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Original Article

Unveiling the neural roadmap: Using fMRI to examine the impacts of positive, negative, and neutral mood induction on driving behavior – A protocol

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Abstract

Introduction: The potential association between cognitive functions, mood states, and their effect on driving behavior is complex and has been previously studied in most cases suggesting mood and emotion as possible factors in high-risk driving behaviors. However, their outcome measures are subjective and prone to biases. In this study, we add objective physiological data to explore the physiological and behavioral background of the relevance of mood in high risk driving by functional magnetic resonance imaging (fMRI).

Methods: In this study, 28 male right-handed drivers, aged between 20 to 30 years will be randomly selected from records of drivers in the central traffic department and included in the study. Each participant will drive virtually in an fMRI-compatible driving simulator, after positive, negative, and neutral mood induction, and fMRI will be performed to explore driving-related brain activity alterations and the impact of mood state on these effects. All data analyses will be performed using MATLAB (MathWorks, Natick, MA) and the Statistical Parametric Mapping (SPM12) software package.

Results: This protocol study introduced a novel protocol to induce positive, negative, and neutral moods and study the impact of mood on driving.

Conclusion: Comparing brain activity during driving after positive, negative, and neutral mood induction, this study will help to understand effects of different mood states on driving behavior. Furthermore, comparing the fMRI images of driving under different mood states will clarify the physiological foundation of the impact of mood states on driving behavior. The results of this study will help to introduce physiologically informed preventive or reinforcement strategies to control mood states while driving, and therefore might help to reduce a significant proportion of preventable car accidents.

Introduction

Traffic accidents are a relevant cause of global social and economic problems. About 1.3 million people die each year due to traffic accidents worldwide, and car accidents are a leading cause of death for children and young people aged from 5 to 29 years. An estimated number of 20 to 50 million people suffer non-fatal but disabling injuries caused by car accidents, which impose enormous costs on individuals, their families, and society as a whole, equating to 3% of a country's annual gross domestic product.[1] This highlights the relevance of taking a closer look at driving processes, especially with respect to the exploration of possible ways to reduce casualties.

Road accidents, including accidents due to poor driving skills, technical defects or environmental factors, are sometimes unavoidable. Nevertheless, a significant portion of traffic accidents occurs due to human errors.[2,3] Driving is a complex process that requires highly coordinated motor, cognitive and perceptual skills.[4] Appropriate quantitative observation of nervous system-

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related processes involved in driving is thus important for the analysis of driving behavior to reduce accidents related to driving errors.[5]

External as well as individual factors which determine driving behavior have been explored.[6] Recognizing the contribution of individual factors to the development of high-risk driving behaviors is relevant for the assessment of the likelihood of future accidents.[7] High-risk driving behavior is defined as behavior that increases the likelihood of a vehicle accident.[8] This includes aggressive driving, high speed, erratic lane changes, not wearing a seat belt, driving under the influence of alcohol or drugs, and driving under fatigue.[2]

Previous studies have identified personality traits, including being excitable or adventurous, mood, and transient emotional states such as anger, anxiety, and a positive view of driving violations as risk indicators for past, present, and future accidents. Certain personality traits that are related to engagement in high-risk driving behaviors including risk-taking propensity, physical/verbal hostility and aggression have been identified as important predictors of future accident risks.[8-16]

A limited number of studies suggest a role of mood and the style of expression of emotions for the risk of accidents and driving performance, including perception of risks in driving and attitudes towards high-risk driving. Positive mood can increase the likelihood of high-risk driving by reducing perceived risk or increasing risk-taking attitudes.[8,15-23] These initial studies suggest the relevance of mood and emotion for the driving process as possible factors of involvement in high-risk behaviors while driving, and the requirement to study these in more detail.

