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SHORT REPORT

Exploration of Categorization and Category-Based Induction on Waste Sorting: A Follow-Up Observation by NeuroSky MindWave

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Abstract: Waste sorting, as an embodiment of behavioral cognition, is regulated by two cognitive processes, namely, Categorization (C) and Category-Based Induction (CBI). This study employed the event-related potential (ERP) technique to assess whether there is a transformation between C and CBI in waste sorting cognition, in order to help individuals establish a correct waste sorting behavior. We reported a case of intervention in waste sorting education with a 58-year-old Chinese woman to discriminate whether such intervention facilitates the transition between C and CBI. The results showed that the waste sorting cognition follows a developmental model as C-CBI-C, where education may help the subject build a cognitive framework for waste sorting by altering inherent misperceptions and filling gaps in classification knowledge. The results also noticed that FN400 is identified as a characteristic waveform in the CBI process, by which it is indicated that the first 4 to 7 days of education is a critical period for establishing the cognitive framework. Through a comparison of the ERP waveforms at different stages of intervention, the results are insightful to help individuals improve their cognition of waste sorting.

Keywords: ERP, education, FN400, waste sorting, categorization, category-based induction

Introduction

The rapid growth of waste generation poses a challenge to urban sustainable development.[1] The sudden emergence of the coronavirus disease (Covid-19) has exacerbated the clinical waste production, such as large number of discarded test strips, placing huge pressure on municipal waste management system.[2,3] Clinical waste is a category of hazardous waste, due to its quantity, concentration, and infectious properties, which may cause significant harm to human health and the environment if managed improperly.[4,5] Hazardous wastes can be in the form of solids, liquids, sludges, which are sourced from various industries, eg, chemical production and manufacturing.[6] They are highly toxic, corrosive, as well as explosive, and improper storage or disposal may result in environmental contamination.[7] To select appropriate management option, it is important to have a clear understanding of the nature of the waste components.

For hazardous waste management, waste sorting is considered as a measure of source reduction, as it improves the recycling efficiency, and mitigates the environmental impacts regarding disposal.[8] Particularly, waste sorting is a prerequisite for materials recycle and energy recovery, which not only restricts the possible mixing of toxic and hazardous components but also reduces the associated risk.[9] However, waste sorting is also a complex cognitive process. How to conduct individuals to establish a correct waste sorting cognition is a precondition to improve the classification performance.

Waste sorting is the embodiment of cognition, possibly regulated by Categorization (C) and Category-Based Induction (CBI).[10] The former is the grouping of multiple objects into different categories,[11,12] eg, regarding leftovers as kitchen waste. The latter is an inferring process whereby individualis likely to have similar characteristics in the

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corresponding group.[13] For example, discarded mercury thermometer is considered to be a typical hazardous waste, from which it can be inferred that lead-acid battery is also a hazardous waste, as they may contain similar poisonous ingredients, such as heavy metals.

Both of the Categorization (C) and Category-Based Induction (CBI) are reasoning process based on the existing knowledge and experience.[14] The former is a similarity-based and fundamental decision-making process, whereas the latter is a cognition enhancement through learning in order for conscious decision-making.[15,16] The transition from categorization to category-based induction indicates a shift in categorical-operational thinking from preoperational to concrete operational thinking,[17] in which CBI facilitates decision-making for encountered issues by using existing knowledge.[14] The more complex the knowledge in a particular domain, the more beneficial it is to reason based on causal relationships between premise and conclusion.[16]

