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Emotion-Related Shifts in Prefrontal Connectivity and Driving Speed: An FMRI Study

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Statements and Declarations

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Conflict of interest disclosure

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethics approval statement

This study was conducted in accordance with the Declaration of Helsinki and was approved by the Ethics Committee of Tabriz University of Medical Sciences (IR.TBZMED.REC.1400.1053).

Patient consent statement

Informed consent was obtained from all individual participants included in the study.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Authors' contributions

MG constructed an idea or hypothesis for research and manuscript. SR and MN planned methodology to reach the conclusion. SR, HS organized and supervised the course of the project or the article and taking the responsibility. AL, HS and MG took responsibility in execution of the experiments, data management and reporting. SR took responsibility in doing the literature review. SR and MN took the responsibility in the construction of the whole or body of the manuscript. All authors read and accepted the final manuscript.

Abstract

Introduction: Understanding the potential links between cognitive functions, mood states, and driving behavior is challenging, with prior research often highlighting mood and emotions as possible contributors to risky driving patterns. This study explores how mood may influence driving behavior through changes in brain activity.

Methods: A within-subject crossover fMRI study initially enrolled 28 right-handed male drivers aged 20–30. Following fMRI quality-control procedures, 24 participants were included in the final neuroimaging analyses. Participants completed a virtual driving task within an fMRI-compatible simulator after undergoing positive, negative, and neutral mood induction. Brain activity was analyzed using SPM software.

Results: All mood conditions were successfully induced with comparable effectiveness and rapid resolution toward baseline. Functional connectivity analysis showed that similar prefrontal networks centered on the medial prefrontal cortex (mPFC) were engaged across mood states, with positive mood characterized by predominantly positive correlations and negative and neutral mood states showing more extensive negative connectivity patterns. Driving speed was significantly lower in positive mood (106.49 ± 58.02 km/h) compared to negative (132.85 ± 47.38 km/h) and neutral mood (140.97 ± 47.79 km/h, $P<0.001$). Whole-brain analyses revealed more extensive suprathreshold activation differences in the positive versus neutral condition, whereas the negative versus neutral comparison showed relatively more spatially restricted suprathreshold activation.

Conclusion: The study found that positive mood was associated with slower driving speeds and distinct patterns of prefrontal functional connectivity compared with negative and neutral mood states.

Keywords: automobile driving; mood; affect; fMRI; prefrontal cortex; functional connectivity

Introduction

Imagine you're behind the wheel, the open road ahead, and your favorite playlist is blasting through the speakers. Music is often known as a distraction for driving. But what if it is not only a form of distraction, but more importantly shaping driver's mood and that's what influences the

entire driving experience, by changing brain activity? Understanding the potential links between cognitive functions (e.g., attention, decision-making), mood states, and driving behavior is challenging, with prior research often highlighting mood and emotions as possible contributors to risky driving patterns.

The act of driving is a complex task that demands well-coordinated motor, perceptual, and cognitive skills [1]. Driver focus is essential for safety, and mood plays a role in influencing this focus [2]. Mood affects cognitive and behavioral processes in meaningful ways, which are supported by underlying neural activity, with high-risk driving behaviors linked to both perceived risk and attitudes toward risky driving.

The relationship between mood and driving behavior has been widely investigated, with substantial evidence indicating that affective states influence risk-taking through multiple cognitive and behavioral pathways. Previous studies have shown that both positive and negative mood states can modulate driving behavior by altering risk perception, risk attitude, and attentional processes. For instance, negative affect has been associated with increased risk perception and changes in driving behavior, although the magnitude and direction of these effects vary across experimental paradigms and contextual factors. Whereas, positive affect has been linked to both safer decision-making and, in some contexts, increased violations depending on situational demands [3,4]. Experimental and survey-based studies further demonstrate that mood states influence risky driving behavior through cognitive mediators such as risk perception and attitude, with negative affect often exerting stronger effects than positive affect [5]. In addition, specific emotional states such as anger, anxiety, sadness, and pleasure have been shown to differentially influence driving behavior, either by promoting aggressive driving or by modulating caution and attentional control [6,7].

Moreover, mood-related effects on driving are shaped by interacting psychological factors, including perceived stress, driving anger, and individual traits, which can mediate or moderate the relationship between affect and risky driving behaviors [8,9]. Studies have also shown that emotions can influence driving both directly and indirectly by altering attentional processes and task demands, highlighting the context-dependent nature of these effects [10]. Furthermore, external factors such as music-induced mood changes have been demonstrated to influence driving performance and behavior [11,12]. Finally, systematic reviews indicate that both positive

and negative affect are associated with risky and reckless driving behaviors, although the magnitude and direction of these effects vary across contexts and methodologies [13].

Most studies investigating how mood influences risky driving rely on self-reported data, which may be biased by factors such as social desirability [14,15]. There is a need for studies using objective measures to monitor driving behavior and investigate the neural impact of mood on driving, aiding understanding of the underlying mechanisms.

The interplay between driving and emotional brain networks is complex, involving various neural systems. Driving engages cognitive processes like attention, perception, and decision-making, which activate brain regions such as the prefrontal and parietal cortex, and basal ganglia [16]. Emotions also affect driving by altering activity in areas linked to affective processing, including the amygdala, insula, and prefrontal cortex [17]. Exploring these interactions can contribute to interventions that mitigate the emotional impact on driving, potentially enhancing road safety.

The correlation between cognitive functions, mood states, and driving behavior remains intricate and not fully clarified. This study aims to explore how mood influences driving speed, a key behavior indicator, and its neurological basis using fMRI data through a simulated driving task. Our hypotheses are: 1) Positive, negative, and neutral mood states influences driving behavior, particularly speed; 2) Positive, negative, and neutral mood induction activates emotional networks that interact with cognitive control regions; 3) Positive, negative, and neutral mood states are associated with concurrent changes in brain activity and driving speed.

Methods and Analysis

Study design

This study employed a within-subject crossover design to investigate the effects of induced mood states (positive, negative, and neutral) on driving behavior and its neural correlates. Twenty-eight participants were initially enrolled and completed the experimental protocol. Following preprocessing and quality-control assessment of the fMRI data, 24 participants were retained for the final neuroimaging analyses.