Safe driving depends on the ability of drivers to maintain focus, and mood is one of the factors that affect this ability.[15] Mood can relevantly affect cognitive and behavioral processes. High-risk behaviors related to driving are influenced by two main cognitive components, including perception of risk in driving and attitudes toward high-risk driving. Positive mood can increase the likelihood of high-risk driving by reducing perceived risk or increasing risk-taking attitudes, while negative mood has antagonistic effects, as suggested by some studies.[24] In contrast, some other studies describe that positive mood is associated with increased sensitivity to loss and consequently the tendency to avoid danger and the desire for safer alternatives.[25] In some recent behavioral studies it has moreover been shown that relaxed positive mood leads to a lower level of inclination to drive recklessly compared to the induction of initial positive, negative, or neutral emotions in young people, and driving with high arousal, regardless of the positivity or negativity of the mood, leads to a greater tendency for high-risk driving compared to the induction of positive mood associated with calmness, or neutrality. Thus, these studies suggest that the role of mood quality on driving is indecisive, but rather the arousal component is critical for driving behavior. The role of positive and negative mood in high-risk driving behaviors is thus not completely clear at present.[26,27]

Previous studies about the effect of positive and negative mood on high-risk behaviors while driving have been conducted solely based on questionnaires completed by participants to assess the tendency to take risks while driving.[26,27] Such studies face limitations because of subjectivity of the answers, including social desirability, which limits the informative value of the outcomes of respective studies. There is thus a need for studies which allow to monitor objective driving behavior, and to explore the respective physiological background of the impact of mood on driving behavior to understand mechanisms.

Functional magnetic resonance imaging (fMRI) provides a way to objectively measure brain activity related to simulated driving behavior in a variety of situations, to provide information about task-related activation of brain areas, and hereby its physiological background.[28]

The interaction between driving behavior and brain networks relevant for emotions is a complex and dynamic process that involves multiple neural systems. On the one hand, driving requires a range of cognitive processes, such as attention, perception, memory, and decision-making, which involve a network of brain regions including the prefrontal cortex (PFC), parietal cortex, and basal ganglia.[29] On the other hand, emotions can influence driving behavior by modulating the activity of brain regions involved in affective processing, such as the amygdala, insula, and PFC.[30] Understanding the interaction between these two brain networks is important for improving road safety via developing interventions to mitigate the effects of emotions on driving behavior.

The correlation between cognitive functions, different mood states and their effect on driving behavior is complex, and still remains unclear. In this study, we aimed to unravel the relationship between real driving behavior and mood, and reveal its physiological background through fMRI data, using a simulated driving task. Our hypotheses in this study are as follows:

- Mood alters driving behavior.
- Induction of mood activates mood networks, and alters activity of cognitive networks.
- Respective alterations of mood network activity are associated with driving behavior.

Methods

Study design

The objective of this study is to determine the impact of induced neutral, positive and negative mood states on driving behavior with a specific dedication on physiological foundations, as revealed by fMRI. To this end, we will conduct a crossover study in 28 male right-handed drivers, aged 20 to 30 years. Each participant - after combined auditory and visual positive, negative and neutral mood induction – will drive virtually in an fMRI-compatible driving simulator, and fMRI will be conducted during driving, to identify task-related activity, and connectivity patterns in the different mood conditions. The order of conditions will be balanced in this crossover study.

Participants

The sample size of the study, considering a Cohen's effect size of f = 0.5, 80% power estimates, and an alpha error of 0.05 for the primary outcome measure one-factorial ANOVA, was estimated by Cochran's sample size formula, and resulted in 24 participants. Taking possible data loss due to inappropriate data acquisition or withdrawal from the study into account, 28 participants will be recruited.

Based on records of drivers in the central traffic department of Tabriz city, 28 male right-handed drivers between 20 and 30 years will be randomly selected and included in the study, in order to remove the effect of participants' brain function heterogeneity. Inclusion criteria will be at least 2 years of actual and daily driving experience, with a valid driving license and without any psychiatric illness or nerve/brain-related diseases based on a General Health Questionnaire.[31] Participants with daily consumption of alcohol, caffeine or smoking will be excluded from the study. Right-handedness will be assessed using the Edinburgh handedness scale.[32] All participants will be required to fill in the Manchester driver behavior questionnaire (Consistency = 0.33, Reliability = 0.77).[33] Potential participants with claustrophobia, a pacemaker or metal implants embedded in their body, which can affect MR imaging, will be excluded. Prior to the test, the status of smoking, and drinking alcohol/coffee will be checked. All participants will provide written informed consent after receiving a detailed explanation of all procedures. Participants will be also allowed to quit the study at any time without giving reasons. The present study was approved by the local Ethics Committee and is in line with the Declaration of Helsinki.

