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Review and synthesis of expert perspectives on user attribute and profile definitions for fashion recommendation

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ABSTRACT

A key obstacle in personalised fashion recommendations is the challenge of capturing user physical attributes at a large scale, which limits exclusively computational methods (like machine learning) to readily available attributes whose influence on recommendation accuracy is variable. Expert advice is a potential means of identifying influential user attributes. However, individual experts often disagree or offer conflicting advice. Thus, identifying areas where expert advice is or isn't consistent, in the context of user attributes and profiling is critical. Here, we characterise the breadth of expert definitions of user attributes and profiles through an exhaustive assessment of 156 years of advice literature. Expert definitions of body colouring, shape, and personality attributes are extracted and compared. The range of attribute-value relationships and profile definitions in each domain is described, and coherence among authors for each domain is discussed.

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1. Introduction

As consumers turn more frequently to online fashion shopping channels, searching the product space is a persistent challenge. Consumers must filter an immense array of options to find clothing they prefer. Recommender systems serve to help users (persons getting outfit suggestions from the system) filter the set of possible options by prioritising options that are more likely to be of interest. In contrast to more traditional recommendation domains (like movies, books, or consumer products), fashion recommendation benefits from understanding characteristics of the user's physical self in addition to more typical user profile information like demographics and purchase histories.

However, typical methods for measuring predictive power of individual attributes generally rely on large datasets and machine learning approaches. Large datasets of user physical attributes and corresponding fashion preferences are not readily available, and collecting such information is a difficult prospect. Easily available datasets are typically limited to unconstrained 2D images, product text descriptions and reviews, and retailing metadata, none of which are optimised for learning relationships between user attributes and garment/outfit attributes, or relationships among garment attributes within an outfit. As such, the field has struggled to identify influential attributes or establish effective standardised profile definitions. For these reasons, a theoretically-driven approach to identifying high-potential user attributes would help to inform an evidence-based strategy for developing standard user profile definitions. One potential source of such information is expert knowledge. However, fashion expertise is rarely empirically validated, and expert opinions are often inconsistently articulated or even conflicting (Collin, 1986; Saiki & Makela, 2007).

Here, we seek to map the scope of expert knowledge specifically in the domain of identifying attributes used to define a user profile for recommending *aesthetic* garment/outfit matches (clothing that will suit or flatter the individual user). Aesthetic assessment involves a degree of subjectivity, which often confounds recommendations. However, it is not clear whether or not the *attributes* used to define or predict aesthetic relationships are more stable than the *relationships* between body attributes, garment attributes, and aesthetic outcomes. In other words, it may be true that the fundamental elements that influence how an individual's physical aesthetics relate to garment or outfit aesthetics are stable, while the specific garment characteristics matched to specific body attributes may change with shifting trends. Here we consider expert knowledge that focuses on the personal features of the user in three categories (body colouring, body shape, and personality), in order to better understand the trends and consensus in expert opinion on these topics. Our aim

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is not to evaluate the recommendations of experts for what clothing should be worn by what kind of physical wearer, but rather to determine if there are attributes that are consistently included over time and across authors and to identify the challenges inherent in collecting and using these attributes in user profiling for recommender systems. With this knowledge, we can then inform targeted research into validating and/or implementing these approaches for recommender systems.

2. Background

Relationships between user physical attributes and successful garment and outfit recommendations have been shown in several studies (Hidayati et al., 2018; Hsiao & Grauman, 2020; Piazza, Süßmuth, & Bodendorf, 2017). While some of this work is motivated by solving, for example, user challenges of selecting the right size in online shopping scenarios, here, we focus on predicting aesthetic matches suited to the user's physical body. In the recommender systems literature, approaches that consider user physical attributes are typically piece-meal and non-standard, with each author identifying salient (or available) attributes from a different data source or user group, e.g. (Costa, Silva, Rocha, Maia, & Vieira, 2018; Hidayati et al., 2018; Piazza et al., 2017). In many cases, assumptions and conjectures must be made to fill holes in the available data sources.

A few studies have worked to establish ontologies of user and/or garment attributes, toward more consistency in defining features of the recommendation space. However, again here these ontologies are often inconsistent and the source of the attributes represented is not always clear (Ajmani, Ghosh, Mallik, & Chaudhury, 2013; Goel, Chaudhury, & Ghosh, 2015; Vogiatzis, Pierrakos, Paliouras, Jenkyn-Jones, & Possen, 2012). Ideally, a standardised ontology would define a best-fit set of attributes that can be used to effectively model relationships between user and garment/outfit attributes. Because of the difficulty of obtaining many user and garment attributes, it is essential to identify those attributes that are influential in recommendation accuracy, such that the right problems can be solved.

Seeking expert knowledge is an alternative approach to identifying salient attributes. Techniques like sensory evaluation and qualitative interviews can be used to identify and define attributes and establish ontologies (Ling, Hong, & Pan, 2020; Zhang, Zeng, Liu, Yan, & Dong, 2018). However, expert knowledge gained from interview-based methods can be difficult to parse because expert stylists often rely heavily on tacit knowledge, the underlying principles of which are more difficult to articulate in the moment. Advice in book form, on the other hand, often contains more fully-developed theoretical perspectives and more comprehensive coverage of the full scope of the recommendation space. While tacit knowledge often manifests as case examples, published literature often takes a broad, generalisable approach to appeal to as many different consumers as possible.