In order to identify whether there is a shift between C and CBI in waste classification cognition, this study introduces the event-related potential (ERP) technique to discriminate such transition. CBI requires similarity comparisons of reasoning premises, concepts, basic theories, etc., thus may increase an individual's response time and peak latency (PL).[18] It is hypothesized that the lower the individual's affirmation of the induction result, and the greater the cognitive conflict is in the CBI process. In such context, the amplitude of FN400 (A negative deflection within a 200–600 millisecond time window, which peaks approximately 400 milliseconds after the stimulus is presented) reflected in the event-related potential (ERP) is significantly smaller than that in the categorization process. Besides, the amplitude of sustained negativity (SN), which exists in a 500–1000 millisecond time window with long-time negative deflection and anterior central distribution, is also significantly larger than that in the categorization process.[19] This study explores whether there is significant difference in the dominant cognition process regarding different types of waste classification by investigating individuals' response time, peak latency, FN400 amplitude and SN amplitude. Through a comparison of the ERP waveform with or without the education interventions, the results may lay a foundation for development of abrochure for the waste classification.

Materials and Methods

With regard to the selection of experimental subject, the main inclusion criteria are: family member of permanent urban residents who are willing to sort waste and have not received any education on sorting. The main exclusion criteria are ① the subject does not have normal vision; ② the subject has a history of traumatic brain injury or mental illness. The ultimately selected subject among the volunteers is a right-handed 58-year-old female and a local resident of Chengdu City, undertaking all the household works, who has not participated in waste classification education and electrophysiological experiments before. The experiment was approved by the Ethics Committee of Southwest Jiaotong University (Approval Number: SWJTU-2103-037 NSFC). The subject was informed in detail about the electroencephalogram (EEG) experiment, and explained that the experiment will not cause any harm to her physical health. The subject approved consent for the study.

The subject was corrected to normal vision before the experiment. According to the Standard for Domestic Waste Classification and Treatment in Chengdu City, the waste is divided into four categories: recyclables, hazardous waste, kitchen waste and other waste. Pictures corresponding to 60 types of garbage were evenly selected based on the guide brochure of waste classification, to form a test sample.

The experimental design was given as follows: First, the experimental instruction was given in a white text on the black background. Second, the subject was asked to pay close attentions to the garbage picture displayed on the computer screen, and press the button marked by the capital A, B, C and D (corresponding to the four categories of garbage, A to the recyclables, B to the hazardous waste, C to the kitchen waste and D to other waste) to judge its category. Third, garbage pictures were randomly selected from each waste category of the test sample, to form a total of 24 multiple choice questions for the test. These questions were presented randomly. After all the 24 questions were answered, the ending remarks were given. Before the experiment formally started, the subject was informed by a brief description of the sorting task, and asked to perform 3 consecutive exercises that were not counted in the final results, in order to be familiar with the operation. The subject participated in the experiment for 29 consecutive days at 11:00 am every day, lasting about 20 minutes. After the end of each experiment, the subject was informed by the results, and there was an explanation of the wrong answers.

If the subject presses the right button between 200–2000ms after the garbage figure appears, it is recorded as correct. However, pressing the wrong button pressed or failing to press the button within the specified time is recorded as an error. The response times (RTs) of the correct and incorrect answers were recorded to distinguish whether C and CBI have significant differences. The sorting test was divided into two groups: long-time response (corresponding to CBI process) and short-time response (corresponding to Categorization process), and the difference in the correct answer rate was distinguished by using the *t*-test. The misclassified wastes and their associated characteristics, as well as the subject's response time for each misclassification were investigated to infer the dominant cognitive process.

The experiment uses a portable EEG recording device, developed by NeuroSky, which is non-invasive to the human body by using dry electrode sensors.[20] The recording electrode is placed on Fp1 (left prefrontal cortex, only in contact with the skin), and the reference electrode is clamped to the left earlobe. The sampling frequency is 512 Hz, and data is recorded by connection to a laptop via Bluetooth. To reduce the 60 Hz line noise, a 58–62 Hz trap filter was used. The abrupt voltage offset was artificially removed. Using the "Infomax" method embedded in the "runica()" function of EEGLAB, an independent component analysis was performed on the ephemeral metadata.[21] Such an approach is useful for identifying and removing components that may cause large artefacts, including blinks, lateral eye movements, muscle tone, etc.[22]

Results

Behavioral Results

The subject has a good judgement ability on garbage classification. The average accuracy of the subject's 29 answers was 97.84%, with a minimum accuracy of 79.17% on a single test. The accuracy during the experiment showed an increase at first and remained stable until day 14 (Figure 1). It decreased on day 15, and then increased on day 17 and remained stable afterwards. The response time of the subject changed significantly, decreasing from 1814.3 ms to 850 ms, with an average response time of 886.32 ms. It showed a downward trend in the early stage of the experiment (day 1 to day 7) and increased on day 15.

