Research Paper

Neurophysiological Markers of Cognitive Failures in Drivers: An Electroencephalography Study

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ABSTRACT

Introduction: Cognitive failures (CFs) during driving significantly contribute to traffic accidents and fatalities. This study aimed to investigate neurophysiological markers of CF in drivers using electroencephalography (EEG).

Methods: Thirty taxi drivers were classified into high and low CF groups based on CF questionnaire (CFQ) scores. EEG signals were recorded during eyes-closed rest and eyes-open Go/No-Go (GNG) tasks to assess brainwave patterns and lobe-specific activation. Statistical analyses included t-tests, repeated measures analysis of variance (ANOVA), and Pearson's correlations.

Results: Drivers with high CF showed reduced delta, theta, and gamma activity—particularly in the temporal and occipital lobes—suggesting impaired cognitive processing. In contrast, low-failure drivers exhibited increased delta, theta, and alpha power in frontal and occipital regions. Elevated beta activity in the parietal lobe of high-failure drivers may reflect compensatory processing. Gamma power was consistently lower across all brain regions in this group.

Conclusion: These results highlight specific EEG frequency bands as potential objective markers for identifying CF in drivers, offering implications for early cognitive assessment and the development of evidence-based safety strategies in driving contexts.

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Highlights

- EEG can objectively identify CFs in professional drivers, even when behavioral tasks show no differences.
- Drivers with high CF scores show reduced theta and gamma power, especially in the temporal and occipital lobes.
- Gamma-band power differences between high and low CF groups reflect distinct patterns of neural activation during cognitive tasks.
- Parietal beta power is associated with faster response times and may indicate compensatory processes in drivers prone to cognitive errors.
- Combining EEG with behavioral measures reveals latent cognitive vulnerabilities in drivers that may not be captured by performance alone.

Plain Language Summary

Safe driving requires attention, remembering important details, and making quick decisions. Sometimes drivers experience "cognitive failures (CFs)" — such as forgetting, getting distracted, or making small mistakes. This study used brain wave (EEG) recordings from taxi drivers to search for objective signs of these CFs. Thirty drivers were tested with a simple attention task while their brain activity was measured. Drivers with more self-reported CFs did not make more mistakes on the task, but their brain patterns were different: they showed reduced brainwave power in specific frequency bands (especially gamma and theta) and distinct activation in brain areas linked to attention and memory. These findings suggest that EEG can detect hidden (latent) thinking problems in drivers, even when their task performance seems normal. Using EEG as a tool could help spot risks early and improve road safety for everyone.

Introduction

In recent years, driving safety has emerged as a paramount concern (Saha et al., 2017). Traffic accidents in urban areas have exhibited alarming trends. For instance, the total number of roadway fatalities in the United States reached 42,939 in 2021, a 14% increase from the previous year. Pedestrians and other vulnerable road users have also faced elevated risks in these environments, contributing to an increase in urban traffic-related fatalities (National Highway Traffic Safety Administration, 2023).

Driving is a complex cognitive task that involves various processes, including attention, perception, decision-making, and visuomotor integration (Vilchez et al., 2024). Failures in these skills can lead to errors and accidents with severe consequences, particularly in professions that require high levels of attention and concentration, such as driving. Cognitive failure (CF) in drivers refers to the psychological obstacles that impede their ability to process traffic conditions and engage in the motor planning necessary for driving (Saha et al., 2017). Urban drivers may be more susceptible to these cognitive errors due to the specific demands of their jobs, including navigating heavy traffic and the need to focus and react quickly to changing road conditions (Kazemi et al., 2017). Recent studies have demonstrated that drowsiness, fatigue, distraction, and speeding remain major factors that undermine a driver's ability to perceive hazards, recognize critical situations, and maintain proper control over the vehicle, often resulting in serious road accidents (Merlhiot & Bueno, 2022).

Investigations into CFs across various occupations underscore their significance (Abbasi et al., 2021; Kazemi et al., 2017; Mortazavi et al., 2022). Research has demonstrated that cognitive errors are a primary contributor to traffic accidents and are associated with increased rates of driving mistakes, lapses, and violations (Allahyari et al., 2008). CFs, characterized as errors in simple tasks resulting from memory, attention, or action issues, have substantially impacted driving safety and accident rates (Wickens et al., 2008).