Although there is no shortage of formally-expressed fashion and dressing advice, there has been very little assessment of expert opinions. Expert advice spans from assessment and typing of users to prescriptive relationships between garments and between garments/outfits and the user's profile. Here, we introduce a comprehensive assessment of a particular facet of expert advice: defining user profiles through body attributes. While the books assessed have been published and have been purchased by users, determining extent to which the advice has been accepted is beyond the scope of this study. An underlying assumption is that coherence among expert perspectives in terms of the attributes used to define types and, in the types, used in matching users to garments, may indicate attributes/types that are more influential in the prediction model and more likely to produce good recommendations. Our objective is to explore the degree to which these expert-defined attributes agree between experts and across time. Further, we explore the manner in which attributes are defined, which may inform future efforts to formalise or automate attribute and type definitions.

3. Materials and methods

3.1. Sample

Our search exhaustively explored fashion advice books exclusively (excluded websites, magazines, videos, and other formats), as they are the dominant format for comprehensive, formal advice publication and span a longer period of time than vlogs, websites, and videos. Books were initially identified through worldcat.org and archive.org searches for 'clothing and dress', 'color in clothing', 'women's clothing', and 'beauty, personal', as well as our university library under LOC classifications TT490-695 (Clothing manufacture, dressmaking, tailoring), RA773-788 (Personal health and hygiene (includes clothing and beauty), and GT5002370 (Costume, Dress, Fashion)). A snowball sampling approach was used to identify more books referenced by first-round books. Finally, a few theses/dissertations dealing with related topics were identified, and additional books were derived from the reference lists in those documents.

Only books relating to adult female fashion and published in English were collected. This included some books that were originally published in other countries (Italy, France, etc.) in a different language and then published in the US or UK in English. For inclusion, a minimum of 20% of total length must be dedicated to dressing advice. (Most books included were solely about dressing advice, but some also contained substantial sections on related topics like dressmaking, hair, etiquette, etc.) Self-published books were excluded from analysis. Finally, 25 of the 430 books that met inclusion criteria were not accessible, and therefore were excluded.

3.2. Analysis

The rate of publication was assessed using publication year for each book, and a 5-point moving average applied to smooth the data for better peak analysis. From the set of books that met inclusion criteria, a preliminary analysis was conducted to identify the typology frameworks used by authors to classify user types. This analysis yielded the following typology frameworks: Body Shape, Personal Coloring, Personality/Personal Style, Occasion, Age, and niche categories such as maternity or specific business domain. These categories overlap with the user profiling categories employed in recommender systems literature (Guan, Qin, Ling, & Ding, 2016). Of these, for the purposes of this analysis we focused on the first three typology frameworks (Body Shape, Personal Coloring, and Personality/Personal Style).

3.2.1. Extracting attributes and attribute values

For each book meeting the inclusion criteria, user attributes and their defined values, as identified by the author, were extracted. Attributes were only included in our analysis if they were described as influencing dressing advice. Attributes were initially extracted from the earliest edition of books with multiple editions, provided that edition was accessible. Additional attributes were extracted from each edition where information changed from the previous.

For each of the 3 typology frameworks, attributes and attribute values defined by the authors were extracted in the author's vocabulary. Features that did not have a semantic type label were not included. Expertise of the research team was used to extract central attributes and values: instances where authors described edge cases in attribute values were included (for example, 'may have red highlights'.) Subsequently, author vocabulary was filtered: when definitions were found to be consistent, similar modifiers were reduced to a single value (e.g. translucent, transparent); and spelling differences (e.g. grey vs. gray) and similar words (ash vs. ashy) resolved. Where necessary, expert judgement (including a review of historical context) from the research team was used to interpret similar words.

In advice related to physical colour, most authors listed skin, hair, and eyes as the most important – or only – considered attributes. However, authors differed in how they defined values of each attribute (e.g. chroma, undertone, etc.). Some authors listed other colour attributes such as eyebrows, lashes, lips, and other feature attributes such as texture, but these were rare and less influential for clothing selection than hair, skin, and eye colour; thus, they were excluded from analysis.

3.2.2. Assessing types: color

To evaluate the scope, author-defined colour types were extracted in the author's vocabulary. For each type, the prescribed attribute-value relationships were recorded. For many types, multiple attribute-value relationships were defined by authors. Given the potential for racial bias in our historical sample, the range of skin colours included were then examined to determine the level of inclusivity of skin colours for different races by authors.

3.2.3. Assessing types: body

Only explicitly labelled body types were included in our analysis. For each type definition, the author's approach to defining attribute values and/or attribute relationships was recorded as either quantitative (defining measurements or proportions numerically) or qualitative (defining attribute values or relationships in text descriptions). For each defined type, the author's text description as well as the defined attribute-value relationships were recorded.

Unique body type names (in the authors' vocabulary) were initially recorded to capture the scope of semantic variability. They were subsequently compared based on attribute-value relationships, and redundancies were removed. The most commonly used type name was used for each group of redundant types.

Finally, for body types further analysis of type-modifying attributes was conducted. These are attributes that are not used to *define* a type but are used to modify dressing advice for individuals *within* a type. For example, advice for an individual with an hourglass body type (defined by bust, waist, and hip breadths) may be modified by the individual's leg length. In addition, the number of identified values for each modifying attribute were counted (e.g. the 'shoulders' attribute may be defined as 'sloping', 'square', 'broad', or 'narrow'). Finally, the weight of each attribute was calculated as a proportion of the number of values for each attribute compared to the total number of values for all modifying attributes.

3.2.4. Assessing types: personality

Personality types were rarely attribute-driven in the same way that colour and body types were. Personality types were most commonly aspirational, rather than based on existing physical attributes of the user. Personality types were typically defined based on one of the following schemas: user physical attributes, user attitude/lifestyle, user dressing habits and preferences, or aspirational appearance of the user.