To optimize experimental control and reduce carryover effects, the experiment was conducted in two separate fMRI sessions for each participant. In each session, neutral mood was paired with one emotional condition (positive or negative), allowing within-session comparisons between neutral and emotional states. The order of sessions (positive-neutral vs. negative-neutral) was randomized and counterbalanced across participants to minimize order effects.

Participants

An a priori sample size calculation was performed using G*Power 3.1 [18], for the primary behavioral outcome (mean driving speed), assuming a repeated-measures ANOVA, an anticipated large effect size ($f = 0.50$), a statistical power of 80%, and a two-sided significance level of $\alpha = 0.05$. Because no previous fMRI studies employing an identical mood-induction driving paradigm were available to inform the expected effect size, a large anticipated effect was assumed for planning purposes in accordance with conventional power analysis recommendations [19]. Twenty-eight participants were therefore recruited. Following preprocessing and quality-control assessment of the fMRI data, four datasets did not satisfy the predefined quality-control criteria and were excluded prior to group-level statistical analyses. Consequently, all neuroimaging analyses were performed on a final sample of 24 participants.

Male drivers were recruited to minimize gender-related mood variations, thus ensuring that gender did not affect the results. Only male participants with at least two years of daily driving experience and no history of psychiatric or neurological disorders were included. Right-handedness was assessed using the Edinburgh Handedness Inventory [20]. Participants also completed the Manchester Driver Behaviour Questionnaire (MDBQ) [21] to characterize their habitual driving behaviour and confirm that all participants met the study's eligibility criteria regarding regular driving experience. MDBQ scores were not included as outcome variables in the present analyses. Participants with claustrophobia, pacemakers, or metal implants were excluded. Smoking and alcohol/caffeine intake were monitored before testing. Individuals with specialized musical training were also excluded to minimize variability in emotional responses to music-based stimuli. Written informed consent was obtained from all participants prior to study enrollment and participation.

Mood Induction

Prior to the main fMRI experiment, a separate pilot validation study involving 160 participants was conducted to identify and validate the most effective mood-induction stimuli. Individuals with neurological, psychiatric, severe sensory disorders, or specialized musical training were excluded from the pilot study. Candidate video clips were created by pairing music, selected through literature and expert consultation with professionals in psychology and music [22], with affectively matched images from the International Affective Picture System (IAPS) [23]. For each mood (positive, negative, and neutral), five two-minute candidate videos were created using unique music-image combinations.

Participants in the pilot study, blinded to mood content, viewed these clips and rated their mood at baseline, immediately after, and during recovery, using a valence self-report measure adapted from Ribeiro et al. [24], which in turn was based on the emotional adjective framework proposed by Plutchik [25]. Rather than a standardized psychometric questionnaire, this measure consisted of nine emotion adjectives, including three positive (happy, excited, euphoric), three negative (sad, melancholic, distressed), and three neutral (neutral, indifferent, unresponsive) descriptors. Participants selected the adjective that best represented their current emotional state. For each mood category, the three adjectives represented increasing levels of emotional intensity and were assigned ordinal scores of 1, 2, and 3, whereas adjectives from the remaining categories were scored as 0. Consequently, scores within each mood category ranged from 0 to 3. Repeated-measures ANOVA was used to evaluate temporal changes in mood ratings and to identify the videos that most effectively induced the intended mood and demonstrated rapid recovery toward baseline.

Based on the pilot validation results, the most effective mood-induction videos were selected for the main fMRI experiment. Specifically, two positive, two negative, and four neutral videos were retained. Main study participants were randomly assigned to undergo either the positive–neutral or negative–neutral session first in a randomized, counterbalanced manner.

Because the effectiveness and temporal characteristics of these stimuli had already been established during the pilot validation study, repeated quantitative mood assessments were not incorporated into the main fMRI experiment in order to minimize interruption of the scanning protocol and maintain a consistent experimental design.

Driving Simulator

An fMRI-compatible simulator, designed after a prior study was used [26]. The simulator included a steering wheel, accelerator, brake pedal, and a visual display. Non-magnetic materials ensured MRI compatibility, and the electronic circuits were housed outside the MRI room.

Driving Task

Each participant completed two fMRI sessions, each consisting of four experimental blocks. In one session, neutral mood was paired with positive mood induction, while in the other session, neutral mood was paired with negative mood induction. Thus, all participants experienced all three mood conditions across the two sessions. The order of sessions and blocks was randomized and counterbalanced across participants to control for potential order effects. Each block consisted of approximately 3 minutes of mood induction followed immediately by a 2-minute simulated driving task. This design was chosen to allow sufficient time for mood induction while maintaining an overall scanning duration acceptable for participants.

The simulated driving task consisted of a simplified highway environment with multiple lanes, in which participants were able to perform lane changes but were not exposed to complex traffic scenarios such as intersections or dense traffic. No explicit speed limits were imposed within the simulation, and traffic density was kept minimal to avoid external constraints on driving behavior. Participants were instructed to drive as they normally would in a real-world highway setting, without being given specific goals regarding speed or time. This approach was chosen to capture naturalistic driving behavior under different mood conditions.

During each block, driving speed was continuously recorded as a primary behavioral outcome. For each participant , the continuously sampled speed values were averaged across the entire two-minute driving block to obtain a single mean driving-speed value for each block. Because the neutral condition was performed once in each of the two experimental sessions, the mean driving speed across the two neutral blocks was subsequently averaged to obtain a single participant-level value representing the neutral condition. These participant-level mean values for the positive, negative, and neutral conditions were used in the repeated-measures statistical analyses. The schematic design of the fMRI conductance is shown in figure 1.

FMRI acquisition

Imaging was performed at the National Brain Mapping Laboratory in Tehran, Iran, using a 3 Tesla MRI scanner (Siemens, Germany). Structural images were acquired using a T1-weighted 3D MPRAGE sequence (TR = 1900 ms, TE = 2.52 ms, flip angle = 9°, field of view = 256 × 256 mm^2, slice thickness = 1 mm, no gap).

Functional images were obtained using a T2-weighted echo-planar imaging (EPI) sequence sensitive to blood oxygen level–dependent (BOLD) contrast (TR = 2000 ms, TE = 30 ms, flip angle = 90°, field of view = 220 × 220 mm^2, matrix size = 64 × 64, yielding an effective voxel size of approximately 3.4 × 3.4 × 3.5 mm^3, slice thickness = 3.5 mm, no gap, and 32 axial slices covering the whole brain. Approximately 600 EPI volumes were acquired during each imaging session (approximately 1,200 volumes per participant across both sessions). Custom head molds minimized head motion during imaging [27].