In this context, research has investigated electroencephalography (EEG) to assess cognitive performance in driving, focusing on visual alertness, motor planning, and motor execution (Saha et al., 2017). EEG is a non-invasive, portable, safe, and cost-effective technology widely accepted and requiring relatively short data acquisition times. This technique examines brain activity by recording electrical brain waves, thereby facilitating the investigation of cognitive and neurological alterations. It is a valuable tool for understanding cognitive performance and monitoring mental states. Numerous studies have shown that different brain frequency bands, including delta, theta, alpha, beta, and gamma waves, provide valuable insights into an individual's cognitive state and brain function (Liu et al., 2023; Peng et al., 2022; Ronca et al., 2024). Recent EEG-based studies have demonstrated the effectiveness of neurophysiological indices—such as theta and alpha band activity—in detecting drivers' CFs, mental workload, and drowsiness in real-world and simulated driving scenarios, highlighting the potential of brain-monitoring systems to improve road safety (Di Flumeri et al., 2018; Di Flumeri et al., 2022; Ronca et al., 2024; Saha et al., 2017).

In a study involving non-professional drivers performing a simulated driving task until fatigue onset, the results indicated increased slow-wave activity across cortical regions, particularly in the theta and alpha frequency bands. No significant changes were observed in delta wave activity. However, fast wave activity notably increased in the frontal regions. This finding suggests that as fatigue progresses, the brain compensates by enhancing beta activity to maintain attention and vigilance, highlighting the importance of EEG in assessing cognitive load and performance (Craig et al., 2012).

Liu et al. (2023) conducted an EEG-based analysis to investigate drivers' cognitive workload during an on-road experiment. Their findings indicated that delta waves had a minimal impact, with activity primarily localized in the temporal lobe, suggesting a connection to memory processes. Theta waves increased in response to higher cognitive demands, particularly in the frontal and temporal regions associated with reasoning and judgment. Alpha waves demonstrated significant activation in occipital and temporal areas during increased workloads, highlighting their role in visual processing. Beta waves were strongly associated with psychological functions and visual processing, with heightened activity observed in the frontal and occipital lobes during intense cognitive tasks. This study emphasizes the direct influence of cognitive workload on driving performance and safety.

In a study by Li (2023), driving was performed under conditions designed to induce cognitive distraction and increase mental load. The results indicated that a task primarily engaging the driver's auditory working memory had a greater impact on changes in brain activity than a task mainly involving the driver's visuospatial working memory, which entailed relatively less mental load.

The study conducted by Ronca et al. (2024) involved participants driving in two distinct settings: Urban and highway environments. In these scenarios, participants were assigned secondary tasks in addition to the primary driving task to modulate their attention. The findings indicated that the EEG-based distraction index was highly effective at detecting differences in driver distraction between urban and non-urban scenarios, revealing a significantly higher level of distraction in the urban setting. This outcome is likely attributable to the drivers managing multiple distractions inherent to the urban environment, such as pedestrians, crossing vehicles, traffic signals, and other elements that are naturally part of the urban driving experience.

Given the significance of CF as a primary factor in execution errors and driving accidents, its assessing and examining are crucial. CFs have been predominantly evaluated using self-report tools, such as the CF questionnaire (CFQ), which has gained popularity among researchers due to its simplicity and convenience. However, few studies have directly investigated the relationship between CFs and EEG indicators, leaving the associated brainwave changes relatively unexplored. Since EEG is a non-invasive and precise tool for assessing cognitive functions and various mental states, its employment for detecting CFs can provide an objective and reliable method. This approach highlights specific patterns of brain activity associated with these failures. This study aimed to bridge this gap by comparing individuals with high levels of CF to those with low or negligible levels, examining EEG indices to explore potential connections between CFs and brainwave activity.

Therefore, the present study investigated changes in brain activity, as measured by EEG, between the CF and non-CF (NCF) groups. This study aimed to address the following research questions:

Is there a significant difference in the cognitive performance of drivers from the CF and NCF groups while completing a Go/No-Go (GNG) cognitive task?

Are there significant differences in the brainwave frequencies (delta, theta, alpha, beta, and gamma) of drivers between the CF and NCF groups?

Are there significant differences in the activity of various brain lobes (frontal, parietal, temporal, occipital, and central) between drivers in the CF and NCF groups?

Which brainwave frequency and brain lobe exhibit the most significant changes due to CF?