4. Results

A total of 431 books were identified for inclusion, which represented 383 unique books (after removing multiple editions). These were authored by 387 unique individuals. Books included were published in the US ($n = 356$), UK ($n = 69$), France ($n = 4$), Japan ($n = 1$) and Australia ($n = 1$). All books were published between 1811-2021. Publication rates for these books are shown in Figure 1.

4.1. Body coloring results

Colour attributes were extracted from 54 books by 57 unique authors, spanning 1863–2014. Hair, eye, and complexion colour attributes were identified. Hair colour was defined using 356 unique values, including modifiers (such as light/dark, rich, warm/cool). Complexion colour was defined using 317 unique values (excluding undertones and freckles), which represent 160 unique hues. Eye colour was defined using 319 unique values, representing 126 unique hues.

273 unique colour profiles were named by authors. Figure 2 shows types named by at least 3 authors. A distinct shift was observed after 1978, when 'seasonal' colour analysis was introduced for colour typing. Figures 3 and 4 show the influence of this shift, pre- and post-1978. Of the 54 books reviewed, 20 published prior to 1971 considered only body colouring for Caucasian people and two considered only dark skin tones. 31 of the 32 books published from 1971 to present are more inclusive and considered the full range of skin colours. Figure 5 shows the distribution of books and the skin colours considered by year.

4.2. Body shape results

Body shape attributes were extracted from 71 books by 89 unique authors, spanning 1876–2019. There were 554 instances of attribute-value pairs defined by authors. Some attributes had values assigned for length and width. For example, waist could be described as short or long when discussing length but as wide or small when discussing width. 4% of authors expressed attribute values quantitatively, and 86% expressed values qualitatively. 10% used a combination of quantitative and qualitative values. The attribute-value pairs spanned 15 body attributes, and for these attributes a total of 51 unique values were defined. Table 1 shows

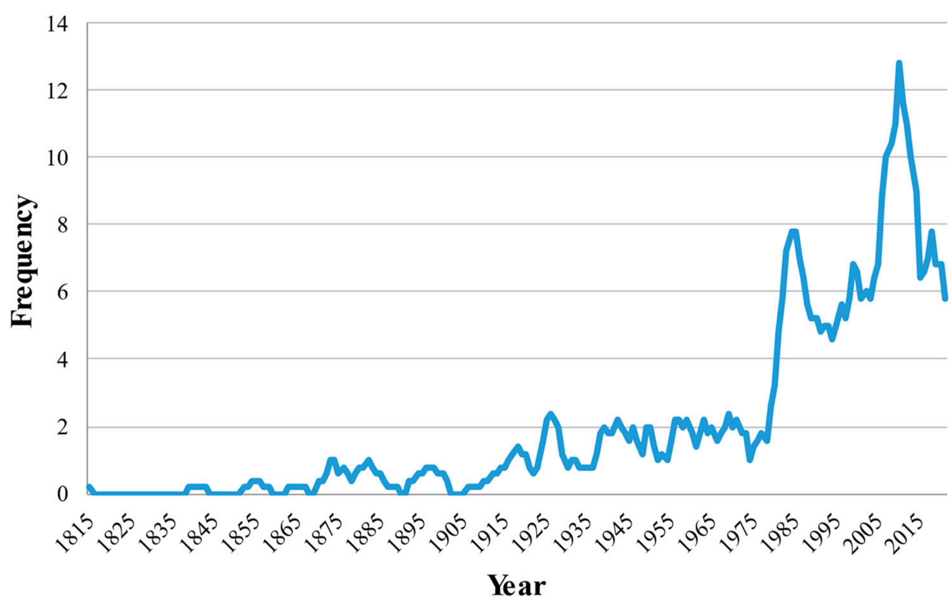

Figure 1. Moving average of dressing advice books by publication date.

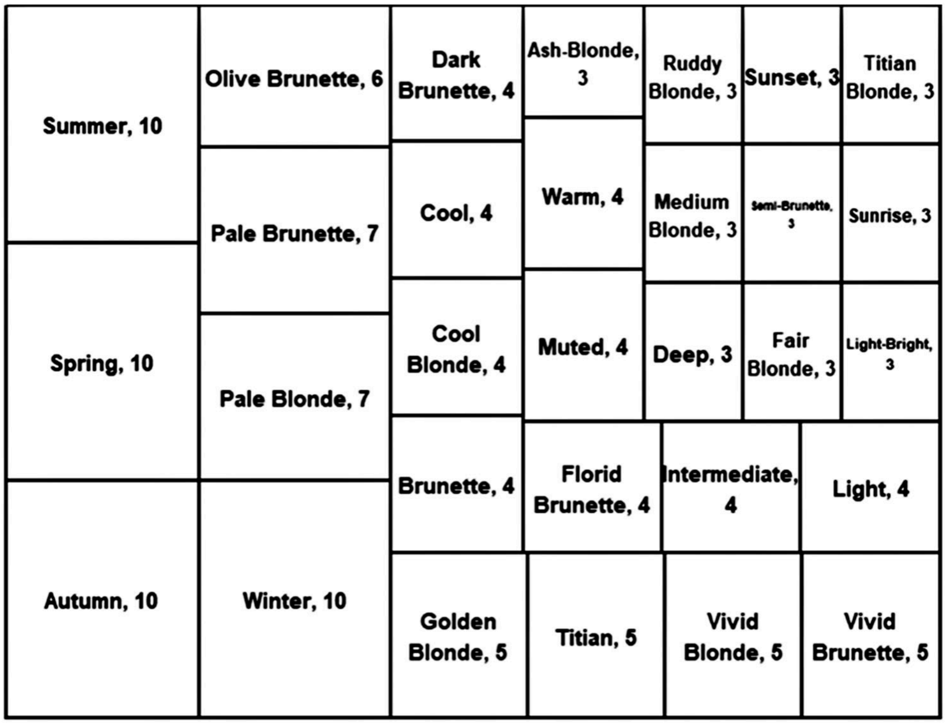

Figure 2. Colour types named for all years.

