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COGNITIVE STYLES AND PSYCHOPHYSICAL TASKS PERFORMANCE: A LATENT CLASS ANALYSIS STUDY

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Abstract

The contribution of cognitive styles to solving cognitive tasks was widely studied so far. However, most of these studies assess the contribution of each cognitive style separately, not addressing the critical issue of various styles interactions. The purpose of our study was to reveal distinct subgroups characterized by multiple style dimensions, and further assess between-group differences in signal detection/discrimination tasks performance. We carried out an experiment (N=120), in which we assessed five cognitive styles (augmenting-reducing, leveling-sharpening, flexibility-rigidity of cognitive control, equivalence range, and focusing-scanning) as well as psychophysical tasks performance indices. In order to identify subgroups, characterized by multiple style dimensions, we performed latent class analysis and then assessed between-group differences in signal detection/discrimination tasks performance indices. We analyzed models consisted of four and five classes due to their classification quality characteristics (information criteria, entropy, absolute and relative Likelihood ratio tests) as well as the analysis of groups' structure. A specific group was revealed in both models, including subjects with such style dimensions as 'reducing', 'sharpening', 'flexibility' and 'scanning'. Such cognitive styles combination was related to the increase of sensory sensitivity as well as decrease of response confidence. We suggest that it reflects group's abilities to draw attention to significant stimulation features, creating its detailed image, and inhibit impulsive responses. We highlight the necessity of studying not only effects of separate cognitive styles, but also their interactions. We suggest that our results could have practical implications in professional selection of specialists performing perceptual tasks under uncertainty.

Keywords: Cognitive style, psychophysics, individual differences, latent class analysis.

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1. Introduction

The concept of cognitive style (CS) was initially introduced to highlight individual differences in organizing, representing, and processing information (Cools & Rayner, 2011; Kozhevnikov et al., 2014; Nosal, 2009). However, over the long-term studies the initial idea faced numerous challenges. The current issue in CS field was metaphorically characterized as 'jungle' or 'snow-slip' (Nielsen, 2014), reflecting the inconsistency in different authors' views, the lack of adequate methodology and accumulation of the variety unsystematized empirical facts. Last works aim at critical analysis of the early studies, as well as introduce scientific programs, suggesting the way of overcoming crucial challenges and outlining perspectives of field improvement.

The issue of understanding the way CS are related to each other is recognized as one of the most pressing and controversial (Cools & Rayner, 2011; Kozhevnikov et al., 2014; Nosal, 2009; Zhang et al., 2012). CS, along with other style constructs, such as learning, thinking, intellectual styles etc., are recognized as 'instrument bound' — that is, they are characterized by relatively strict connection to the particular instrument or technique. That leads to apparent difficulties in generalization of empirical data and theoretical conceptualization of results. In general, empirics preceded theory, and therefore researchers were forced to build on specific and concrete operationalized definitions of CS. The expand of empirical studies was not accompanied by the corresponding increase of summarizing theoretical works (Cools, Rayner, 2011; Moskvina & Kozhevnikov, 2011; Nielsen, 2014; Nosal, 2009). Furthermore, many authors highlight the ongoing increase in already large number of separate isolated CS dimensions as well as corresponding diagnostic tools (Cools & Rayner, 2011; Moskvina & Kozhevnikov, 2011; Nielsen, 2014; Zhang et al., 2012).

2. Problem Statement

The variety of integrative models contributing to the issue of systematizing and clustering existing CS has been suggested so far (Kozhevnikov et al., 2014). However, to the authors' best knowledge, despite the large body of literature exploring individual differences in solving various types of tasks exists (see, for instance, Izmalkova & Blinnikova, 2017; Shoshina & Shelepin, 2014), empirical studies assessing the effects of CS interactions (or combinations of multiple CS) are still lacking. Moreover, it is crucial to systematize and organize distinct CS dimensions within the context of this being one of the controversial issues.