Materials and Methods

In this experimental study, 30 drivers with a Mean±SD age of 36.52±4.88 years (age range: 29 to 45 years) and a mean experience of 7.7±2.68 years were recruited from urban taxi drivers. Based on the total CFQ scores, participants who scored 41 or above were assigned to the CF group (n=20), while those who scored below 41 were assigned to the NCF group (n=10).

The inclusion criteria for participation in this study were as follows: Drivers employed by city taxi companies must be within the age range of 20-50 years and have a minimum of 2 years of work experience; participants must not have any dependency on narcotics or substances that impact the nervous system, psyche, or emotional state; participants were required to be in good physical health and mental well-being (no diagnosis of cardiovascular and cerebrovascular diseases, somatic diseases, mental diseases, malignant tumors, or other primary health conditions); they were all right-handed; only male drivers were included in the research group (as female drivers were underrepresented in the population); and participants were required to be sufficiently alert at the time of testing. To ensure this, the Karolinska sleepiness scale (KSS) was administered prior to EEG recording, and only individuals scoring three or lower were included in the study. This assessment ensured that EEG readings were not influenced by participants' sleepiness or fatigue levels (Manaenkov et al., 2023).

Individuals were excluded from the study if they demonstrated a lack of cooperation in answering questions or if their questionnaires contained missing items or logical errors.

Procedures

All experimental sessions were conducted at a privacy clinic coordinated with a certified medical professional. Upon arrival, participants received a detailed verbal explanation of the study objectives and procedures. Before initiating the study, participants signed informed consent forms, acknowledging their voluntary participation and understanding that their data would be strictly confidential and used solely for scientific purposes. The Ethics Committee of Shiraz University of Medical Sciences approved all experimental procedures. Before initiating the study, participants' alertness was assessed using the KSS. Participants were instructed to obtain sufficient sleep the night before the experiment and to refrain from consuming caffeinated beverages, smoking, or using any medications or stimulants for at least 12 hours before the session. Additionally, all experimental sessions were conducted within the same time window (9:00 AM to 2:00 PM) to minimize circadian variation.

To ensure familiarity with the experimental tasks, participants were first introduced to the GNG task and allowed to complete a short practice session. Following this, EEG preparation was performed according to the international 10–20 system. A suitable EEG cap was selected based on head size and properly positioned on the participant's scalp. After injecting conductive gel into the electrodes to ensure optimal signal quality, a soft elastic net was placed over the EEG cap to help secure the electrodes, maintain stable contact, and reduce signal noise throughout the recording session, ensuring accurate brainwave measurements. Participants were asked to minimize speaking and to refrain from moving their head or body to reduce muscle and motion artifacts.

EEG data were recorded under two conditions. First, a two-minute resting-state session was conducted with participants sitting quietly with closed eyes. Next, EEG signals were recorded while participants performed the GNG task, which took approximately 5-7 minutes, depending on the participants' task completion speed. The experimenter monitored data quality throughout the session, and any necessary adjustments were made in real-time to ensure accurate signal acquisition.

Upon completion of the recordings and confirmation of acceptable data quality, the EEG equipment was removed, and participants were thanked for their cooperation before leaving the clinic. Each session lasted approximately 30-40 minutes, including setup, task performance, and equipment removal. Figure 1 shows a schematic representation of the study protocol.

CFQ

The CFQ, developed by Broadbent, consists of 25 items targeting four domains: Memory, nominal memory, attention, and exercise. This questionnaire considers different aspects of cognition, cognitive characteristics, various theories of CFs, and the contexts and layers in which CFs occur (Broadbent et al., 1982).

