Influence of Peer Recommendation on the Neural Dynamics of Preference-Based Decision Making

Tim Reinboth

Supervised: Marios Philiastides

March 2016

Influence of Peer Recommendation on the Neural Dynamics of Preference-Based Decision Making

Abstract

While social information has been shown to alter neural activity during decision making, the temporal dynamics of this effect remain elusive. Here, we applied event-related analysis of electroencephalography (EEG) to investigate the effect of peer recommendation on the decision making process underlying a simple consumer decision. Our preference-based binary choice paradigm revealed an effect of peer recommendation during evidence integration. We observed reduced EEG-signal strength when a recommendation was present, consistent with previous evidence of attenuated frontal lobe activity in the presence of social information. Absent an effect of the recommendation on choice outcome, the neural effect could not be unequivocally interpreted. We suggest a possible modulation of frontal activity via an engagement of the reward mechanism, ostensibly developed in order to bias individuals towards prosocial decisions.

KEY WORDS:	DECISION MAKING	EEG	SOCIAL INFLUENCE	VALUE BASED

Introduction

Perceptions of quality are biased by social information, such as advice or recommendations (Biele et al, 2011; for review: Izuma, 2013). Indeed, social information affects consumer behaviour (Duhan, 1997), even when it is indirect (Biele, Rieskamp & Gonzalez, 2009). In a society increasingly reliant on aggregated collective judgment on the internet, it becomes important to understand the nature of this effect (Muchnik, Aral & Taylor, 2013). In its pursuit, neuroeconomics emphasizes investigating the neurobiological mechanisms by which decisions are made (Glimcher & Rustichini, 2004; Camerer, Loewensetin & Prelec, 2005; Sanfey et al, 2006).

Recently, neuroeconomic research has begun to explore the finer points of the decision making process by investigating the specific effects of factors such as social influence (e.g. Zaki, Schirmer & Mitchell, 2011) and branding (Philiastides & Ratcliff, 2013). This follows the consolidation of large sections of the decision making literature behind diverse variants of a class of models known as drift diffusion models (DDMs; Ratcliff, 1978; Ratcliff & Rouder, 1998; 2000; Philiastides & Sajda, 2005; 2006; Malmaud et al, 2010; Krajbich et al, 2015). The models share the same fundamental characterization of the decision process, which posits that noisy evidence for competing alternatives is extracted and integrated until the accumulated evidence for one alternative reaches a certain specific threshold at which point a response is initiated (Armel, Rangel & Krajbich, 2010; Krajbich et al, 2012).

This framework permits the integration of results from research on perceptual and value-based decision making since the computational problem has similar properties in both cases (Malmaud et al, 2010; Philiastides, Biele & Heekeren, 2010). Using results obtained from perceptual decision making research to inform investigations of the dynamics of value-based decision making has facilitated their exploration to a similar level of detail as those of perceptual decision making (Philiastides et al, 2010; Philiastides, Ratcliff & Sajda, 2006). However, exactly how different components constitute the value process remains unknown (Hunt et al, 2012).

The present work was designed to help resolve this uncertainty. Using a modified version of Philiastides & Ratcliff (2013) forced binary choice paradigm, we used electroencephalography (EEG) to investigate the effect of social influence, in the form of peer recommendation, on behaviour and neural dynamics of a simple consumer decision. The investigation focussed on the frontal cortex, given the localization of activity related to value computation to diverse regions within this area, primarily ventromedial- and dorsolateral prefrontal cortex (VMPFC; DLPFC; Philiastides & Sajda, 2007; Kennerley et al, 2009; Biele et al, 2011; Hare et al, 2011; Zaki, Schirmer & Mitchell, 2011).

Behaviourally, social information has been shown to bias choices towards alternatives with social rewards (Behrens, Hunt & Rushworth, 2009). Recommendations incur social rewards derived from aspects of the choice such as conformity, which have been shown to influence behaviour (Klucharev et al, 2009). Social information may affect behaviour even when no direct reward is expected as a result of a lifelong associative learning process that biases individuals towards prosocial decisions through, where prosocial refers to a decision that follows social influence (Hunt et al, 2008). The bias is taken to result from the rewards expected for making prosocial choices (Behrens et al, 2008).

Beliefs about the origin of the recommendation are key, and certain beliefs about trustworthiness and quality of advice can nullify or reverse the conventional effect (Behrens et al, 2009). In the present study, it was indicated that peers had recommended items of clothing, a socially relevant category for which a particular susceptibility to peer influence has been established in female, urban late adolescents (Wilson & MacGillivray, 1998).

The present study focussed on the characterization of the temporal dynamics of the decision making process. Previous studies of the dynamics of decision making according to the DDM have identified three core components that should be replicated by the present study (Philiastides & Sajda, 2005; Philiastides et al, 2006; Philiastides, Heekeren & Sajda, 2014). In chronological order of appearance during decision making, the components correspond to effects related to evidence encoding (~150ms), task difficulty (~220ms), and evidence integration (~280ms). The first and last components are likely to be modulated by task difficulty (Malmaud et al, 2010).

With respect to neural activity related to social information such as advice, previous work suggests reduced activity in decision-related regions in the presence of explicit social information (Biele et al, 2011; Engelmann et al, 2009). An attenuated reward signal on trials during which advice is offered versus trials with no advice is implicated in this effect (Biele et al, 2011; Coricelli et al, 2005). It may be that a generalised reward mechanism for prosocial behaviour biases judgements towards the recommended alternative (Behrens et al, 2009). Indeed, choices that have been made socially relevant by peer recommendation could act as secondary inducers of reward circuitry (Erk et al, 2002; Schaefer & Rotte, 2006), which modulates frontal activity (Ichihara-Takaneda & Fukahashi, 2008). The observed reduction in activity in decision-related regions has been termed “cognitive off-loading” (Engelmann et al, 2009).

More fundamentally, there is evidence that social influence alters the uptake of available sensory evidence (Germar et al, 2013) or modifies the values assigned to a stimulus during evidence integration (Zaki et al, 2011). Both suggestions result from observations of an increase in frontal activity in the presence of social information. The present work aimed to discriminate between these alternatives while replicating the pattern of results typical for our paradigm.

Method

Participants

Twenty-three right-handed female volunteers (mean age= 19.8 years, σ = 1.96) were recruited for this study. All had normal or corrected to normal vision and none reported a previous history of neurological problems or current intake of prescription medication. Informed consent was obtained according to the procedure of the local ethics committee of the University Of Glasgow School Of Psychology. Participants were thoroughly debriefed upon completion of the study.

Stimuli

A set of 220 images of items of clothing from high-street vendors had previously been obtained from the web. Images were placed on a uniform grey background and were resized to 330 x 330 pixels. Stimuli were placed in the centre of either a blue or green rectangle of 360 x 360 pixels depending on condition that created a frame of width 30 pixels. The hues of blue and green used were equiluminant, to control for low-level perceptual effects.

Behavioural Paradigm

In Task 1 (see supplementary information; Fig. 1.1), participants provided preference ratings for all 220 items of clothing on a scale from 1 (really don't like) to 7 (really like) in increments of one. Items were presented in the centre of the screen, above a scale represented by stars (Fig.1.1). Participants responded using number keys 1 – 7 at the top of the keyboard. No time limit was imposed. Participants were free to change their response and had to confirm ratings before proceeding to the next item.

On the main task (Task 2; Fig 1.2), participants were required to make binary choices between two items. Items that formed pairs were drawn from the same category of clothing (e.g. trousers, dress, sweater) to ensure the alternatives could be readily compared. For each participant, items were paired to create a continuum of differences in ratings, ranging from -6 to 6 given our scale (1 - 7). The absolute value of this difference, referred to as item difference rating, is taken as a measure of task difficulty. In the absence of recommendations larger differences are considered to represent lower difficulty, the hardest decision being the indecision point. Differences were grouped into 5 bins ([-6, -5, -4]; [-3, -2,-1]; [0]; [1, 2, 3]; [4, 5, 6]), renamed difficulty level (1 – 5), in order to ensure sufficient trials per condition and to keep the total length of the experiment within a reasonable limit.

A total of 350 participant-specific pairings were generated for both the recommendation present and recommendations absent conditions (70 trials per difficulty level each; N=700 trials in total). During this process, the stimuli were split into two groups of 110 stimuli assigned to each recommendation condition in such a way as to create the smallest difference in mean rating across the groups. The items in the group assigned to the recommendation present condition were further split into items to be recommended and not, such that no item was recommended on some trials and not recommended on others. Participants were told the recommendation had been derived from the ratings given by 283 previous participants. All participants were told they were participant 284.

The task comprised four blocks of 175 pairs, with a non-constrained rest period between blocks. Recommendation conditions were interleaved within every block. The recommendation was delivered by placing the recommended item in a green frame and the non-recommended item in a blue frame. On recommendation absent trials, both items were presented in a blue frame.

On each trial, two items were presented on either side of a fixation cross and participants had a maximum of 1,750ms to indicate which they preferred to purchase. Participants were instructed to respond as soon as they made a decision. Choice was indicated by pressing the left or right arrow key (using right index and middle finger respectively) corresponding to the position of preferred item on screen. Items were removed from the screen as soon as a decision was made, and their offset followed by a randomly jittered interstimulus interval during which only a fixation cross was presented (1,250 – 1,750ms).

EEG Data Acquisition

EEG-data were recorded during Task 2 using a Brain Products amplifier (Brain Vision, UK) at a sampling rate of 1000Hz. Data was recorded using a Brain Vision Recorder. A reference electrode was placed on the left mastoid process. A ground electrode was placed left of centre on the chin. Input impedances were reduced to <30kOhm before onset of recording. Responses and reaction times were recorded using a computer keyboard (Cedrus Corporation, San Pedro, CA, USA). Data were acquired in an electronically shielded room.

EEG Data Pre-processing

A 0.5 - 40 Hz band-pass filter was applied to remove slow dc drifts and high frequency noise. Participants performed an eye movement calibration task to allow for later removal of artefacts related to eye movement (e.g. blinks). The task consisted of three sections, in which participants were instructed to blink repeatedly focussing on a central fixation cross, and to perform saccades first horizontally and then vertically by following a moving fixation cross. By timing the visual cues, principal component analysis could be employed to detect and remove linear components corresponding to blinks and saccades of the EEG-data collected during Task 2 (Parra et al, 2005). Data were baseline corrected with an interval of 100ms prior to stimulus onset to prevent slow alpha frequency-related changes in activity at trial onset.

Epochs locked to stimulus onset were subsequently constructed around task events. A time window of -100 – 900ms was defined, such that the full time range of the decision making process can confidently considered to be included. A sliding window of 50ms was applied to smooth data prior to statistical tests conducted on the EEG-data. By moving the window in 10ms steps, we obtained smoothed event-related potentials (ERPs) of 100 time windows per trial.

