectrum were more interested in fitting in and looking appropriate. Women and fashion innovators were more interested in expressive experiences in dressing, at the expense of efficiency in decision-making. Both genders were interested in decreasing waste in the wardrobe. This supports the idea that a recommender system might extend to point-of-purchase decisions, to avoid purchases that are unlikely to provide utility in outfit recommendations.

Interestingly, users were much less interested in trendiness in their dressing decision. Many studies seek to augment the ability to identify and incorporate trends into fashion recommendation. However, it seems that the majority of users are much less interested in trend-following than they are in improving their individual appearance. It is possible, of course, that these two things are intertwined in ways that the user may not be conscious of. It is also possible that users interpret being “trendy” in a negative way (either because they don’t perceive their choices as part of a larger trend framework, or because they seek to differentiate from mass-market trends).

2.2.3 Constraints of the Wardrobe Moment

In our studies, time spent deciding what to wear imposed a significant constraint on the decision-making process. We found 61.54% of male respondents reported spending less than five minutes dressing on an average day, and 95.39% spent less than 10 minutes dressing. We found 42.97% of female respondents spent less than five minutes on an average day, and 80.47% spent less than 10 minutes. On a “special” day, 38.46% of male participants and 60.94% of female participants reported spending more than 10 minutes on this decision.

Participants were asked to evaluate on a five-point Likert scale the degree to which or the frequency with which a set of variables increased the difficulty of their daily dressing decision. These variables and the average level of influence reported by male and female participants are shown in Figure 5. Unlike the set of values outlined in the previous section, none of these variables showed a visible relationship to consumer spectrum score.

For female respondents, the most significant sources of dressing difficulty were trouble with aesthetics/looking good, finding an outfit that meets today’s needs, and having too few options. Male respondents showed overall lower levels of difficulty arising from these variables, but the most significant sources of difficulty were having too few options, finding an outfit that meets today’s needs, and not having anything clean. Having too many options was the least significant source of difficulty for both male and female respondents: an interesting result, considering the evidence discussed above of wardrobe size and percent in use. This may be evidence of boredom with an over-reinforced subset of the population (a result of decision-making heuristics at play) rather than a true lack of options.

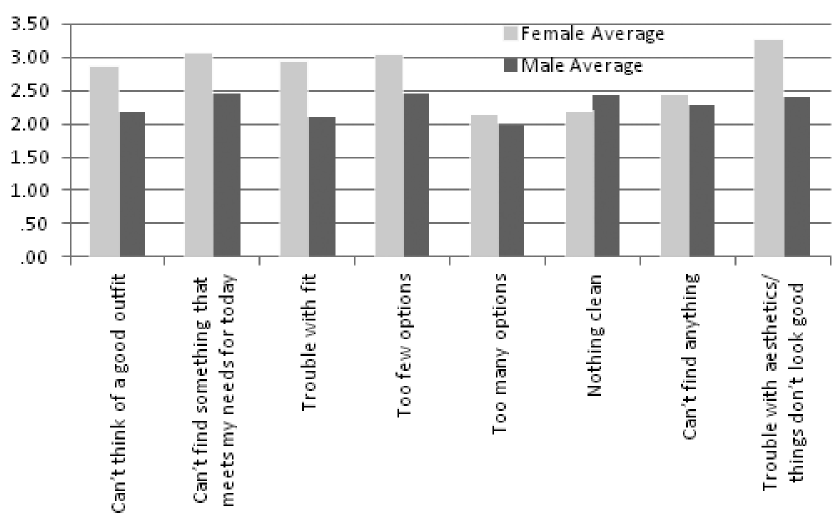

Figure 5: Male and female participants’ ratings of variables increasing the difficulty of the dressing decision

Interestingly, the sum of all difficulty ratings for each user (total difficulty) showed no evident relationship to consumer spectrum score. This would indicate that users across the spectrum experience high and low levels of difficulty in dressing. However, the variables influencing difficulty are not likely to be consistent across all users, and must be customized to the individual.

2.2.4: Variables of the Wardrobe Moment

The variables outlined in the previous section describe constraints or sources of difficulty in making the dressing decision: areas where a recommender system might offer assistance to the user. In addition to these constraints, we queried respondents about the variables that influenced the decision of what garments should be worn together and on a given day: variables that will assist the system in generating "good" recommendations. This brings into play temporal variables that are related to the day in question, as well as probing individual priorities in evaluating the goodness of an outfit.

We asked participants to rate on a five-point Likert scale how often or how much a set of variables factored into their daily dressing decision. Those variables and the mean of male and female participants' responses are shown in Figure 6.

