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On the Design of Sales Support Systems for Online Apparel Stores

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Abstract. Many online shops apply several sales support systems, e.g., recommender systems, sorting and filtering tools, to support buyers during the shopping process. Although, the research highlights the positive effect of such systems, the current study questions its applicability in online shops for products which serve users' needs to be unique like apparel or luxury products. We analyze female users' buying behavior of apparel products in a laboratory setting and find that users with high trendiness undertake in general more search steps. Further, we find that most users rely during their search process on different sorting and filtering as well as on keyword search tools than on personalized and non-personalized recommendations. Further, we find that users with high trendiness did not use top seller lists and "wear with it"-recommendations. Moreover, the assistance of top seller lists did not lead to final choice of products (i.e. zero conversion rates).

Keywords: Sales Support Systems, Recommender Systems, Apparel Stores, Trendiness, Need for Uniqueness

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1 Introduction

Many online shops apply several sales support systems, e.g., recommender systems [1, 2], sorting and filtering tools or interactive decision aids [3-5], to support buyers during the shopping process [6]. Such systems aim at reducing consumer's search costs [7] to efficiently find products that match consumers' preferences, and help to discover of new products which might be interesting for the consumer. As shown by previous research, such sales support systems can lead either to demand shifts from blockbuster to niche products and thus to increased sales diversity [6, 8-10] or to demand concentration on blockbuster products [11].

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However, consumers perceive the usefulness of such sales support systems differently depending on the type of product [12]. For example, search goods [13], such as electronics, which can be objectively described by their attributes, are easier to process for recommendations than experience goods [13] (e.g. perfumes or books), which involve the subjective perspective of a consumer [12]. Some sales support systems utilize aggregated consumer preferences, like top seller lists or collaborative filters that generate product recommendations using the principle "customers who bought this item also bought…". Although previous research has shown that such kind of quality cues have a positive impact on the buying decision [6, 11, 14], we expect that they might not be appropriate for products which serve consumer's needs for uniqueness [15], such as apparel or luxury products. Apparel has the function of expressing someone's individuality (or the need to be unique) to the outside world [16] and thus consumers might not want to dress just like others. The identity signaling function of clothing may have an effect on the perception of the recommendation of popular products, so-called top sellers. Therefore, it is unclear, whether the generally believed benefits of sales support systems based on aggregated consumers' preferences can be transferred to the apparel shopping domain without adjustment. Although some stream of research works on improving recommender systems for apparel products [17-19], to the best of our knowledge no study investigated, whether the sales support systems based on aggregated consumer preferences are appropriate for products which serve consumers' needs for uniqueness and status signaling.

The current paper reports the results of our explorative study. We observe shopping behavior of female users in a laboratory setting to explore whether and how consumers use sales support systems in online apparel stores. We find that sales support systems which are built on aggregated consumer preferences like top seller lists are related to lower conversion rates. Our findings provide us with a useful basis for the design of future studies to improve the design of sales support systems in online apparel stores.

Due to the expansion of shopping apparel online, our research is of high practical relevance. Recently, the share of apparel in the online shopping environment has experienced a boost in many parts of the world. In Germany, revenues have more than tripled from 2006 (2.81 billion Euros) to 2013 (10.3 billion Euros) [20]. Current web technology developments leverage long believed disadvantages related to buying apparel online e.g., unsatisfied need to touch, missing possibilities to find correct fit and shopping experience [21], and convince more and more consumers to shop clothes online. Examples for innovative approaches include "Upcload" (www.upcload.com), a system that measures body dimensions through a webcam to reduce consumer's risk perception on correct fit and a virtual shopping assistant that interacts with the consumer, developed by "Fluid", a US software company. On the website of aboutyou.de (http://www.aboutyou.de/) users can upload photos of celebrities and get recommendations to copy their styles or user can design their own shoes.

The remainder of the paper is structured as follows: In section 2 we embed our research into the prior work on sales support systems. Section 3 summarizes fashion peculiarities and current sales support systems and discusses to what extent these are applicable to the apparel industry. Then, we describe our study setup. Section 5 presents our results. Finally, we conclude our work by discussing the main findings and limitations of the current study and give an outlook for further research.