Behavioural Data Analysis

For each participant, we computed proportion of recommended item choice and mean reaction time (RT; averaged across both recommended and non-recommended item choices) for each of the five levels of difficulty, separately for the recommendation present and recommendations absent trials. The conditions could be compared by proportion of recommended items chosen because difficulty level of the recommendation absent condition contained sufficient information on which item would be recommended to dummy code a recommendation. Significant effects were tested for using a 2 (recommendation condition) x 5 (difficulty level) repeated measures analysis of variance (ANOVA). For the analysis of reaction times (RTs), data were collapsed across difficulty levels equally far from the indecision point resulting in three levels of item difference ratings (difficulty level [1, 5], [2, 4], 3), since the sign of the difference was assumed to have had no effect on the difficulty of the decision when the recommendation is absent.

A criterion was implemented whereby participants (N=2) who chose against the preference they indicated in Task 1 on more than 40% of trials in the most extreme difficulty bins (1,5) of Task 2 were excluded from further analysis. This criterion served as a measure of the reliability of the item ratings obtained in Task 1.

Event-Related Potential Analysis of EEG

EEG data were analysed by computing event related potentials. (ERPs) These were obtained from three frontal sensor clusters: far frontal cluster (FF: NFpz, FPz, F1, F2), frontolateral cluster (FL: F7, F8, FT7, FT8), and frontomedial cluster (FM: AF1, AF2, F1, F2, Fz, FC1, FC2, FCz; Fig 3.1 D). ERPs were computed as a sample mean and for each participant individually. In the absence of both a significant main effect of recommendation condition and significant interaction of difficulty and condition, data were collapses across recommendation decision before ERPs were computed. To test for significant differences in brain activity, participant ERPs were used to conduct ANOVAs on ERPs in relation to significant behavioural effects. The ANOVA was conducted for all 100 windows of the smoothed EEG-data. Results were corrected for multiple comparisons using the false discovery rate (Benjamini & Hochberg, 1995). This method is designed to quantify the best trade-off between identifying true and incurring false positives (Storey, 2002).

Given mean response times between ~750 – 900ms, response processes can be assumed to be initiated around 600ms post-stimulus. It has been shown this is sufficient time for decisions to reach accuracy of ~80% (Koch, Rangel & Milosavljevic, 2011). Given five participants had mean RTs below 650ms, effects as early as post 500ms post-stimulus are confounded with response processes. The present analysis will focus on effects prior to this cut-off.

Results

Behavioural Results

There was no evidence of a significant difference in the proportion of recommended items chosen whether the recommendation was absent or present ($F = 0.109$, $p = 0.741$). There was no evidence of a modulation of the role of peer recommendation by difficulty level or task difficulty, i.e. item difference rating ($F = 0.638$, $p = 0.425$; $F = 0.015$, $p = 0.901$). Difficulty level proved a direct indicator of the proportion of recommended items chosen ($F = 505.7$, $p < 0.001$; $F = 363.5$, $p < 0.001$), where difficulty level refers to which bin the item pair was selected from. Since higher difficulty levels reflected increased percentage of preferred items recommended. This is interpreted to indicate that participants chose the items they preferred in both conditions. Indeed, the percentage of preferred items chosen increased at more extreme item difference ratings ($F = 25.087$, $p < 0.001$).

Item difference rating was also significantly correlated with percentage preferred stimuli chosen ($F = 85.92$, $p < 0.001$). An effect of item difference rating on percentage preferred stimuli chosen is to be expected given an effect of difficulty on percentage recommended stimuli chosen since it reflects an effect on proportion recommended stimuli chosen after difficulty levels are combined into three item difference rating bins.

Item difference rating was a direct indicator of RT, with lower item difference ratings, i.e. higher decision difficulty –resulting in longer RTs ($F = 9.272$, $p < 0.01$). Reaction times were broadly symmetrical around the indecision point. The absence or presence of the recommendation did not modulate RT ($F = 0.052$, $p = 0.819$). Also, recommendation condition did not differentially effect RTs across item difference ratings ($F = 0.022$, $p = 0.882$; Figure 2.1).

Given anecdotal evidence that some participants purposefully chose against the recommendation when uncertain about their preference on a recommendation present trial, post-hoc analysis of the behavioural data was carried out to investigate a possible obscured effect. Participants were rank ordered by percentage of recommended items chosen and divided into two groups of eight, with the middle five participants being excluded. Mean proportion recommended items chosen was significantly different across the resulting subsamples (Welch two-sample t-test: $t (9.81) = -6.278$, $p < 0.001$). Which group participants belonged to was then factored into the model and another ANOVA computed.

Whether participants chose recommended items more or less on average did not interact with any of difficulty level, item difference or recommendation condition towards predicting either proportion recommended chosen or RT (p-values all > 0.3; Figure 2.2), nor was it directly predictive of choice proportion or RT (p-values > 0.1).

EEG Results

Difficulty Level

Having found a significant main effect of difficulty level on proportion of recommended items chosen this factor was investigated further. Different levels reflected different degrees of preference for the recommended stimulus. Classical ERPs were observed in all three clusters, constituted by an early peak putatively showing early encoding of stimuli and ramping slopes from around 400ms consistent with slopes seen during evidence accumulation (Vugt et al, 2012).

None of the three clusters demonstrated differences in signal strength that reached statistical significance after correcting for multiple comparisons (Figure 3.1*A* – *C*). This is not surprising absent any complex effects or interactions and since equally eccentric levels of difficulty correspond to the same item difference rating, i.e. level of task difficulty.

Item Difference Rating

As opposed to difficulty level, item difference rating did show differences in signal strength that remained statistically significant following correction for multiple comparisons in both the FF cluster and FM cluster (Figure 3.2*A; C*). For the FF-cluster, two time windows, at 150 – 300ms ($p < 0.05$) and 440 – 900ms post-stimulus ($p < 0.01$) retained statistical significance. Four time windows from the FM cluster were at 150 – 290ms ($p < 0.05$), 270 – 300ms ($p < 0.05$), 470 – 530ms ($p < 0.05$) and 830 – 900ms ($p < 0.05$) post-stimulus.

No time window retained statistical significance in the FL-cluster (Figure 3.2*B*). Generally, significant differences in signal strength occurred when ERPs of decisions at the indecision point (item difference 3) were noticeably different from ERPs of decisions where a preferred choice was present (item differences 1 and 2). The effects inside the window of <500ms post-stimulus all show this pattern.

Within this time window, the difference in ERPs across item difference ratings is reflected in a difference in slope for the FF-cluster (Fig 3.3*A*). A change in slope can be taken to reflect an analogous change in input, be it sensory or integrated evidence, and has been shown to be modulated by task difficulty (Philiastides & Sajda, 2005). The FM-cluster also exhibited an effect akin to a transposition of the ERP along the y-axis as a function of item difference rating (Fig. 3.3*B*). This suggests the effect is not related to increasing RT at higher difficulties, which would manifest as a translation along the x-axis instead. Instead, a translation along the y-axis suggests a general difference in signal strength. The absence of single-trial analysis makes a more detailed analysis of response dynamics and time course impossible.

A neural component related to task difficulty has been previously identified in studies of perceptual decision making at ~220ms post-stimulus (Philiastides et al, 2006). Indeed, peak difference in ERPs of the difference conditions for the FF-cluster in the present study was at ~210ms. However, higher task difficulty is related to lower absolute activity in the present study, inconsistent with the suggestion that the D220 reflects the recruitment of additional resources (Philiastides et al, 2006; Fig 3.3A). The scalp topography of this component also shows a different distribution to the D220, with more anterior high negative frontal activity (Fig. 3.3*C*). Meanwhile, computing the difference in signal strength between the highest and lowest task difficulty does show a strong centrofrontal effect (Fig 3.3*D*).

An early component identified in the FM-cluster ~130ms has been previously identified in perceptual studies and related to behavioural performance (VanRullen & Thorpe, 2001; Fig 3.3*B*). Early components have been related to low-level feature processing (Johnson & Olshausen, 2003) though no differences in low level features dependent on item difference rating exist in the present study. Topographical layout of the scalp potentials showed a distributed frontocentral effect, consistent with the suggestion that the brain must recruit additional resources (e.g. attention) when a decision is hard (Philiastides et al, 2006; Fig 3.3*E*).

A later component also identified in the FM-cluster may be related to recurrent processing, given the time between components is broadly consistent with 130ms mean reverberation time (VanRullen & Koch, 2003). Recurrent processing reflects integration of information that underlies perception (Philiastides & Sajda, 2006). A late component peaking at ~340ms related to task difficulty would reflect a change in the activity underlying the integration of evidence as a function of task difficulty.

Indeed, feedback processing mediates attention (Super et al, 2001), and stronger absolute activation may reflect stronger recruitment of attentional resources to make more difficult choices. Attention has been shown to affect evidence accumulation (Krajbich et al, 2012) and could affect evidence integration as well. While the effect on accumulation reflects random shifts due to low-level stimulus features that affect how attribute values are sampled (Milosavljevic et al, 2011), the present results indicate a potential effect of attention on integration would be a systematic change as a function of task difficulty.
It should be noted that none of the identified differences in ERPs within the decision window retain statistically significance when a more strict correction for multiple comparisons is applied (Holm's).

Recommendation Condition

Despite the absence of a significant behavioural main effect of recommendation, comparing ERPs of the levels of recommendation may produce meaningful results, albeit difficult to interpret. Indeed, the FM-cluster, though neither FF- nor FL-cluster, showed differences in signal strength that remained statistically significant after correction for multiple comparisons (Fig. *3.4A – C*). Given the absence of any behavioural effect due to recommendation condition, correction for multiple comparisons was repeated on the original data by conducting the more conservative correction for family-wise error (Holm's test). Statistically significant differences in signal strength between recommendation absent versus present conditions were retained for a time window 280 – 580ms ($p < 0.05$; 380 – 580ms, $p < 0.01$; time window 45, i.e. 325 – 375ms, $p = 0.052$; Fig. 3.5*A*).

Peak difference in ERPs occurred ~320ms post-stimulus. The topography of difference in signal strength during this time window presents a large negative central cluster suggestive of an effect mediated by attention (Fig 3.5*B*). However, the signal of greater magnitude was observed on trials during which the recommendation is absent as opposed to present. An increased engagement of attentional resources should have produced the opposite effect. Current results suggested an attenuation of neural signals due to social influence. Absent a behavioural effect it is uncertain whether the reduced activity was decision-related. It might be noted that task-related variability is commonly identified in the literature (Behrens et al, 2009).

It has been suggested that the effect of social influencing factors such as a recommendation would be mediated by the value difference between alternatives (Hunt et al, 2008). This predicts a modulation of signals relevant to the given social information by differences in subjective value ratings. To test the task relevance of the ERP-difference observed for data collapsed across difficulty levels, a post-hoc computation of ERP difference at effect peak (~330ms) for recommendation absent and present conditions for each item difference rating was conducted.