The longest response time is 3494 ms, and the shortest response time is 295 ms. Grouping by the interval of the experimental data is beneficial to reveal data characteristics.[23] The 29 experiments were divided into two groups, corresponding to the Categorization and CBI process. The group distance was set to 1599.5 ms, and the segmentation

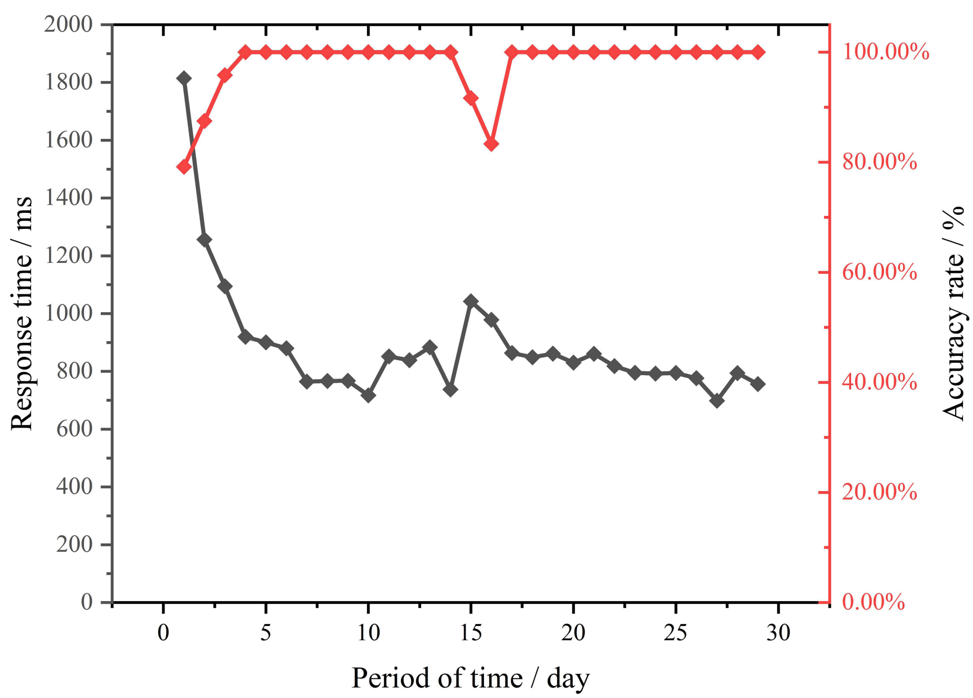

Figure 1 Change of response time and accuracy rate.

point was set to 1894.5ms. There were 22 data in the long response time group, in which the average RTs is 2576.77 ms, and the accuracy rate is 63.64%. There were 674 data in the short response time group, in which the average RTs is 840.10 ms, and the accuracy rate is 98.96%. The response time ($F(1, 20)=886.478$, $P<0.01$) and the accuracy rate ($F(1,20)=147.748$, $P<0.01$) of the two groups are significantly different.

Among the four types of garbage, only recyclables and other waste were misclassified (Figure 2). Other wastes were misclassified as kitchen wastes (4 times), recyclables (2 times) and hazardous waste (4 times), accounting for 67% of the total misclassifications. Recyclables were misclassified as kitchen waste (once), other wastes (three times) and hazardous waste (once), accounting for 33% of the total misclassifications.

