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To run with the herd or not: Electrophysiological dynamics are associated with preference change in crowdfunding

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ABSTRACT

The herd instinct is a common feature of human society and is frequently encountered in a myriad of other human social interaction including entertainment, fashion, and the adoption of new gadgets. Indeed, social influence, taking account of others' actions in one's decisions, is ubiquitous in our daily life. With the growing prevalence of crowdfunding investments, an increasing number of studies are currently focused on how social influences impact such behavior. Moreover, only a few studies have examined its neural correlates and the value of evaluating social influence as a possible predictor of herd behavior especially regarding crowdfunding. The present study aims to parse the neural processing of social influences on crowdfunding investment and examine whether neural signals can be correlated with an individuals' willingness to invest. Our results demonstrate that the greater ones' choice deviates from the overall group judgement, there is a resulting increased deflection of the feedback related negativity (FRN). However, the averaged and single trial analysis reveal that the subsequent P300, rather than the feedback related negativity, reflects the magnitude of social influence on individual behavior. Single trial analysis of the EEG data shows that, in addition to the behavioral manipulation, the deflection of the P300 is a robust signal, which is associated with the behavioral adjustment following an individual's awareness of the group opinion at the trial-by-trial level. The current study freshly extends the growing literature on social influences on decision making stemming from another's action to the new investment possibilities of crowdfunding investment and notably observes that the P300 component at the outcome stage evidently is associated with the behavioral-decision making shift evoked by following the herd.

1. Introduction

In the current digital age, crowdfunding has gained momentum as a proven tool to enable financing by leveraging the internet to raise funds from the public encompassing not only a vast variety of entrepreneurial projects (Asch, 1951; Cialdini and Goldstein, 2004; Deutsch and Gerard, 1955), but also for artistic endeavors (Ordanini et al., 2011; Schwienbacher and Larralde, 2010). Indeed, crowdfunding is becoming a vital novel strategy in raising capital and hence the factors that contribute to successful crowdfunding are of keen interest to both practitioners and researchers (Elleflamme and Lambert, 2014). Hence, we suggest the notion that pervasive social influences also strongly frame crowdfunding marketing. From the perspective of people who undertake crowdfunding to finance their projects, the pervasiveness of social influences should enable greater success. On the flipside from the investor's perspective, it is critical to identify the actual potential value of the fund-raising project and avoid the trap of following the herd in unwise and unprofitable investments. Therefore, our research aims to understand how social information affects individual preferences and behavior in crowdfunding projects and thereby enable both investors and solicitors to make more propitious decisions.

As the recent studies suggests, investors in crowdfunding respond to the actions of others, which contributes considerably to the popularity of the crowdfunding projects. For instance, Agrawal et al. (2011) observe that the individuals are more willing to invest when the fundraising goal of the projects are approaching. In an empirical study, Zhang and Liu

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(2012) show that well-funded borrowers tend to attract more funding and a computational model suggests that such behavior can be viewed as an active observational (rational) learning rather than simply and passively mimicking their peers. Based on previous empirical studies, in the current study, conducted under-controlled laboratory-based conditions, we examine the extent to which social influence affects the valuation of the fundraising project and contributes to the change of an investor' behavior.

Additionally, prompted by the research momentum generated in the emerging disciplines of neuroeconomics and cognitive social neuroscience, a growing number of researchers have undertaken to examine the neural processing involved in social conformity to better appreciate the brain mechanisms underlying such behavior (Berns et al., 2005; Chung et al., 2015; Huang et al., 2014; Klucharev et al., 2009; Mason et al., 2009; Shestakova et al., 2012; Suzuki et al., 2016; Toelch and Dolan, 2015; Xie et al., 2016; Zaki et al., 2011; Zubarev et al., 2017). One of the foremost theories to emerge from these studies and that accounts for social conformity is reinforcement learning underpinned by brain reward mechanisms (Huang et al., 2014; Klucharev et al., 2009; Shestakova et al., 2012; Toelch and Dolan, 2015). Using functional magnetic resonance imaging (fMRI), Klucharev et al. (2009) show that anterior cingulate cortex (ACC) activation coupled with the deactivation of the nucleus accumbens (NAcc) is correlated with group opinion conflict in an attractiveness rating task. Therefore, conflict with others' belief or behavior apparently recruits common brain regions involved in the neural representation of reward prediction error, a key characteristic of reinforcement learning.

Recently, several electrophysiological studies of social conformity are reported. Consistent with the notion of reinforcement learning, Chen et al. (2012) demonstrate that a dissimilar choice from others triggered a more negative feedback-related negativity (FRN) that predicts conforming behavior. Additionally, Shestakova et al. (2012) find a cascade of brain signals for conflict detection for deviation from social norm that results in subsequent behavioral adjustment. Specifically, they find that an early FRN peaking at 200 ms is elicited by the conflict between individual and group opinions, whereas a later component peaking at 380 ms reflects the conforming behavioral change.

The current study aims to identify the neural mechanism of social conformity characterizing crowdfunding and to detect the electrophysiological signal(s) that are potentially associated with people's subsequent preference change. To our knowledge, our research is the first study to examine crowdfunding and its underlying neural process modelled on its relationship to social conformity employing EEG in a financial decision-making context. Specifically, in a crowdfunding context, we investigate whether the evoked neural signals people encountered with social conflict are substantially associated with people's preference change in the group direction in a trial-by-trial manner. We applied a variant version of the rating task initially developed by Klucharev et al. (2009) to test the extent to which individuals "Willingness-To-Invest" for dozens of crowdfunding projects are modulated by their awareness of crowd opinion and simultaneously recorded their electrophysiological signals.