A 2 x 3 within-subjects ANOVA (recommendation conditions x item difference ratings) did not confirm that task difficulty modulates signal difference ($F = 0.238$, $p = 0.627$). This suggests a non-parametric effect independent of difficulty that is due, instead, to the simple presence of the recommendation, consistent with previous results indicating an effect due to the simple presence of advice (e.g. Biele et al, 2011).

Discussion

The present work was designed to explore the influence of social information on a simple consumer decision. We computed ERPs from EEG-data to investigate the influence of peer recommendation on the neural dynamics of that decision. Consistent with earlier evidence (Biele et al, 2011; Coricelli et al, 2005; Engelmann et al, 2009), our results suggest that peer recommendation reduces frontomedial brain activity. Temporally, we localised this effect to a time window suggestive of an effect of peer recommendation on evidence integration. There was no evidence of a corresponding behavioural effect. Typical temporal dynamics of value-based decisions were partially replicated.

Influence of peer recommendation

The effect observed in FM-cluster ERPs when comparing recommendation levels is difficult to interpret absent a behavioural effect. It can be said that the late onset of the effect contradicts the conclusion that social information alters the uptake of available sensory evidence (Germar et al, 2013). The timing of our results is more consistent with a modulation of the value-encoding process by peer recommendation (Zaki et al, 2011). This converges with the literature in suggesting that social influence modifies the value assigned to a stimulus (Izuma, 2013). The issue may be complicated further by the fact that selection and integration of evidence are aspects of a single dynamical process (Mante et al, 2013). This leaves open the exact effect peer recommendation may have on the computation of choice.

The scalp topography (Fig 3.5*B*) of the difference between ERPs of the recommendation conditions suggests an attention-related effect. In line with Engelmann et al's (2009) suggestion of “cognitive offloading”, this may reflect the reduced engagement of attentional resources when social information is present. Absent a behavioural effect, this offloading is more difficult to interpret, since the information that incurs the offload does not seem to be relevant to behaviour. Elsewhere, the “offload” was suggested to be the result of an associative learning process that leads individuals to intuitively expect a reward for engaging in prosocial behaviour (Behrens et al, 2008).

Indeed, the effect we observed could be mediated by the reward mechanism, implicated in value-based social decision making by previous work (Biele et al (2010); Coricelli et al, 2005). However, the subcortical regions constituting the human reward circuitry themselves are difficult to investigate using EEG (Plichta et al, 2013), but activity in this network has diffuse effects throughout the cortex that can easily be measured by the technique (e.g. Plichta et al, 2013; Fouragnan et al, 2015). A more sensitive paradigm paired with functional imaging is required to delve deeper into these questions.

Importantly, the ostensible bias incurred by an expected reward for prosocial behaviour is taken to be mediated by social reinforcement values assigned to each choice option in either case (Germar et al, 2013). The assigned value depends on the expected reward at consumption (Malmaud et al, 2010), and there is considerable evidence that this value is modulated by social information (Behrens et al, 2009). Indeed, clothing takes a central role in social comparison among urban young adult women, who feel strongly influenced by peers in their choice of clothing (Wilson & MacGillivray, 1998). This leads to a high perceived reward for prosocial choice (Behrens et al, 2008).

In this framework, the absence of a behavioural effect and presence of a neural effect may imply that the peer recommendation was of insufficient import to the participants to cause them to adjust their behaviour. The neural effect is evidence that the recommendation influences the computations underlying decision formation, the absence of a behavioural effect indicates this had no influence on decision outcome. In terms of the computations underlying value-based choice, the value assigned to the recommendation may ultimately have been too small to bias behaviour.

If the recommendation influenced value comparison as opposed to value assignment, we might expect a parametric modulation of the influence of recommendation by item difference rating since the relative weight of a constant value of the recommendation would change deepening on the subjective value difference between items (Rangel, Camerer & Montague, 2008). An influence on either process would be consistent with the timing of the observed effect (Rangel & Hare, 2010). While our study cannot resolve the exact influence of peer recommendation, future work could do so along these lines.

Additionally, various factors may insulate against judgment bias introduced by a social gesture, including expertise (Kirk, Harvey & Montague, 2011). As such, the absence of a behavioural effect may reflect participants' familiarity with making choices between items of clothing. Indeed, recent EEG results indicate task familiarity modulates the decision process (Harris et al, 2014). Thus, the absence of a behavioural effect may be related to the manner in which the recommendation was operationalized (Izuma et al, 2013).

Participants may have felt the information was not relevant, or may not have trusted the recommendation, both of which can nullify the expected effect (Behrens et al, 2009). The first process of value-based decision making is computing a representation of the decision problem (Rangel et al, 2008) and it could be that the manner in which the recommendation was operationalized in our study incurred a very limited relevance to the imminent decision.

An option to remedy this would be to rely on a more direct recommendation (Biele et al, 2011). However, an indirect recommendation, which more closely approximates aggregated collective judgements online, should show an effect given social information has been shown to bias behaviour even when indirect (Hunt et al, 2008). To illuminate this, it may be advisable to conclude similar paradigms with a questionnaire in the future, in order to obtain data on the influence participants felt the recommendation, in our case, had on their decision.

Modulation by task difficulty

It has been shown previously that quantities associated with task difficulty continuously modulate scalp potentials (Philiastides et al, 2014). The D220 is a specific difficulty related component that may correspond to a direct influence of task difficulty on the decision process (Philiastides & Sajda, 2006). We identify a temporally similar component, which nonetheless cannot be the same as it does not seem to be predictive of the timing of an associated late component we also identify. It is noteworthy that greater task difficulty was associated with reduced activity in our study. This might be the case if the component were related to the value difference signal that is accumulated over the decision period (Philiastides et al, 2010). In this context, reduced activation may reflect reduced or noisier evidence for one preferred alternative.

The orbitofrontal cortex (OFC) has been diversely implicated in encoding subjective value and value comparison (Erk et al, 2002; Zaki et al, 2011). If task difficulty modulates value comparison, this suggests a possible localisation of this effect to OFC. Indeed, OFC does seem to be responsive to value difference (FitzGerald, Seymour & Dolan, 2009). The reduced activity for greater difficulty observed in the present task converges with increased activity previously reported for increased value difference at OFC (Zaki et al, 2011). By this account, the FF-cluster effect we report may reflect the encoding of subjective value difference, if it can be shown that an increase in this ratio is paralleled by an increase in signal strength. The relationship to task difficulty would be a parametric modulation of value difference signal as a function of task difficulty.

Within the DDM, this is expected to lead to longer RTs for more difficult decisions because the accumulator takes longer to reach the decision threshold (Krajbich et al, 2015). The behavioural effect of task difficulty on RT reflects the identity of item difference rating and difference in subjective value of the choice alternatives. Longer RTs are the direct result of a smaller difference between the subjective value of each option, and smaller differences lead to slower accumulation of the difference signal towards the criterion that initiates a response (Krajbich et al, 2015).

The early (~130ms) and late (~310ms) effects observed in the FF-cluster showed the expected greater activation for more difficult decisions. These results converge well with the literature (e.g. Johnson & Olshausen, 2001; VanRullen & Thorpe, 2003; Philiastides et al, 2006; Philiastides & Sajda, 2006). Ostensibly related to evidence acquisition and integration respectively, both effects suggest the recruitment of additional resources to make relatively more difficult decisions (Philiastides et al, 2006). The topography of the effects implicated distributed frontomedial regions reinforcing a possible role of attention. This is putatively recruited to a greater extent when there is less evidence, i.e. decisions are harder. That both evidence accumulation and integration are modulated by task difficulty converges with the notion of their as two components of a single dynamical process posited by the DDM (Mante et al, 2013).

Task-related factors

The role of task difficulty also implies that macroscopic effects observed in EEG-data may be as much explainable by differences in task design as they are reflective of common underlying processes (Philiastides et al, 2014). Indeed, task-dependency of neural networks implicated in similar computations remains an open question (Hare et al, 2011). Meanwhile, idiosyncratic, task-related differences also highlight the ultimately limited relevance of results from perceptual decision making to the value-based literature. As in the comparison of the present work with earlier studies from our group (Philiastides & Sajda, 2006; Philiastides et al, 2006), the finer points of the neural mechanisms suggested by individual tasks will likely continue to show at least slight differences. Though adaptive coding allows the comparisons across domains (Krajbich et al, 2015), it is crucial to the investigation of ever more subtle influences that the origin of these task-related differences is explored.

Recall too, that the value comparison process under the DDM is neither deterministic nor optimal (Malmaud et al, 2010). Despite non-stochastic stimuli, noisy is introduced into the computation because value is assigned by sequential and stochastic extraction of features (Armel et al, 2010). Here, a task-related influence is captured by differences in fixation on each choice alternative (Armel et al, 2010). This is driven by low-level perceptual features such as salience (Milosavljevic et al, 2011) and by initial value of each choice alternative (Armel et al, 2010). To resolve the influence of such factors, the present study might have benefited from eye tracking and pupilometry, both of which have been shown to be informative in respect to the decision process and outcome (e.g. Satterthwaite et al, 2007; Cavanagh et al, 2014). In their absence, the degree to which our results were influenced by these features remains uncertain, as does the role of these biases.

Integration with functional imaging literature

The effect of social influence is not on a special set of neural responses, but modulatory of activity throughout the neural networks associated with preference judgements (Harvey et al, 2010). This is consistent with significant EEG-results, which reflect strong activity of neural populations (Philiastides & Sajda, 2006). Despite the poor spatial resolution of EEG, the present results may contribute to the identification of underlying neuromodulatory regions by implicating regions previously correlated to computations our results suggest are relevant.

With regard to recommendation condition, the present results tentatively suggest a reward-mediated effect. There is evidence of reward processing in VMPFC, but reports are of both attenuated (Biele et al, 2011) and increased activity (Hare et al, 2011; Kirk et al, 2011; Germar et al, 2013) Again, that discrepancy may be the consequence of task-related factors (Milosavljevic et al, 2011). In this case, an analysis of the task idiosyncrasies that incur differential activity of the VMPFC could illuminate its varying role in different kinds of decisions.

Meanwhile, previous results suggested an independent evaluative system may play a key role in social modulation of preference (McClure et al, 2004). This is broadly consistent with the associative learning mechanism that may underpin the neural effect of peer recommendation and would lead us to expect an identifiable shared response in task of this nature. Given the broad implication of OFC, this region may be another candidate for closer analysis, particularly given its implication in reward-related processing during consumer decisions (Erk et al, 2002).

In addition to VMPFC, posterior and anterior medial frontal cortex (pMFC; aMFC) have been shown to be modulated by social influence and susceptibility to social influence respectively (Izuma et al, 2013). The notion of susceptibility raises the additional concern of interindividual differences but also offers a possible avenue to explore these, since greater susceptibility may be related to increased aMFC activity. Indeed, functional imaging aimed at clarifying the varying contribution of different task- and participant-related factors would yield the two-fold benefit of a more detailed picture of the decision process and a better idea of its fundamental mechanism.