ERP Results

There is no correlation between the peak latency and the response time ($F(1,27)= 0.351$, $P<0.01$). Repeated measurement variance of the peak latency showed that the intra-subject effect is not significant ($F(1,27)=0.832$, $P<0.01$), whilst the inter-subject effect is significant ($F=2073.300$, $p<0.01$). The peak latency fluctuates around 383.98ms, and does not change with the accuracy rate. With regard to the same type of waste, the intra-subject effect is not significant at different response times. However, the inter-subject effect is significant when stimulated by different types of waste. It is thus inferred that the peak latency is affected by the types of waste, not influenced by the subject's proficiency in the experimental procedure. However, the response time gradually decreases as the proficiency increases (decrease in cognitive computing time).[24]

When the subject is uncertain whether the classification is correct or incorrect, the CBI may be activated, indicated by the negative wave occurring in 200–600 ms, namely FN400. In this experiment, it was observed that negative waves

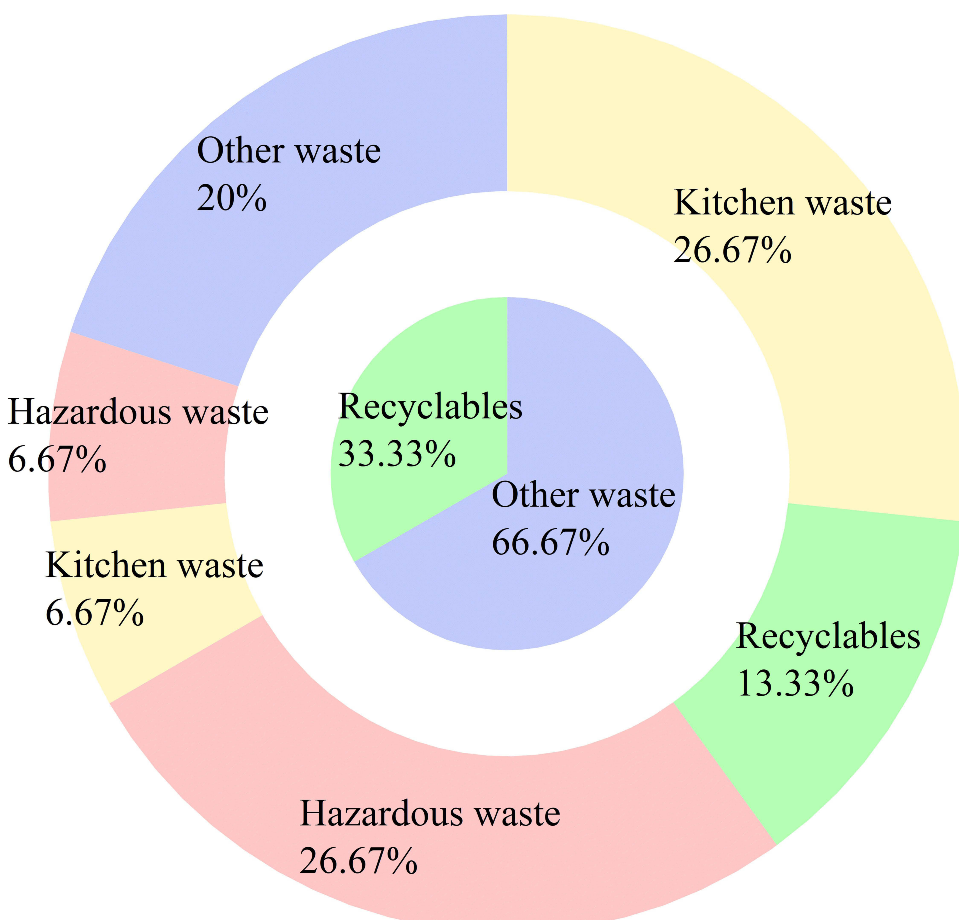

Figure 2 Distribution of the misclassifications.