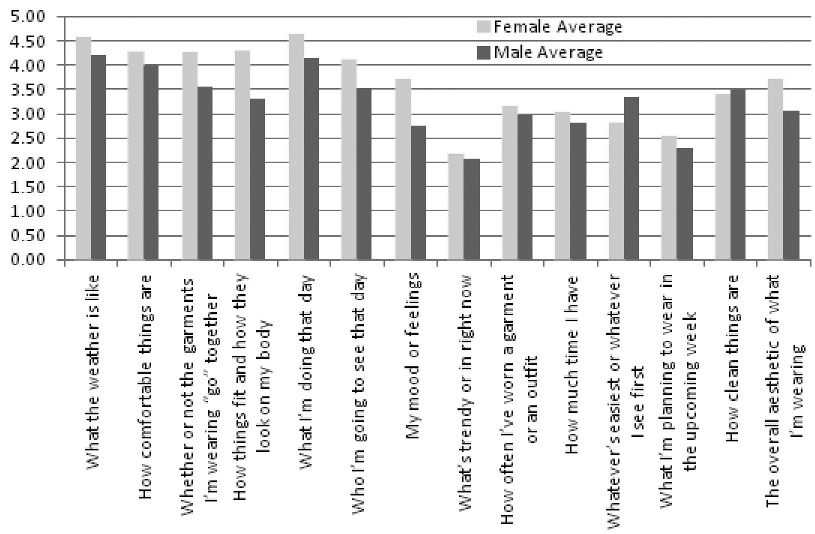

Figure 6: Male and female participants' ratings of variables influencing the dressing decision

As seen in Figure 6, the order of relative influence of variables is not exactly the same between male and female respondents: female respondents prioritize the aesthetic element of fit over the comfort component, while male respondents rank the aesthetic component far less influential. For female participants, mood takes precedence over cleanliness, where for male participants, cleanliness and ease of access are far higher in priority. We see similar influence of consumer spectrum score on some variables: fashion leaders are more likely to prioritize overall aesthetic than fashion followers, but the opposite is true for wearing whatever's easiest or seen first, as seen in box plots in Figure 7.

These data illuminate potential differences in sub-groups of users. Some users may appreciate a pragmatic recommender system that accounts for logistical variables like weather, activity, and laundry status and prioritizes speed of the dressing decision. Others may appreciate an exploratory system that affords inspiration rather than prescriptive advice. As might be expected from typical socialization, women seem more sensitive to aesthetic elements that influence coordination of garments and suitability for a given body shape.

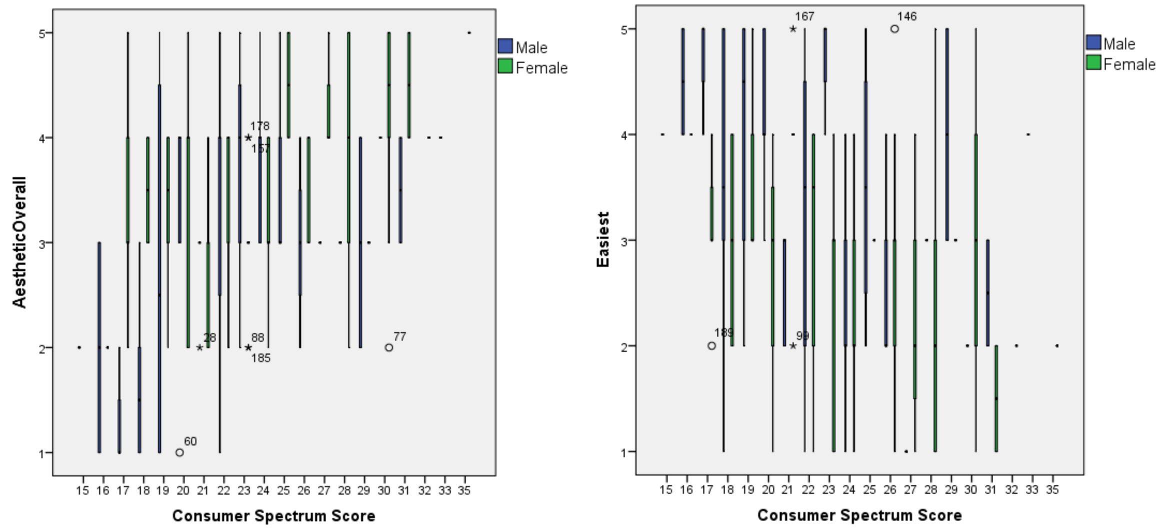

Figure 7: Influence of consumer spectrum score on importance of overall aesthetic (a) and ease of dressing (b)

2.2.5: Outfit-Building Strategies

Lastly, we sought to investigate the strategies at play when respondents began building an outfit in the wardrobe moment. This category has implications for user interface design. In our preliminary work, which involved more open-ended questions about dressing, many participants reported employing a consistent starting-point in their outfit-building process. Many users cited starting with a single garment (most often the bottom) to build an outfit ("I usually pick out one item I think is particularly appropriate, and build an outfit around it."), but others describe this as a more emotional choice: "I decide which color would match my mood (i.e. I feel....yellow today). I then check the weather to see which items I can combine that have that color and mood and still be practical." As with most of the factors investigated here, in the wardrobe moment these heuristics often help the user to limit the immense quantity of possible options.