3. Research Questions

In this study we attempted to address two issues. First, we were wondering whether we could reveal distinct profiles and groups, representing five style dimensions, and second, we questioned whether individual differences in psychophysical tasks performance exist between the revealed subgroups.

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4. Purpose of the Study

In this paper, while we refer to our earlier work dealing with individual CS differences in psychophysical tasks performance (Volkova & Gusev, 2017), the focus is different. While in referred study we aimed at exploring how separate CS affect sensory performance, in the present study our goal is to reveal a set of subgroups characterized by multiple CS dimensions (augmenting-reducing, leveling-sharpening, flexibility-rigidity of cognitive control, equivalence range, and focusing-scanning) using latent class analysis (LCA) method, and further assess between-group differences in signal detection/discrimination tasks performance.

5. Research Methods

A total of 120 participants (42 males and 78 females) with normal or corrected-to-normal vision took part in this experiment: 112 of them performed both CS tests and psychophysical tasks, 8 of them performed CS tests only.

The experimental session started with two psychophysical tasks, each of which had two difficulty levels (easy and hard): (1) visual signal detection 'yes-no' (YN) task, where a distractor was added to the original procedure, and (2) 'same-different' loudness signal discrimination (SD) task. A detailed description of the tasks, including stimuli, instructions, software and apparatus, is presented in our previous paper (Volkova & Gusev, 2017). We assessed sensory sensitivity (A′), strictness of criterion index (YesRate), RT, RT stability (SDRT) and confidence (Conf) for each task.

After YN and SD tasks participants performed a set of CS tests: (1) Leveling-Sharpening House Test (Santostefano, 1971), (2) Stroop Color-Word Interference Test (Stroop, 1935), assessing flexibility-rigidity of cognitive control, (3) Object Sorting Test (Gardner et al., 1959), evaluating equivalence range, and (4) Size Estimation Test (Gardner et al., 1959), appraising focusing-scanning and augmenting-reducing. The median split was used to divide sample in two dimensions for each CS.

Data was processed using IBM SPSS Statistics 22.0 and Mplus 7.

In order to reveal the groups with different combination of CS we performed LCA. This mixture-model method is based on the idea that it is possible to reveal a class as a categorical latent (unobserved) variable that may serve as a possible explanation of subjects' heterogeneous response patterns in a manner that they belong to different subgroups. In general, LCA, along with the cluster analysis, addresses the issue of classifying and clustering respondents, in our case – based on subject's belonging to a certain CS dimension. This statistical procedure seems to us to better fulfill our goals and objectives because of its specific features. In contrast to cluster analysis, in which participants are clustered based on the distances, LCA builds upon the probability of belonging to the group. Moreover, one of the big advantages of this method is that it is developed to deal with categorical data (Geiser, 2013). Since in our study we use the median split to divide sample into two CS dimensions, we get categorical (binary) data for each of the five CS.

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6. Findings

Therefore, we suggested that we could reveal several distinctive CS profiles, allowing us to categorize the sample into groups, and then analyze the significance of between-group differences. For this purpose we compared models with different numbers of latent classes (table 1).

There were 31 distinct CS patterns, consisted of the scores for each CS dimension, which were then grouped in classes. Table 1 shows that both AIC and BIC increase alongside the growth of the number of classes, indicating that based on the information criteria solely we should choose to the model with two latent classes. However the trend in entropy indicates, in contrast, that classification quality improves along with increasing the number of classes, since this parameter reflects the mean probability that subject belongs to 'his' or 'her' class. Now we appeal to absolute and relative Likelihood ratio tests (LRT), that compare the estimated k-class model to (k-1)-class model. According to both absolute and relative LRTs, the model with two latent classes fits the data better than the model with no classes, and the model with four classes show the better fit than the model with three classes, i.e., we could reject the model with fewer classes based on the LRT significance level. It is noteworthy that the model with three classes cannot be considered as fitting the data better than the model with two classes. Whereas the entropy shows clear growth in four-class model compared with three-class model, LRTs indicate that models with larger numbers of classes (five to seven) do not significantly exceed the model with four classes and one another (Nylund et al., 2007).