Mood induction selection

To induce mood efficiently during the test, the technique of simultaneous induction of mood with music and images via a video will be used.[34] The International Affective Picture System (IAPS), which is a collection of more than 1000 classified images, will be used to induce mood with images.[35] 200 images related to each of the mood types will be randomly selected from the images in this collection consisting of 600 positive mood images, 600 negative mood images, and 300 neutral mood images, and from this collection, 40 images will be randomly selected for each piece of music. The music introduced by the Conklin and Perkins study will be used to induce mood by music.[36] The selected music pieces are:

- Negative music pieces: Funeral March (Chopin), The planets: Mars (Gustav Holst), Eliz Iza (Alan Stivell), Night on Bald (Mussorgsky), Adagio in G Minor (Albinoni)
- Positive music pieces: Once Upon a Time (Yanni), Swan Lake: Mazurka (Schaikovsky), Toy Symphony (Mozart), Marriage of Figaro (Mozart), Eine kleine Nachtmusik (Mozart)
- Neutral music pieces: Symphony No. 9 (Anton Dvorak), The Planets: Neptune (Gustav Holst), Canon in D (Pachelbel), Symphony 40 in G Minor (Mozart), Variations for Winds, Strings and Keyboard (Steve Reich)

To select the best-suited pieces to induce positive, negative, and neutral mood during the experiment, a total of 15 videos (5 videos for each type of mood) were made by combining the selected 15 music pieces with the selected images. We will choose the best-suited 8 videos, namely the videos with the highest mood induction rate immediately after watching, and the highest washout rate 2 minutes after watching (4 neutral, two positive and two negative) for final mood induction during the fMRI task. The length of each video was 3 minutes, since the study by Conklin and Perkins demonstrated that 3 minutes are needed in order to induce mood through the pre-specified music, and the effect of inducted mood will be washed out in 2 minutes.

Then 60 healthy adult participants, who are blinded to the study, will be divided into 3 random groups based on a random sequence generator[37] and each group will watch 5 random videos of 3 different emotional qualities. Then, emotional state will be evaluated at 4 time points: (A) before watching the video, (B) immediately after watching each video, (C) two minutes after watching the video and (D) four minutes after watching the video. The emotional state will be evaluated by choosing one of nine adjectives adapted from the Nature of Emotions Questionnaire[38]: Three adjectives related to positive mood (happy, excited and elated), three adjectives related to negative mood (sad, melancholic, and anxious) and three adjectives to evaluate neutral state (neutral, indifferent, and unresponsive).

Then the best 8 videos (4 neutral, two positive and two negative) for final mood induction during the fMRI task will be chosen as the videos with the highest rate of immediate relative mood induction and best washout rate during the 2 minute washout periods.

Driving simulator

The fMRI-compatible driving simulator was designed based on a study by Kim et al.[39] The driving simulator in this study is composed of a steering wheel, an accelerator, a brake pedal, and a visual system providing driving images. The steering wheel length and height and pedal position can be adjusted to compensate for differences in the subject's height.

The digital part of the circuit, which includes the processor and logic level conversion subsystems, is placed outside the MRI room and is connected to the sensors and analogue equipment inside the room by a 6-meter connecting cable. To prevent penetration of magnetic noise inside the cable, a two-layer shield of mesh and film is used, which is shielding the environmental noise. Due to the length of the data transmission cable and the presence of high level noise, the transmission signal is amplified from 0-5V to 0-24V to reduce signal fading in the transmission channel.