Limitations

The present paradigm faces a number of limitations incurred by its reliance on aggregated data. In calculating smoothed ERP's, we averaged both across participants and across time, and the amount of information lost during this process is considerable. As a result, conclusions with respect to exact timing of observed effects must be considered tentative. Moreover, ERPs also confound the variability in the evidence accumulated, starting point of the decision process and duration of nondecision components (Krajbich et al, 2012).

Any attempt to model the influence of peer recommendation will need to take this into account. It has been shown that these factors can be dissociated using single-trial analysis (Ratcliff, Philiastides & Sajda, 2009). On the other hand, individual trials introduce considerable heterogeneity of responses of individual neurons (Philiastides et al, 2014). In this respect, ERPs are easier to interpret, but cannot unequivocally relate observed components to specific stages in the decision making process (Philiastides & Sajda, 2006). While aggregate data face large limitations, the consensus remains that they continue to represent a useful tool for analysis precisely because of their relative easiness to interpret.

Our analysis of the influence of peer recommendation on neural dynamics is limited most by the nature of our behavioural data. Absent an identifiable influence of the recommendation on behaviour it is difficult to relate the neural effect to a precise stage of the underlying process. This is the case particularly in the context of a literature in which an effect is commonly identified but remains ambiguously assigned (e.g. Erk et al, 2002; Zaki et al, 2011; Germar et al, 2013). The mechanism underlying of the corresponding decision, and the component regions could only be explored tentatively. The importance of careful operationalization of social influence was also exacerbated by the influence of task-related factors. Future work should aim to explore and identify a behavioural effect before proceeding.

Ecological validity provides a final challenge to our results, and reflects a systematic challenge to the decision making literature, and indeed laboratory-based experimental work in general (Skorepa, 2011). In our study, participants thought they were receiving recommendations aggregated over the fictional previous participants who had supposedly completed the same task.In a participant's mind, the recommendations would have been made purely on the basis of seeing the same images also presented to her. This makes the present recommendations different from the aggregated collective judgements that motivated our study, since the latter are typically made after using the product. In our study, the absence of any engagement with the physical product by the ostensible recommending party may have reduced the value of the recommendation to the participants by removing an important dimension of the underlying value-judgement.

Consequently, recommendations in the present study may be relatively superficial. As a result of recommendations based on only superficial information, our paradigm may fail to faithfully reproduce the collective judgements motivating our study (Muchnik et al, 2009). In having fallen short of reproducing the natural decision with full accuracy, the paradigm may fall short of capturing the richness of consumer decision making more generally too (cf. e.g. Herve & Mullet, 2009). The crucial point is to reiterate a call for attention to details of task-design, which may prove crucial to the validity of results. Future and indeed past results must be interpreted carefully, with keen awareness of the nuances of tasks and the phenomena under investigation.

Summary

Our results contribute to an account whereby social information presented during a decision acts to attenuate activity in the human frontal cortex. This effect is likely mediated by the differential engagement of the reward mechanism in the presence of social influence. We observed that neural activity is modulated by peer recommendation, even absent a behavioural effect. The present findings converge with the established literature on an influence of task difficulty on neural dynamics of decision making at both evidence accumulation and integration. These results must be understood in the context of considerable inter-task variability and seem broadly consistent with functional imaging results to date.

Future Directions

Within the current paradigm, the essential next stage is to more compellingly operationalize social influence. This will permit an exploration of the dynamics of decision making when the influence is carried forward to bias behaviour. In addition, future work would do well to apply both single-trial analysis and computational modelling in order to develop our understanding of the finer mechanics of the influence of social influence on value-based decision making. This should also contribute to continued efforts to codify a number of influences on the fundamental decision making mechanism that underlies perceptual and value-based decision according to the DDM.

The present and associated research also carries potential applications to neuromarketing (Lee, Broderick & Chamberlain, 2007). The extent to which decisions are biased in a variety of situations by social influence among other factors, may be the core of that nascent research direction (Breiter et al, 2014). This research could have important applications to economics too, if it succeeds in challenging long-standing assumptions about the rationality and self-interestedness of consumer behaviour (Muchnik et al, 2013).

Notes

We wish to thank Gavin Shields for his assistance during the testing phase.

References

Armel, C., Rangel, A., & Krajbich, I. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience, 13*(10), 1292-1298. doi:10.1038/nn.2635

Behrens, T. E. J., Hunt, L. T., & Rushworth, M. F. S. (2009). The computation of social behavior.*Science, 324*(5931), 1160-1164. doi:10.1126/science.1169694

Benjamini, Y & Hochberg, Y (1995) Controlling the false discovery rate: a new and powerful approach to multiple comparisons. *Journal of the Royal Statistical Society. Series B (Methodological), 57*(1), 289-300.

Biele, G., Rieskamp, J., & Gonzalez, R. (2009). Computational models for the combination of advice and individual learning. *Cognitive Science, 33*(2), 206-242. doi:10.1111/j.1551-6709.2009.01010.x

Biele, G., Rieskamp, J., Krugel, L. K., & Heekeren, H. R. (2011). The neural basis of following advice. *PLoS Biology, 9*(6), e1001089. doi:10.1371/journal.pbio.10010

Breiter, H. C., Block, M., Blood, A. J., Calder, B., Chamberlain, L., Lee, N.. . Zhang, F. (. (2015). Redefining neuromarketing as an integrated science of influence.*Frontiers in Human Neuroscience, 8*doi:10.3389/fnhum.2014.01073

Camerer, C., Loewenstein, G., & Prelec, D. (2005). Neuroeconomics: How neuroscience can inform economics.*Journal of Economic Literature,43*(1), 9-64. doi:10.1257/0022051053737843

Cavanagh, J. F., Wiecki, T. V., Kochar, A., & Frank, M. J. (2014). Eye tracking and pupillometry are indicators of dissociable latent decision processes.*Journal of Experimental Psychology. General,143*(4), 1476-1488. doi:10.1037/a0035813

Coricelli, G., Sirigu, A., O'Doherty, J. P., Critchley, H. D., Dolan, R. J., & Joffily, M. (2005). Regret and its avoidance: A neuroimaging study of choice behavior. *Nature Neuroscience, 8*(9), 1255-1262. doi:10.1038/nn1514

Duhan, D. F., Johnson, S. D., Wilcox, J. B., & Harrell, G. D. (1997). Influences on consumer use of word-of-mouth recommendation sources.*Journal of the Academy of Marketing Science,25*(4), 283-295. doi:10.1177/009207039725400

Engelmann, J. B., Capra, C. M., Noussair, C., & Berns, G. S. (2009). Expert financial advice neurobiologically "offloads" financial decision-making under risk. *PloS One, 4*(3), e4957. doi:10.1371/journal.pone.00049

Erk, S., Spitzer, M., Wunderlich, A. P., Galley, L., & Walter, H. (2002). Cultural objects modulate reward circuitry.*Neuroreport, 13*(18), 2499-2503. doi:10.1097/00001756-200212200-00024

Fehr, E., & Camerer, C. F. (2007). Social neuroeconomics: The neural circuitry of social preferences. *Trends in Cognitive Sciences,11*(10), 419-427. doi:10.1016/j.tics.2007.09.002

FitzGerald, T. H. B., Seymour, B., & Dolan, R. J. (2009). The role of human orbitofrontal cortex in value comparison for incommensurable objects. *Journal of Neuroscience, 29*(26), 8388. doi:10.1523/JNEUROSCI.0717-09.2009

Fouragnan, E., Retzler, C., Mullinger, K., & Philiastides, M. G. (2015). Two spatiotemporally distinct value systems shape reward-based learning in the human brain. *Nature Communications, 6*, 8107. doi:10.1038/ncomms9107

Germar, M., Schlemmer, A., Krug, K., Voss, A., & Mojzisch, A. (2014;2013;). Social influence and perceptual decision making: A diffusion model analysis.*Personality and Social Psychology Bulletin,40*(2), 217-231. doi:10.1177/0146167213508985

Glimcher, P. W., & Rustichini, A. (2004). Neuroeconomics: The consilience of brain and decision. *Science,306*(5695), 447-452. doi:10.1126/science.1102566

Hare, T. A., Schultz, W., Camerer, C. F., O'Doherty, J. P., & Rangel, A. (2011). Transformation of stimulus value signals into motor commands during simple choice.*Proceedings of the National Academy of Sciences of the United States of America,108*(44), 18120-18125. doi:10.1073/pnas.1109322108

Harris, A., Adolphs, R., Camerer, C., & Rangel, A. (2011). Dynamic construction of stimulus values in the ventromedial prefrontal cortex: E21074. *PLoS One, 6*(6) doi:10.1371/journal.pone.0021074

Harvey, A. H., Kirk, U., Denfield, G. H., & Montague, P. R. (2010). Monetary favors and their influence on neural responses and revealed preference. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience,30*(28), 9597.

Hervé, C., & Mullet, E. (2009). Age and factors influencing consumer behaviour. *International Journal of Consumer Studies, 33*(3), 302-308

Hunt, L. T., Woolrich, M. W., Behrens, T. E. J., & Rushworth, M. F. S. (2008). Associative learning of social value.*Nature, 456*(7219), 245-249. doi:10.1038/nature07538

Hunt, L. T., Kolling, N., Soltani, A., Woolrich, M. W., Rushworth, M. F. S., & Behrens, T. E. J. (2012). Mechanisms underlying cortical activity during value-guided choice. *Nature Neuroscience, 15*(3), 470-476. doi:10.1038/nn.3017

Ichihara-Takeda, S., & Funahashi, S. (2008). Activity of primate orbitofrontal and dorsolateral prefrontal neurons: Effect of reward schedule on task-related activity. *Journal of Cognitive Neuroscience, 20*(4), 563-579. doi:10.1162/jocn.2008.20047

Izuma, K. (2013). The neural basis of social influence and attitude change. *Current Opinion in Neurobiology, 23*(3), 456-462. doi:10.1016/j.conb.2013.03.009

Johnson, J. S., & Olshausen, B. A. (2003). Timecourse of neural signatures of object recognition. *Journal of Vision,3*(7), 499-4. doi:10.1167/3.7.4

Kennerley, S. W., Dahmubed, A. F., Lara, A. H., & Wallis, J. D. (2009). Neurons in the frontal lobe encode the value of multiple decision variables. *Journal of Cognitive Neuroscience,21*(6), 1162-1178. doi:10.1162/jocn.2009.21100

Kirk, U., Harvey, A., & Montague, P. R. (2011). Domain expertise insulates against judgment bias by monetary favors through a modulation of ventromedial prefrontal cortex. *Proceedings of the National Academy of Sciences of the United States of America,108*(25), 10332-10336. doi:10.1073/pnas.1019332108

Klucharev, V., Hytönen, K., Rijpkema, M., Smidts, A., & Fernández, G. (2009). Reinforcement learning signal predicts social conformity. *Neuron, 61*(1), 140-151. doi:10.1016/j.neuron.2008.11.027

Koch, C., Rangel, A., & Milosavljevic, M. (2011). Consumers can make decisions in as little as a third of a second. *Judgment and Decision Making, 6*(6), 520-530.