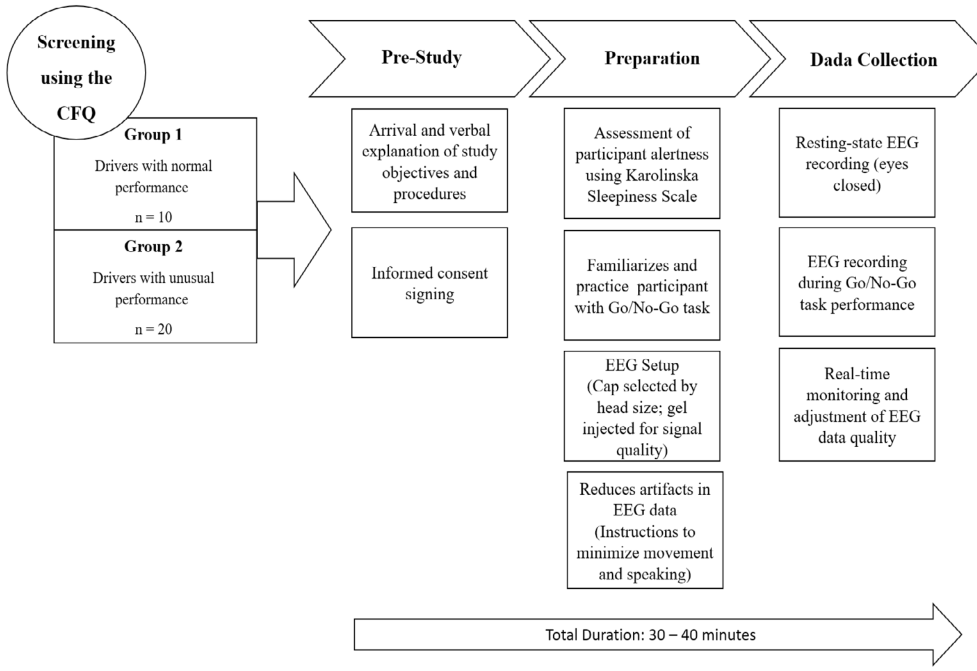

Figure 1. Overall experimental procedures

A study by Rast et al. (2009) indicated that the CFQ items load on three different factors:

- Forgetfulness: "A tendency to let go from one's mind something known or planned, for example, names, intentions, appointments, and words".

- Distractibility: "Mainly in social situations or interactions with other people, such as being absentminded or easily disturbed in one's focused attention".

- False triggering: "Interrupted processing of sequences of cognitive and motor actions".

In a reliability study by Allahyari et al. (2008) conducted in an industrial setting, the CFQ demonstrated high reliability, with a Cronbach's α of 0.96, indicating excellent internal consistency.

The CFQ score ranges from 0 to 100, with higher scores indicating more frequent CFs. The categories based on CFQ scores were as follows:

- Low CF: 25–41

- Moderate CF: 41–82

- High CF: Scores above 82.

Cognitive task

The CF and NCF groups performed the GNG computer task while their EEG was recorded simultaneously. The GNG task is designed to assess the ability to inhibit motor responses (Karthaus et al., 2020). It has been widely utilized in neuroimaging studies to evaluate inhibitory control and sustained attention, critical for safe driving. While it does not entirely mirror the complexities of real-world driving, it offers a controlled framework for assessing cognitive control. Its relevance to driving research is supported by studies, such as Hatfield et al. (2017), who used EEG during simulated driving with a GNG task to decode actions, such as braking, underscoring its neural validity. Additionally, the task has effectively modelled driver fatigue, distraction, and risky decision-making behaviors (Ba et al., 2016), making it a practical tool when immersive simulations are not feasible. Thus, its utility in exploring neurophysiological markers of cognitive functions is well-supported, providing valuable insights when used with techniques, such as EEG.

The GNG task is a computerized task comprising a large number of trials. During the task, a series of "go" and "No-Go" stimuli is presented to a subject, who is required to respond as quickly as possible to "go" stimuli but refrain from responding to "no-go" stimuli. Repeated presentations of the "Go" stimulus create a prepotent motivation to respond during the trials, making inhibition of