Statistical methods

Functional imaging data were preprocessed using SPM12 (Wellcome Trust Centre for Neuroimaging, London, UK) implemented in MATLAB. Preprocessing steps included slice timing correction, realignment for motion correction, co-registration of functional and structural images, normalization to the standard MNI space, and spatial smoothing using a Gaussian kernel of 6 mm full width at half maximum (FWHM).

A general linear model was constructed to model the BOLD response during the driving periods following each mood-induction condition. Condition-specific regressors corresponding to the positive-, negative-, and neutral-mood driving blocks were entered into the first-level model, and voxel-wise contrasts were subsequently computed to compare positive versus neutral and negative versus neutral driving conditions. For the seed-based functional connectivity analysis, connectivity was evaluated separately for the positive-, negative-, and neutral-mood driving conditions. The mean BOLD time series was extracted from the medial prefrontal cortex (mPFC) seed region and correlated with the time series of every voxel in the brain for each condition. Individual participant correlation maps were transformed using Fisher's r-to-z transformation and subsequently entered into separate group-level one-sample t-tests to generate condition-specific connectivity maps. For the neutral condition, connectivity estimates from the two neutral driving

runs were averaged to obtain a single participant-level connectivity map before group-level analysis. Whole-brain analyses used $p<0.001$ thresholds. Additionally, a seed-based connectivity analysis used the medial prefrontal cortex (mPFC) as an ROI, with group-level statistics conducted on Z-transformed correlation maps.

The mPFC was selected as the region of interest due to its well-established role in both emotional regulation and cognitive control processes, including decision-making and risk evaluation, which are critical for driving behavior [28-30]. Given its involvement in integrating affective and executive functions, the mPFC provides a suitable neural substrate for examining the interaction between mood states and driving performance.

Additionally, in the pilot study, repeated-measures ANOVA was used to evaluate temporal changes in mood ratings and to identify the most effective candidate stimuli within each mood category. In the main experiment, behavioral differences in driving speed across mood conditions (positive, negative, and neutral) were analyzed using a repeated-measures ANOVA in the final sample of 24 participants. Effect size was reported as partial eta squared (ηp^2). Post hoc pairwise comparisons were adjusted using the Bonferroni correction. Statistical significance was set at $p < 0.05$ and IBM SPSS Statistics 27 was used for the analysis.

To complement the hypothesis-driven seed-based connectivity analysis, the same first-level GLM was additionally used to perform an exploratory whole-brain voxel-wise analysis of the driving periods. Thus, both analyses were based on the same condition-specific driving regressors; however, whereas the seed-based analysis quantified functional connectivity relative to the mPFC, the whole-brain analysis examined voxel-wise activation differences across the entire brain. Positive-versus-neutral and negative-versus-neutral contrasts were generated from the same first-level model. This exploratory analysis was intended to provide qualitative visualization of distributed activation patterns rather than formal statistical comparison of the spatial extent of activation between contrasts. Resulting statistical maps were expressed as F-statistics, reflecting the magnitude of condition-related variance across voxels [31].

These maps were used to visualize the spatial extent and distribution of condition-specific neural activity patterns at the whole-brain level. Group-level statistical maps were generated and displayed in standard anatomical space using orthogonal views (sagittal, coronal, axial).

Statistical maps were thresholded at a voxel-wise level of $p < 0.001$ (uncorrected), corresponding to $F \geq 3.10$. Given the exploratory nature of this analysis and the aim to visualize distributed activation patterns, no additional correction for multiple comparisons was applied at the cluster or voxel level.

The distribution of participant-level mean driving speeds was assessed prior to analysis, for normality using graphical inspection and the Shapiro–Wilk test. Potential outliers were evaluated using boxplots and standardized residuals. No observations were excluded on the basis of driving-speed values alone.

Results

Mood induction status

In the pilot validation study (N = 160), candidate mood-induction videos were evaluated using repeated mood assessments obtained at baseline, immediately after video presentation, and during the recovery period. Repeated-measures ANOVA demonstrated significant temporal changes in mood ratings for the neutral condition (Greenhouse–Geisser-corrected $F(1.853, 450.392) = 4.355$, $P = 0.016$) and the negative condition ($F(1.697, 198.593) = 15.246$, $P < 0.001$), consistent with successful mood induction followed by a return toward baseline during recovery. The positive condition demonstrated a similar temporal pattern, with the overall effect of time approaching toward statistical significance ($F(1.895, 229.307) = 3.015$, $P = 0.054$). No significant Time × Movie interaction was observed for any mood category, indicating consistent responses across the candidate videos within each mood category (figure 2). Based on these findings, the most effective videos were selected for use in the main fMRI experiment.

Seed-based functional connectivity patterns across mood conditions

In driving with positive mood, activity in bilateral mPFC as seed region correlated positively with bilateral anterior PFC (aPFC) and bilateral dorsal anterior cingulate cortex (ACC), bilateral orbitofrontal cortex (OFC) and right dorsal posterior cingulate cortex (PCC). Furthermore, they were negatively correlated with right visuomotor cortex, left pars orbitalis, bilateral OFC and frontal eye fields (FEF) (Figure 3.A).

In driving with negative mood, a generally similar, yet more extensive network was revealed on a q(FDR) corrected map. More extensive regions of bilateral OFC, bilateral antPFC and bilateral dorsal ACC were correlated with bilateral mPFC seed, in addition to bilateral pars orbitalis. Also more extensive regions of bilateral FEF and bilateral OFC were negatively correlated in addition to left dorsolateral PFC (dlPFC) and left pars orbitalis and some regions of left aPFC (Figure 3.B).

In driving with neutral mood, the general pattern of q(FDR) correlated map sharing general similarities, although it included only more confined regions of bilateral aPFC and bilateral OFC in positive correlation; and yet more extensive regions of bilateral pars orbitalis and bilateral aPFC, along with bilateral FEF, bilateral OFC and bilateral dlPFC in negative correlation (Figure 3.C). (red indicates positive correlation, blue indicates negative correlation).