appeared in the ERP during 190–400ms, shown in Figure 3. The advance of FN400 and its corresponding small amplitude may be due to the fact that the task of waste classification is transferred from superordinate to superior, that is, the specific garbage is classified into its own category.[25] FN400 can be observed in the range of 300–500ms in the second time session (days 4 to 7) and the third time session (days 8 to 14). The amplitude and SN amplitude in

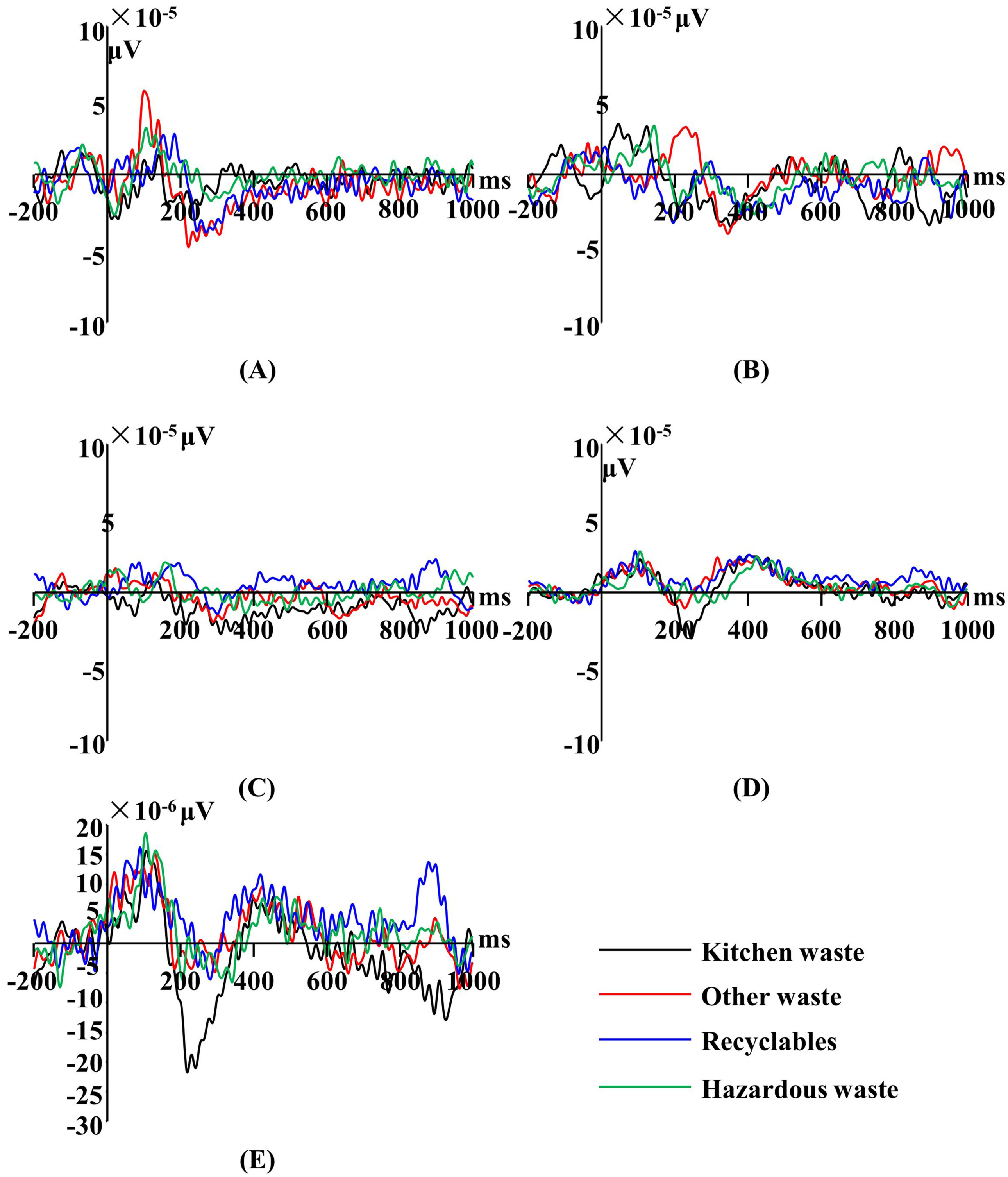

Figure 3 Group-level based average ERPs. (**A**) Average ERP in the first stage (1–3 days), (**B**) average ERP in the second stage (4–7 days), (**C**) average ERP in the third stage (8–14 days), (**D**) average ERP in the fourth stage (15–29 days), (**E**) ERP generated by different types of waste.

the second time session are slightly larger than those in the third time session. Combined with the behavioral results, as the response time in the first and second time sessions (days 1 to 7) showed a downward trend, and the classification errors appeared on the days 1, 2, 3, 15 and 16, respectively, corresponding to the first time session (days 1 to3) and the fourth time session (days 15 to 29), it can be inferred that the second time session is dominated by the CBI. In addition, the decrease of SN amplitude in the third time session indicates the decrease of cognitive conflict, that is the CBI decreases and the Categorization increases. At the same time, the negative wave peak at 200ms is in accordance with the waveform of N2 family.[26] N2 often appears in repeated non-target stimuli, i.e., the strange stimuli during the repeated training, which is composed of N2a, N2b and N2c. Among them, this experiment may trigger N2a, caused by the keyboard sound when answering questions. Figure 3 shows that the waveforms generated by the waste classification have little discrimination except for the discrimination of kitchen waste. It is thus inferred that the subject has similar degrees of judgement in the classification of the four types of garbage. The reason why kitchen waste produces a larger FN400 is that the components contained in kitchen waste have a strong correlation with its category. Since the subject is a housewife, who is responsible for the daily life of the family, she clearly understands how to sort out the kitchen waste.

A single sample *t* test on the peak delay period under misclassification is shown in Figure 4. It is identified that there is a significant difference in the peak delay period between the misclassification and the correct classification, except that other waste is misclassified as kitchen waste. The peak latency when misclassified as kitchen waste is longer than that when correctly classified, indicating that such a misclassification is a CBI. For example, the subject firmly believes that the defaced lunch box should be classified as the kitchen waste in terms of her inherent knowledge, but the actual