Survey participants in this study were asked to indicate which of a set of possible choices (generated from earlier preliminary work) was their most common starting-point in outfit building. As seen in Figure 8, this is most commonly a top or a bottom garment, but there is some variability between male and female participants, as well as some evidence of other starting-points in use.

Again here, male users are more motivated by pragmatics and efficiency (starting with whatever is first seen or clean) than female users, who may start with a color or a favorite garment. Interestingly, male users were more equally likely to start with a top or a bottom, while female users had a clear preference for starting with tops. Together, these results suggest that a recommendation system should start the interaction by offering (or allowing the user to select) a single garment, and building an outfit around that garment. However, for some users, other options may be of interest.

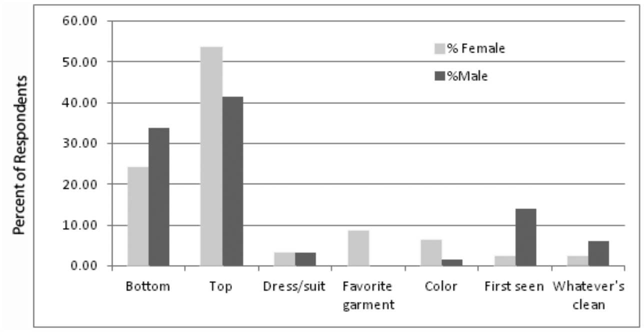

Figure 8: Most common starting point in outfit building

3 ASSESSING GARMENT COMBINATIONS

The crude combinometrics calculation described in Section 2.2.1 at first glance seems improbably high. How many of those garment combinations are actually usable outfits? To approach this question, we used the real-life working wardrobe of one female "fashion innovator" participant and built all possible outfit combinations. A random sample of outfits was assessed by a panel of raters to determine the proportion that is feasibly "wearable".

3.1 Method

Our test wardrobe consisted of 137 items cataloged from a female user's wardrobe: 77 tops, 10 bottoms, 10 dresses, and 5 jackets. Tops were categorized as one of 3 layers (inner, garments that are worn under things; middle, garments that can be worn alone or above the inner layer; and outer, garments worn above inner and/or middle garments.)

Each bottom was combined with each inner-layer and middle-layer top, to form the first set of outfits. Then, middle-layer tops were added to inner-layer+bottom outfits. Outer-layer garments were then added to all previous outfits. Finally, dresses were added as single-layer outfits, as well as in combination with each outer-layer top. This algorithm generated 491,185 total outfits. Garments were used in an average of 22.5 outfits, with a distribution between 1 and 70 garments (Figure 9).

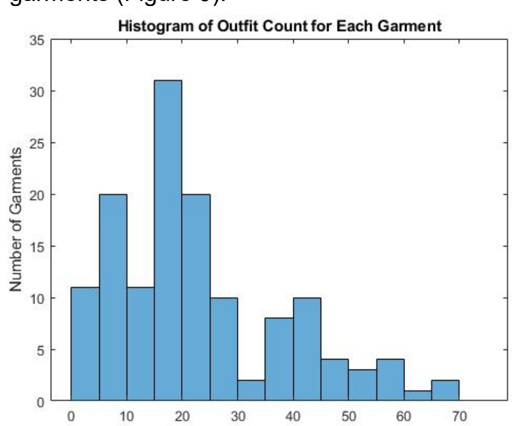

Figure 9: Number of outfits per garment

3.1.1 Rating Outfits

A random sample of 1000 outfits was extracted for evaluation from all possible outfits. Each outfit was rated on a 5-point rating scale as follows:

5: This is a great outfit; I can imagine someone looking good wearing exactly this.

4: This is an ok outfit. It might have some style problems, or it might be a little bland, but it's wearable.

3. This is a wearable outfit, but it has some problems. These garments could technically be worn together, but the outfit doesn't work very well.

2: This outfit has serious problems, it would be hard to imagine someone wearing it, but a few people might.

1: This outfit is not wearable; I can't imagine anyone wearing it in public.

The objective of this rating scale was to assess whether or not outfits were “wearable” – and to avoid to the extent possible individual preference, trend, or styling assumptions. Garments were photographed individually, lying flat on a surface (not on a body), and “outfits” were presented as a series of garment photographs. Each outfit was evaluated by 5-7 raters (mean 6.64): 3 “expert” raters (members of the research team, following a calibration exercise) and 2-4 crowdsourced raters. Crowd raters were drawn from 3 sources: our Apparel Design program, targeted advertisements on Facebook, and Amazon Mechanical Turk.