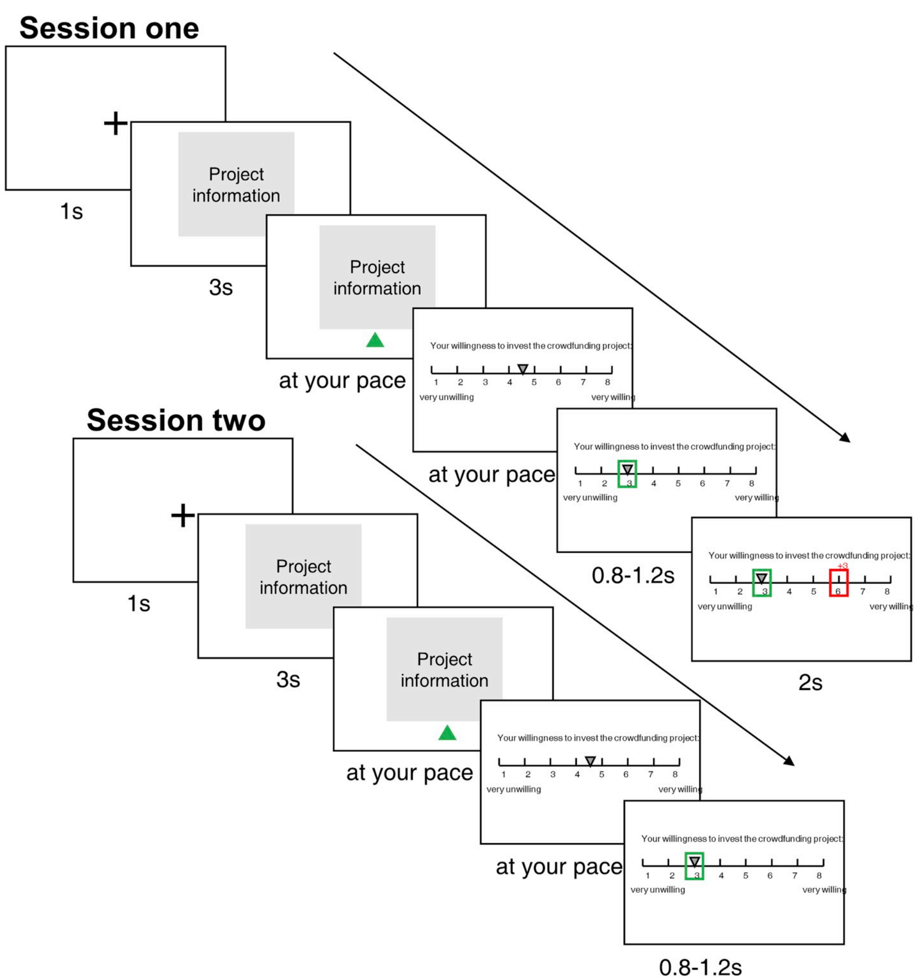

Fig. 1. The task procedure. In session one, a cross is shown for 1 s at the beginning of each trial. Participants have at least 3 s to learn about the crowdfunding project and rate their willingness to invest at their own pace. Finally, the group rating appears in a red rectangle. In session two, participant would rate the same crowdfunding projects again. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

We focus on the neural response at the stage of group opinion revelation (Fig. 1) and examine whether the ERP amplitudes observed at this stage reflects the detection of an individual's deviation from the group rating. We also examine whether the deflection of the amplitude at this stage is associated with the subsequent actual preference change of their willingness to invest. Based on the previous electrophysiological studies over the outcome evaluation, two ERP components, FRN and P300, are examined.

FRN, a negative deflection peaking between 180-300 ms at frontal scalp and localized in ACC, has been shown to be associated with negative feedback (eg., monetary loss, electric shock, social disapproval), prediction error and evaluating motivational/affective impact of outcomes (Cohen and Ranganath, 2007; Gehring and Willoughby, 2002; Yeung et al., 2005). The neural basis of reinforcement learning suggests that a prominent prediction error signals is likely manifested by the FRN mediated by the mid-brain dopamine system (Pfabigan et al., 2011; Talmi et al., 2013). We suggest the notion that the inconsistency of the willingness to invest according to the group decision can be described by reward prediction error theory and is hypothesized to result in a similar neural effect as observed in classic reward prediction error experiments. Therefore, the FRN component is a judicious candidate to represent the conflict between personal and group opinions. For instance, Chen et al. (2012) and Shestakova et al. (2012) demonstrate that incongruence with group rating triggers more negative FRN and its amplitude increases with the size of conflict. Thus, we hypothesize that the amplitude of FRN is more negatively deflected as individual ratings diverge from group ratings and the magnitude of the effect increases with the scope of the deviation.

P300 is an ERP component which is a large positive-going potential at central/parietal electrode locations (Katayama and Polich, 1998). To account for this late ERP component, there are several possible perspectives regarding the cognitive significance of P300. For example, one view is that this component reflects the allocation of mental resources and salience of the stimuli. In studies related to decision making under risk, this component is reported to manifest the magnitude of the outcome (Nieuwenhuis et al., 2005). Additionally, this component is also sensitive to the motivational significance of the outcome. Interestingly, the majority of recent studies indicate that the gain outcome elicits a larger amplitude of P300 as opposed to the loss outcome. As mentioned previously, the FRN is the key component to represent the valence effect of the feedback (Ma et al., 2011; San Martin, 2012; Wu and Zhou, 2009; see detail discussion in San Martin (2012)). Therefore, while some recent studies suggest that there are quite a few common currencies for these two ERP components, they still play dissociated roles in the cognitive processing of the stimuli at the stage of outcome evaluation. Therefore, given the significance of the group rating, we predict that instead of representing the conflict of the self vs. group's opinion by the FRN, the P300 might reflect the degree of conformal behavior in the current crowdfunding setting.

Applying a crowdfunding task with manipulating information about group (the 'herd') opinion, the current study examines the extent to which social information modulates the willingness to invest for proposed projects. Behaviorally, we predict that the subjects are susceptible to the group's opinion and consistently follow suit. Notably, we predict that the simultaneous recordings of the ERP signal not only reflect the processing of social information but also inform the dynamic adjustment to the subjects' conformal behavior under the realistic crowdfunding investment task employed in the study. Dipping into both behavioral and electrophysiological toolkits, in a controlled laboratory setting, the current project aims to gain insights on how social influence modulates investment behavior in the burgeoning crowdfunding marketplace. Finally, we aim to reveal the underlying neural mechanism of group influence on crowdfunding.