the attribute values, their defined values, the number of unique values for each attribute, the frequency of attribute-value pairs being identified by authors for this attribute, and the attribute weight (frequency of attribute-value pair identification normalised by the number of values for this attribute and expressed as a percentage of the total normalised attribute-value pair identification frequency for all attributes).

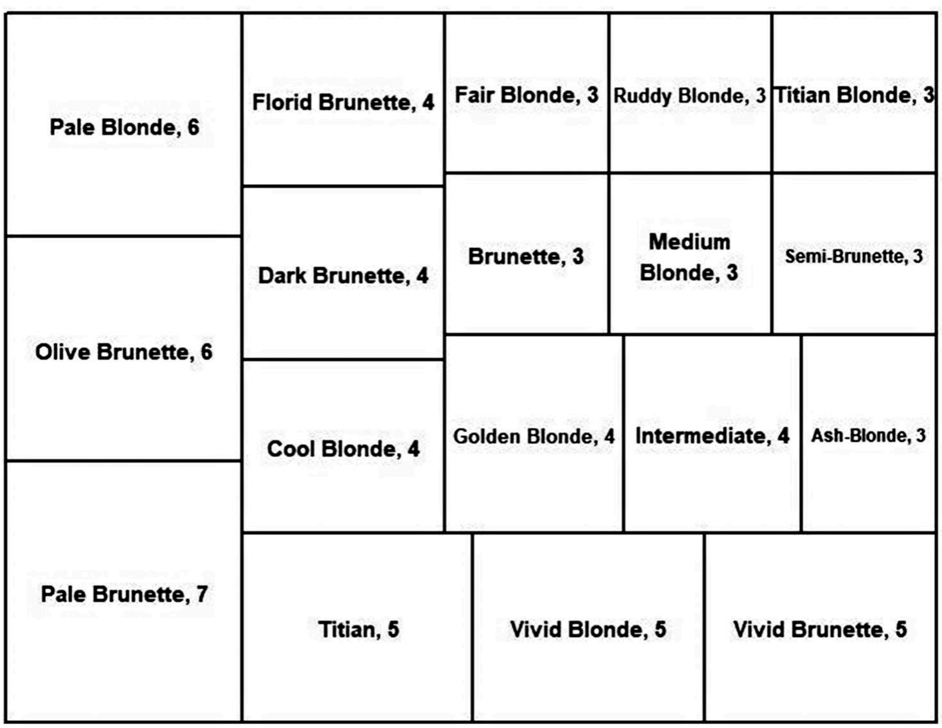

Figure 3. Colour types named pre-1978.

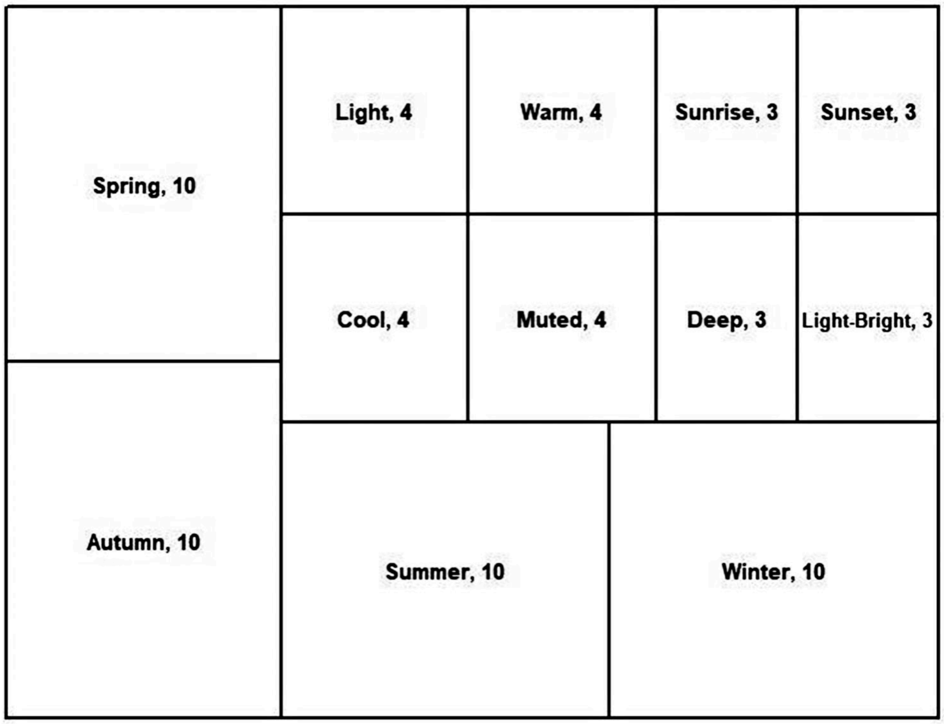

Figure 4. Colour types named post-1978.