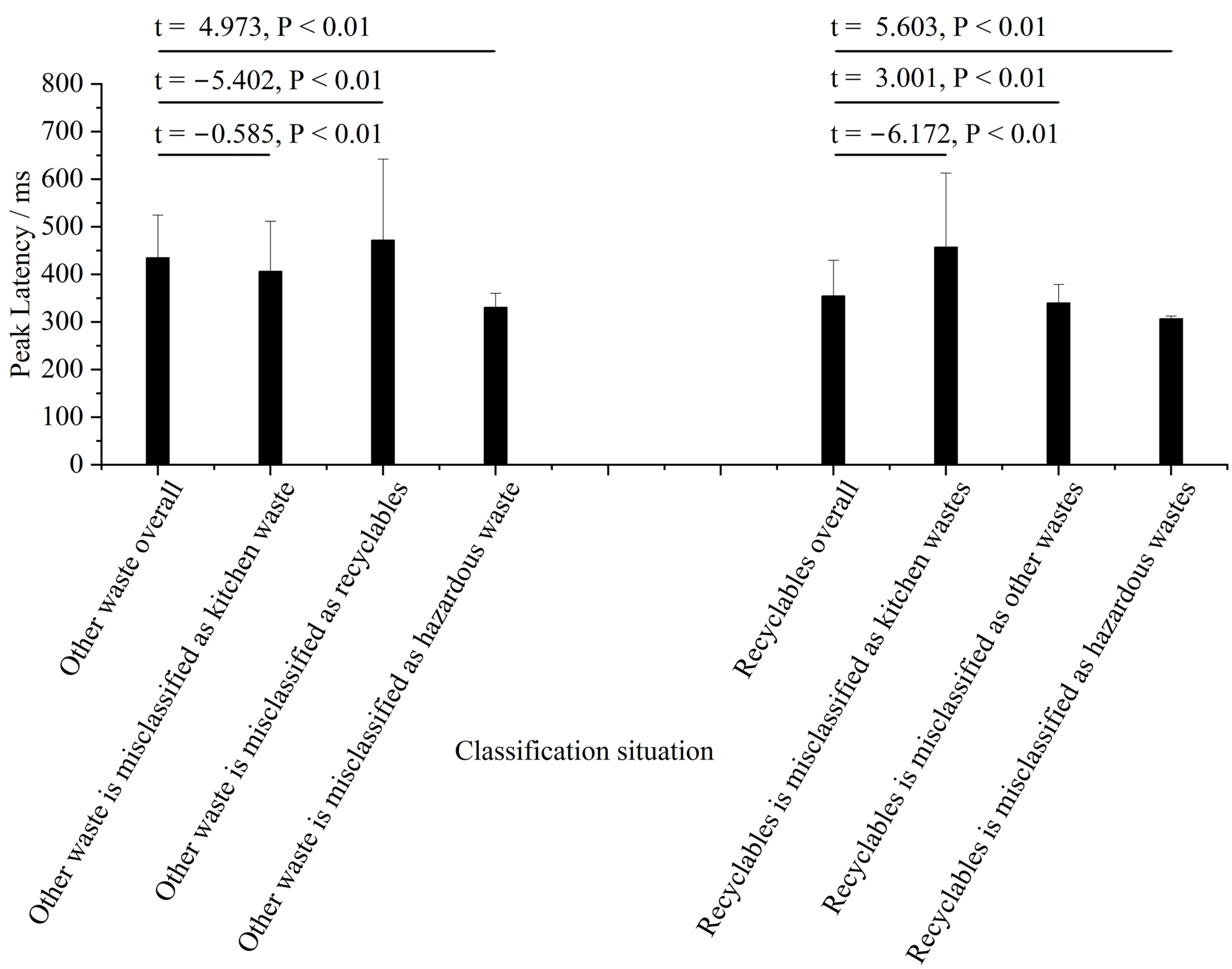

Figure 4 Peak delay period of the misclassifications.

judgment is wrong, causing confusion in the classification. The peak latency of misclassification as hazardous waste is shorter than that of correct classification, indicating that such a misclassification is a categorization. For example, the subject presumes dry batteries as hazardous waste because of the harmful and toxic components contained.

Discussion

The accuracy rate showed an upward trend in the short term, and it declined in days 14 to 18 . In the follow-up, the accuracy rate was stable at 100% during the days 19to 29. This process may imply that the initial stage of cognition is dominated by categorization. The correction-based feedback leads to an increase in garbage sorting cognition. The cognitive content has become more complex and the CBI ability is gradually improving.[27] There is a decrease in accuracy occurred when the complete cognitive framework was not established (the third time session shown in Figure 1), which is consistent with the results given in Fisher and Sloutsky.[8] With repeated trials, the subject gradually develops a CBI framework, which gives rise to a high level of accuracy. However, it is also important to note that a longer duration of the experimental stimulation may lead to a decrease in the subjects' willingness to participate, which may further affect the accuracy rate.[28]

Excluding the influence of the 150–350ms negative wave from the average ERP waveforms (see Figure 3), there is a small negative wave at 300–450ms, which may be due to the fact that the subject's judgement on a waste that is far from her common sense. At the same time, the SN amplitude is larger than the waveform amplitude, indicating a larger cognitive conflict, which is consistent with the dominant features of CBI.

