Synchronized Multi-list User Interfaces for Fashion Catalogs

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ABSTRACT

Several online catalogs use carousels to present thematic lists of products, based on different optimization criteria. While this makes it possible to search for items according to diverse relevance perspectives, it hardly supports an integrated evaluation, which is key to critical consuming behavior. To address this issue, we propose a *synchronized multi-list model* that (i) enriches item presentation by visualizing its evaluation and (ii) enables the user to simultaneously center the carousels of the multi-list on the item in her/his focus of attention, showing its ranking in each list. This type of visualization is aimed at enhancing the transparency of results by enabling the user to simultaneously compare products across all the evaluation criteria applied within the multi-list.

As a testbed for our model, we selected fashion catalogs, with the aim of making users aware of clothes' evaluation with respect to the sustainability and ethical issues concerning the production practices applied by their brands. In a preliminary user study, we analyzed users' gaze behavior to reveal how people interact with the carousels of the multi-list for product comparison. The results show that people explored the position of items in all the carousels, following a pattern that differs from the top-left triangle observed in traditional multi-lists, and they selected items having a fairly good ranking, showing their interest in sustainability and ethical standards.

CCS CONCEPTS

• **Information systems** → *Web searching and information discovery*; *Recommender systems*; • **Human-centered computing** → *Interaction techniques.*

KEYWORDS

Transparent User Interfaces, Environmental Sustainability, Ethics, Recommender Systems

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1 INTRODUCTION

Several online catalogs use carousels to present thematic lists of products, based on different optimization criteria; for instance, in food recommender systems, recipes might be ranked depending on their estimated calories, amount of fat, sugar, and so forth [4, 17]. While this makes it possible to search for items according to diverse relevance perspectives, it hardly supports a transparent, overall assessment of their evaluation, which is key to critical consuming behavior [10]. For instance, the same item might be highly ranked in one list, and badly ranked in another one, and the user might be interested in checking all the lists to assess its suitability (e.g., searching for a food recipe with low fat *and* low sugar).

To address this issue, we propose a *synchronized multi-list model* that (i) enriches item presentation with a visual representation of its evaluation and (ii) enables the user to simultaneously center the carousels of the multi-list on the item in her/his focus of attention, showing its ranking in each of the lists. When the user selects an item i to inspect its properties, all the lists center themselves on i and highlight it, showing how many better and worse products are available in their rankings. Thus, the user can assess the suitability of i with respect to all the evaluation criteria by vertically browsing the multi-list. This visualization is aimed at enhancing the transparency of results and increasing the awareness of users when making choices.

As a testbed for our model, we selected fashion catalogs, with the aim of making users aware of clothes' evaluation with respect to the various sustainability and ethical issues concerning the production practices applied by their brands [9, 13]. For this test, we developed a multi-list user interface whose upper carousel sorts items according to an overall evaluation of sustainability and ethical standards. The other carousels are sorted by more specific criteria. In a preliminary user study, we analyzed users' gaze behavior to reveal how users browse the multi-list. We found that, even though people mainly focus on the upper carousels, they explore the ranking of items in *all* the lists, showing their interest in multiple evaluation criteria. Specifically, users follow a "T" pattern that differs from the top-left triangle observed in traditional multi-lists [3]. Moreover, they select

items that are well positioned with respect to sustainability and ethical standards, suggesting a possible influence of visualizing item evaluations in the carousels [1].

In the following, Section 2 outlines the related work. Sections 3 and 4 describe the data we used and our visualization model. Section 5 presents the user study and Section 6 describes its results. Section 7 concludes the paper.

2 RELATED WORK

Several e-commerce and media streaming sites, like Netflix [12], show search results by using multiple carousels that represent "thematic" lists of items, each one tagged by a specific topic, or by the optimization criterion applied to sort them. Hu and Pu pursued multi-lists to increase the diversity of the suggestions while reducing choice overload [7]. Chen and Pu used them to group items by characteristics such as "cheaper and lighter, but with lower processor speed" [15]. In comparison, we propose synchronized multi-lists to enhance item comparison and transparency across evaluation criteria.

Previous researchers observed that users' navigation behavior in multi-lists differs from the one observed in single lists. Chierichetti et al. [3] noticed that the user's attention in 2D user interfaces is mainly focused on the top-left triangle of the window. However, other researchers do not generalize user behavior and suggest analyzing it site by site. Zhao et al. [21] developed an efficient methodology to predict gaze in grid-based user interfaces through eye-tracking, and Wu et al. [18] proposed to analyze log data to reveal a propensity to positions in the user interface. Some works show that, in a multi-list user interface, people tend to select the items from the upper lists [5, 17]. Our work partially confirms this finding but shows that, in a synchronized multi-list, users vertically explore all the lists.