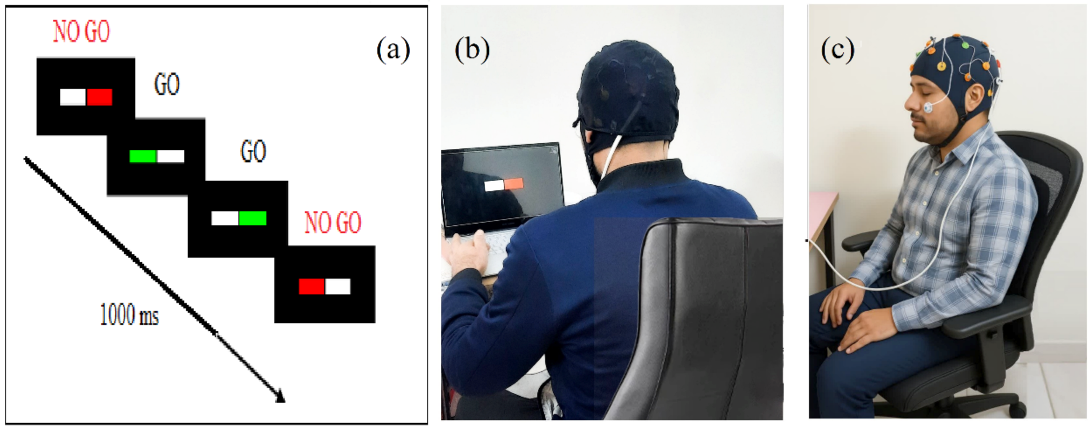

Figure 2. Experimental protocol

a) Illustration of the go/ no-go task interface used in the study, b) The EEG recording during the performance of the GNG task (eyes open condition), c) The EEG recording during the resting condition (eyes closed)

Note: Rectangles with "white and green" and "white and red" appeared randomly on the screen. If one rectangle was red, no response was required. If one rectangle was green, the participant had to press the "?" or "Z" button, depending on whether the green rectangle was on the left or right.

this prepotent response during "no-go" stimuli challenging (Nguyen et al., 2021; Van Royen et al., 2022).

In the present study, the GNG task consisted of 120 trials. Each trial lasted 1000 ms, followed by an inter-stimulus interval (ISI) of 1500 ms. In each trial, the visual stimulus (i.e. the colored rectangles) was presented on the screen for 1000 ms. During this time, participants were expected to respond if the trial was a go condition. Thus, the stimulus duration and the response window were concurrent. During the task, pairs of rectangles in the colors "white and green" and "white and red" appeared randomly on the screen (Figures 2a and 2b). If one of the pairs of rectangles included a red rectangle, participants were instructed to withhold their responses. However, if one of the pairs included a green rectangle, the response depended on its position. Specifically, if the green rectangle was on the right and the white rectangle was on the left, participants must press the "?" button as quickly as possible. Conversely, if the white rectangle was on the right and the green rectangle was on the left, participants were instructed to press the "Z" button at maximum speed. All participants used a fixed response mapping (i.e. "Z" for left-side green stimuli and "?" for right-side green stimuli). Response counterbalancing was not applied since all participants were right-handed, and the response keys were spatially balanced. This approach reduced variability and maintained consistency across trials. In other experimental contexts, however, counterbalancing response mappings may be beneficial to control for potential lateralized response tendencies.

During the GNG task, several performance metrics were recorded, including omission errors, commission errors, and response times.

An omission error occurs when a participant fails to respond to a target stimulus (go trial). This is defined as when the participant does not press the "?" or "Z" button when one of the pairs of rectangles included a green rectangle, indicating a go trial.

A commission error is recorded when a participant responds to a non-target stimulus (no-go trial). This happens when the participant presses the "?" or "Z" button in response to a pair of rectangles that included a red color, indicating a no-go trial.

Response time is measured as the interval between the pair of rectangles on the screen and the participant's response by pressing the "?" or "Z" button. This metric reflects the speed at which participants react to target stimuli (Khodadadi & Amani, 2014).

EEG data collection and processing

EEG data were recorded using a bio-amplifier system manufactured by Medicom MTD Ltd. The data were stored and processed with Encephalan-EEGR 121 software (Medicom MTD Ltd). A standard 10/20 linked ears

Table 1. Electrode position distribution

Location	Electrode Name		
	Left	Right	Central
Prefrontal lobe	Fp1	Fp2	-
Inferior lobe	F7	F8	-
Frontal lobe	F3	F4	Fz
Central lobe	C3	C4	Cz
Temporal lobe	T3	T4	-
Posterior lobe	T5	T6	-
Parietal lobe	P3	P4	Pz
Occipital lobe	O1	O2	-
Auricular	A1	A2	-

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reference montage EEG system was employed, with individuals grounded peripherally. The reference electrodes were placed at A1 and A2, and the ground electrode was positioned at FZ.

Brain frequency activity was recorded from 19 channels in different lobes (Table 1 and Figure 3). An EEG cap was used in conjunction with a cleaning gel for the head surface and a connecting gel for the active electrodes to record the signals.