After noise removal, the signal is returned to the range of 0-5 volts by conversion circuits and passes through a distortion filter so that it can be read by the microcontroller. After this step, the signal is received by the microcontroller and translated into understandable commands (turning left, turning right, acceleration and brake) for the computer and simulator software.

All components used in the steering wheel and pedal are composed of nonmagnetic parts. No magnetic metal has been used in the design of the steering rod. The iron parts used in the sensors have been replaced by plastic or brass components prepared by 3D printing or turning. All parts of the arm are made of plastic and wood and are connected by glue. The designed arm is mechanically and electronically fully MRI compatible.

Driving task

The design of the study includes 2 sessions (A: Positive vs. neutral mood induction; B: Negative vs. neutral mood induction) and 4 blocks in each session. The order of blocks in each session will be the same for all participants and the order of sessions will be selected counterbalanced based on a computer random sequence generator[37] and will be sealed in envelopes. The blocks in each session consist of 3 minutes of neutral vs. positive/negative mood induction, followed by virtual driving for 2 minutes. During the simulated driving task, several driving behavior measurements, including speed, acceleration, lane deviation, reaction time to obstacles, and brake reaction time will be recorded. The schematic design of the fMRI conductance is shown in Figure 1.

FMRI procedure

First, the experimental procedures will be explained to the participants, and informed consent will be obtained. Structural MRI will be performed using T1-weighted, three-dimensional magnetization prepared rapid acquisition gradient echo imaging at the beginning of the task, before the fMRI imaging (3D MPRAGE; repetition time (TR) = 1.8 s, echo time (TE) = 2.21 ms, flip angle (FA) = 10°, field of view (FOV) = 256 × 256 mm^2, 176 slices, voxel size = 1.0 × 1.0 × 1.0 mm^3). While driving, functional brain images will be acquired using a T2*weighted echoplanar sequence (repetition time (TR) = 1.75 s, TE = 30 ms, FA = 40°, FOV = 256 × 256 mm^2, 60 slices, voxel size = 2.5 × 2.5 × 2.5 mm3, 377 time points) using a 3T MRI scanner (Magnetom TrioTim, Siemens Medical Systems, Erlangen, Germany) and a 32 channel head coil.