In the present work, we associate numerical labels with items to visually summarize their evaluation, for each criterion, so that the user can also assess their absolute position in the respective evaluations (e.g., 2.8/5). This aspect distinguishes our model from the "nutrition labels" proposed in [4] for the classification of food recipes because our labels support a finer-grained comparison of the options to choose from.

3 DATA

We collected data about clothes by scraping the Zalando website from February to March 2022. For each garment, we retrieved the category (e.g., skirt), the first available image, the data about its color(s) and material, the price, and the brand producing the item. The dataset we obtained includes 30,722 items produced by a total of 2,730 brands. To obtain rich feature vectors describing the clothes with stylistic information, we analyzed their pictures using the pre-trained model based on ResNet50, from the MMFashion library [11]. In this way, for each item i, we obtained a 1000-dimensional vector $\vec{v_i}$ of binary features such as "knit", "print", "striped", "pocket" and so forth, describing its aspect. Moreover, to comply with the fact that, in some cases, the colors of clothes specified in the catalog are non-standard (e.g., "taupe", "driftwood", etc.), we inferred the color of i in a standard scale using a convolutional neural network trained specifically for our dataset, using transfer learning on ResNet50 [6].

As far as the information about brands' sustainability and ethical standards is concerned, we use the Good On You platform [19] to retrieve data. This platform evaluates in the [1, 5] range (where 5 is the best value and 1 the worst one) the environmental sustainability (denoted as "environment rating"), workers' well-being ("labour rating"), and respect for animals ("animal rating") in the production cycle [20].

4 SYNCHRONIZED MULTI-LIST

Figure 1 shows the multi-list user interface, which visualizes a set of clothes belonging to a selected category (in the figure, jumpers, and cardigans for women). The top of the page displays the details of the item in the user's focus of attention, and an expandable description of the overall sustainability and ethical standards of its brand, associated with an icon that represents this evaluation dimension. The label in the image summarizes the item's score in [1, 5], using color coding to graduate values from green (good values) to red (bad ones). This score is the arithmetic mean of the "environment rating", "labour rating" and "animal rating" values of the brand provided by Good On You. Below the description of the aggregated sustainability and ethics information, three expandable components describe these aspects, each one associated with a representative icon.

The user interface shows a list of 30 clothes in four ranked lists ("CLOTHES SORTED BY" ...), which are sorted left to right in descending order of the criterion specified in their title. Building on the results about users' attention described in [5], we placed the list sorted by aggregated sustainability and ethics in the first position to promote data summarization.

In each list, every image has a label that shows the item score in the respective evaluation criterion. When the user clicks on an image, its border becomes black, the user interface shows the details of the clothes (that becomes the item in focus) and all the lists center themselves on it, as in Figure 1.

As this preliminary work focuses on people's interests in sustainability and ethical standards, we did not use any recommender system to personalize the list of items presented in the user interface. For each category of clothes C to be visualized (e.g., jumpers and cardigans for women), we selected the 30 items to be shown in the following way: first, we evaluated the overall sustainability and ethical standards (in [1, 5]) of the items of the dataset that belong to C and we created a set $I = \{i_1, \ldots, i_{50}\}$ including 25 clothes having a low evaluation, and 25 having a high one. Then, we extracted from I a subset of 30 items that are most different from each other in shape and color. We obtained these items as follows:

(1) First, we computed the pairwise similarity σ between the items of I. Given two items $i, j \in I$:

$$\sigma(i, j) = AVG(\sigma_{col}(i, j), \sigma_f(i, j)) \quad (1)$$

In Equation 1, σ_{col} is the color similarity and is defined as: $\sigma_{col}(i, j) = 1 - \delta(i, j)$, where $\delta(i, j)$ is the color difference between i and j and is computed using ΔE CIEDE 2000 [16]. Moreover, $\sigma_f(i, j)$ is the Jaccard similarity between the feature vectors of the two items ($\vec{v_i}$, and $\vec{v_j}$, see Section 3).