Of the attributes defined in Table 1, only 6 were observed as being type-driving attributes. These were length, width, bust, shoulders, waist, and hips. 176 unique types were recorded in the authors' vocabulary, which were reduced to 89 names after author vocabulary was filtered to remove synonyms. Figure 6 shows the frequency of all type names occurring at least three times in the dataset. Once type definitions were used to remove redundant type names, the resulting set included 19 unique type definitions. These types are outlined in Table 2, as well as the frequency with which they were defined, and the time frame in which they were observed.

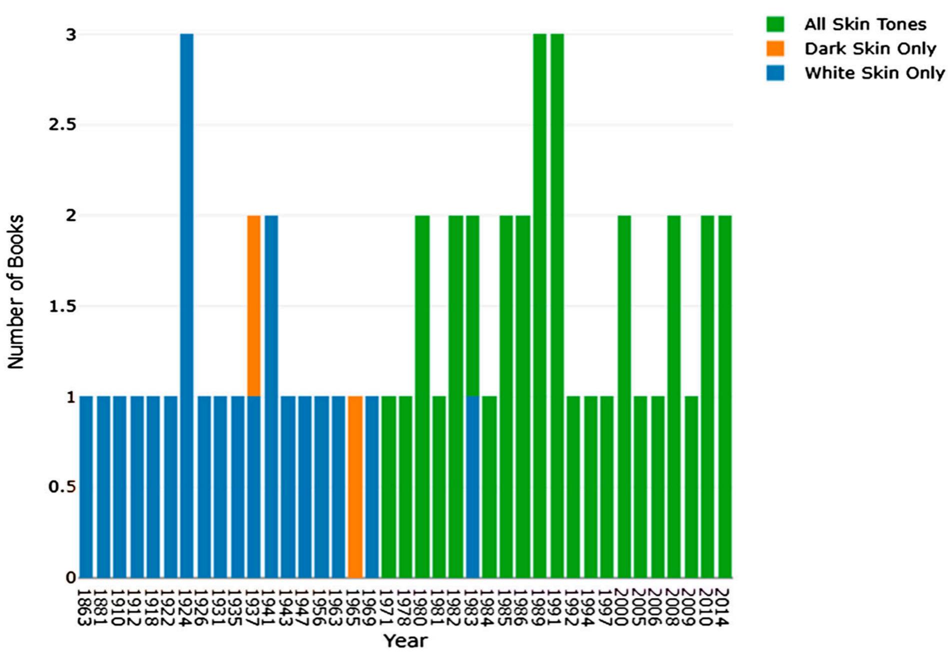

Figure 5. Consideration of skin tones by authors.

Table 1. Body attributes.

	Length	Width	Depth	Identification Frequency	Attribute Weight
Entire Body	Short	Heavy / Stout		15	3%
	Tall	Thin			
Neck	Long	Thick		50	8%
	Short	Thin			
Shoulders	Square	Broad / Wide		80	13%
	Sloping / Round	Narrow			
Arms	Long	Heavy		45	8%
	Short	Thin			
Upper Arm		Large		4	3%
Wrists		Heavy		3	1%
		Thin			
Hands	Large			8	3%
	Small				
Bust	High		Large / Full /Big	66	11%
	Low		Small / Flat		
Back		Broad	Sway	11	2%
		Narrow			
Waist/Abdomen	Long	Thick / Wide	Protruding / Prominent	100	13%
	Short	Small			
Hips/Bottom		Large / Wide	Big/ Large / Heavy	72	12%
		Narrow	Flat		
Legs	Long	Heavy		42	7%
	Short	Thin			
Thighs		Heavy / Large		15	5%
		Thin			
Calves		Heavy / Large / Thick		13	4%
		Thin			
Ankles		Large / Thick		13	4%
		Small / Thin			
Feet	Long	Large / Broad		11	2%
	Short	Narrow			

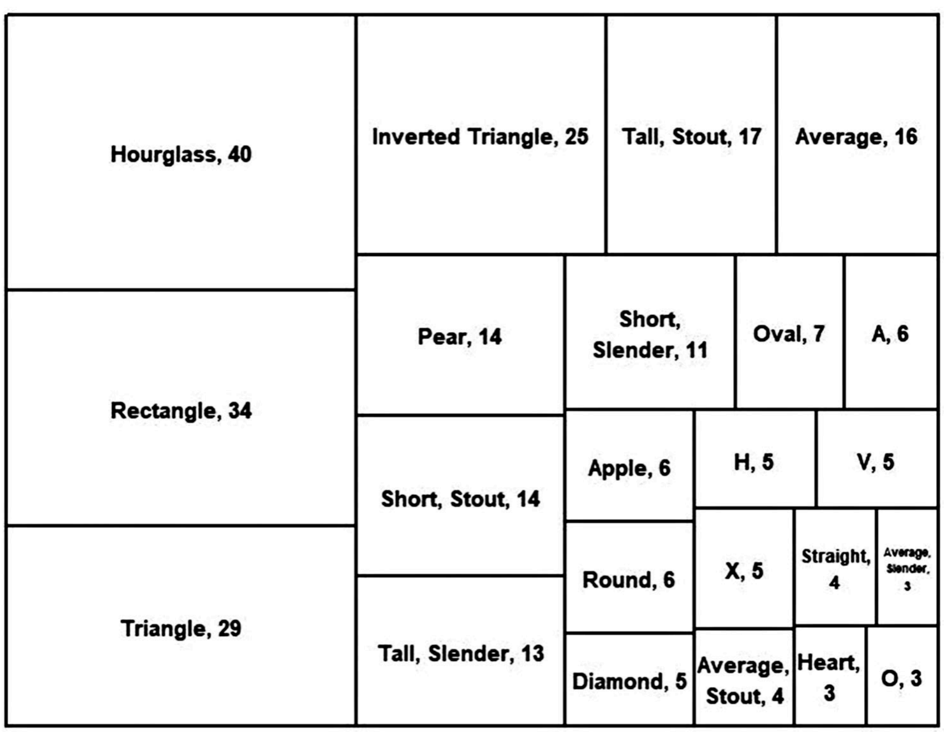

Figure 6. Body type names occurring at least three times.