2 Related work

2.1 Sales Support Systems

The vast amount of applied sales support systems in online stores can be classified along two dimensions: user's involvement (active/passive) and the grade of personalization (yes/no). Table 1 classifies different sales support systems along these two dimensions.

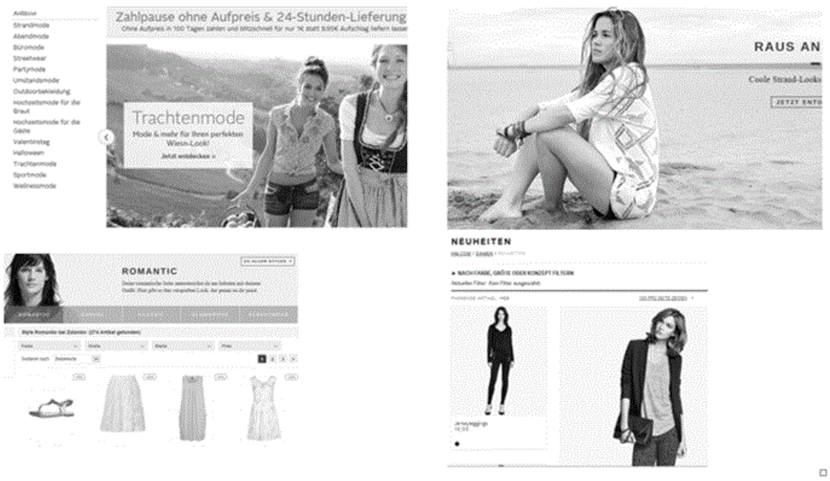

Fig. 1. Examples of non-personalized recommendations in online apparel stores

There are three types of recommender systems that are widespread and have been successfully used in many domains: collaborative filters, content-based recommender systems and hybrid recommender systems [2, 22]. Collaborative filters build consumer profiles based on similarities in consumers' purchases or product ratings to generate recommendations [22]. Content-based systems build correlations among products the customer has previously purchased [23] or rated positively [24]. A combination of both is called a hybrid recommender system. Top seller lists and editors' advice are non-personalized recommendations. Online apparel store specific recommendations, like banners with some outfit, style guides and recommendations for specific occasions or seasons, are also examples of such non-personalized recommendations (see Fig. 1).

Interactive decision aids are based on customer interaction [3-5]. They support the user in the decision what to buy and where to buy and aim generally at reducing the product consideration set. Simple sorting and filtering tools (e.g., on price, color etc.)

are classified as such interactive decision aids, but also more sophisticated tools like comparison matrices [3, 4] pertain to this category. Generally they divide the search process into two steps: First a consumer views a range of available products quickly to determine which products are worth further consideration. In the second step the consideration set of products underlies "in-depth" comparisons, the review of product details, for example. Such interactive decision aids (if applied) improve decision quality as well as efficiency of purchase decisions [3-5].

Table 1. Classification of sales support systems

	Passive user involvement	*Active user involvement*
Personalized	Recommender systems	Personalized search engines
Non-personalized	Top seller lists Editors' advice Banners, style guides	Interactive decision aids Search tools Sorting and filtering tools

In addition to comparison matrices and interactive recommender agents, online shops provide input text fields and search filters to facilitate consumers' search as another type of sales support systems which require user interaction [6]. Personalized search engines which take user profile into account while searching are an example of personalized sales support systems requiring active user involvement.

2.2 Recommender systems for fashion.

Some stream of research works on improving recommender systems for apparel products, which is challenged by characteristics of apparel products. Constantly changing collections and product assortments [19] enforce weaknesses related to collaborative or content-based filters such as the "cold-start-problem" [25]. Furthermore, [19] argue that current online shops focus on transaction data instead of building customer profiles. This leads to recommendations that are very close to previously purchased products. As collaborative filters and content-based systems mostly do not offer enough data for cross-category recommendations, they develop a knowledge-based approach, which is based on styles extracted from marketing texts. In order to exploit the potential of recommender systems, they build a consumer model which is supposed to recognize tastes and styles to suggest products on a cross-category level.