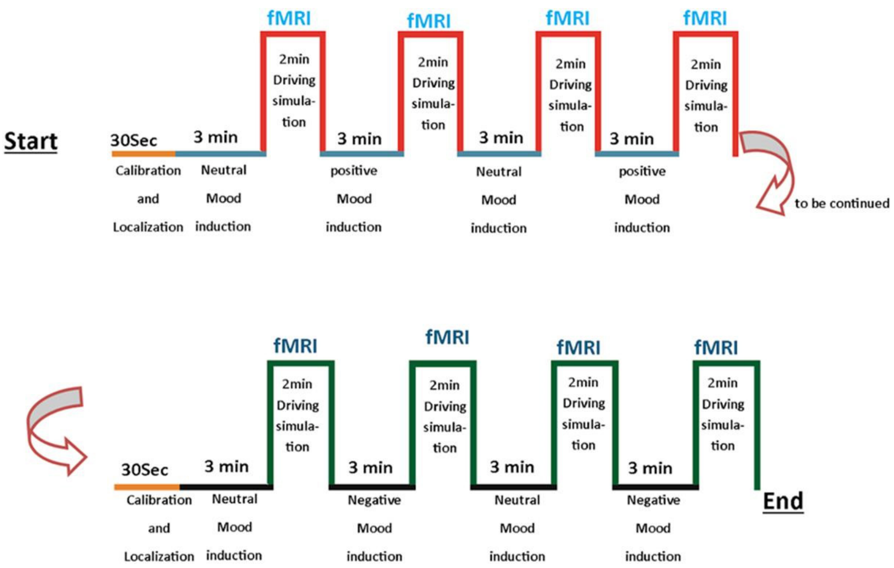

Figure 1. Schematic design of the fMRI study timeline

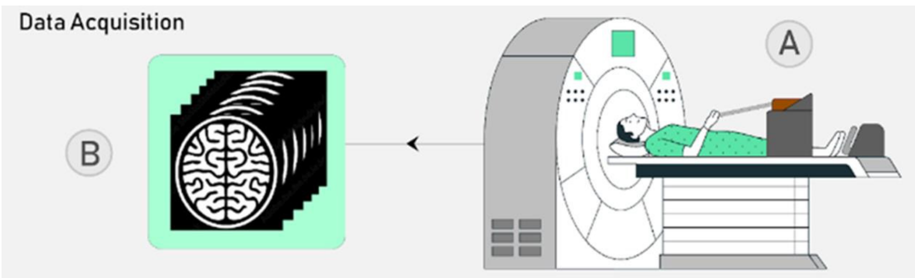

Figure 2. The setting of fMRI data acquisition while driving

Participants will use both hands to drive and the right foot to accelerate and brake (Figure 2). Visual driving information will be displayed on the screen. Before the experimental session, participants will be required to practice with the simulator in a simulation environment until they can drive effortlessly. Effortless driving is going to be defined by participant's statement regarding handling of the driving task and reaching a constant number of driving errors, including a speed more than 75 mph, drifting out of the lane for more than 2-3 seconds at a time, or more than 5-10 times during the simulation, maintaining a following distance of less than 2 seconds from the vehicle in front of the participant for more than 5%-10% of the simulation time. In order to avoid head motion during the task, customized head molds will be used during imaging.[40]

In order to make sure that the mood was induced properly during the induction, the Nature of Emotions Questionnaire will be applied after each block of driving under mood.[38] The video used for the induction of mood in each block will be different from other blocks. The used videos in each block will be identical for all participants.

Statistical methods

For the behavioral analysis, one-factorial ANOVAs will be used to evaluate the effect of mood (positive, negative, or neutral) on driving task variables (speed, acceleration, lane deviation, reaction time to obstacles, and brake reaction time).

All data analyses will be performed using MATLAB (MathWorks, Natick, MA) and the Statistical Parametric Mapping (SPM12) software package (Wellcome Trust Centre for Neuroimaging, London, UK). Prior to analysis, the functional images will be corrected for slice timing and motion, and will be spatially normalized to the standard Montreal Neurological Institute (MNI) template. The normalized images will be then smoothed using a 6mm full-width at half-maximum Gaussian kernel.

A general linear model will be used to identify brain regions that show significant differences in BOLD response between driving under the positive, negative and neutral mood conditions. The positive and negative driving conditions are modeled as the experimental condition, and the neutral driving condition is modeled as the control condition. The regressors will be convolved with a canonical hemodynamic response function and its temporal derivative to model the expected BOLD response.

Voxel-wise whole brain analyses will be performed using a threshold of $P<0.001$ (uncorrected), and a cluster extent threshold of $P<0.05$, family-wise error (FWE) corrected for multiple comparisons. Additionally, we will perform a region of interest (ROI) analysis using the amygdala and PFC sub-regions (ventromedial prefrontal cortex [vmPFC], dorsolateral prefrontal cortex [dlPFC], orbitofrontal cortex [OFC], and anterior cingulate cortex [ACC]) as selected ROIs based on previous studies showing that these regions are parts of both, the emotion, and driving brain networks.[29,30]

In order to identify brain networks and investigate differences in connectivity between mood states, statistic connectivity analysis will be performed. For the static connectivity analysis, we will use a seed-based approach, in which the mean BOLD time series will be extracted from the ROIs. Correlation coefficients between the seed ROI and all other voxels in the brain will be calculated for each participant, and the resulting correlation maps will be transformed to Z-scores using Fisher's r-to-z transformation. Group-level statistics will be performed using a one-sample t-test on the Z-transformed maps, with age and gender included as covariates of no interest.