Krajbich, I., Lu, D., Camerer, C., & Rangel, A. (2012). The attentional drift-diffusion model extends to simple purchasing decisions.*Frontiers in Psychology,3*, 193. doi:10.3389/fpsyg.2012.00193

Krajbich, I., Hare, T., Bartling, B., Morishima, Y., & Fehr, E. (2015). A common mechanism underlying food choice and social decisions.*PLoS Computational Biology, 11*(10), e1004371.

Lee, N., Broderick, A. J., & Chamberlain, L. (2007). What is ‘neuromarketing’? A discussion and agenda for future research. *International Journal of Psychophysiology, 63*(2), 199-204. doi:10.1016/j.ijpsycho.2006.03.007

Malmaud, J., Koch, C., Rangel, A., Huth, A., & Milosavljevic, M. (2010). The drift diffusion model can account for the accuracy and reaction time of value-based choices under high and low time pressure.*Judgment and Decision Making, 5*(6), 437-449.

Mante, V., Sussillo, D., Shenoy, K. V., & Newsome, W. T. (2013). Context-dependent computation by recurrent dynamics in prefrontal cortex. *Nature,503*(7474), 78. doi:10.1038/nature12742

McClure, S. M., Li, J., Tomlin, D., Cypert, K. S., Montague, P. R., & Montague, L. M. (2004). Neural correlates of behavioral preference for culturally familiar drinks.*Neuron, 44*(2), 379-387. doi:10.1016/j.neuron.2004.09.01

Milosavljevic, M., Navalpakkam, V., Koch, C., & Rangel, A. (2012). Relative visual saliency differences induce sizable bias in consumer choice.*Journal of Consumer Psychology, 22*(1), 67-74. doi:10.1016/j.jcps.2011.10.002

Muchnik, L., Aral, S., & Taylor, S. J. (2013). Social influence bias: A randomized experiment.*Science, 341*(6146), 647. doi:10.1126/science.1240466

Parra, L. C., Spence, C. D., Gerson, A. D., & Sajda, P. (2005). Recipes for the linear analysis of EEG. *Neuroimage, 28*(2), 326-341. doi:10.1016/j.neuroimage.2005.05.032

Plichta, M. M., Wolf, I., Hohmann, S., Baumeister, S., Boecker, R., Schwarz, A. J.. . Brandeis, D. (2013). Simultaneous EEG and fMRI reveals a causally connected subcortical-cortical network during reward anticipation. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience, 33*(36), 14526.

Philiastides, M. G., & Sajda, P. (2006). Temporal characterization of the neural correlates of perceptual decision making in the human brain. *Cerebral Cortex (New York, N.Y. : 1991), 16*(4), 509-518. doi:10.1093/cercor/bhi130

Philiastides, M. G., Ratcliff, R., & Sajda, P. (2006). Neural representation of task difficulty and decision making during perceptual categorization: A timing diagram. *Journal of Neuroscience, 26*(35), 8965-8975. doi:10.1523/JNEUROSCI.1655-06.2006

Philiastides, M. G., & Sajda, P. (2007). EEG-informed fMRI reveals spatiotemporal characteristics of perceptual decision making. *Journal of Neuroscience, 27*(48), 13082-13091. doi:10.1523/JNEUROSCI.3540-07.2007

Philiastides, M. G., Biele, G., Heekeren, H. R., & Ungerleider, L. G. (2010). A mechanistic account of value computation in the human brain.*Proceedings of the National Academy of Sciences of the United States of America,107*(20), 9430-9435. doi:10.1073/pnas.1001732107

Philiastides, M., Auksztulewicz, R., Heekeren, H., & Blankenburg, F. (2011). Causal role of dorsolateral prefrontal cortex in human perceptual decision making. *Current Biology,21*(11), 980-983. doi:10.1016/j.cub.2011.04.034

Philiastides, M. G., & Ratcliff, R. (2013). Influence of branding on preference-based decision making.*Psychological Science,24*(7), 1208-1215.

Philiastides, M. G., Heekeren, H. R., & Sajda, P. (2014). Human scalp potentials reflect a mixture of decision-related signals during perceptual choices. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience,34*(50), 16877-16889. doi:10.1523/JNEUROSCI.3012-14.2014

Rangel, A., Montague, P. R., & Camerer, C. (2008). A framework for studying the neurobiology of value-based decision making. *Nature Reviews Neuroscience, 9*(7), 545-556. doi:10.1038/nrn2357

Rangel, A., & Hare, T. (2010). Neural computations associated with goal-directed choice. *Current Opinion in Neurobiology, 20*(2), 262-270. doi:10.1016/j.conb.2010.03.001

Ratcliff, R. (1978). A theory of memory retrieval.*Psychological Review, 85*(2), 59-108. doi:10.1037//0033-295X.85.2.59

Ratcliff, R., & Rouder, J. N. (1998). Modeling response times for two-choice decisions. *Psychological Science, 9*(5), 347-356. doi:10.1111/1467-9280.00067

Ratcliff, R., & Rouder, J. N. (2000). A diffusion model account of masking in two-choice letter identification.*Journal of Experimental Psychology: Human Perception and*

Performance, 26(1), 127-140. doi:10.1037/0096-1523.26.1.127

Ratcliff, R., Philiastides, M. G., Sajda, P., & Shiffrin, R. M. (2009). Quality of evidence for perceptual decision making is indexed by trial-to-trial variability of the EEG. *Proceedings of the National Academy of Sciences of the United States of America,106*(16), 6539-6544. doi:10.1073/pnas.0812589106

Sanfey, A. G., Loewenstein, G., McClure, S. M., & Cohen, J. D. (2006). Neuroeconomics: Cross-currents in research on decision-making. *Trends in Cognitive Sciences,10*(3), 108-116. doi:10.1016/j.tics.2006.01.009

Satterthwaite, T. D., Green, L., Myerson, J., Parker, J., Ramaratnam, M., & Buckner, R. L. (2007). Dissociable but inter-related systems of cognitive control and reward during decision making: Evidence from pupillometry and event-related fMRI.*Neuroimage, 37*(3), 1017-1031. doi:10.1016/j.neuroimage.2007.04

Schaefer, M. & Rotte, M. (2006) Favorite brands as cultural objects modulate reward circuitry. *Brain Imaging: NeuroReport 18*(2), 141-145.

Skorepa, Michal (2009) Decision Making: A Behavioral Economic Approach. Palgrave-MacMillan, NY.

Storey, J. D. (2002). A direct approach to false discovery rates. *Journal of the Royal Statistical Society. Series B (Statistical Methodology), 64*(3), 479-498. doi:10.1111/1467-9868.00346

VanRullen, R., Thorpe, S. (2001) The time course of visual processing: from early perception to decision making. J Cogn Neurosci 13:454--461.

van Vugt, M. K., Simen, P., Nystrom, L. E., Holmes, P., & Cohen, J. D. (2012). EEG oscillations reveal neural correlates of evidence accumulation. *Frontiers in Neuroscience, 6*, 106. doi:10.3389/fnins.2012.00106

Wilson, J. D., & MacGillivray, M. S. (1998). Self-perceived influences of family, friends, and media on adolescent clothing choice. *Family and Consumer Sciences Research Journal, 26*(4), 425-443. doi:10.1177/1077727X980264003

Figures

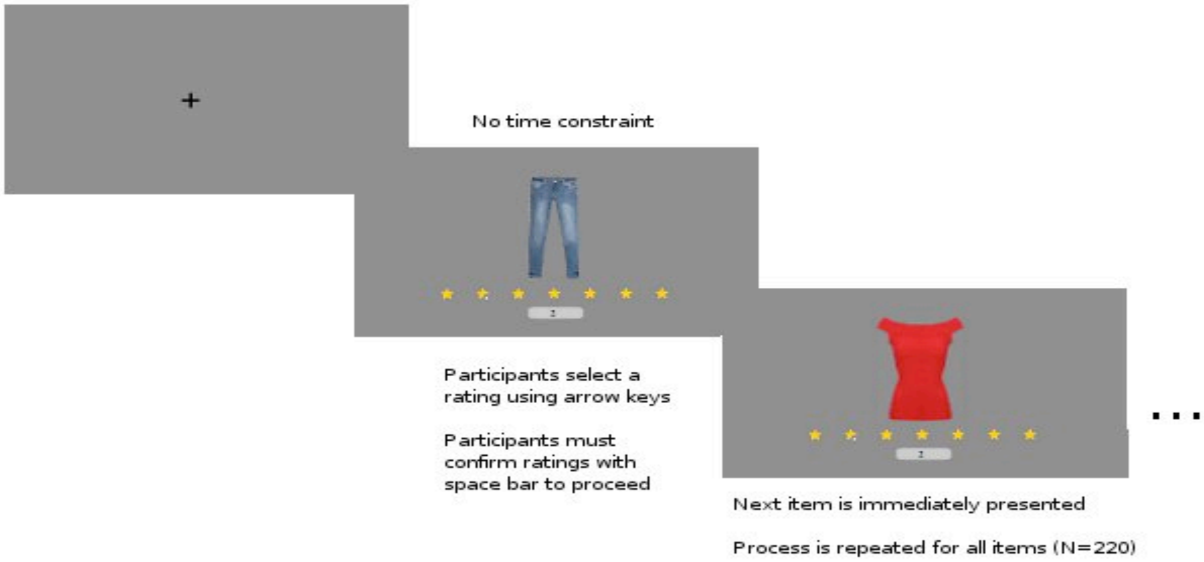

Figure 1.1: Task 1. Participants were presented with an item and asked to indicate a preference using a corresponding number key. Item offset followed confirmation of the indicating rating by the space key. The onset of the next item followed immediately.