The data were analyzed using Python's Magnetoencephalography and EEG (MNE) package. To remove alternating current (AC) power supply noise, notch filters were applied at 50 Hz and 100 Hz. The data were then band-pass filtered between 0.1 and 50 Hz. To address ocular artifacts (e.g. blinks and eye movements), electrooculography (EOG) channels were recorded simultaneously with EEG. Independent component analysis (ICA) was performed to identify and remove components correlated with EOG activity based on their time course and scalp topography. This ICA-based EOG correction approach is considered the gold standard for multi-channel

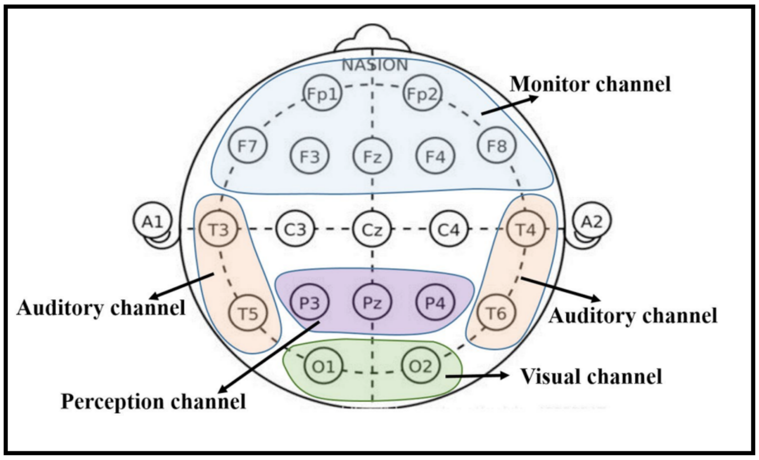

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Figure 3. Electrode placement and functional categorization of EEG channels

Note: The electrodes were grouped into five anatomically and functionally defined AOIs: Frontal (monitor channel; F7, F3, Fz, F4, F8, Fp1, Fp1), central (sensorimotor channel; Cz, C3, C4), parietal (perception channel; P3, Pz, P4), occipital (visual channel; O1, O2), and temporal (auditory channel; T3, T4, T5, T6).

Table 2. CFQ scores and GNG task scores of CF and NCF groups

Measures		Mean±SD		P
		NCF Group (n=10)	CF Group (n=20)	
CFQ domain	CFQ total	35.7±4.11	53.4±3.84	0.000*
	Forgetfulness	17.5±3.1	26.46±2.31	0.000*
	Distractibility	13.2±2.39	19.86±4.98	0.000*
	False triggering	5.1±1.2	7.46±1.68	0.002*
GNG task Indicator	Commission errors	0.7±0.82	1.77±4.62	0.480
	Omission errors	0.0	0.07±0.28	0.393
	Inhibition scores	119.3±0.82	118.15±4.6	0.447
	Response times (ms)	453±92.37	449.15±83.63	0.918

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Abbreviations: CFQ: Cognitive failure questionnaire; CF: Cognitive failure; NCF: Non-cognitive failure; GNG: Go/no-go.
*P<0.05.

EEG with EOG recordings, ensuring effective artifact removal while preserving neural signals (Ronca et al., 2024). After artifact correction, spectral power density was computed for five frequency bands: Delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–49.5 Hz). The channels were grouped into five areas of interest (AOIs): frontal, central, parietal, occipital, and temporal (Figure 3). The absolute power for each AOI was calculated by averaging the channels within each region across both eyes-closed resting-state and GNG task conditions (Figures 2b and 2c).

Statistical analysis

Behavioral data were analyzed using independent-samples t-tests to compare the CF and NCF groups on questionnaire and GNG task measures, after verifying homogeneity of variances using Levene's test. EEG spectral power values were analyzed using separate mixed-design repeated-measures analysis of variance (ANOVA) for each frequency band (delta, theta, alpha, beta, gamma). Each ANOVA included condition (eyes-closed resting vs. GNG task) and AOI (frontal, central, parietal, temporal, occipital) as within-subject factors, and group (CF vs NCF) as a between-subject factor.

Mauchly's test was used to assess the sphericity assumption, and Greenhouse–Geisser corrections were applied where necessary. To control for type I error in post hoc comparisons between AOIs within each frequency band, Bonferroni correction was applied via SPSS. All reported post hoc P values are Bonferroni-adjusted, and statistical significance was evaluated using α=0.05. Main effects and interactions not involving multiple comparisons were assessed using the conventional threshold.