Table 01. Comparison of models with diverse number of classes

Parameter	2 classes	3 classes	4 classes	5 classes	6 classes	7 classes
AIC (Akaike information criteria)	825.008	831.391	838.132	846.818	854.299	864.659
BIC (Bayesian information criteria)	855.671	878.778	902.244	927.655	951.861	978.946
Sample-size adjusted BIC	820.894	825.032	829.529	835.971	841.208	849.324
Entropy	0.725	0.744	0.782	0.858	0.868	0.867
Vuong-Lo-Mendell-Rubin Likelihood ratio test (LRT) (significance level)	0.005	0.067	0.036	0.278	0.441	0.663
Relative Lo-Mendell-Rubin LRT test (significance level)	0.006	0.074	0.040	0.288	0.453	0.666

As a result, we have chosen to the four-class model due to its fit characteristics and the analysis of the structure of revealed groups, i.e. the CS dimensions. Nonetheless, we have analyzed both four- and five-class models due to the interpretation of groups structure obtained.

Tables 2 and 3 present the data on class counts and proportions, as well as average probabilities for class membership for models with four and five classes, respectively. As is clear from them, the groups in both models appear to be unequal in terms of size. On the one hand, groups' size imbalance can raise the question of model's theoretical and practical significance and furthermore complicate statistical analysis. On the other hand, smaller groups may reflect unique and specific CS profiles.

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Table 02. Four-class model: characteristics of revealed classes

Class	Class counts and proportions	Average latent class probabilities for most likely latent class membership				Groups structure
		1	2	3	4	
1	68 (64%)	0.944	0.051	0.005	0.000	No common style dimensions
2	34 (25%)	0.230	0.770	0.000	0.000	Focusing
3	5 (3%)	0.208	0.021	0.771	0.000	Augmenting, sharpening, flexibility, broad equivalence range, focusing
4	13 (8%)	0.279	0.000	0.000	0.721	Reducing, sharpening, flexibility, scanning

Table 03. Five-class model: characteristics of revealed classes

Class	Class counts and proportions	Average latent class probabilities for most likely latent class membership					Groups structure
		1	2	3	4	5	
1	6 (5%)	0.713	0.000	0.120	0.167	0.000	Reducing, rigidity, broad equivalence range
2	13 (11%)	0.087	0.913	0.000	0.000	0.000	Reducing, sharpening, flexibility, scanning
3	30 (25%)	0.070	0.000	0.842	0.088	0.000	Reducing, focusing
4	50 (42%)	0.105	0.000	0.019	0.877	0.000	Sharpening
5	21 (18%)	0.000	0.000	0.034	0.000	0.966	Augmenting, sharpening

Moreover, tables 2 and 3 show CS dimensions, common to all subjects belonging to a certain group (column 'Groups structure'). For instance, class 4 in four-class model and class 2 in five-class model were the same and consisted of subjects, showing 'reducing', 'sharpening', 'flexibility', and 'scanning' together, regardless of the dimension of 'equivalence range' CS. It is noteworthy that there were no common style dimensions for class 1 in four-class model. Hence, this may mean that only three distinct classes can be revealed in this model, whereas the fourth one consisted of subjects who were not included in any of the other groups.

We used one-way ANOVA with LSD multiple comparisons test in order to assess between-group differences. It showed several significant effects of latent class membership factor on psychophysical tasks performance indices. Tables 4 and 5 present only significant effects.