2. Method

2.1. Participants

Thirty healthy, right-handed undergraduate and postgraduate students (6 females, aging from 18 to 26 years, mean age = 22.68, SD = 2.32) from Zhejiang University, participated in our study. Subjects had no history of current or past neurological disorders or mental diseases and provided informed consent regarding the experimental procedure before the experiment started. This experiment was approved by the Neuromanagement Laboratory ethics committee of Zhejiang University. Data of five participants were discarded: three subjects' data were unusable due to technical difficulties with the apparatus and data of another two showed excessive recording artifacts. Altogether, data from twenty-five subjects were used in the final analysis.

2.2. Stimuli and procedure

All the stimuli in our study were extracted from a Chinese crowdfunding website, Zhongchou (http://www.zhongchou.com/). The Zhongchou website, established in 2013, has become one of the largest crowdfunding websites in China. We selected 135 projects (10 for preliminary tests and 125 for formal experiments) from hundreds of extant projects on the site, which covers all the seven represented categories including technology as well as public benefit projects. To control for other possible confounding factors contributing to the willingness to invest, such as the number of likes the project has accrued, the number of inventors and so on, we excluded all other information provided on the Zhongchou site and only retained the kernel information about the project content, viz. the title and the main picture.

This experiment consisted of two sessions and each session included two blocks containing 60 or 65 trials each. In an electrically shielded, soundproofed room with dim light, the participants sat in a chair 100 cm away from computer screen with a visual angle of $2.58^{\circ} \times 2.4^{\circ}$ and manipulated the keypad to complete the tasks. In the first session (see Fig. 1), participants were told that the study was about their willingness to invest in a crowdfunding project. All they needed to do was to assess the project and decide their willingness to invest in a crowdsourcing project as described on the computer screen. They were told that their choice to invest or not should reflect a real-life choice. Preceding the formal experiment, the participates conducted a brief exercise to become familiar with the procedure and environmental setting. Each trial started with a '+' in the center of the black screen for 1 s, then a crowdfunding project was presented for 3 s followed by a green triangle informing the participants to press the 'enter' key if they have learned the information of the project. The purpose of this design is to ensure that participants have sufficient time to learn about the project since the task is not as simple as other 'conformity' tasks, e.g. the 'See Beauty' task (Klucharev et al., 2009; Shestakova et al., 2012; Zaki et al., 2011), and demands engagement of more complicated cognitive processing. Then participants were instructed to rate at their own pace and their willingness to invest was evaluated using an eight-point Likert scale ranging from 1 (very unwilling) to 8 (very willing). The inverse grey triangle appeared in the middle of the rating scale indicate participants could press '1' with their thumbs to move the triangle to the lower edge of the screen or press '3' to move to the higher edge. After they confirmed their choice by pressing the 'Enter' key, a green rectangle immediately highlighted the selected number (first rating). At the end of each project trial, the average rating of the other students in the same school (group rating) was revealed to the participants with a red rectangle for 2s after an interval from 0.8s to 1.2s (averaging interval was 1s). The individual rating deviations from the group rating were presented to the participants upon their own assigned rating (0, ± 1, or ± 3 points, Fig. 1). Notably, we manipulated group ratings in order to leverage the level of conflict between individual and group decisions. The deviation between individual and group ratings, as well as the order of stimuli, were randomized across participants.

We did not inform participants that they will again rate the same projects in the 2nd session in advance. This is done so that participants are unlikely to deliberately attempt to remember their own ratings of crowdfunding projects. This is crucial since participants are unexpectedly asked in the second session to rate the same project again towards establishing the impact of social influence flow on crowdsourcing decision making.

The second session (see Fig. 1 below) is identical to the first session except the subjects were no longer informed of the group's opinion and were unexpectedly asked to rate the projects again (second rating) in a randomized order of the projects. The second session allows the participant to adjust (or not) his/her decision and reveals his/her sensitivity to group opinion. After finishing the experiment, all the participants received a payment of 40 yuan (about 7 dollars).

2.3. Electroencephalogram data recording

Electroencephalogram (EEG) data is continuously recorded (band pass 0.05–100 Hz, sampling rate 1000 Hz) form 64 scalp sites with a Neuroscan Synamp2 Amplifier (Scan 4.3.1, Neurosoft labs, Inc. Virginia, USA). The left mastoid is used as a reference. The vertical electrooculogram is monitored by the infra-orbital and supra-orbital electrodes on the left eye and the horizontal electrooculogram is recorded from electrodes on the outer canthi of both eyes. The EEG signals are recorded with electrode impedance under 5 kΩ.

2.4. Data analysis

The analysis of EEG data is conducted in Scan 4.5 (Compumedics NeuroScan Inc., Herndon, Virginia, USA) and Letswave 6 (Mouraux and Iannetti, 2008), a free EEG signal-processing toolbox under the MATLAB environment. The EEG data is first preprocessed in Scan 4.5: data are re-referenced to the average of the bilateral mastoid electrodes and ocular artifacts are removed (Semlitsch et al., 1986). The data then are exported to MATLAB and further analysis is carried out with Letswave 6 (https://www.letswave.org/). Continuous data are analyzed using a bandpass filter between 1 and 30 Hz and are segmented into epochs from 200 ms before the onset of the screen where crowd willingness to invest shows to 800 ms after that onset, with first 200 ms as baselines. Trials containing amplifier clipping, bursts of electromyography activity, or peak-to-peak deflection which exceed ±100 μV are excluded before the procedure of averaging separately for each condition. Finally, statistical analyses are performed in SPSS and Stata statistical software (SPSS Inc., Chicago, USA; StataCorp, Stata StataCorp Texas, USA.).

Since the Likert rating is ordered discrete values, ordinal probit regression is applied for the analysis of behavioral change to show the effect of the group opinion manipulation. The observations within subjects are not independent and therefore clustered standard error is used for the regression analysis. Repeated measure ANOVA is applied to analyze the percentage of trials that show whether the subjects change their attitude or not within each condition. Repeated measure ANOVA is used for the EEG analysis and logistic regression is implemented to analyze the single trial analysis of the EEG data.

3. Results

3.1. Behavioral results

Due to the manipulated group ratings, the number of different conflict trials where the group rating is different from individual's rating varies across participants. From −3, −1, 0, 1, and 3, the average numbers of the Likert ratings are (mean ± SD): 24.28 ± 4.42, 24.64 ± 2.22, 21 ± 0, 23.36 ± 2.22, 23.72 ± 4.42 respectively. No significant difference is observed in the trial numbers of the four conflict conditions ($F(3, 96) = 0.637$, $p = 0.593$, $\eta^2 = 0.020$).