Similarly, [18, 26] use consumer characteristics such as facial color or human morphology to build an ontology for the generation of recommendations in form of style advice rules. Likewise, [17] develop a system with the aim to facilitate outfit combination. It is able to recommend a complete outfit suiting a new piece of garment the user has specified as well as new combination possibilities within the users' wardrobe [17].

Another approach to generate personal recommendations on a social shopping platform offering fashion as well as other products is the use of Facebook profile data [27]. With the semantic interpretation of user profile data they achieve recommendation improvements up to 74% compared to randomly recommended items. This approach requires the user to be logged in on the shopping platform and to permit the linkage to his Facebook profile to obtain recommendations.

All the presented approaches do not address the identity signaling characteristics of the apparel products. Further, they are in the development phase and are not implemented in real online apparel shops. Hence, most of the real shops implement conventional collaborative filters or top seller lists which are based on aggregated consumer preferences and do not take into account the need for uniqueness of the consumers. In the next section we discuss the appropriateness of the different sales support systems we identify as currently implemented in online apparel stores.

3 Research Conceptualization

Individuals pursue uniqueness through consumption of goods which differentiate them from others [15, 28]. [28] found that consumers' need for uniqueness is associated with buying of "scarce, innovative, and customized products and to consumers' preferences for unusual shopping venues" [28]. Especially clothing has an identity signaling function. This is manifested in two ways: In desire for social identity and in desire for uniqueness [16]. People often express group affiliation by wearing similar clothes, popular brands [29], and following clothing styles of prominent people e.g., of the Duchess of Cambridge [30]. Uniqueness desires evolve within these groups but also as demarcation of other social groups [16]. Consumers might then satisfy their needs for uniqueness using different colors [16] or even designing their own pieces of clothing or shoes.

Table 2 lists sales support systems we identified in current online apparel stores. In the following we discuss their applicability to the apparel industry. In-shop keyword search and filters are options that facilitate the search process within the shop. They require the consumer's interaction as well as determination on a product category (in-shop keyword search) or measurable product attributes (filters). Therefore, they might highly support "directed buying" [31].

Top seller lists and collaborative filters are widespread in different types of online stores and their success has often been examined in research. However, we hypothesize that the identity signaling function of apparel and the resulting need for uniqueness constitute limitations for those systems in the apparel industry. [32] find that the users with higher social status in a virtual environment purchased rare and very expensive items. Such behavior is referred as "conspicuous consumption". Vice versa one can expect that the individuals who are seeking to preserve their high social status would not buy products which are preferred by other consumers. [28] find that consumers with higher need for uniqueness prefer less popular retail stores.

Recently, new fashion specific support systems have evolved. These tend to group products by dimensions different from their product category. This approach requires a comprehensive perspective on apparel, for example considering a complete outfit instead of an individual product group. Products can be grouped by style, by occasion or by season. "Zalando" for example, the most popular German online fashion store, provides a “wear it with”- recommendation for each product (http://www.zalando.de/).

Table 2. Benefits and suggested applicability of sales support systems

Sales Support System	*Expected benefit*	*Applicability for apparel stores*
In-shop keyword search	Help to find the searched product quickly	Good
Sorting filters	Help to reduce the scope of the consideration set	Good
Top seller lists	Non-personalized recommendation	Might not function well, because users tend to be unique and do not want to buy products already bought by many others
Collaborative recommender	Help to find new products	Might not function well, because users tend to be unique and do not want to buy products already bought by many others
„Wear it with“-recommender	Help to find suitable products – enables cross-category purchases	Good
Unspecific banners	Inspiration	Might support user’s need to be unique
New In	Help to explore new trends	Might support user’s need to be unique
Style Guide	Help to follow “fashion idols”	Might support user’s need to be unique
Occasion/Event	Help to find occasion adequate products, simultaneously reducing search costs	Good
Season	Predicts consumers’ current interests	Important, as collections change frequently