First, we found significant effects of latent class membership in four-class model on sensitivity index A′ in both easy ($F=4.032$, $p=0.010$, $eta=0.114$) and hard ($F=5.051$, $p=0.003$, $eta=0.140$) YN tasks. As is clear from table 4, class 4 showed highest sensitivity. As mentioned above, class 4 consisted of subjects with such CS dimensions as 'reducing', 'sharpening', 'flexibility' and 'scanning'. Our previous study showed that these CS dimensions relate to higher accuracy of solving signal detection tasks, i.e. higher sensory sensitivity, due to their specific features in contrast to opposite dimensions of corresponding CS (Volkova & Gusev, 2017). In particular, they have an advantage in sensitivity due to their ability to: (1)

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create detailed and precise image of perceived stimuli ('sharpening'), (2) inhibit automatic impulsive answers ('flexibility', 'scanning'), (3) draw attention to stimulation features, relevant to the task, and ignoring the irrelevant ones ('scanning') (Gardner et al., 1959; Kozhevnikov, 2007; Kozhevnikov et al., 2014; Santostefano, 1971).

Table 04. [Significant between-group differences in performance indices for four-class model]

Task	Performance index	Class 1	Class 2	Class 3	Class 4	Significance level
Easy YN	A′	0.790	0.764	0.847	0.916	0.010
Hard YN	A′	0.751	0.736	0.863	0.892	0.003
Easy SD	Conf	0.864	0.906	0.807	0.787	0.012
Hard SD	Conf	0.824	0.884	0.767	0.733	0.006

Similar results were achieved for five-class model (F=3.864, p=0.006, eta=0.142 for easy YN task; F=4.604, p=0.002, eta=0.167 for hard one), where the same group showed advantage in sensory sensitivity (table 5).

We have also found significant effects of latent class membership factor in four-class model on response confidence in both easy (F=3.803, p=0.012, eta=0.096) and hard (F=4.410, p=0.006, eta=0.109) SD tasks. As shown in table 4, subjects belonging to class 2 were more confident in their responses, compared to other groups. As mentioned earlier, class 2 included 'focusers', regardless of other CS dimensions. In our opinion, one possible reason of this effect may lie at the characteristics of attention allocation, inherent to 'focusers' in contrast to 'scanners' (Gardner et al., 1959; Kozhevnikov, 2007). 'Focusers', thus, tend to draw their attention to bright or strong signals, though now always relevant to the task, but still raising stronger sensory impressions. We suggest that due to brighter sensory impressions, 'focusers' experience correspondingly higher confidence, in its turn.

Table 05. [Significant between-group differences in performance indices for five-class model]

Task	Performance index	Class 1	Class 2	Class 3	Class 4	Class 5	Significance level
Easy YN	A′	0.758	0.916	0.753	0.785	0.848	0.006
Hard YN	A′	0.723	0.892	0.723	0.745	0.833	0.002
Easy SD	Conf	0.782	0.787	0.900	0.876	0.860	0.017
Hard SD	Conf	0.746	0.733	0.875	0.837	0.822	0.018

The results obtained for five-class model were quite similar (F=3.157, p=0.017, eta=0.106 for easy SD task; F=3.120, p=0.018, eta=0.104 for hard one). As presented in table 5, subjects belonging to classes 3, 4 and 5 were more confident in their responses than ones belonging to classes 1 and 2. This finding requires further study, since it reflects complicated interactions of multiple CS dimensions.

It is noteworthy that for both models the class, demonstrated relatively highest sensitivity in YN tasks, showed at the same time the lower response confidence in SD tasks.

7. Conclusion

Using the LCA method, we identified distinct groups, characterized by multiple CS dimensions. Although our findings require further investigation, we would like to highlight that studying not only effects

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of separate CS, but also CS interactions is an issue of critical importance within the framework of style field in psychology.

Regarding individual differences in psychophysical tasks performance, we managed to reveal a specific group, that shows both high sensory sensitivity and low response confidence. Since the perceptual uncertainty, inherent to psychophysical tasks, is a key component of professional activity of wide range of observers (for instance, radar stations operators, air traffic controllers), our findings may have a practical outcome in professional selection of specialists, performing perceptual tasks under special conditions at their full sensory capacity.

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