Group differences in driving speed

A repeated-measures ANOVA demonstrated a significant effect of mood condition on driving speed ($F(2,46) = 21.30$, $P < 0.001$, $\eta_p^2 = 0.48$). Bonferroni-adjusted pairwise comparisons showed that driving speed was significantly lower during positive mood (106.49 ± 58.02 km/h) than during negative mood (132.85 ± 47.38 km/h, adjusted $P = 0.004$) and neutral mood (140.97 ± 47.79 km/h, adjusted $P < 0.001$). The difference between negative and neutral mood was not statistically significant (adjusted $P = 0.16$).

Whole-brain activation patterns across mood conditions

To complement the seed-based connectivity findings, whole-brain voxel-wise analyses were performed to examine distributed activation patterns associated with different mood conditions during driving.

The comparison between positive and neutral mood revealed more extensive suprathreshold activation of significant activation differences across both hemispheres, involving extensive regions of the frontal, parietal, and temporal cortices. The corresponding F-statistic values ranged from 3.10 to 10.36, indicating robust and spatially distributed neural modulation associated with positive mood (Figure 4A).

In contrast, the negative versus neutral comparison demonstrated a more spatially restricted suprathreshold activation difference, with significant clusters primarily observed in prefrontal and insular regions, and to a lesser extent in posterior cortical areas. The F-statistic values for this contrast ranged from 3.10 to 5.34, reflecting a more focal pattern of neural modulation (Figure 4B).

Discussion

This study used functional magnetic resonance imaging (fMRI) and functional connectivity analysis to look into the brain correlates of driving in different mood states (positive, negative, and neutral). We can learn more about the consistency and generalizability of the findings by contrasting the findings of this study with those of earlier research. Numerous studies have investigated how mood affects brain activity while performing various cognitive tasks, offering an important background for understanding our findings.

Our investigation discovered diverse patterns of brain activity and functional connectivity linked to various mood states while driving, which is consistent with prior research on mood induction. Across a range of cognitive activities, the activation of prefrontal areas, such as the medial prefrontal cortex (mPFC), anterior prefrontal cortex (aPFC), and orbitofrontal cortex (OFC), has consistently been linked to the regulation of positive mood state [32,33]. Also corroborating our findings of positive connections between bilateral aPFC and bilateral dorsal anterior cingulate cortex (ACC), prior research has demonstrated that inducing a positive mood is linked to enhanced connectivity between the mPFC and other prefrontal regions [33,34]. Positive mood state, on the other hand, have been linked to decreased activity in areas such the OFC, aPFC, and dorsal ACC, demonstrating heightened emotional processing and regulation mechanisms [35-37].

Similar results were seen in our study, in which the connectivity pattern during the negative mood condition involved the mPFC together with bilateral OFC, bilateral aPFC, and bilateral dorsal ACC. These observations are consistent with previous reports describing the involvement of prefrontal and limbic regions across different mood states during cognitive tasks. Together, these findings suggest that mood states are associated with distinct patterns of neuronal activity

and functional connectivity within brain regions involved in emotion regulation, attentional processing, and cognitive control [33,37,38].

It is important to keep in mind that different methodologies, such as the selection of mood induction techniques, stimuli, and sample characteristics, may have an impact on how different research interpret their results. For example, utilizing various mood induction techniques, such as music, imagery, or movie clips, may trigger a range of emotional reactions [32,34,39].

In our study, the highest mean driving speed was observed during the neutral mood condition, whereas the lowest mean speed occurred during the positive mood condition. Qualitatively, the functional connectivity maps demonstrated distinct connectivity patterns across the three mood conditions, with the neutral condition exhibiting the broadest pattern of negative functional connectivity and the positive condition showing comparatively less extensive negative connectivity. Although these neural and behavioral findings occurred in parallel, the present study did not directly evaluate brain–behavior relationships at the individual level. Therefore, these connectivity patterns should not be interpreted as mechanistic explanations for the observed differences in driving speed. Rather, they suggest that different mood states are accompanied by distinct patterns of prefrontal functional organization during driving.

Interestingly, although the neutral condition demonstrated the highest mean driving speed, the difference between the neutral and negative conditions was not statistically significant. Accordingly, the present findings should not be interpreted as indicating that neutral mood promotes riskier driving than negative mood. Instead, under the present experimental conditions, both neutral and negative mood states were associated with higher driving speeds than the positive mood condition. Future studies incorporating formal brain–behavior correlation analyses will be required to determine whether individual differences in functional connectivity are directly related to driving behavior.

However, given the absence of external constraints such as speed limits or traffic density, these findings should be understood as reflecting relative behavioral modulation across mood states rather than absolute real-world risk.

The whole-brain voxel-wise analysis provided complementary insight into how mood states influence distributed neural activity during driving. The more extensive activation patterns

observed in the positive versus neutral comparison appeared to involve more extensive suprathreshold activation, potentially reflecting increased integration across cognitive and affective systems.

In contrast, the more localized activation differences in the negative condition showed a more spatially restricted pattern under the applied exploratory threshold, particularly within prefrontal and insular regions implicated in cognitive control and emotional processing. Together with the functional connectivity findings, these results highlight that mood-related effects on driving are reflected not only in network interactions but also in the spatial distribution of brain activity.

To increase road safety and lower the number of auto accidents, it is essential to comprehend how emotional states affect driving behavior. It is possible to create interventions and methods to encourage safer driving habits and reduce accident risk by recognizing the brain mechanisms behind mood-induced driving behavior. For instance, public awareness efforts emphasizing the value of having a stable emotional state and enticing drivers to be more watchful of their actions while driving. Similar to this, therapies for negative mood state could encourage ways for regulating emotions and adaptive coping to lessen worry and excessive caution when driving. To support drivers in keeping their minds calm and focused while driving, these therapies may include stress management approaches, cognitive reappraisal tactics, and mindfulness-based practices.

This study represents one of the first investigations to characterize mood-related changes in both functional connectivity and driving behavior during simulated driving using fMRI. Nevertheless, several limitations should be acknowledged. First, the study was conducted using a simulated driving paradigm and a relatively small sample, which may limit the generalizability of the findings to real-world driving conditions. Future studies employing larger and more diverse cohorts, as well as more ecologically valid driving environments, are warranted. Second, individual differences in emotional regulation strategies and habitual driving behavior may have influenced the observed responses and should be considered in future investigations. Furthermore, the experimental design required relatively long combined mood-induction and driving blocks to allow sufficient development of the targeted emotional state before behavioral assessment. Although this approach improved ecological validity for studying sustained mood during driving, it reduced the statistical efficiency of the block design and may have increased

susceptibility to low-frequency BOLD signal fluctuations. This design therefore represents a necessary compromise between effective mood induction and conventional fMRI optimization.