3.1.1. Conformity effect

To overall show the conformity effect, we first calculated the behavioral changes reflecting subject's willingness to invest (Cousineau, 2005; Morey, 2008). As we predicted, participants changed their willingness to invest in shifting in the direction of group ratings (see Fig. 2A). On average, positive deviation of the group rating from a participant's first rating (group rating minus first rating) resulted in an increased willingness to invest in the second session (conforming change: second rating minus first rating), whereas negative deviation from group rating resulted in a decrement (reduced investment). Moreover, in the no conflict trials participants showed almost no change in willingness to invest (see Fig. 2A). As shown in Fig. 2A, a larger conflict with group rating results in a greater adjustment.

To analyze the extent to which social information modulates behavioral adjustment, we first ran an ordinal probit regression analysis with the conforming change as dependent variable and the 5 levels of deviations as dummy independent variables with the standard error clustered at the individual level. In summary, changes in investment clearly reflect deviations from group opinion. Table 1 shows the summarized regression coefficients and standard errors of paired condition comparisons derived from the regression analysis. For example, the +3 deviation from the group opinion has a larger behavioral adjustment than that of +1 ($\beta_1 = 0.334$ (se. = 0.056), $p < 0.001$). In general, there is a linear trend between the group opinion manipulation and behavioral adjustment. In addition, to examine the potential asymmetric effect of the positive-negative deviation, we further include the four deviated conditions (±1, ±3) and run the regression in a 2 (magnitude: 1, 3) by 2 (valence: +, -) design of the group opinion. We observe that there is a prominent effect of the magnitude ($\beta_1 = 0.322$ (se. = 0.084), $p < 0.001$) and no effect for valence ($\beta_2 = 0.041$ (se. = 0.099), $p = 0.679$) or interaction effect ($\beta_3 = 0.014$ (se. = 0.090), $p = 0.881$). These results show that the behavioral adjustments are symmetric toward both positive and negative deviations from the group opinion. In conclusion, the results suggest that there is a prominent conformity effect in the willingness to invest especially when the conflict with group opinion is large.

To examine the robustness of the behavioral results, we further explored the effect of conflict on the probability of conforming change and examined the twin effects of magnitude and valence. As Fig. 2B shows, the percentages of conforming change (the number of trials followed by conforming change divided by the number of trials in that condition) is higher in the large conflict condition (mean = 53.9%, se = 4.0%) than small conflict situations (mean = 36.7%, se = 2.3%). A two-way within participants repeated-measures ANOVA using magnitude (large/small conflict) and valence (positive/negative conflict) as independent factors, shows a significant main effect of conflict magnitude ($F(1, 24) = 47.930$, $p < 0.001$, $\eta^2 = 0.666$). The main effect of conflict valence ($F(1, 24) = 0.002$, $p = 0.965$, $\eta^2 = 0.000$) and the interaction between conflict magnitude and conflict valence ($F(1, 24) = 1.269$, $p = 0.271$, $\eta^2 = 0.050$) are not significant. This analysis confirms the effect of the group information on conforming behavior.

3.1.2. Regression to the mean

A possible confound in our data analysis is suggested by the argument that the effect of conformity is simply explained by "regression to the mean" (Ihmels and Ache, 2018). For example, in our paradigm, when the first rating is 8 (7, 6, 5), the group rating has a higher probability to be a lower rating than 8 (7, 6, 5) and simultaneously the second rating tends to be lower than first rating, which may be mistakenly interpreted as conformity. A similar artifact in interpretation may occur when the first rating is 1 (2, 3, 4). In Yu and Chen, (2014) , they suggest three potential strategies to control for "regression to the mean": (1) choosing the trials in which the first ratings across different conditions are matched, (2) adding the first rating as an independent variable into the regression model, (3) adding a control group which does not have group feedback. To minimize the possible problem of

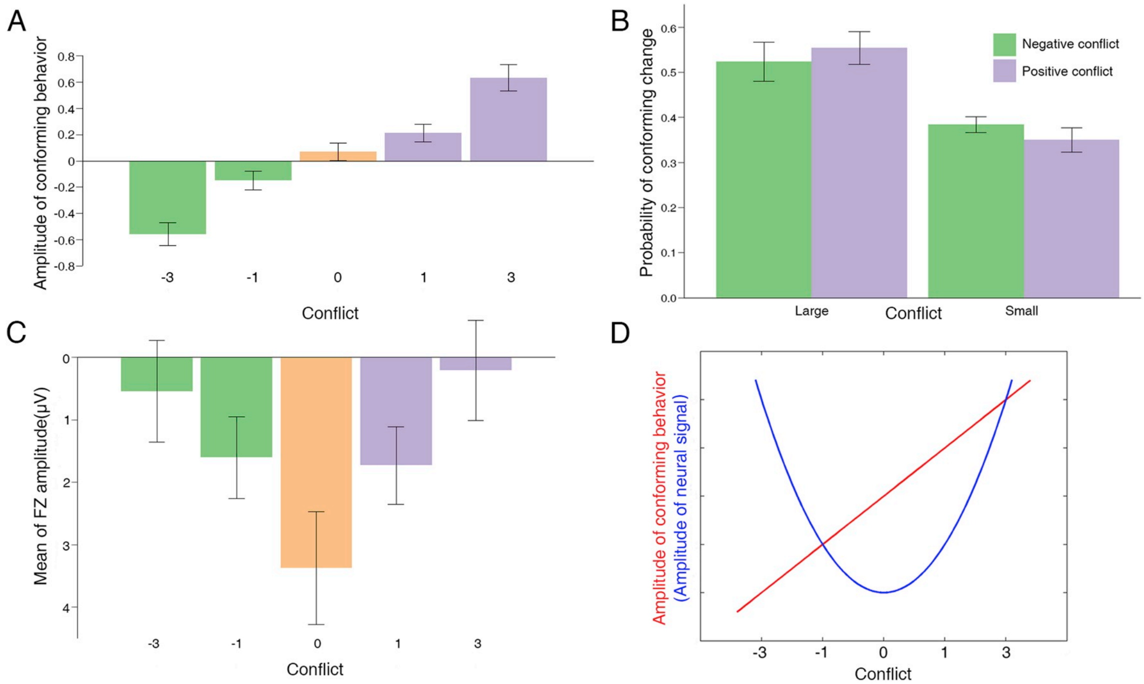

Fig. 2. (A) Mean behavioral conformity effect. The picture illustrates that the change in individual willingness to invest in session one and session two. On average, the change was in line with the group willingness. (B) Mean probability of behavioral conformity effect. A large conflict with group opinion had a high probability to conform to group regardless of valence of the deviation. (C) Mean FRN response for 5 conflict conditions. The larger conflict evoked a more negative FRN. (D) The different patterns of behavioral change and neural signals toward group ratings.