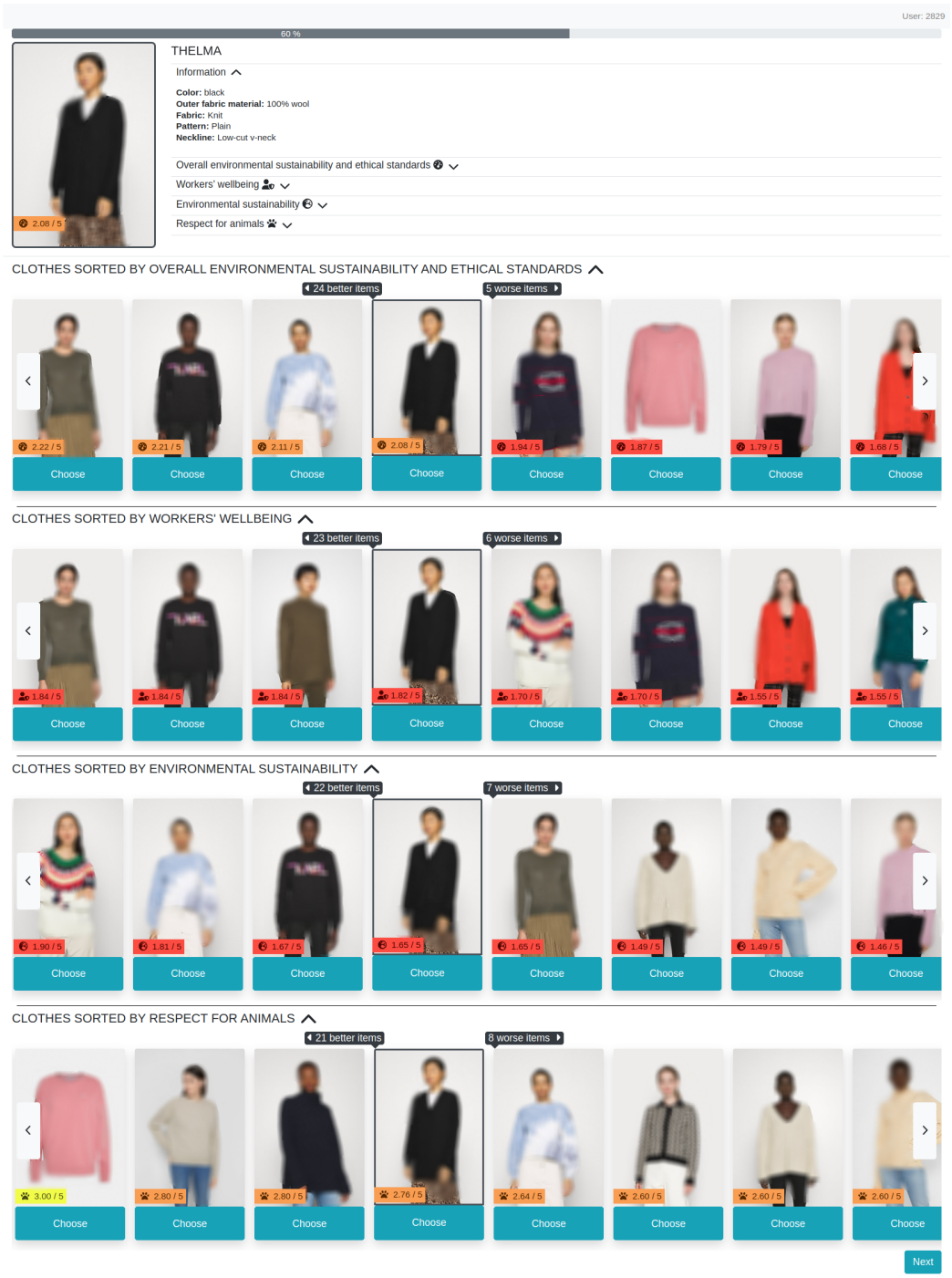

Figure 1: User interface of the multi-list visualization model, showing jumpers and cardigans for women. The images of the models are blurred for publication purposes.

Figure 2: Heatmap derived from the eye-tracking data. The color scale indicates the total number of glances in the portions of the user interface, from 1117 (red) to 28 (yellow). We denoted the four lists with short names to enhance the readability of the figure.

(2) Then, we built a list L including all the pairs of items $i, j \in I$, with their associated pairwise similarity σ. We then sorted L by descending similarity.
(3) To obtain the subset of dissimilar items, we removed 20 elements from L by iterating on the sorted list of pairs, from left to right. For each pair (i, j):
   - If $i \in L$, then we removed i from L;
   - If $i \notin L$ (because it was removed in a previous cycle of the iteration) but $j \in L$, then we removed j from L;
   - Otherwise, we skipped the pair.