Although the mood-induction stimuli were rigorously validated in a separate pilot study prior to the imaging experiment, repeated quantitative mood assessments were not performed during the main fMRI protocol. Consequently, variations in mood intensity during scanning could not be directly evaluated. In addition, the present study did not include formal brain–behavior correlation analyses linking individual functional connectivity measures with driving-speed outcomes. Therefore, the observed neural and behavioral findings should be interpreted as parallel mood-related effects rather than evidence of a direct mechanistic relationship. Finally, the whole-brain voxel-wise analyses were performed using an uncorrected statistical threshold and were intended as exploratory visualization of activation patterns rather than formal statistical comparisons between mood conditions. Because direct voxel-wise contrasts and quantitative cluster-level statistics were not performed, differences in the spatial extent of activation should be interpreted cautiously. Future studies incorporating corrected voxel-wise inference, quantitative cluster-level reporting, and formal brain–behavior association analyses will be important to validate and extend these findings.

Conclusion

The study demonstrated that mood significantly influences driving behavior and neural connectivity during simulated driving tasks. Participants exhibited the lowest driving speeds in positive mood conditions, indicating a more cautious approach. Conversely, neutral mood conditions were associated with the highest speeds, suggesting increased risk-taking. Additionally, fMRI results showed enhanced connectivity in the medial prefrontal cortex during positive mood state. These findings suggest that emotional states can impact driving performance and decision-making processes, emphasizing the importance of considering mood in discussions of road safety.

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Figures

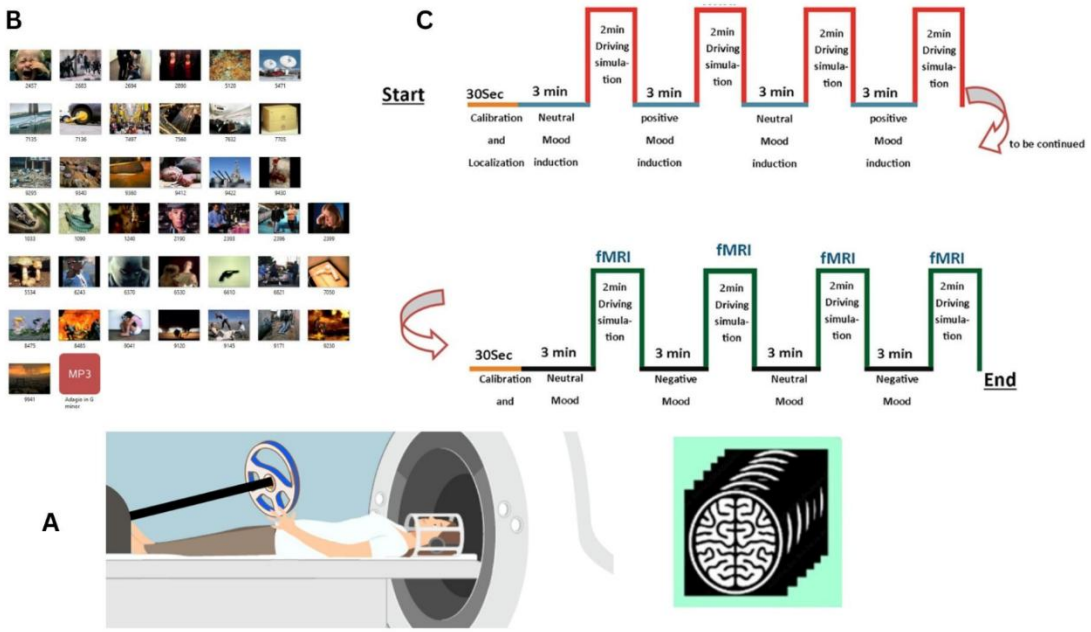


Figure 1. Design and setup of the study. A) Schematic design of the simulator driving with the simulator; B) A sample of videos that were prepared for mood induction by combining IAPS photos and music pieces; C) Timeline of blocks and sessions of data acquisition.

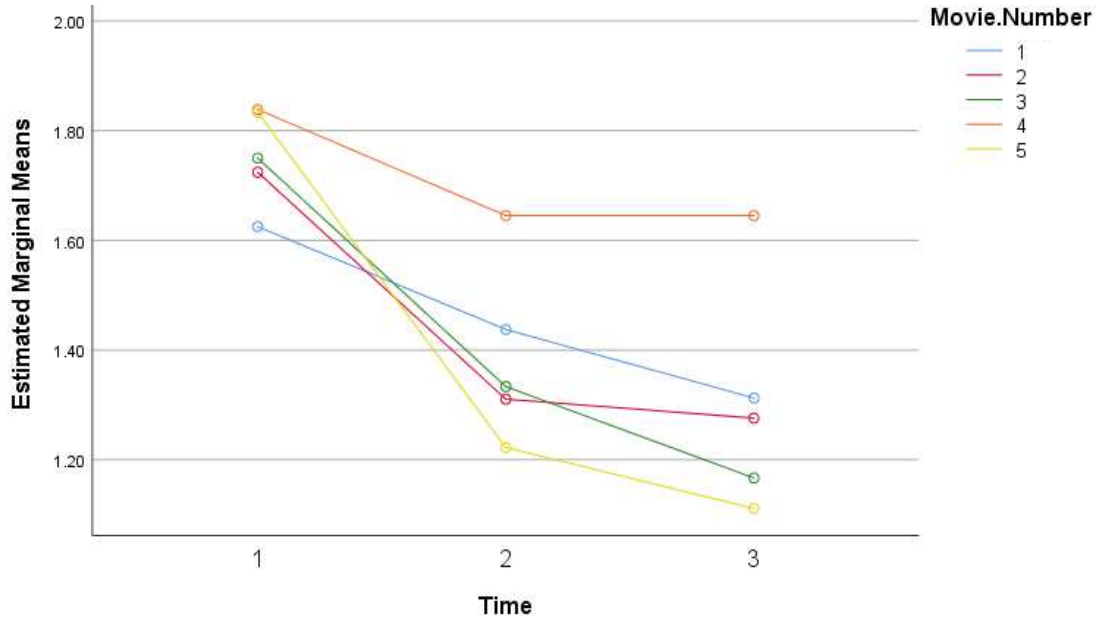


Figure 2.A. Mood induction status immediately, 2 minutes, and 4 minutes after watching the movies for negative mood induction.