Additionally, in order to measure fluctuations of connectivity patterns over time and reveal transitions between different brain states, a dynamic connectivity analysis will be performed. For the dynamic connectivity analysis, we will use a sliding window approach, in which the BOLD time series is segmented into overlapping time windows with a 50% overlap. For each window, we will calculate the functional connectivity between the same ROIs used in the static connectivity analysis using the same seed-based approach. The resulting correlation coefficients will be Fisher-transformed to Z-scores and concatenated across all windows to create a dynamic connectivity matrix for each participant. We will then calculate the mean and standard deviation of the dynamic connectivity matrices for each participant and perform group-level statistics using a two-sample t-test, with age and gender included as covariates of no interest.

To identify the whole-brain connection patterns related to each mood state, we will also apply a seed-based connectivity analysis, using the amygdala, vmPFC, dlPFC, OFC and ACC as the seed regions of interest. Then, using a false discovery rate correction at $P<0.05$ and voxel-wise statistical analysis, we will locate areas exhibiting significant changes in connectivity strength across mood states. To identify changes of whole-brain connectivity patterns related to mood states generated by the driving task, resting-state fMRI data obtained before and after the driving task will be used. Overall, the neural networks affected by the impact of good, negative, and neutral mood states on driving behavior will be identified by our whole-brain connectivity investigation.

To correct for multiple comparisons, we will use the FWE correction at the cluster level, with a threshold of $P<0.05$. The resulting clusters will be identified using the SPM Anatomy Toolbox and reported in MNI coordinates. Additionally, we will calculate effect sizes using Cohen's d and report these for significant findings.

We will conduct post-hoc analyses to explore the relationship between functional connectivity between the amygdala, vmPFC, dlPFC, OFC and ACC and individual differences in driving behavior, as measured by reaction time, speed variability, and lane deviation. We will use regression models to examine the moderating effects of mood on the relationship between their connectivity and driving behavior.

Finally, correlation analyses will be conducted between the behavioral measures of driving performance and the fMRI data to investigate the relationship between neural activity and behavior. A non-parametric permutation test will be conducted to test the significance of the correlations while controlling for multiple comparisons. We will also conduct a regression analysis to explore the effects of mood on the correlation between neural activity and driving behavior.

Discussion

The available literature on the role of different mood states on driving behavior was so far mainly based on questionnaire data. Results are therefore subjective, and show a large heterogeneity, which makes it almost impossible to draw conclusions on how mood alterations affect driving behavior. The findings of the current study will provide relevant data to shed light on the mechanism of mood-driving behavior correlations, with its objective design. Comparing fMRI results of driving under different mood states will unravel correlations and interactions of driving- and mood-related neural networks and will probably determine why different mood states have different effects on driving behaviors and help to clarify the reasons for heterogeneous results of previously published studies. These findings will improve our understanding of how driving and mood states interact with each other, and deliver relevant information about respective physiological underpinnings. This might pave the way for the introduction of different preventive or reinforcement strategies to control or alter mood states while driving, and therefore reduce preventable car accidents significantly.

Furthermore, the dataset and results of this study might be useful for generating driver-friendly applications, with the help of machine learning algorithms, to detect and alter a driver's mood while driving in order to prevent high risk driving and therefore, car accidents. Such applications will increase the performance and reliability of transportation systems, including self-propelled and manually-controlled vehicles; therefore today, machine learning methods are among the areas of interest for researchers and conducting machine learning algorithms based on such results will broaden the horizon of our findings in everyday life.

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Authors' Contribution

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Competing Interests

None declared.

Ethical Approval

This study was approved by the Ethics Committee of Tabriz University of Medical Sciences (IR.TBZMED.REC.1400.1053).

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This study has not received funding.

Study Highlights

What is current knowledge?

- Up to know, role of mood on driving behavior has only been studied with subjective methods; and the results show huge differences varying from completely negative to completely positive effect, for each type of mood.

What is new here?

- This study introduces a novel strategy to to induce proper and more effective positive, negative, and neutral mood. It also introduces a new method to study driving behavior, objectively; which reduces the role of confounding factors such as personal interpretation.

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