   We stopped the iteration as soon as 20 items were removed from L, resulting in the final list of 30 elements to be shown in the user interface.

5 PRELIMINARY USER STUDY

From November 15 to December 15, 2022, we carried out a small user study to understand how people interact with the synchronized multi-list.[1] For this purpose, we developed a web-based application whose user interface we described in Section 4. The application supports the presentation of various categories of clothes but we restricted the experiment to jumpers and cardigans.

For the user study, we recruited adult people by spreading an invitation message in public mailing lists and social networks. The participants joined the experiment voluntarily, without any compensation. The test application asked them to read an informed consent and declare that they were ≥18 (mandatory to continue the test). Then, it guided them in all the steps of the study, without imposing any time limits on the execution of the tasks.

To guarantee the participant's privacy, the application did not collect her/his name or any other identifying data. At the beginning of the interaction, it generated a numerical identifier to tag the anonymous data it acquired (see below). Then, it asked the user whether (s)he wanted to explore a set of clothes for women or for men, and it displayed the clothes, asking to choose the preferred one. During the interaction, the application logged the participant's actions in the user interface and tracked the eye gaze to detect the portions of the user interface (s)he inspected. We used the open-source WebGazer.js library [14] that employs common webcams to infer the eye-gaze locations on a web page in real-time. This library detects an eye-gazing event each time the user's eyes change focus.

[1]This is a portion of a larger user study that has been approved by the Ethics Committee of the University of Torino (Protocol Number: 0244699).

6 RESULTS

14 participants successfully carried out the test through its end. On average, the experiment lasted about 18 minutes. In the following, we report the distribution of participants' data.

- *Gender:* 4 females, 10 males, 0 non-binary, 0 not declared. *Age:* 21-30 (13) and 51-60 (1).
- *Education level:* middle school (1), university (10), PhD (3).
- *Background:* technical (4), scientific (8), humanities (1), other backgrounds (1). *Familiarity with ICT:* advanced (9), average (3), novices (2).
- *Usage of online booking and e-commerce platforms:* daily or almost daily (1), a few times a week (8), a few times a month (2), a few times overall (3).
- *Importance of brands' sustainability and ethical standards in the selection of clothes (in [1, 5]):* participants considered environmental sustainability (Mean = 3.93, Standard Deviation = 1.27), workers' well-being (M = 4.00, SD = 1.24), and respect for animals (M = 3.71, SD = 1.27) as fairly important.

Figure 2 shows the heatmap of the eye gaze data we collected. Each row represents a list and the color scale denotes the total number of glances on the visualized portions of the list. The largest number of glances is positioned in the central part of the screen.

By crossing eye-tracking data with the logged clicks and scrolls, we can associate participants' glances with the items in their focus of attention; i.e., users scroll the lists and focus on the central displayed area. We infer that people look at the items that are adjacent to those in focus. Specifically, they look more frequently at the left items, which are higher-rated than the right ones. Moreover, as observed in [5, 17], the number of glances progressively decreases from the top lists to the bottom one. However, the whole central column of the heatmap receives a large number of glances, down to the lowest list. As the lists are synchronized, this means that people inspect the evaluation of the items of interest in all the sustainability and ethics criteria. This is key to enhancing their awareness of how items are positioned w.r.t. the respective evaluation criteria. Moreover, this could be an insight that people appreciate the transparency offered by the multi-list and the labels.

From the logged actions, we observe that the mean ranking of the selected items in the upper carousel of the multi-list is 4.25/30 (Standard Deviation = 3.81). This shows that participants selected products that are highly ranked in environmental sustainability and ethical standards. While these results refer to a very limited sample size, they suggest that enriching the presentation of clothes with data about the sustainability and ethical standards of their brands positively influences users' selection decisions.

7 CONCLUSIONS

We described a preliminary user study aimed at investigating user interaction with a synchronized multi-list model that (i) enriches item presentation with a visual representation of its evaluation and (ii) enables the user to simultaneously center the carousels on the item in her/his focus of attention, displaying its ranking in each of the lists. The results show that users explore the position of products in all the carousels of the multi-list, denoting their intent to assess the evaluation of items across all the represented evaluation criteria. Moreover, users choose products having a fairly good ranking w.r.t.

overall sustainability and ethical standards, suggesting a possible influence of the visual presentation of evaluations on their selection decisions. In our future work, we plan to integrate a recommender system to rank the items by fusing users' stylistic preferences with their interest in sustainability and ethics. We also plan to investigate nudging techniques to enforce responsible product consumption [2, 8].

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