Table 2. Body types.

Type	Definition	Frequency	Time Period
Inverted Triangle	Bust > Hips	7	1947–2016
Pear	Bust < Hips	3	2005–2014
Rectangle	Bust = Waist = Hips	8	2000–2016
Hourglass	Bust & Hips > Waist	10	1947–2016
Apple	Bust & Hips < Waist	5	2004–2012
Inverted Triangle	Shoulders > Hips	30	1981–2019
Triangle	Shoulders < Hips	36	1981–2019
Rectangle	Shoulders = Waist = Hips	30	1981–2019
Hourglass	Shoulders & Hips > Waist	32	1947–2019
Oval	Shoulders & Hips < Waist	21	1987–2019
Average	Average Height Average Weight	13	1922–1991
Average, Stout	Average Height > Average Weight	6	1946–2005
Average, Slim	Average Height < Average Weight	7	1946–2014
Short, Average	< Average Height Average Weight	4	1941–1977
Short, Stout	<Average Height > Average Weight	14	1877–1997
Short, Slender	< Average Height < Average Weight	13	1877–1981
Tall, Average	> Average Height Average Weight	3	1946–1977
Tall, Stout	> Average Height > Average Weight	14	1877–1981
Tall, Thin	> Average Height < Average Weight	14	1877–1981

4.3. Personality results

Personality/style type results were extracted from 35 books over the time period from 1924 to 2019, written by 44 unique authors. From these, 202 types were extracted, which represented 108 unique types after removing redundancies. 23 types were identified by more than 1 author. 16 of the 35 books (45%) used celebrity examples to illustrate each type (range 1936–2019). Figure 7 shows the types identified by a minimum of three authors.

5. Discussion

A full historical analysis of dressing advice literature is outside the scope of this paper. However, Figure 1 affords some insight into the contexts in which authors developed the prescriptive advice assessed here. The frequency of book publication is quite low prior to around 1915, where it increases to around 2 books per year. In 1914, the Smith-Lever act established cooperative extension services aligned with US land grant universities. Combined with the Smith-Hughes act of 1917, which

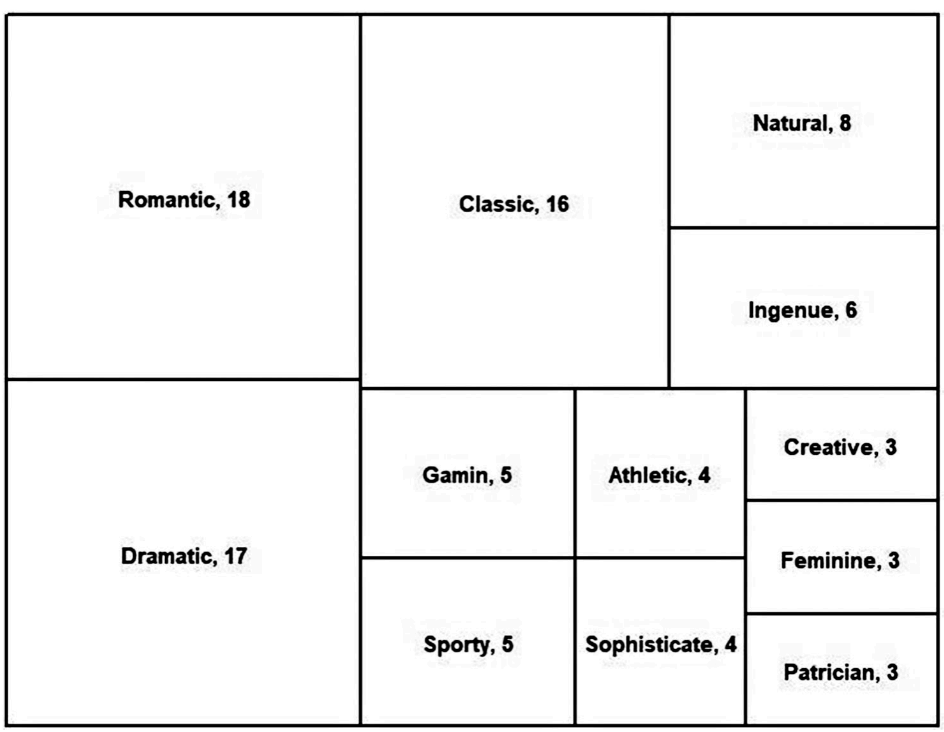

Figure 7. Personality types.

designated federal funding for vocational education, these pieces of legislation quadrupled the reach of the field of Home Economics, which included the formal study of clothing design and clothing behaviours (Carleton, 2002).

Publication rates remained low until the late 1970s, when they spiked to 8 books per year, settling around 6 books/year for the 1990s and early 2000s. The late '70s and early '80s saw women entering the workforce in increased numbers, and adapting to business dress practices (Molloy, 1977). Further, at this time fashion design began to adopt a more mix-and-match approach, developing modular garments that could be paired in different ways rather than full ensembles. This is also the time period in which women began to wear trousers in more formal environments. Further, the 'seasonal' approach to body colouring profiles was first introduced in 1978 by Bernice Kentner in *Color Me a Season* (Kentner, 1979). It was later popularised by Carole Jackson in *Color Me Beautiful* (Jackson, 1987) and gained considerable traction in the fashion advice market (as is seen in Figures 3 and 4).