Table 1
The results of opinion manipulation derived from regression analysis. The results show that the differences between each of the paired conditions are significant. For example, based on conflict −3 as the reference group, the coefficient of 0 condition is 0.495 and *p*-value is 0.000, which indicates the −3 deviation significantly leads to a lager negative behavioral change compared to 0.

Baseline value	Conflict				
	Conflict: −3	Conflict: −1	Conflict: 0	Conflict: 1	Conflict: 3
Conflict: −3	–	0.321*** (0.084)	0.495*** (0.082)	0.606*** (0.0880)	0.941*** (0.105)
Conflict: −1		–	0.173*** (0.047)	0.285*** (0.050)	0.619*** (0.061)
Conflict: 0			–	0.112 (0.051)	0.446*** (0.065)
Conflict: 1				–	0.334*** (0.056)
Conflict: 3					–

t statistics in parentheses.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

'regression to the mean', we selected trials where the participants' first ratings were 4 or 5 and divided them into two parts (peer-higher and peer-lower conditions) (Huang et al., 2014; Zaki et al., 2011). After using this filter, we found there was no difference between peer-higher and peer lower conditions in the first ratings (t $(24) = -0.278$, $p = 0.783$). However, the difference in the second rating after seeing the group rating between peer-higher and peer lower conditions was significant (t $(24) = 4.073$, $p < 0.001$) and the second rating in peer-higher condition (mean = 4.848, se = 0.122) was higher than that in peer-lower condition (mean = 4.382, se = 0.140). Additionally, we further used regression analysis to examine whether the conformity effect was observed when we controlled for "regression to the mean". The first rating and the discrepancies between individual first rating and group rating were used as independent variables and the second rating was the dependent variable. If there is solely an effect of "regression to mean", the coefficient of the discrepancies between individual first rating and group rating should not be significant. Otherwise, a conformity effect is indicated. In our experiment, the coefficient of the discrepancies was highly significant indicating a conformity effect and was a powerful predictor of the second rating ($\beta_1 = 0.099$ (se = 0.017), $p < 0.001$). Both strategies employed to analyze the possible confound of "regression to mean" indicated that the second rating after facing the group rating was influenced by the group rating, implying an effect of social conformity and not 'regression to the mean'. Therefore, we included all the trials in the statistical analysis.

3.1.3. *Ambiguous situations*

Earlier studies report that the conformity effect is strongest in ambiguous situations (Cialdini and Goldstein, 2004). For example, Shestakova et al. (2012) and Huang et al. (2014) demonstrated that the size of the conformity effect was larger in the ambiguous condition where the standard deviation (SD) of the first rating for each face was higher. Prompted by these previous findings we computed the SD for each project across all the subjects and found in contrast to previous studies, no evidence for a stronger conformity effect under ambiguity. The SD ranged from 1.130 to 2.318. Projects whose SD was lower than the 30th lowest SD (SD ≤ 1.5) and whose SD was higher than the 30th highest SD (SD > =1.810) were respectively chosen as unambiguous projects and ambiguous projects. A two-way ANOVA was carried out with ambiguity (unambiguous and ambiguous) and group ratings (peer-high and peer-low) as within-subject factors and we found that neither the interaction effect (F $(1, 24) = 0.883$, $p = 0.357$, $\eta^2 = 0.035$) nor the main effect of ambiguity (F $(1, 24) = 0.030$, $p = 0.864$, $\eta^2 = 0.001$) was significant.

3.2. *ERP results*

We focus on the ERP brain signal at the stage of the presentation of group rating immediately following subjects' rating of willingness to invest. Due to the fact that collapsing the raw data across multiple electrodes could increase the signal-to-noise ratio of the ERP data (Luck, 2014; Luck and Gaspelin, 2017), the averaged voltage at the frontal and parietal electrodes are calculated for FRN and P300 respectively dependent on their scalp topographic distribution (Fig. 3B, Fig. 4B). Their time windows are determined by visual inspection of grand-averaged waveforms of ERP components (Helden et al., 2009; Leng and Zhou, 2014; Shang et al., 2017). For FRN, as exhibited in Fig. 3A, we observe that there is an elicited FRN in the frontal scalp. Based on previous research and brain topography as illustrated in Fig. 3B, we choose 180–230 ms time window to compute the mean amplitudes at the six frontal electrodes (F1, FZ, F2, FC1, FCZ and FC2) for subsequent statistical analysis. There is no significant asymmetric effect of the valence behaviorally (−1 vs. 1, −3 vs. 3) and we hence combine the deviations with the same magnitude for the analysis (Fig. 3A). A two-way ANOVA with repeated measures reveals an interaction effect between magnitude and electrodes (F (2.592, 62.207) = 3.253, $p = 0.034$, $\eta^2 = 0.119$). To examine the potential difference between negative and positive deflection, we further collapse the large and small deviation and carry out a repeated ANOVA analysis between five different conflicts and electrodes (F (6.911, 165.857) = 2.572, $p = 0.016$, $\eta^2 = 0.097$) (Fig. 2C). As illustrated in Fig. 2 (panel D), whereas there is a linear correlation between the group opinion deviation and subsequent behavioral change, the EEG signals exhibit a "U" shaped trend. Three-way within participants repeated-measures ANOVA (magnitude: large/small conflict, valence: positive/negative and six electrodes) demonstrates a main effect of conflict magnitude (F (1, 24) = 5.714, $p = 0.025$, $\eta^2 = 0.192$) whereas the effect of conflict valence (F (1, 24) = 0.088, $p = 0.769$, $\eta^2 = 0.004$), and the interaction between conflict magnitude as well as conflict valence are not significant (F (1, 24) = 0.047, $p = 0.830$, $\eta^2 = 0.002$). In summary, the conflict between individual and group rating elicits a more negative FRN, which is proportional to the magnitude of conflict: the larger the conflict magnitude, the more negative the FRN.