4 Methodology and Data

To study whether and how the consumers use different sales support systems we conducted a video analysis of buying behavior. For this purpose we gave the participants a shopping task and recorded their buying behavior using “Camstasia Recorder 8”. The shopping task consisted in assembling an outfit online for a school reunion celebration held in a beautiful restaurant. The only limitation was a 300 Euro budget restriction. There was no time limit and the participants were free in their choices of shops, number of items etc. Finally, the participants were asked to save links to their selected apparel items using the link fields in a small web application developed for this study. The number of link fields was unlimited. If a participant changed her mind on an already saved product, she could annotate the replacement in the subsequent link field. In addition, we asked for user demographics like age, education, income level and shopping habits.

We decided to conduct a video analysis due to explorative nature of our study. An alternative measurement would be a clickstream analysis [31, 33, 34], which, however, is not applicable in our study, as we did not want to restrict participants in their choice of online shops. The setting of the study had to be as realistic as possible.

By designing the study we controlled for several factors which might influence user's shopping behavior. First, [31] distinguish between directed and exploratory shopping. Whereas directed search is associated with "a specific or planned purchase in mind" [31], exploratory search is related to hedonic browsing and knowledge building behavior [31]. To limit the interplay of other shopping behaviors we primed the shopping task as a directed buying, i.e. the participants had to choose one outfit.

As discussed by [16], people simultaneously strive for social group identification and differentiation within the group. With purpose to reduce the need for social identity and to intensify participants' need for uniqueness and statuses signaling we gave the task to assemble an outfit for a school reunion celebration as the people want to present themselves from positive perspectives in such situations.

Table 3. Measure of user's trendiness

	Items
1	Apparel plays an important role for me.
2	In fashion I am one step ahead of others.
3	I enjoy buying in selected apparel stores.
4	I am fascinated by trying new roles with different clothes.
5	I like wearing clothes that emphasize my body.
6	My friends often buy clothes which they have seen at me.
7	I enjoy trying new fashion brands.
8	I always know what is "In" and what is "Out" in fashion.
9	I am always looking for new apparel ideas.
10	I read regularly fashion magazines and catch up on new trends.

Third, user characteristics such as fashion involvement might influence to which extent the need for uniqueness arises [35, 36]. E.g., [35, 36] distinguish fashion followers, fashion innovators, fashion opinion leaders and innovative communicators and find that fashion innovators and innovative communicators have higher needs for uniqueness than the other groups. Therefore, we control for user's desire to be a trendsetter in apparel products. To measure this personal trait we constructed a scale using findings of [37] and [38]. Table 3 provides the used items. We measure user's trendiness on a 5-point Likert [39] scale (1=strongly disagree, 5=strongly agree).

We limit the study to female participants because men and women differ in shopping strategies and style categories [40, 41]. We raffled five Amazon vouchers in value of 20 Euros among participants.

After the completion of the data collection phase, we coded the video records on several dimensions, like the number of visited stores, the number of the visited pages and products etc. and the usage of different sales support systems. Further, we put down whether a particular sales support system was used in the selection of the product (conversion rate) or not.

5 Results

5.1 Participants and Sample Summary Statistics

34 female participants took part in our study in December 2013. As 3 participants failed to accomplish the task of picking at least one single product we can only evaluate 31 of the 34 result sets, which results in a 97% response rate.

Participants' age is between 14 and 39 with 78.9% being between 20 and 24. About three quarters of the participants have accomplished their "Abitur" as highest educational degree, while 21.2% own a graduate degree. Monthly income amounts from 500€ to 1500€ for 27.3% of the participants; 69.7% have less than 500€ per month at their disposal.

Regarding online apparel shopping habits the participants buy apparel once in 3 to 6 months (32%). Monthly expenses for apparel ranged from 50 to 100 Euros which is in line with the official statistics on shopping habits for clothing: In 2010, monthly expenses of German women amount to 41 – 57 Euros depending on their place of residence [42].