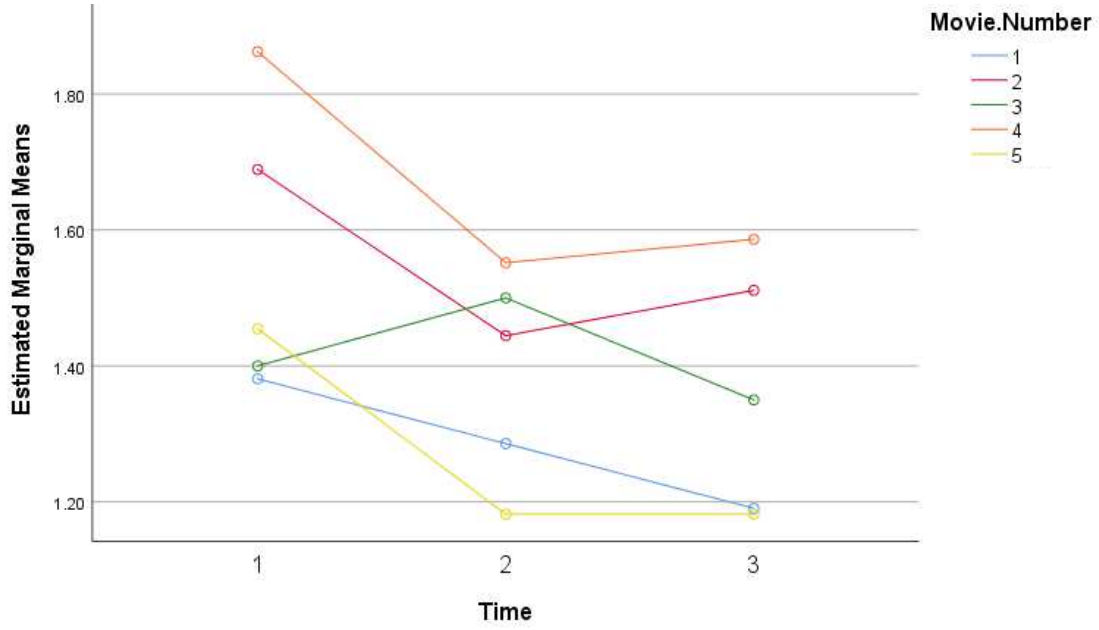


Figure 2.B. Mood induction status immediately, 2 minutes, and 4 minutes after watching the movies for positive mood induction.

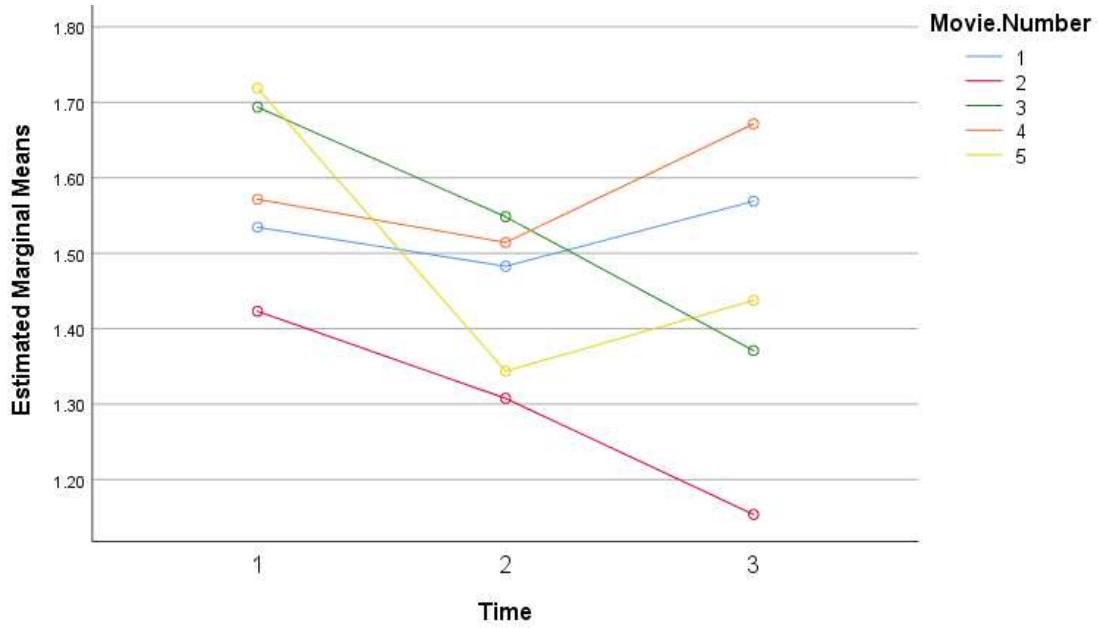


Figure 2.C. Mood induction status immediately, 2 minutes, and 4 minutes after watching the movies for neutral mood induction.