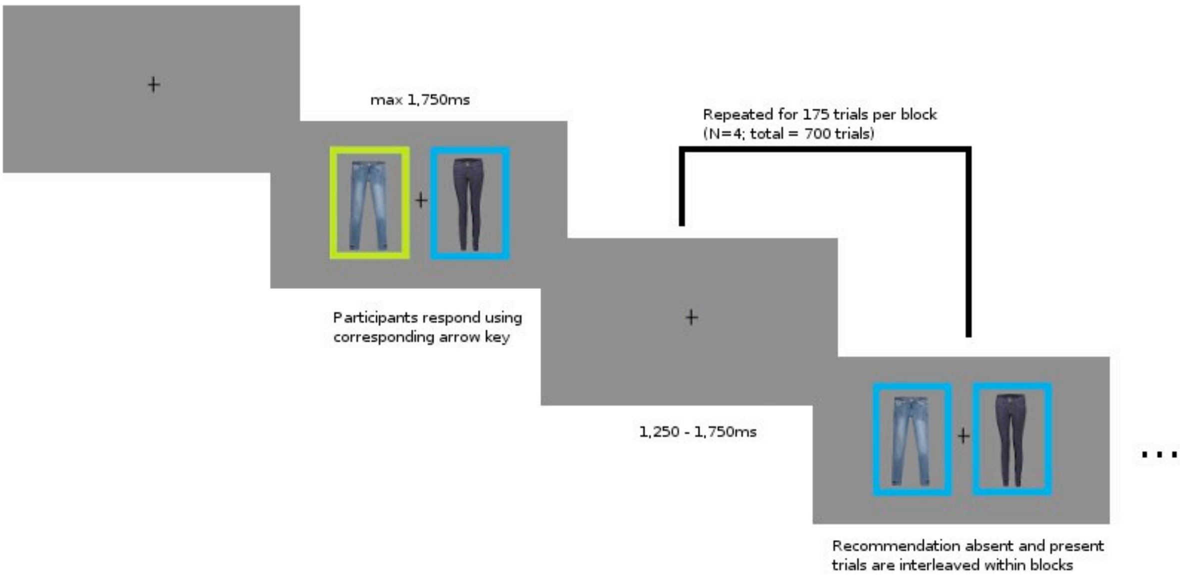

Figure 1.2: Task 2. Participants were asked to fixate on the centre of the screen. Pairs of items were presented for up to 1,750ms, during which participants indicated their preference using the corresponding arrow key. A response was immediately followed by stimulus offset. An ISI of between 1,250 and 1,750ms displayed just the fixation crossed before the onset of the following trial. Recommendation conditions were randomly interleaved throughout the task.

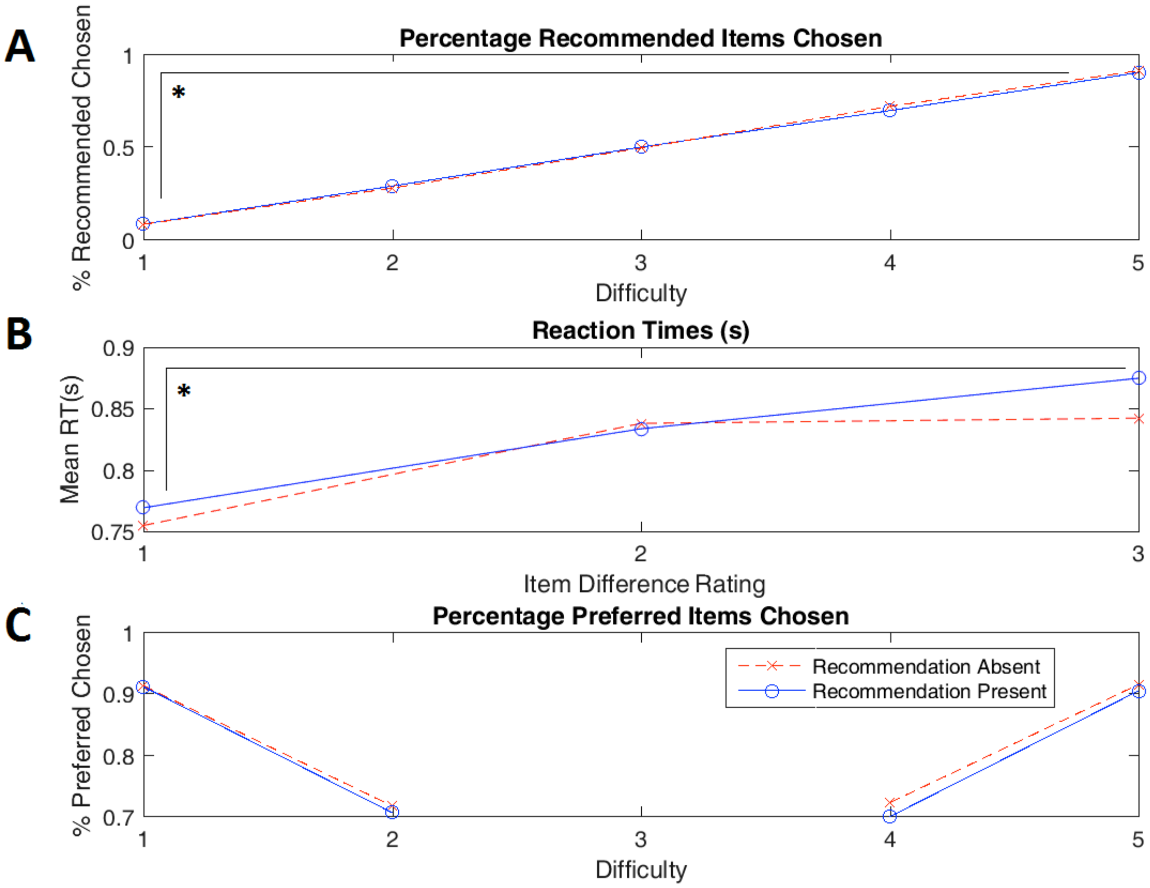

Figure 2.1: Behavioural Results (N=21). ***A.*** Percentage recommended items chosen as a function of difficulty and recommendation condition. Only main effect of difficulty ($p < 0.001$). ***B.*** Reaction times as a function of task difficulty, as captured in item difference rating, and recommendation condition. Only main effect of item difference ($p < 0.01$). ***C.*** Percentage preferred items chosen as a function of difficulty and recommendation condition – no values at difficulty = 3 since item difference = 0, i.e. neither item is preferred. Decisions are symmetrical around the indecision point.

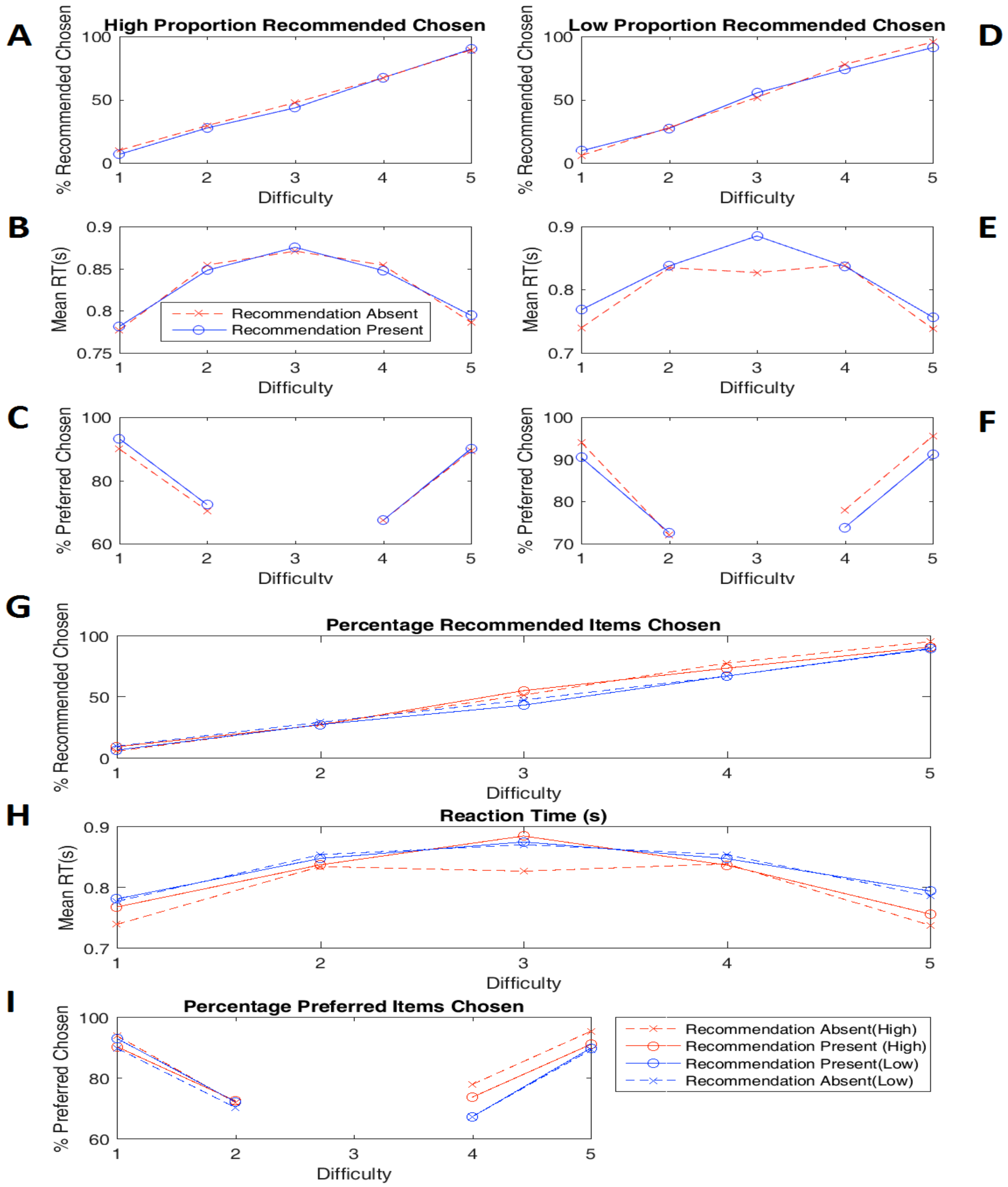

Figure 2.2: Behavioural results for two subsamples median split along rank order of overall percentage recommended items chosen. ***A. - C.*** Behavioural results for subsample of participants with relatively high proportion of recommended items chosen. ***D. - F.*** Behavioural results for subsample of participants with relatively low proportion of recommended items chosen. ***G. - I.*** Behavioural results of subsamples in comparison. ANOVA results for the factor group (high versus low proportion recommended chosen) did not reach significance.