In the misclassification, the plastic products in the recyclables were misclassified as other waste. A possible reason is that the subject may classify the garbage based on the similarity of materials and their applications, resulting in incorrect classification. In contrast with the corresponding peak latency, it can be inferred that there are two reasons for misclassification. One is the lack of cognition, ie, the relevant classification knowledge is lacking to cause wrong results; the other is cognitive error, that is, there is a positive judgment on the waste category, but such judgment is actually wrong. Therefore, the correction on inherent misconceptions and the establishment of correct induction conditions should be implemented simultaneously when improving the performance of garbage classification.

In this experiment, it can be clear that the first time session and the fourth time session are based on similarity classification. By correcting for the misclassification, the CBI exists in the second and third time sessions, which is consistent with the developmental continuum,[14] ie using known information to achieve unknown generalizations.[15] However, the complex degree is different. Some of the cognitive computations during the CBI process are automatically related knowledge (indicated by their co-occurrence, similarity and proximity), while others are structural knowledge (indicated by accidental, classified and thematic relationships).[14] Apparently, the latter requires more cognitive resources, which is more time-consuming. Combined with the change of response time, the CBI process in the second time session should be the most difficult. Regarding the return to the categorization in the fourth time session, it is inferred that the subject has established a more complex garbage knowledge system, whose cognition has become matured where no structural knowledge needs to be initiated, only memorized, to complete the classification.

It is acknowledged that the study has bias on data analysis. The study is a single subject experiment with no control group, which may cause the ERP waveforms to appear to be specific. In such case, ERPs corresponding to pre- and post-intervention and long/short response times were tested, respectively, and t-tests were used to avoid associations or differences occurring by chance, thereby reducing random errors due to specificity. However, the bias still has impacts on the results. Although the sample size is small, the total number of trials has reached 696 (there are 29 sessions of the experiment, and each session consists of 24 trials), which is able to demonstrate the effectiveness of the intervention. In such context, the data collected from 29 sessions can be analyzed in relation to each other to see if the waste sorting intervention contributes to a shift in cognition from C to CBI. Besides, the experiment is designed to examine changes in cognitive processes during the intervention, as reflected by the relative changes in the selected indicators, including response time, peak latency, FN400 amplitude and SN amplitude. The examination does not depend on the changes in the absolute measured values.

Conclusion

The study believes that such a C-CBI-C process can be followed in the education intervention of waste classification, and the first 4 to 7 days is the key time period to establish the correct CBI framework. Further study will center on designing specific ways of educational intervention, eg, what rules should be followed in education, to provide implications on improvement of the waste classification performance.

The study contributes to a better understanding of the cognition of waste sorting and promotes an effective program to guide waste classification. Waste sorting is a complex cognitive process that requires not only judgement, but also bridging the gap between cognition and behavior. Such cognitive processes can be regulated by categorization and category-based induction.

To date, studies have mainly used questionnaires, in-depth interviews, and focus groups to analyze individuals' willingness to participate in waste sorting and identify the associated influencing factors. However, the above research methods are limited by the respondents' perceptions, which may lead to deviations between their expressions of willingness and their actual mental activities.[29] This study provides an access by using neuroscience to observe changes in physiological responses during individual waste sorting. Based on the observation of EEG signals, the implicit mechanisms can be better understood to improve the design of waste sorting education program.

However, the study has some limitations that leave room for further improvement. First, due to a single case study, there is no comparison between different groups. Second, the study only focuses on changes in event-related potentials at the Fp1 electrode, which may not fully reveal the intervention effect due to measurement limitations of the experimental equipment. Future studies will consider increasing the sample size, monitoring and comparing changes in other electrode potentials to explore the appropriate environmental education interventions for different groups.

Ethical Considerations

The study was conducted in accordance with the Declaration of Helsinki and was approved by the Ethics Committee of Southwest Jiaotong University (protocol code SWJTU-2103-037, March 17, 2021).

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Disclosure

The authors declare no conflicts of interest in this work.

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