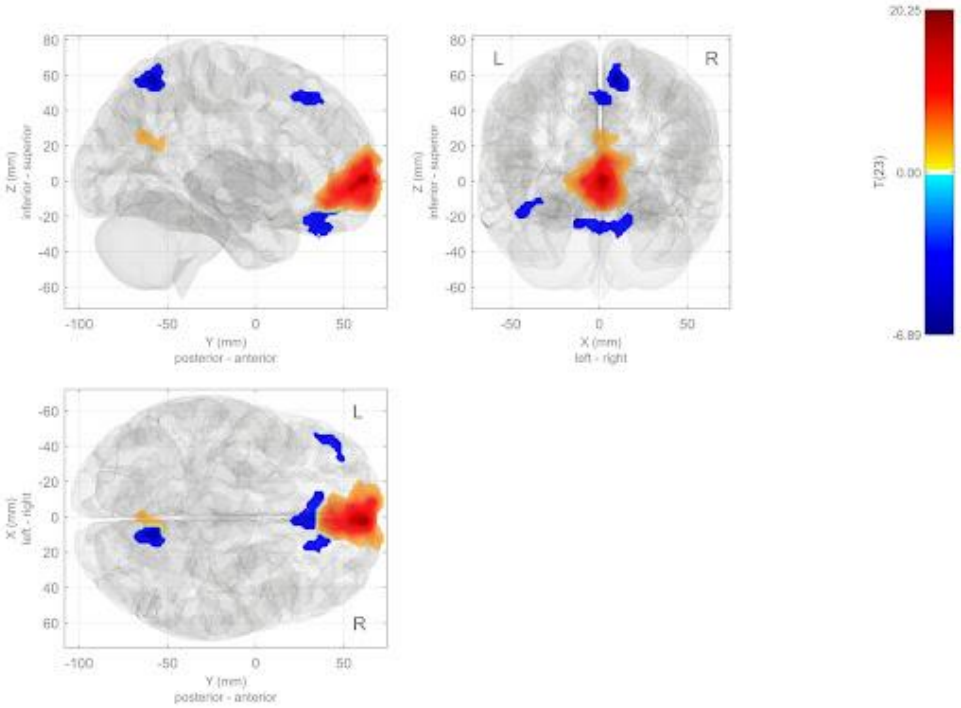


Figure 3.A. Functional connectivity (Fc) maps for the medial prefrontal cortex (mPFC) as seed in positive mood. The displayed T(23) values represent the group-level t-statistics obtained from the final sample of 24 participants (degrees of freedom = 23).

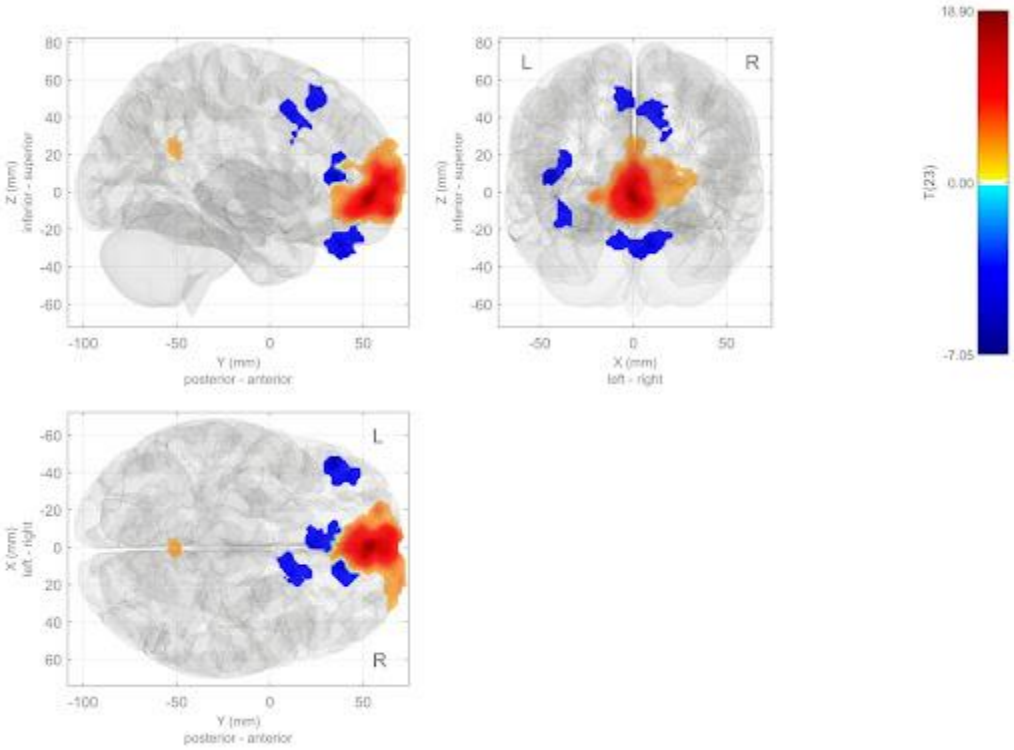


Figure 3.B. Functional connectivity (Fc) maps for the medial prefrontal cortex (mPFC) as seed in negative mood. The displayed T(23) values represent the group-level t-statistics obtained from the final sample of 24 participants (degrees of freedom = 23).

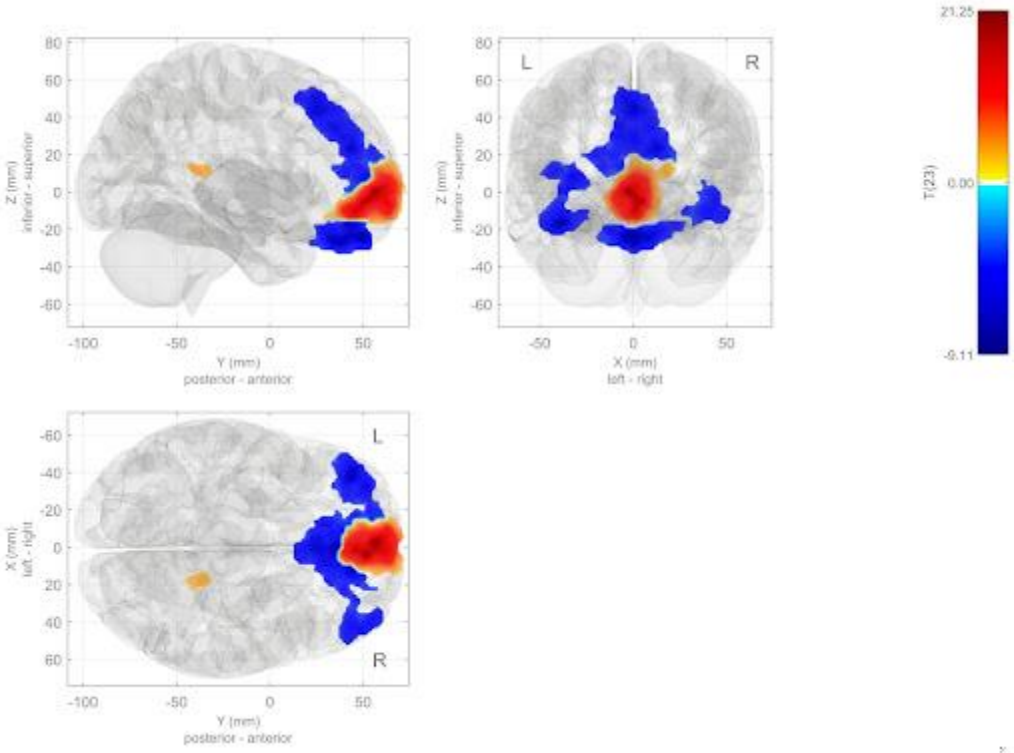


Figure 3.C. Functional connectivity (Fc) maps for the medial prefrontal cortex (mPFC) as seed in neutral mood. The displayed T(23) values represent the group-level t-statistics obtained from the final sample of 24 participants (degrees of freedom = 23).