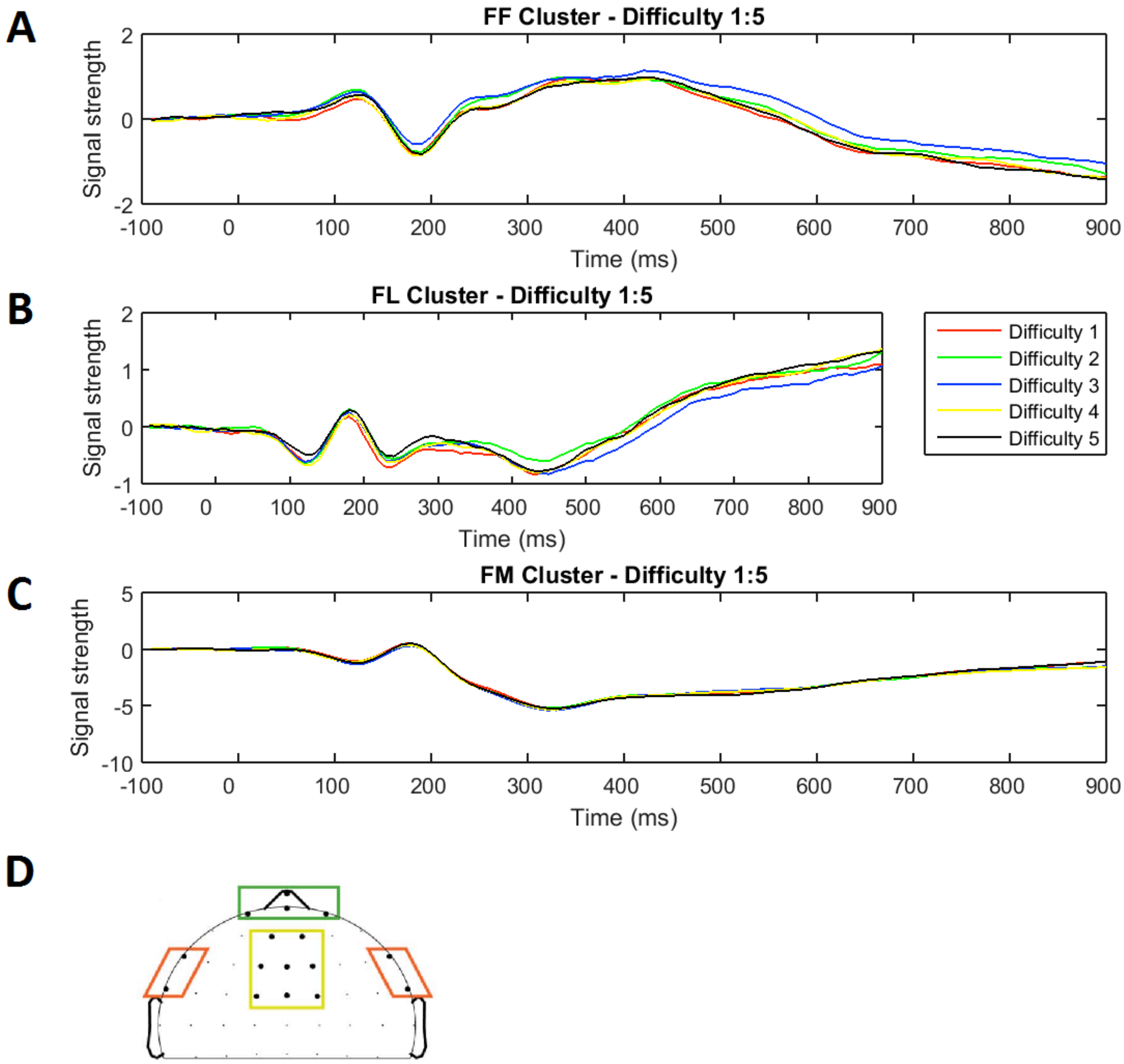

Figure 3.1: ERPs computed for difficulty levels across recommendation conditions. Neither FF-(***A***), FL-(***B.***), nor FM-cluster (***C.***) showed a statistically significant effect of item difficulty on signal strength. Recall however that equally eccentric difficulty levels reflect the same item difference rating, ***D.*** Cluster locations: FF = green; FL = orange; FM = yellow.

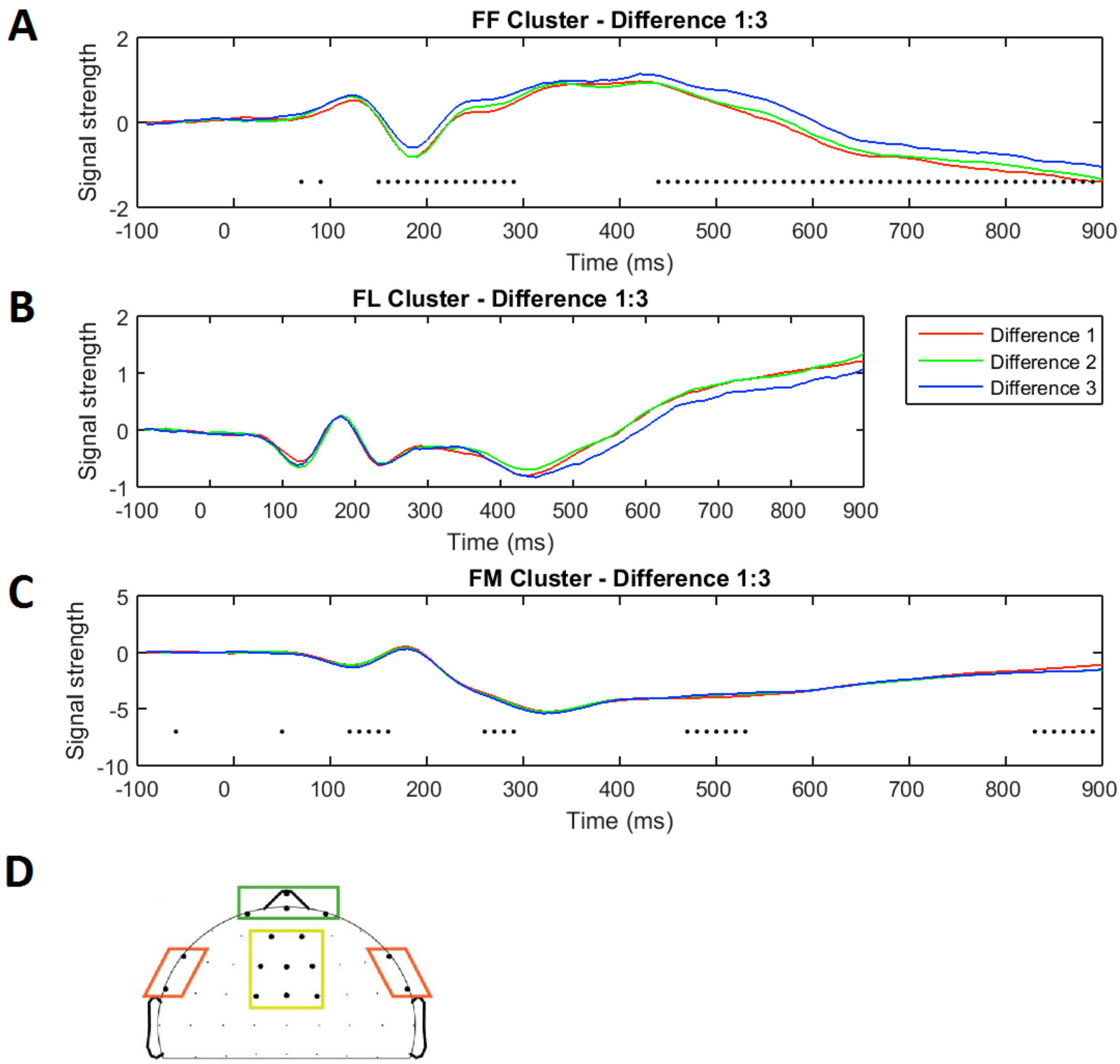

Figure 3.2: ERPs computed for difficulty levels across recommendation conditions. Figures contain 100ms (10 window) baseline, i.e. stimulus onset occurs at window 10. ***A.*** Two time windows with statistically significant differences in signal strength depending on item difference were identified in FF-cluster. An early cluster 150 – 290ms ($p < 0.05$; 220 – 250ms $p < 0.01$) and a continuous late cluster 440 – 900ms ($p < 0.05$; 510 – 810ms, $p < 0.02$) ***B.*** FL-cluster showed no time windows of statistically significant differences in signal strength dependent on item difference ***C.*** Four time windows with statistically significant differences in signal strength depending on item difference were identified in FM-cluster. 120 – 160ms ($p < 0.05$), 270-300ms ($p < 0.05$), 470 – 530ms ($p < 0.05$), 840 – 900ms ($p < 0.05$; 860 – 900ms, $p < 0.01$). ***D.*** Cluster locations: FF = green; FL = orange; FM = yellow.