To further track whether the brain signals at the stage of group outcome revelation is associated with the subsequent behavioral adjustment, we categorized trials into conformity condition and non-conformity condition. The former shows the subsequent adjustment in the same direction as the group rating and the latter does not show such an adjustment. For P300, a prominent P300 discrepancy at the center parietal scalp of the brain is observed in Fig. 4. The peak of the discrepancy is around 300 ms. Hence, we choose the 280–330 ms time window over 6 centro-parietal electrodes (C1, CZ, C2, CP1, CPZ and CP2) for the statistical calculation. As predicted, P300 amplitude that accompanied a conforming behavioral change is more positive than those accompanied by a non-conforming behavior change (F (1, 24) = 7.248, $p = 0.013$, $\eta^2 = 0.232$, ANOVA).

We also investigate whether the neural response at the latency period where the effect of conflicts with group rating was initially revealed is also associated with conforming behavior. Analysis of FRN revealed there was no significant effect (F (1, 24) = 1.193, $p = 0.285$, $\eta^2 = 0.047$, ANOVA) suggesting that the conforming behavior is associated with the amplitude of P300 and not the FRN.

To further confirm the dynamic relationship between P300 amplitude and individual conforming behavior, we carried out a single trial analysis of the EEG data, combined with the behavioral performance. The raw data was first treated by a time-frequency filter towards performing a single trial analysis as implemented in Letswave 6, which effectively increases the signal-to-noise ratio and minimizes biases in interpretation (Hu et al., 2010). To test whether the individual conforms or not, we used an ordinal logistic regression model with original conforming change as dependent variable. We selected 6 electrodes in the central scalp (C1, CZ, C2, CP1, CPZ and CP2) and computed their mean amplitude in a 280–330 ms time window during the conflict trials. Here, we introduced 4 regression models with different independent variables that include the behavioral manipulation: magnitude of conflict (1 representing large and 0 representing small amplitudes), original

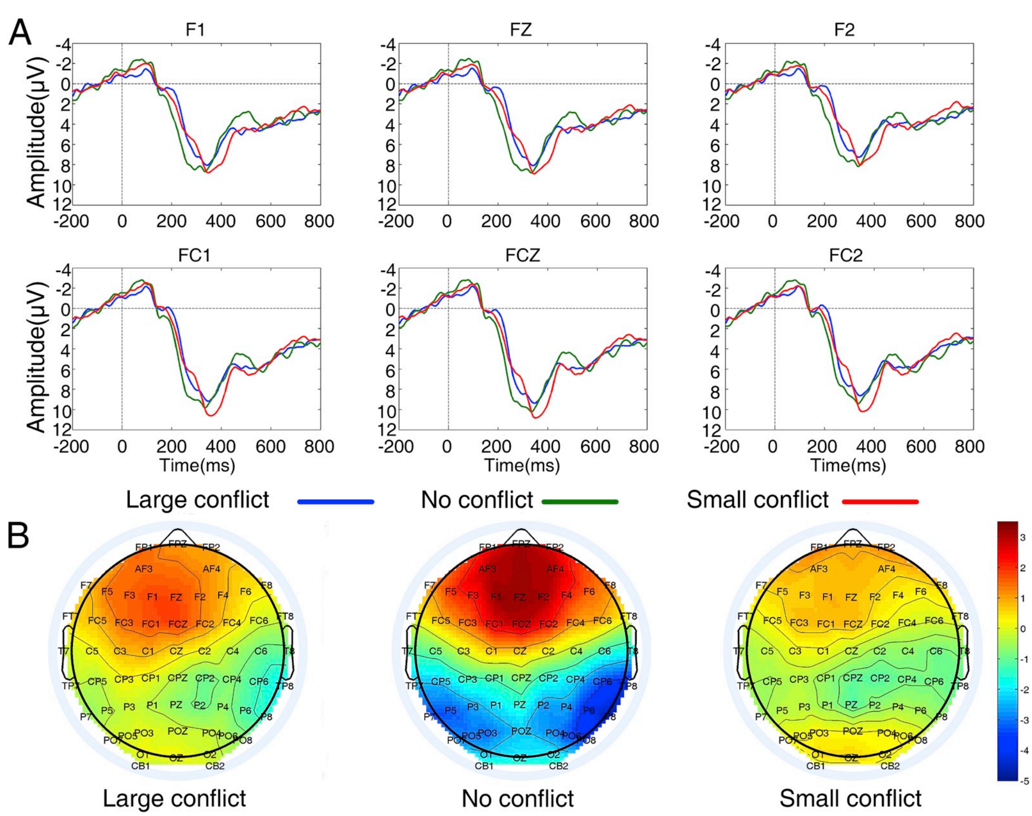

Fig. 3. Social conflict effect. (A) The ERP grand-average waveforms for large conflict, small conflict, and zero conflict conditions at channel F1, FZ, F2, FC1, FCZ, FC2. (B) The topographical map of voltage distribution of these conditions.