The participants scored on average 2.67 with a standard deviation of 0.51 on our constructed trendiness scale. The internal consistency of the scale is quite well; Cronbach's alpha [43] amounts to 0.7. To distinguish between different user groups we split the users according to their score on the trendiness scale into two groups: Users who scored more than 3 points on Likert scale were denoted as users with high trendiness. Seven persons are in this group. Research has shown that self-reporting often diverges from objective judgment. This phenomenon, affected by social desires and approval is known as the self-reporting bias or socially desirable responding [44].With purpose to check for possible self-reporting bias we asked an independent expert (a fashion design student) to evaluate the chosen outfits on the trendiness scale (1 = trendy, 0 = not at all). The agreement between our assignments of users to two groups and the expert evaluations was fair; Kohen's kappa [45] amounts to 38% ($p < .01$).

5.2 General Shopping Behavior

Table 4 presents summary statistics of general shopping behavior. The number of shops visited during a shopping session varied between 1 and 14 shops with an average value of 4.77 and a standard deviation of 3.41. The participants visited on average about 73 pages, about 25 product pages, about two brand pages and entered on average about 5 search terms during their search processes. About 5 products were on average chosen into the final outfit.

Table 4. Summary statistics general shopping behavior

Variable	*Mean*	*SD*	*Min*	*Max*
Number of visited stores	4.77	3.41	1	14
Total number of visited pages	72.81	49.07	6	207
Number of entered search terms	4.55	4.11	0	18
Number of visited product pages	24.61	17.90	1	73
Share of distinct product pages	.58	.27	.15	1
Number of chosen products[1]	4.55	1.23	1	7
Number of visited brand pages	2.06	2.42	0	9
Number of visited category pages	32.26	24.31	1	114
Average number of pages visited in one category	1.22	.31	1	2.6

Table 5. Group differences

	High trendiness		*Low trendiness*		*P-values one-sided T-test*
Variable	*Mean*	*SD*	*Mean*	*SD*	
Number of visited stores	5.71	4.82	4.5	2.96	0.21
Total number of visited pages	94.86	66.76	66.38	42.27	0.09*[2]
Number of entered search terms	4.71	4.03	4.5	4.22	0.45
Number of visited product pages	28.71	21.21	23.42	17.13	0.25
Share of distinct product pages	.54	.17	.59	.29	0.68
Number of chosen products	4.86	.90	4.46	1.32	0.23
Number of visited brand pages	1.43	2.30	2.25	2.47	0.78

[1] Although some users managed to pick only one single product and not a complete outfit, we kept such observations in the sample. The focus of the study was to observe users' search behavior and whether and how the users use sales support systems. We believe that the participants were motivated to find the best dress for the school reunion celebration, regardless of whether they eventually picked one or five products.

[2] Significance level 10%

Number of visited category pages	43.14	30.63	29.08	21.90	0.09*
Average number of pages visited in one category	1.21	.20	1.23	.34	0.54
N	7		24		

Table 5 presents the summary statistics for the user groups with high and low trendiness. The groups are comparable in their shopping frequencies online; group mean differences tests were all insignificant. As we expected that consumers with high trendiness would exhibit more search steps, we conducted one-sided two group mean comparison t-tests with equal variances. However, most differences are insignificant, with except for the total number of visited pages and the number of visited product category pages (for both variables $p < .10$).

5.3 The Use of Sales Support Systems

Table 6 displays the results of the usage of sales support systems. The percent of sample value is the percentage of participants that used the correspondent support system during their shopping session at least once. For the usage of filtering and keyword search tools we additionally counted the absolute numbers.

More than two-third (71%) of the participants used filtering tools and quarter of participants used keyword search tools. Participants used on average four filters and once the keyword search terms.