3.2 Results and Discussion

Figure 10 shows a histogram of outfit ratings, separated by rater group (expert = research team, lay = crowdsourced, overall = both).

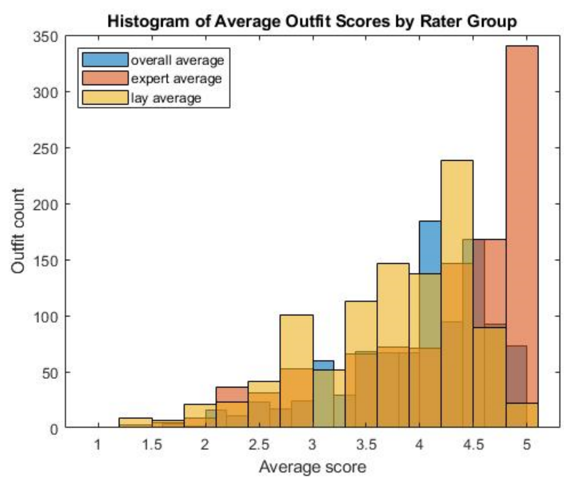

Figure 10: Average outfit score by rater group

Table 1: Percentages of wearable outfits by rater group

Outfit Rating	All Raters	Expert Raters	Lay Raters
>=3 (Could technically be worn together)	90.1%	91.6%	86.0%
>=4 (An “ok” outfit)	61.0%	72.5%	48.6%
=5 (A “great” outfit)	1.2%	34.0%	2.2%

As seen in Figure 10 and Table 1, the vast majority of outfits were perceived as “wearable”. Expert raters trended toward higher scores than lay raters, which may reflect less of a bias toward personal interpretation of each outfit (a broader perspective on whether or not a set of garments could possibly be successful on some individual). Most remarkable is the difference in “5” score outfits (“I can imagine someone looking good wearing exactly this”) – lay raters found only 2.2% of outfits to meet this criteria, vs. 34% for expert raters. Interestingly, this may point to the critical “last mile” of fashion recommendation – the gap between a set of garments and those garments being filtered for an individual wearer and styled effectively. When garments are presented without the context of a specific body in 3 dimensions and specific styling choices (shirts tucked in or out, accessories added, etc.) it is unclear how lay users might draw conclusions about the success of an outfit. An expert may be able to imagine a broader range of options and implementations for a set of garments than a lay person, and communicating that expertise is critically important to the resulting dressing decision. This would imply that the best-case recommender system is able to generate an outfit option visualized on a 3D body, complete with styling recommendations. However, this obviously introduces far more complexity into the recommendation and visualization tasks.

It is important to note, however, that while the vast majority of outfits were perceived as wearable, this method is not able to distinguish between perceptually similar outfits: e.g. a sweater worn over several inner-layer tops may present visually the same outfit, but be counted as distinct outfits in this algorithm. Raters did not compare outfits to each other, and would not have looked for repetition in the test set. However, given the size of the set of possible outfits, it is unlikely that much perceptual similarity was present in the test set.

4 CONCLUSIONS

The results from our survey of individuals’ experiences with the everyday dressing decision highlights consistencies and variation across the consumer spectrum and between individuals in the objectives, obstacles, and strategies employed in the wardrobe moment. Individuals self-report working wardrobe sizes that are relatively small compared to other evidence. Nevertheless, even a small working wardrobe can theoretically produce a vast number of outfit permutations. It is clear that recommender systems can aid users in the efficiency of their dressing decisions and their wardrobe use, and perhaps in improving the aesthetics of their outfit choices. Other objectives like comfort may be harder for recommender systems to influence. Our results also highlight that in some domains, in-home outfit recommendation will require different approaches for different individuals, in order to account for values and priorities as well as sensitivities and preferences: for example, some users may prefer utilitarian systems that prioritize efficiency while others may prefer exploratory systems that afford inspiration and creativity.

The results of our outfit assessment show that both crowdsourced and expert raters find most outfits to be wearable. Even the most conservative assessment – using the 1.2% of outfits that were rated 5 (a “great” outfit) by both expert and crowdsourced raters – yields 5,894 successful outfits from our example wardrobe.

However, this result conflicts with user reports of difficulty finding good options and time spent making a selection. Expert and crowdsourced raters in this study evaluated outfits independent of key variables that may determine the ultimate success or failure of an outfit (the variables considered by users in their dressing decision, such as the wearer's physical attributes, contextual elements like weather and activity, and personality aspects that influence aesthetic preferences.) It is clear that there is more work to be done to better understand the underlying factors that predict a successful outfit. Clearly successful outfit recommendation must ultimately account for the wearer and filter the outfit set accordingly. Understanding these relationships (between garments/outfits and the wearer's attributes) is a further challenge for outfit recommendation.

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