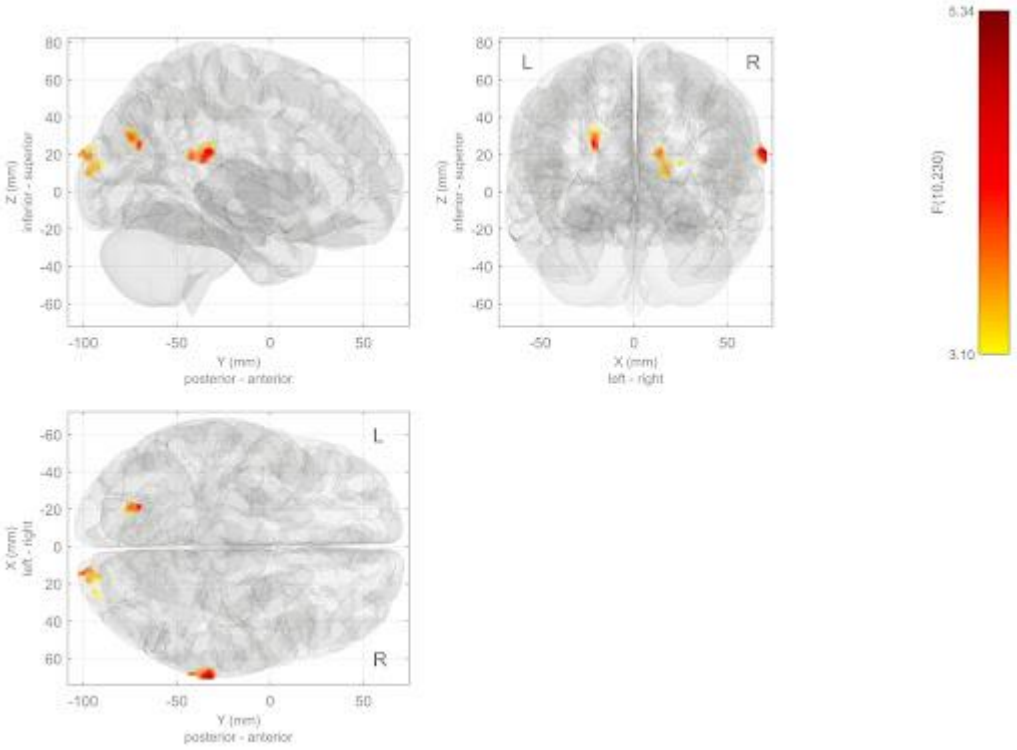


Figure 4.A. Brain regions discriminating positive vs. neutral mood during simulated driving. The displayed F(10,230) values represent the model F-statistics generated by the repeated-measures general linear model implemented in SPM. The reported degrees of freedom correspond to the statistical model and should not be interpreted as the number of study participants.

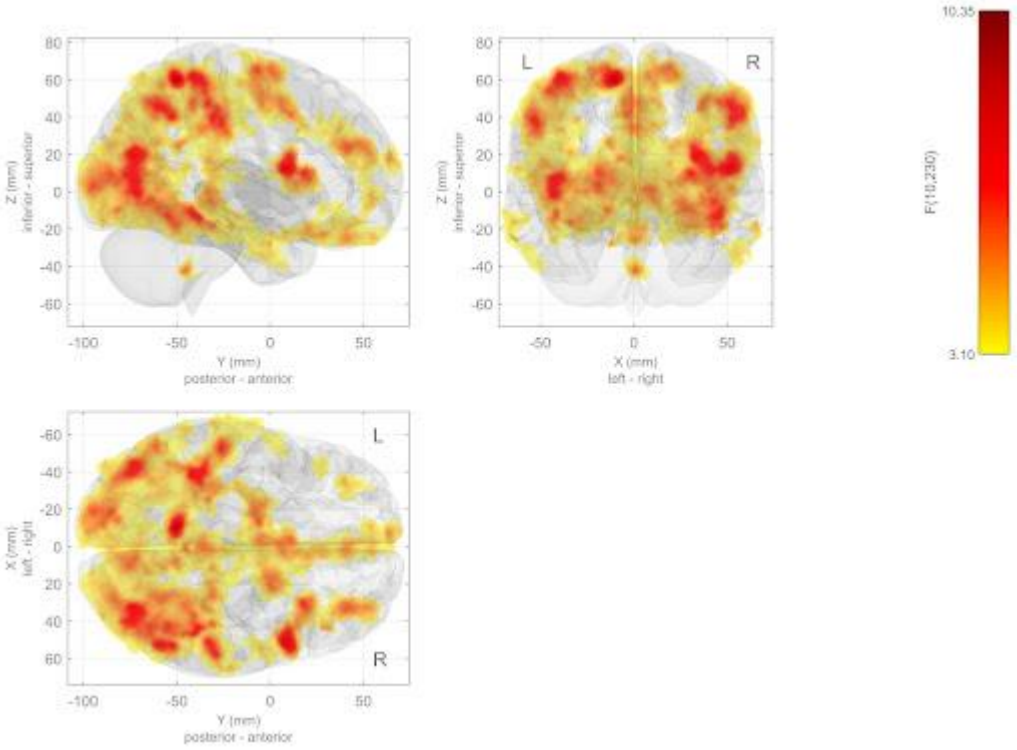


Figure 4.B. Brain regions discriminating negative vs. neutral mood during simulated driving. The displayed F(10,230) values represent the model F-statistics generated by the repeated-measures general linear model implemented in SPM. The reported degrees of freedom correspond to the statistical model and should not be interpreted as the number of study participants.