Table 6. Summary statistics of sales support systems usage

Variable	*Percent of sample*	*Mean*	*SD*	*Min*	*Max*
Number of filters	.71	4	4.93	0	19
In-shop keyword search	.25	1.06	2.11	0	8
Collaborative recommender	.23	-	-	-	-
„Wear it with"-recommender	.06	-	-	-	-
Top seller lists	.19	-	-	-	-
Unspecific banners	.06	-	-	-	-
New In	.10	-	-	-	-
Style Guide	.19	-	-	-	-
Occasion/Event	.16	-	-	-	-
Season	.03	-	-	-	-

The use of filters bears advantages for both the consumer and the store manager. As online stores usually provide a wide range of products, search costs may be high until a desired item is found [7]. Filters offer a mean to reduce search costs by reducing the number of items and hence faster reaching of the shopping goal. Additionally, they provide information about consumers' preferences for the store manager.

A filter is supposed to facilitate the consumer's search process by the restricting the product offer. Hence, one would expect filters to accelerate the decision process in our study, affecting the number of viewed pages and chosen product percentage. Surprisingly, the opposite effect is true: We observe a positive relation between filters and the number of pages and a negative relation between filters and the chosen product percentage. Apparently, a high number of applied filters reduces the product consideration set too strongly which then results in a lower percentage of chosen products among all viewed products.

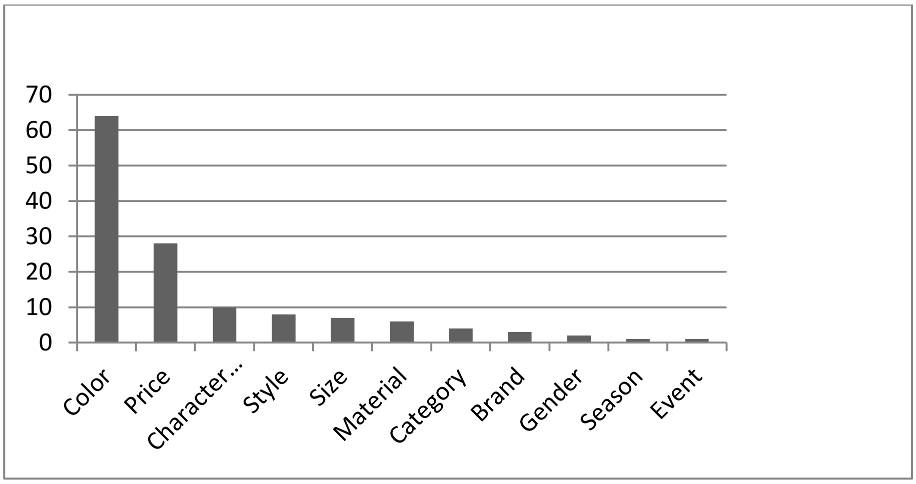

Fig. 2. Frequency of used filter dimensions

Fig. 2 displays product dimensions along which the participants of the experiment filtered their selection set in the online shopping environment. Fig. 2 shows that most people use color filters. The revelation of individual color preferences bears valuable information on consumers and enables store managers to create color profiles for consumers. This is due to the correlation of color preferences and consumers' skin and hair types. There are colors, like violet for example, that support the appearance of pale skin - an effect that is probably not intended by the consumer. [18] suggest application of approved color types to build consumer ontologies based on colors and enabling recommendations that go beyond the purchase history. Further, the findings on the usage of color filters are in line with the study by [16] who find that people differentiate themselves through colors within a social group.

23% of the participants used recommendations from collaborative filters and 6% recommendations from the "wear it with"-recommender. About 19% of the users clicked on the top seller lists and on "style guide" suggestions.

Similarly to the previous section, we compared the sample means of used sales support systems between the users with high and low trendiness. Table 7 provides the summary statistics and shows the results of the one-sided t-tests. Very surprisingly, not one person from the high trendiness group used the top seller lists ($p < .10$) and “wear it with”- recommendations (albeit insignificant group difference). The reason that group mean differences are insignificant despite the obvious differences might lie in the small sample size and high variances. In contrast, recommendations from collaborative filters, banners, “Style guide” and “Occasion/Event”-recommendations led, if used, to conversion rates of about 43%, 100%, 50%, and 100%, respectively. Although the “wear it with”-recommendations were not so frequently used, they led in 50% of cases to selection of a product into the final outfit set.