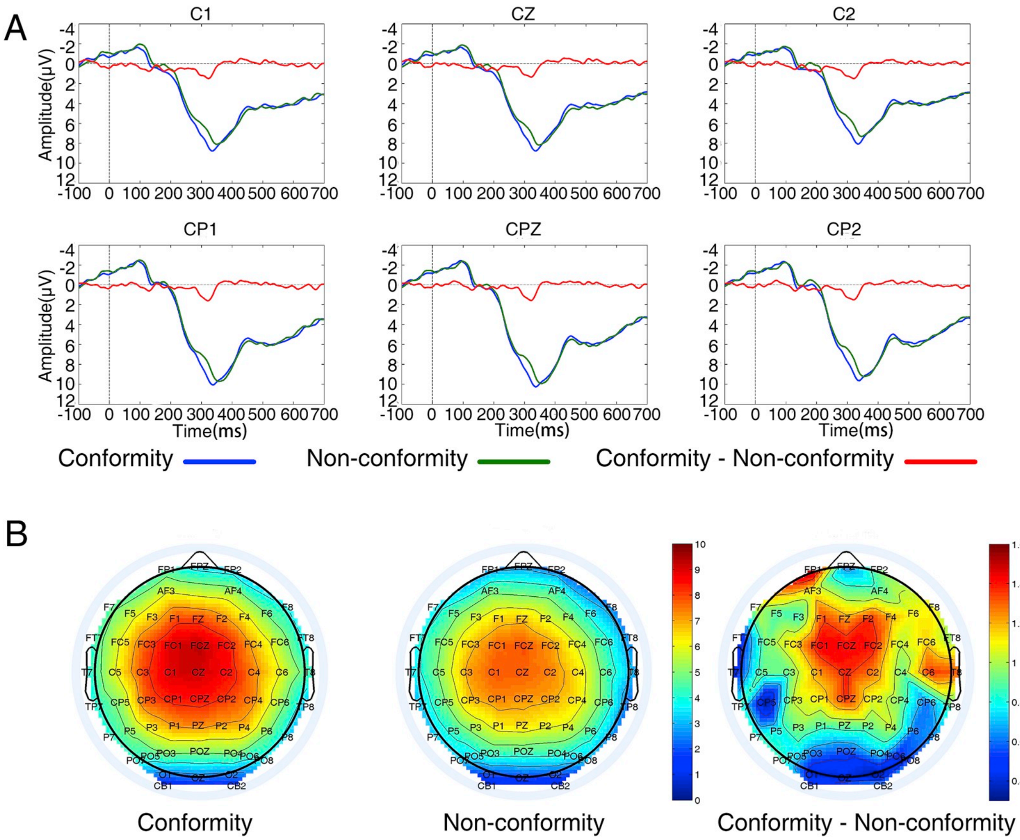

Fig. 4. Social conformity effect. (A) The ERP grand-average waveforms for conformity (blue line), non-conformity (green line) and conformity minus non-conformity (red line) at channel C1, CZ, C2, CP1, CPZ, CP2. (B) The topographical map of voltage distribution of conformity, non-conformity and conformity minus non-conformity. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

amplitude in CZ, CPZ or 6 centro-parietal electrodes, as well as demographic information (sex and age). Model I only uses the behavior data and models II, III and Ⅳ add the ERP signals as well. To reduce the dimension of the electrode variables with high correlations, in model 4, the 1st eigenvalue of 6 electrodes (C1, CZ, C2, CP1, CPZ and CP2) was calculated using principal components analysis (PCA) to represent the centro-parietal electrodes. As shown in Table 2, consistent with the findings from ANOVA analysis, in addition to behavioral manipulation, the P300 deflection at each trial significantly adds to the explanation of the subsequent conforming behavior. Addition of CZ and CPZ gives a higher pseudo R square, which is increased from 0.63% to 0.74% (CZ), 0.76% (CPZ) and 0.73% (1st eigenvalue) respectively. This represents a 15.8%–20.6% increase of the prediction power compared to that based solely on the behavioral information.

Table 2
The ordinal logit regression results with original conforming change as dependent variable. Large conflict equals 1 for large and 0 for small. CZ and CPZ represent the original amplitude in CZ and CPZ. PCA is the value of 1st eigenvalue of 6 electrodes calculated by principal components analysis. It shows the amplitude of CZ and CPZ significantly contributes to the explanation of the level of individual conforming change.

Original conforming change	(1)	(2)	(3)	(4)
Large conflict	0.521*** (0.098)	0.499*** (0.096)	0.497*** (0.096)	0.500*** (0.096)
Sex	−0.00281 (0.196)	0.0109 (0.186)	0.00708 (0.187)	0.00940 (0.187)
Age	0.00227 (0.026)	−0.00185 (0.026)	−0.00258 (0.026)	−0.00173 (0.026)
CZ		0.0199** (0.007)		
CPZ			0.0230** (0.007)	
PCA (for 6 electrodes)				0.00868** (0.003)
N	2400	2400	2400	2400
Wald chi2	31.94	40.78	48.21	43.35
Pseudo R2	0.0063	0.0074	0.0076	0.0073

t statistics in parentheses.
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

4. Discussion

Our primary focus of interest is crowd sourcing and the influences that drive an agent to invest in one or another crowd sourcing enterprise. We use neural imaging (EEG) to reveal the neural underpinnings of these influences on crowd funding. Specifically, we explore the role of social influences, a widely studied bias in human decision making, and seek to determine not only whether it also influences crowd sourcing (an empirical question which only a few studies have so far addressed), but, importantly, to also characterize the neural underpinnings of social influence as related to crowd funding (a second salient empirical question). Hence, our study is novel and firstly adds to the psychological literature on crowd funding, an exceedingly new and important venture capital enterprise, and secondly, this study reveals the neural architecture of biases resulting from social influences on crowd sourcing investors.

Our study significantly contributes to the emerging field of the neuroscience of entrepreneurship by exploring the mechanism through which crowdfunding is modulated by the dynamics of social information flow and especially its neural underpinnings (Genevsky et al., 2017; Genevsky and Knutson, 2015; Knutson and Genevsky, 2018). We first showed that in a controlled laboratory-based crowdfunding context, subjects were inclined to conform to crowd opinion and adjusted their willingness to invest accordingly. Behaviorally, we observed that a conflict between self-rating and group opinion led to a subsequent change of attitude toward the group direction whereas when group and individual ratings were matched no behavioral change was observed. Notably, there was a decided effect of the magnitude of conflict with group opinion. As opposed to smaller deviations between individual and group investment, a larger discrepancy evoked a significantly greater probability that subjects would adjust their willingness to invest.