Pearson correlation analyses were conducted to explore associations between EEG spectral power and behavioral task performance (reaction time, omission errors, commission errors). These analyses were exploratory and not corrected for multiple comparisons. Accordingly, the results are interpreted with caution and intended to inform future hypothesis-driven research. All analyses were conducted using SPSS software, version 22 (IBM).

Results

CFQ scores

The CF group reported significantly higher scores than the NCF group on the total CFQ and its subscales, including forgetfulness, distractibility, and false triggering (P<0.01).

GNG task performance

In contrast, there were no significant differences between the groups in any behavioral performance measures on the GNG task (commission errors, omission errors, response inhibition, or response time). Table 2 presents detailed descriptive statistics and P values.

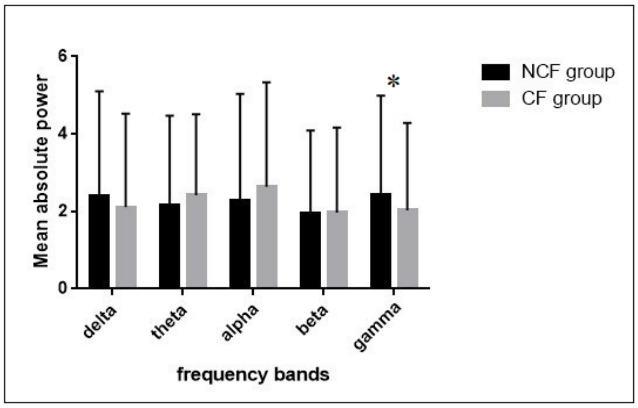

Figure 4. Comparison of mean absolute power for frequency bands in groups

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Note: The CF group exhibited a significantly lower gamma power than the NCF group (error bar: Standard error, $^{*}P<0.05$).

Descriptive analysis of EEG spectral power across brain areas and experimental conditions

To provide a general overview of the EEG spectral power distribution, Table 3 presents the Mean±SD values for each frequency band (delta, theta, alpha, beta, gamma) across five brain regions, for both CF and NCF groups during the resting-state and GNG task conditions. These descriptive statistics are provided for reference purposes only and are not subjected to inferential statistical tests.

EEG activity by frequency band: Effects of condition, region, and group

Delta band

The repeated measures ANOVA revealed no significant main effect of AOI ($F_{4, 112}$=1.95, P=0.11, η^2=0.07), condition ($F_{1, 28}$=1.64, P=0.21, η^2=0.06), or group ($F_{1, 28}$=0.12, P=0.73, η^2=0.004). No significant interactions were observed, including AOI × condition ($F_{4, 112}$=1.55, P=0.19, η^2=0.05), AOI × group ($F_{4, 112}$=1.83, P=0.13, η^2=0.06), condition × group ($F_{1, 28}$=2.68, P=0.11, η^2=.09), or AOI × condition × group ($F_{4, 112}$=1.13, P=0.35, η^2=0.04). These results suggest that delta power remained stable across regions, conditions, and groups.

Theta band

For theta power, a significant main effect of condition was observed ($F_{1, 28}$=7.91, P=0.009, η^2=0.22), with higher power during the eyes-closed condition. The AOI × condition interaction was also significant ($F_{4, 112}$=3.66, P=0.008, η^2=0.12), indicating region-specific modulation. A significant condition × group interaction was found ($F_{1, 28}$=6.73, P=0.015, η^2=0.19), suggesting that controls exhibited more pronounced condition-related modulation than the CF group. The main effects of AOI and group were not significant, nor were the AOI × group or three-way interactions (P>0.05).

Alpha band

A significant main effect of AOI emerged ($F_{4, 112}$=14.55, P<0.001, η^2=0.34), with alpha power highest in occipital and parietal regions. A strong main effect of condition was also detected ($F_{1, 28}$=37.98, P<0.001, η^2=0.58), with increased alpha activity during eyes-closed. The AOI × condition interaction was significant ($F_{4, 112}$=4.03, P=0.004, η^2=0.13), indicating that the task-related reduction in alpha power was more prominent in posterior regions. No significant effects involving group were found (P>0.05).