provides an overview of the conversion rates for the different sales support systems, if the support system led to the selection of an item for the final outfit. Although 19% of the participants click on the top seller lists, the conversion rate amounts to 0%, regardless of the user’s level of trendiness. This supports our hypothesis that top seller lists are not well suited for stores which sell products with identity-signaling characteristics as the people try to be unique. This finding has valuable implication that the motives to be unique cannot be ignored when implementing sales support systems. Similarly, even though 10% of participants clicked on the “New in”-recommender, the conversion rate amounts to zero.

Table 7. Group differences in sales support systems usage

Variable	*High trendiness*		*Low trendiness*		*P-values one-sided t-test*
	Mean	*SD*	*Mean*	*SD*	
Number of filters	4.71	5.65	3.79	4.89	0.34
In-shop keyword search	.86	1.57	1.13	2.27	0.61
Collaborative recommender	.14	.38	.25	.44	0.72
„Wear it with“-recommender	0	0	.08	.28	0.22
Top seller lists	0	0	.25	.44	0.08*
Unspecific banners	.14	.38	.04	.20	0.18
New In	.14	.38	.08	.28	0.33
Style Guide	.29	.49	.17	.38	0.75
Occasion/Event	.29	.49	.13	.34	0.84
Season	0	0	.04	.20	0.70
N	7		24		

In contrast, recommendations from collaborative filters, banners, “Style guide” and “Occasion/Event”-recommendations led, if used, to conversion rates of about 43%, 100%, 50%, and 100%, respectively. Although the “wear it with”-recommendations were not so frequently used, they led in 50% of cases to selection of a product into the final outfit set.

6 Summary, Conclusions, Limitations, and Further Work

As many online stores apply sales support systems, the current study evaluates their applicability to the apparel industry. For this purpose we conduct video analysis of female users' shopping behavior and gain some interesting insights. We distinguish thereby between users with high and low trendiness. Generally, we find that users with high trendiness undertake more search steps. Further, we find that most users rely more on different sorting and filtering as well as on keyword search tools than on personalized and non-personalized recommendations. Online apparel store specific tools like style guide, "new in" and occasion specific recommendations were used at moderate levels by the study participants. Users with high trendiness did not use top seller lists and "wear with it"-recommendations. Moreover, the assistance of top seller lists did not lead to the final choice of products (i.e. zero conversion rates).

Table 8. Conversion rates of used sales support systems

Sales support system	*Conversion rate*
Sorting filters	82.60%
In-shop keyword search	62.50%
Collaborative recommender	42.86%
„Wear it with"-recommender	50.00%
Top seller lists	0.00%
Unspecific banners	100.00%
New In	0.00%
Style Guide	50.00%
Occasion/Event	100.00%
Season	0.00%

Our findings allow us to draw implications for practice. Online shops might then avoid displaying "Top seller" and "customers who bought this also bought…"along the most popular products. Instead, they can try to serve users' need for uniqueness creating unique shopping experiences. As shown in [16] and by our findings, people differentiate themselves from others through a choice of different colors. This would imply that online stores could extend their assortments by different colors. Generally, designers of sales support systems for online apparel stores should be aware and account for users' different motives and needs (even opposing like e.g., for social identity and uniqueness) when buying clothes.

Our work comes not without limitations. First, the evaluated result set is small. We only analyzed 31 shopping videos and the variation between the participants is limited. Hence, our findings indicate only a weak trend in the usage difference of sales support systems by users with different levels of need for uniqueness. Further, the users might behave in a constructed setting differently as in reality. Finally, there might be other factors which might influence users' buying behavior.

Nevertheless, we provide a contribution to current research by deriving improvement opportunities for sales support systems from our study based on video analysis. A task for future research would be then to extent our research to a greater and divergent range of participants. As the next step, we plan to conduct a series of computer-assisted laboratory experiments using clickstream analysis to investigate the phenomena which we revealed in this explorative study more deeply.

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