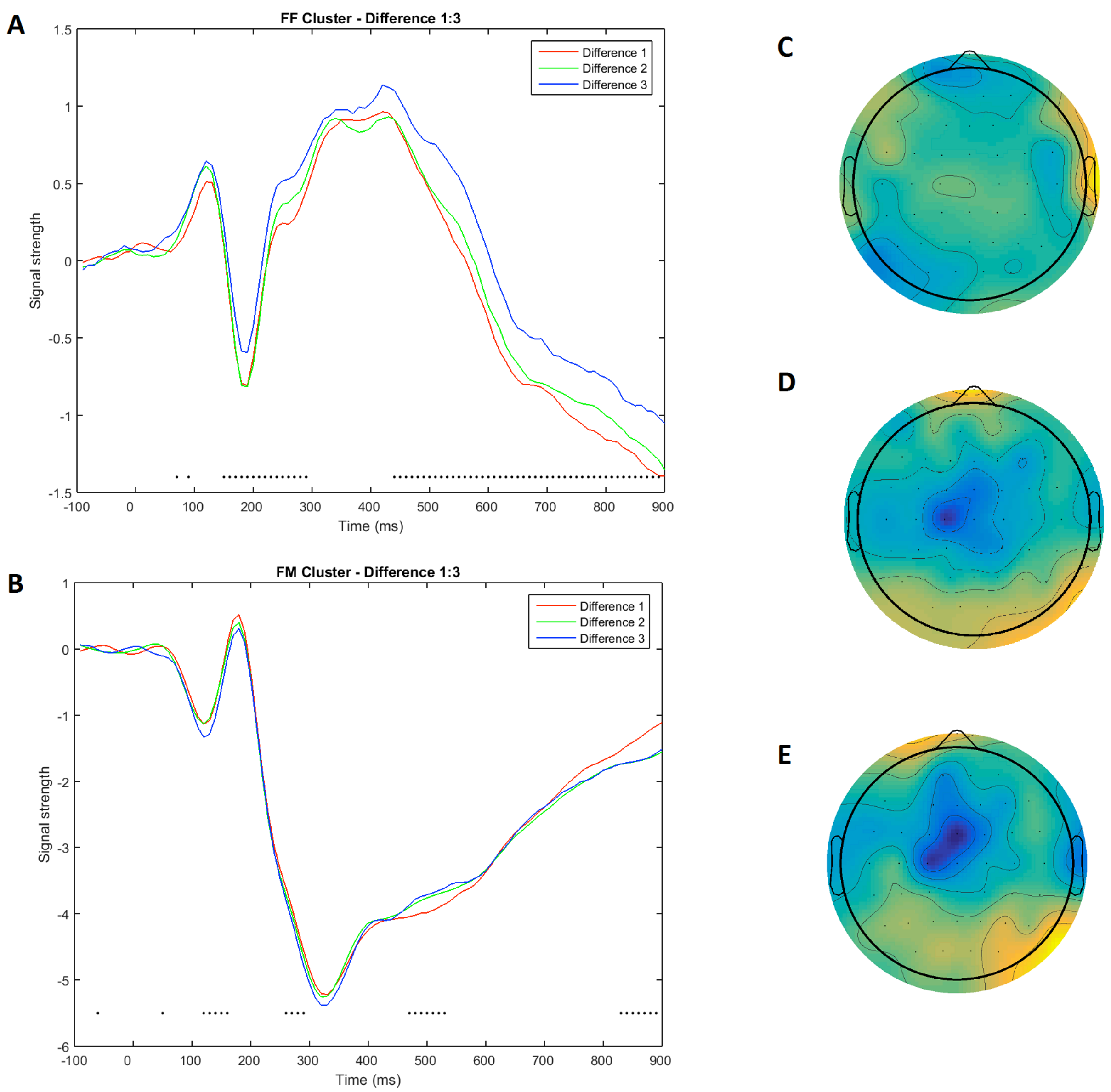

Figure 3.3: Statistically significant ERP components for task difficulty. ***A.*** ERPs for FF-cluster showed a significant intermediate component peaking at ~210ms. ***B.*** ERPs for FM-cluster showed a significant early component peaking at ~130ms. ***C.*** Scalp topography of EEG signal at 210ms showed a farfrontal negative peak, and frontomedial positive cluster ***D.*** Scalp topography of ERP difference at 210ms between highest and lowest item difference showed strong centrofrontal reduced activity, with increased activity related to lower difficulty ***E.*** Scalp topography of early component (~130ms), showed strong, distributed frontomedial negativity, consistent with the engagement of attention.

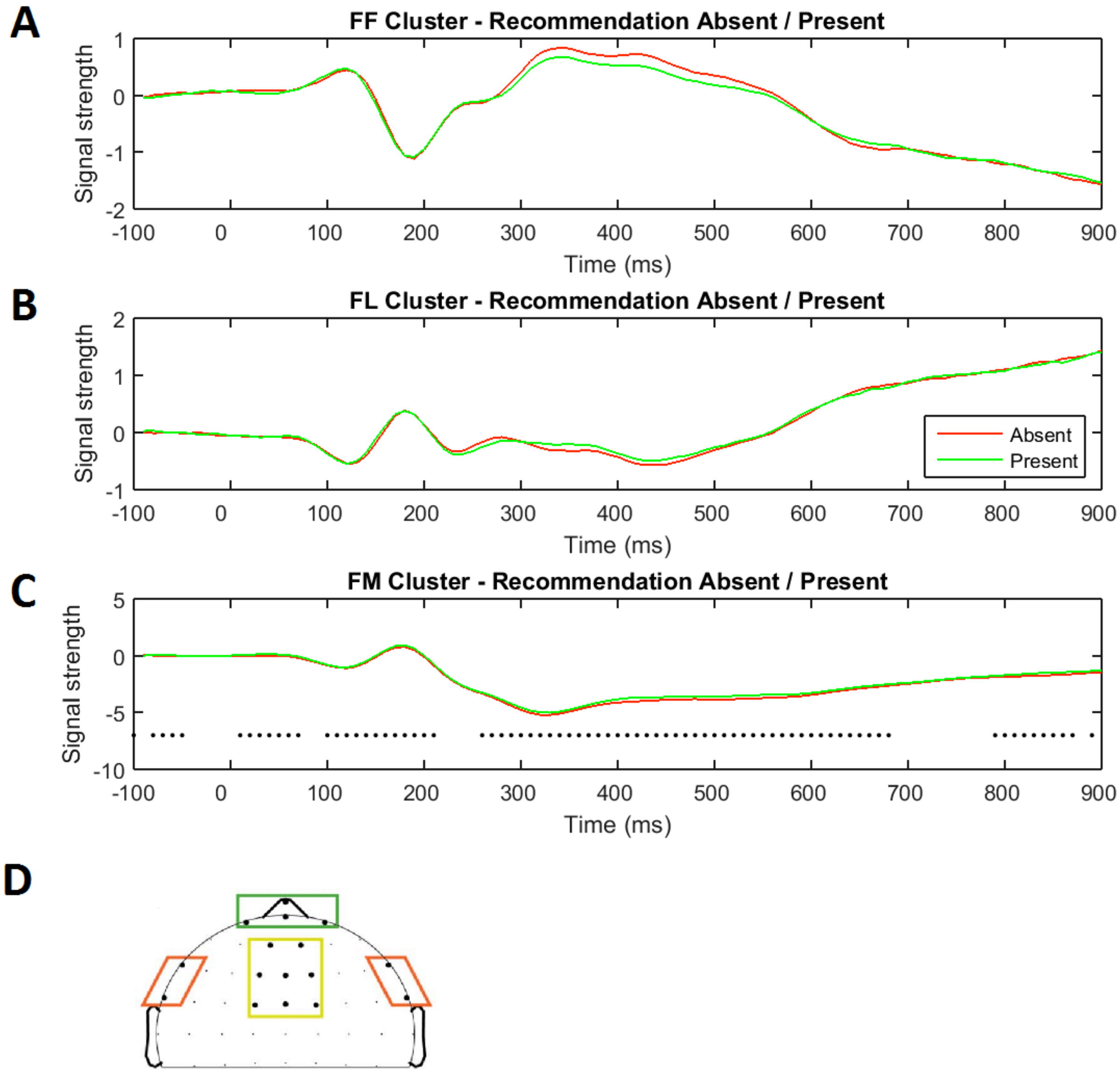

Figure 3.4: ERPs computed across item difficulties for recommendation absent and present levels. Figures contain 100ms (10 window) baseline, i.e. stimulus onset occurs at window 10. Recommendation condition did not show statistically significant differences in signal strength in either FF-(***A.***) or FL-cluster (***B.***). ***C.*** FM-cluster showed statistically significant differences in ERP signal strength in the majority of time windows. A very early effect immediately following stimulus onset (10 – 70ms, $p < 0.02$), and an effect at 100 – 210ms ($p < 0.05$) as well long effect (260ms – 680ms, $p < 0.02$; 270 – 610ms, $p < 0.001$) and a very late effect at 790 – 880ms ($p < 0.05$) ***D.*** Cluster locations: FF = green; FL = orange; FM = yellow.

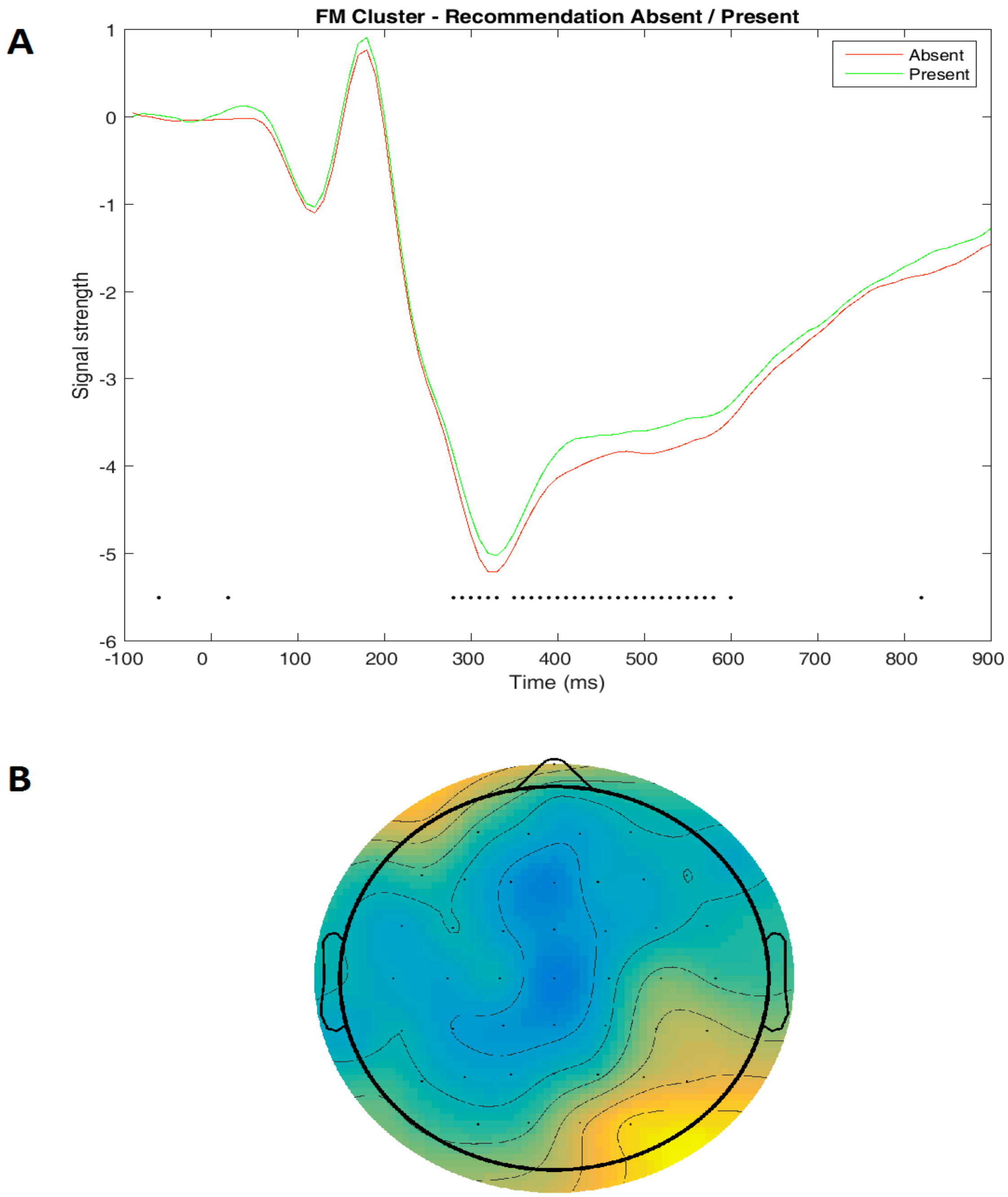

Figure 3.5: Significant EEG-results for recommendation present versus absent despite non-significant behavioural effect. ***A.*** ERPs by recommendation condition corrected for multiple comparisons using Holm's method. One statistically significant effect period from 280 – 580ms ($p < 0.05$; 380 – 580ms, $p < 0.01$; time window 45, i.e. 325 – 375ms, $p = 0.052$) ***B.*** Scalp topography of the ERP difference across recommendation conditions at peak signal difference (window 43, i.e. 305 – 355ms). Topography showed a negative central cluster extended latitudinally over a large central area of the scalp, suggestive of