We are unaware of any herd behavior studies carried out in the context of the emerging financial market of crowdfunding (Genevsky et al., 2017; Genevsky and Knutson, 2015). At the electrophysiological level, we found in the conflict condition that self, compared to group rating differences, elicited a significantly greater negative deflection of the FRN. Intriguingly, when we collapsed the ERP data at the moment when group opinion was revealed to subjects, dependent on whether or not there was a conformal behavioral change, we observed a divergent centro-parietal located component difference. Notably, the conformal behavior was accompanied by a larger P300 deflection. Finally, the single trial EEG analysis confirmed that, at the single event level, the magnitude of this ERP component indexed and enabled tracking the subsequent behavioral adjustment to conform to group opinion.

In their original study, Klucharev et al. (2009) found activation of the ACC when subjects rating is inconsistent with the group opinion. Moreover, Izuma et al. (2010) examine whether the self-rating is consistent with the social desirable group or not. They find that the adjacent DMPFC is involved when decisions are either consistent with the social undesirable group or inconsistent with the social desirable group. Given that the source of the ERP component FRN originates from the ACC and adjacent regions, it is reasonable to infer that the FRN is a likely valid signal to represent the conflict detection in the current study. In addition, two previous EEG studies use conflict with face attractiveness to examine conformity in attributing attractiveness to faces (Klucharev et al., 2009). Huang et al. (2014) finds that the N400 located at the fronto-parietal electrodes represents the deviance of the self-group attitude from the normative group whereas Shestakova et al. (2012) reports that the deflection of the FRN at the frontal electrodes apparently represents the neural correlate of conflict. Our results are consistent with those of Shestakova et al. (2012) and we observe a prominent deflection of the FRN at the frontal electrodes for self-group rating difference. Notably, we also observe a significant magnitude effect, viz. the larger the difference from group opinion, the larger the deflection of FRN.

Curiously, in contrast to Huang et al. (2014), we fail to observe a bi-directional encoding effect of rating. We observe that both negative and positive deviations (self-group ratings) result in similar behavior. Similarly, the FRN deflection shows no effect of valence. We suggest the notion that differences between the current and previous studies are likely attributed to the unique context of studying conformity behavior in crowdfunding.

Several other studies have also investigated whether FRN or other neural signals are associated with subsequent behavior. For example, Cohen et al. (2011) examine reward learning and find the FRN not only represents the gain-loss discrepancy, but the amplitude of the FRN also tracks the behavioral change following a reinforcement learning pattern. However, in another study of decision making under risk (San Martin et al., 2013), the authors observe that whereas the FRN represents the divergence of gain-loss outcome, the P300, and not the FRN, predicts the dynamic behavioral change on subsequent trials. In the electrophysiological studies of conformity, Chen et al. (2012) and his colleague's report that the FRN not only represents the incongruence of the self-group divergence in rating, but it also tracks the behavioral change at the individual level. Subjects showing a larger FRN, are also characterized by a larger behavioral change towards conforming to group investment decision. In theShestakova et al., 2012, whereas the FRN at 200 ms encodes the attitude discrepancy, the behavioral change is represented by a component peaking around 380 ms with a frontocentral electrodes location. However, they treat the later ERP component as a later FRN and infer that there are two stages of error detection. Similar to what is observed in Chen et al. (2012)'s and Shestakova et al. (2012), we also observe the FRN deflection towards normative incongruence. Notably, we identify an ERP component that could account for the subsequent behavioral change, i.e. an ERP signal that informs the individual's adjustment of choice in response to group opinion. We collapse the trials based on whether subjects change their behavior that follow suit or not and find a prominent component that peaks around 300 ms with a centro-parietal electrodes distribution. In our study (Fig. 4), we observe a clear ERP component located at the centroparietal electrodes and its large magnitude deflection precedes conforming behavior. Intriguingly, we confirm this observation at the single trial level and find that the larger deflection of the ERP component at 300 ms is associated with conforming behavior. Importantly, we suggest that the P300 rather than FRN is crucial in explaining the behavioral adjustment at the subsequent session.

As EEG possesses a high time resolution, it provides an excellent instrument to evaluate the dynamic process of temporal decision making. Previous studies of ERP suggest that FRN and P300 likely reflect the dual systems posited in decision making (Kahneman, 2003), viz. the FRN reflects emotional 'fast' processing whereas P300 represents the 'slower' later cognitive evaluation (Leng and Zhou, 2010). The current study of crowdfunding, and its modulation by social information flow, can be viewed through the prism of the postulated dual systems in decision making. The FRN captures the immediate emotional conflict between self and group whereas the later P300 ERP appears to capture the evaluative stage of adjusting one's decision to conform to the direction of the herd.

A salient contribution of the current study is that we observe increased P300 suggesting an associative signal for a behavioral change in crowdfunding context, which is not easily interpreted as an example of reverse causation. Such a neural underpinning could be either context specific solely to an investment task or context general. For example, Shestakova et al. (2012), found that the increased negative deflection of the component is likely indicative of the behavioral change. Therefore, they suggested it should be a later FRN and hypothesized that there are two stages of error detection. In contrast, in our current studies, we found the increased P300 is likely associated with the behavioral change, which we confirmed both at the aggregate and the single-trial level. Such a finding is consistent with several recent studies (eg. San Martín et al., 2013).

Finally, the current study underscores the value of combining neural correlates with behavioral paradigms towards a deeper understanding of crowdfunding and especially how social influences modulate investment decision making. In internet crowdfunding groups, budding investors can see the level of previous investments prior to making the decision to invest or not, suggesting that the flow of social information is a salient cue and has an important role in the project's final success. We model this real-life investment instrument under controlled laboratory conditions and show at the neural level that investors appear to follow dual process thinking and identify two ERPs, FRN and P300, that resonate with fast and slow thinking in the framework of herd behavior in the context of crowdfunding.

Declaration of competing interest

The authors declare no competing financial interests.

CRediT authorship contribution statement

Lei Wang: Conceptualization, Data curation, Formal analysis, Funding acquisition, Project administration, Writing - original draft. **Lu Li:** Conceptualization, Data curation, Formal analysis, Writing - original draft. **Qiang Shen:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Project administration, Writing - review & editing.

Jiehui Zheng: Data curation, Formal analysis, Writing - review & editing. **Richard P. Ebstein:** Writing - original draft, Writing - review & editing.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.neuropsychologia.2019.107232.

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