Another spike is seen around 2010, coinciding with the proliferation of reality TV and makeover shows. At this time, more authors shifted their focus from colour profiling (the 'seasonal' schema remained dominant) to body shape profiles as observed in the publications reviewed. This time period also coincides with a burgeoning body positivity movement, which may contribute to the increased focus on body shape diversity.

5.1. Colour profiling

Across authors, for colour profiling hair, eye, and complexion colours were the dominant attributes. However, a very broad variety of values were identified (close to 200 for each attribute for our most conservative metric, individual hues without modifiers). By contrast, when body colouring is considered in the recommender system literature, while most authors do consider hair, eye, and complexion colouring, values for these attributes are typically much simpler (fewer values defined) and/or not precisely defined (link between attribute values and source data is not clear) (Ajmani et al., 2013; Hao & Hao, 2019). Identifying *unique* values for colour attributes is difficult because natural-language descriptors for colours vary (e.g. fair, pale, ivory). It's possible that definitions may be perceptually very similar, but without a physical colour reference it's difficult to assess the overlap range. Temporal effects may also be evident, as popular terms change (for example 'titian' vs. 'red' hair). A further challenge remains in translating these natural-language descriptors to quantitative representations of colour, and in defining descriptor ranges in quantifiable colour space.

Colour profiling saw some convergence after the introduction of the seasonal approach to colour types. Seasonal colour profiling is also sometimes used in recommender systems research (Ajmani et al., 2013; Goel et al., 2015; Vogiatzis et al., 2012), perhaps because of its dominance in the fashion advice domain. This may reflect some universality or validity to the approach, although to our knowledge it has never been empirically validated (either as an effective means of clustering human body colouring, or as an effective means of predicting successful relationships between individual body colouring and garment/outfit colours.) Further, although post-1978 there was some consistency in authors using this schema to name profiles, the profile definitions themselves were not always consistent: different attribute values were used by different authors to define types.

Importantly, a substantial amount of the literature published prior to 1971 reviewed here considered only body colouring for Caucasian people. There was a shift in this trend in 1971, and thereafter most of the books included a more comprehensive range of skin tones. However, for this reason an analysis based on frequency of occurrence of skin tones is not ideal here, but rather on uniqueness and variability across books.

5.2. Body type profiling

Authors identified more body shape attributes than body colour attributes – 15 individual attributes were identified. However, for these attributes a much narrower range of values were prescribed (51 total). It should be noted that most attribute values were defined in very general terms (e.g. 'too big', 'sloping', 'thin'). Only 14% of authors specified quantitative values or relationships. The waist, hips, and shoulders were the most referenced body areas, and they also represented the areas with the most attribute values of the full set of defined values. The waist was the single most-identified attribute, and also the attribute with the largest number of values defined (5 distinct values in 3 dimensions). The shoulders were perhaps the most surprising attribute – while shoulder width/breadth was often used in place of bust dimensions in defining the silhouette of the torso, authors also defined the shoulder contour specifically as influential in driving clothing recommendations.

The discrepancy between the number of type names used by authors and the unique types identified by our team points to another natural-language challenge in interpreting the labels applied to body profiles, which is also seen in recommender systems literature (Costa et al., 2018; Hidayati et al., 2018; Hsiao & Grauman, 2020; Piazza et al., 2017).

In general, author approaches to body type profiling can be broken down into 3 categories:

- Proportion between Bust, Waist, and Hip (observed approximately 1965–2014)
- Proportion between Shoulders, Waist, and Hip (observed approximately 1975–2019)
- Deviations from an 'Average' height and weight (observed approximately 1905–1990)

Over time, authors introduced more variables in defining body types (moving from a height vs. breadth approach to the upper, middle, and lower torso proportions). Early experts favoured aesthetic goodness concepts drawn from classical art theory and Greek ideas of ratio and proportion, such as the 'golden ratio', which later were abandoned (and have been shown to be inconsistent with other measures of aesthetic success in fashion (Saiki & Makela, 2007)). The idea of there being an 'average' body also fell out of favour over time. The Triangle type is the type most consistently defined by authors, unless the two Hourglass types (those considering 'bust' and those considering 'shoulder') are combined.

For proportion-based types, most dressing advice aims to achieve the illusion of the most desirable proportions identified by the author. The most desirable proportions are typically closest to the Hourglass type (Homer, 2016; Moses, 2016; Warren, 2006), where the bust or shoulders should be relatively even with the hip breadth, and the waist should be smaller (how much smaller varies by year/author). For types centred around an 'average', most dressing advice aims to achieve the illusion of being closer to average or to the ideal fashion figure, by increasing/decreasing apparent height or increasing/decreasing apparent width. Definitions corresponding with the names Oval and Apple are introduced much later than other types, which may correlate with increasing body acceptance trends and/or increasing body size for Western women.

Recommender systems studies show a similar distribution in identification of body types: the types most commonly used by experts (hourglass, triangle, inverted triangle, rectangle, oval/apple) are also frequently used by researchers. However, as with the expert literature, there is considerable inconsistency in the set of types defined by researchers, as well as imprecision in the definition of attributes used to classify types (Costa et al., 2018; Guan, Qin, Ling, & Long, 2018; Hidayati et al., 2018).

5.3. Personality profiling

Personality profiles were the most diverse of the three areas considered here, with 102 unique profiles identified by authors. As these were not driven by physical attributes, personality profile definitions are inherently more subjective. Even frequently-identified types are often defined in different and sometimes overlapping ways. For example, 'Feminine' is used to define the Romantic type 9 times (50%) and is also its own type. The Romantic type is defined as 'Sophisticated' by some and 'Unsophisticated' by others.

The most consistently-defined types over the entire period (1924–2019) were Dramatic and Romantic. Classic and Dramatic were the most frequently-defined types (occurring 18 and 17 times). Classic was introduced much later, but assuming that it continues to be consistently defined it is likely to become the most common profile definition. The Athletic type ceased to be used in 1973, but Sporty appeared beginning in 1983; Athleisure appeared in 2019. The Natural type is also defined as sporty by some authors. Bohemian and Minimalist are relatively newer types.

5.4. Implications for user profiling in recommender systems

Current approaches to user profiling in fashion recommender systems typically focus on information that is easily available and computer-readable. It is not yet known if available information is sufficient or optimal for effective recommendation. This work focuses on an alternative approach: formalising expert knowledge in the domain to enable assessment of expert-derived features and profiles. This study is a first step toward that goal: quantifying and characterising the variability in expert frameworks, reducing redundancy, and preparing these approaches for empirical assessment. However, the characterisation of expert perspectives also sheds light on potential challenges and opportunities for recommender systems.

First, while our analysis reveals considerable variability in attributes and values used by experts, we also find some consistency over time and between authors. For example, colour, body shape and personality were consistent profile elements. Body colouring was usually assessed using the eyes, hair and skin, but there is variability in the semantics, description and definitions assigned to values of attributes. This resembles to some extent the variability in approaches in current recommender system development: similar semantic descriptors are used to classify users and garment styles in the recommender systems literature (Guan et al.,

2018) as found in the domain expert advice literature reviewed but here also the attributes and values used varies. Like fashion experts, researchers individually establish frameworks for articulating user characteristics and don't consistently agree. Because some user features are more difficult to capture (e.g. detailed anthropometric information), especially in conjunction with a rich dataset of garment – and outfit-level attributes that would enable supervised learning, establishing the highest-impact features would enable more efficient systems. Expert frameworks fairly consistently reflect the importance of taking user attributes together (as a relationship between attributes, a profile or type) – for recommendation, this would again provide a means of filtering garment and outfit matches. By empirically assessing these attributes and standardising them, recommender systems can utilise these attributes in connecting user features and garment attributes to integrate user physical profiles in algorithms design.

Second, the dressing advice here is generally focused on cis-gender women, which may translate to feminine-presenting individuals. This was the population most consistently addressed in dressing advice literature, but could limit generalizability to masculine, gender neutral, or transgender clothing advice. However, we believe that determining the most predictive features in profiling cisgender women may reflect one of the more complex recommendation spaces. As the aim in this study is to identify body attributes to be used in building user profiles, many of those attributes may be more related to humans than to a specific gender. If recommendation for cisgender women relies on more attributes than other genders or presentations, it would then be possible to down-select from a larger feature set for other user groups. Within a class of attributes (such as personality), attributes could be expanded to include new values for different groups. However, a fundamental limitation could exist for user groups with atypical body features, which should be assessed in the implementation of any future system.

While body colouring and shape attributes in expert advice tend to lend themselves better to quantification or measurement, personality features address a facet of fashion recommendation that is inherently far more subjective and less easily defined than the more prescriptive domains of body colouring and body shape. Recent studies have explored novel and interesting methods of deriving socio-cultural meaning-making in visual communication of dress, and associating these meanings with garment attributes (Bollacker, Díaz-Rodríguez, & Li, 2016; Guan et al., 2018; Hsieh & Li, 2019; Simo-Serra, Fidler, Moreno-Noguer, & Urtasun, 2015; Zhao et al., 2017). These approaches perhaps can offer experts a new lens through which to formalise the part of fashion expertise that is the most difficult to define. However, personality may also be effectively reflected in other (e.g. collaborative, content-based) learning methods rather than physical attributes.

6. Conclusion

Overall, expert definitions of user profile attributes and attribute values are broader than is reflected in the recommender systems literature. Recommender systems researchers tend to select one model or schema for defining user attributes (else they identify attributes independently of a model, which often results in inconsistencies and gaps in domain coverage). However, while this study illustrates the breadth and complexity of expert definitions, it does not provide consensus on which perspectives are the most valid or predictive of relationships with garment-level attributes. To determine validity of each model, expert profiling and prescriptive advice should be evaluated: perhaps with respect to user or expert assessment of prescribed body/outfit relationships, or perhaps with respect to outfit data sources that have already been deemed 'successful' or 'unsuccessful' in some way. Extracting attribute sets and value definitions as well as profile definitions is the first step toward being able to effectively evaluate expert advice.

While feature engineering is a central research thrust within the domain of recommender systems, work in that area often focuses on computational methods to determine predictive features from available sets – for fashion, it has rarely expanded to include exploring the application domain to identify features that could be collected or informing strategies around which features to invest in collecting. For that reason, fashion practitioners are vitally needed to inform the development of fashion recommender systems and provide standardised concept definitions and formal principles for relationships between garments and users within the context of use. Formalising principles for user definition would have implications both for recommender systems and for the apparel studies field as these features are a formal representation of the implicit knowledge of expert practitioners. Such insight might also have significant implications for the practice of fashion design, styling, and retailing. Future research should focus on defining a more formal ontology for this domain that explicitly clarifies the vocabulary and semantics of the domain and profile attributes. If these ontologies align well, it will simplify aesthetic filtering for fashion recommendation.

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