Beta band

Analysis of beta power showed no significant main effects of AOI ($F_{4, 112}$=2.37, P=0.057, η^2=0.08), condition ($F_{1, 28}$=1.12, P=0.30, η^2=0.04), or group ($F_{1, 28}$=0.01, P=0.91, η^2<0.001). Similarly, all interaction terms were non-significant, including AOI × condition ($F_{4, 112}$=1.88, P=0.12), AOI × group ($F_{4, 112}$=1.46, P=0.22), and AOI × condition × group ($F_{4, 112}$=0.88, P=0.48). These findings indicate that beta power remained essentially unchanged across regions, conditions, and groups.

Gamma band

Gamma band analysis revealed a significant main effect of AOI ($F_{4, 112}$=5.14, P=0.001, η^2=0.16), with the highest power in the parietal and central regions. Although no main effect of condition was observed ($F_{1, 28}$=1.64, P=0.21, η^2=0.06), the AOI × condition inter-

Table 3. Mean absolute power in delta, theta, alpha, beta, and gamma bands

Condition	AOIs	Mean±SD				
		NCF Group (n=10)				
		Delta	Theta	Alpha	Beta	Gamma
Resting conditions (eyes closed)	Frontal	3.72±2.5	2.86±1.51	3.95±3.71	3.2±2.18	3.32±2.4
	Central	4.9±3.61	2.93±1.52	4.53±2.98	4.12±2.29	3.01±2
	Parietal	4.8±2.72	4.16±2.41	4.25±2.56	3.9±2.09	4.25±2.07
	Occipital	2.64±1.83	4.25±2.81	3.34±1.56	2.63±1.6	5.37±2.91
	Temporal	3.8±1.72	2.21±2.42	4.7±2.71	3.14±1.09	3.83±2.26
GNG task (eyes open)	Frontal	4.36±2.8	5.07±3.45	5.31±3.32	2.36±2.02	4.91±2.9
	Central	3.23±3.03	5.87±2.5	5.28±3.14	3.11±1.67	3.83±2.38
	Parietal	3.7±3.3	3.39±2.06	4.86±2.74	4.45±2.54	4.31±2.13
	Occipital	4.87±2.34	2.86±1.51	6.15±1.28	3.56±2.25	4.06±2.18
	Temporal	4.17±1.71	3.97±0.83	3.16±1.19	3.22±2.64	4.83±2.9

Condition	AOIs	Mean±SD				
		CF Group (n=20)				
		Delta	Theta	Alpha	Beta	Gamma
Resting conditions (eyes closed)	Frontal	3.15±2.73	3.9±2.9	3.52±2.41	2.81±2.67	3.7±2.27
	Central	4.54±3.4	4.17±2.76	2.97±2.11	3.66±2.63	3.58±2.45
	Parietal	5.25±3.09	4.5±2.61	4.42±2.4	3.8±2.73	4.43±2.47
	Occipital	4.8±2.03	4.14±2	5.58±2.83	3.49±2.28	5.14±2.72
	Temporal	4.28±2.04	3.64±2.08	3.21±2.5	4.38±3.46	4.6±2.57
GNG task (eyes open)	Frontal	5.02±3.07	4.06±2.94	6.29±2.74	3.04±2.56	3.15±1.67
	Central	3.71±2.63	5.4±2.2	4.52±2.41	3.8±2.36	3.23±1.56
	Parietal	2.68±1.84	3.91±1.77	3.38±2.47	3.67±2.48	3.02±2.31
	Occipital	3.51±2.67	3.71±1.54	4.7±2.28	4.21±2.94	2.14±1.02
	Temporal	4.11±1.91	1.92±0.64	3.56±1.72	3.35±2.11	3.97±2.89

Abbreviations: CF: Cognitive failure; NCF: Non-cognitive failure; AOI: Areas of interest; GNG: Go/no-go.

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action was significant ($F_{4,\ 112}$=5.82, P=0.002, η^2=0.17), reflecting region-specific changes across task states. Specifically, gamma power increased in temporal areas during the GNG task but decreased in occipital and frontal regions. A significant AOI × group interaction was also found ($F_{4,\ 112}$=4.15, P=0.004, η^2=0.13), indicating distinct topographical gamma patterns between the CF and control groups, with the control group exhibiting relatively greater anterior gamma activation (Figure 4). No significant three-way interaction (AOI × condition × group) was detected ($F_{4,\ 112}$=1.13, P=0.35, η^2=0.04).

Table 4. Significant correlations between EEG absolute power and GNG task indicator

AOIs	Frequency Bands	GNG Task Indicator					
		Response Time		Omission Errors		Commission Errors	
		r (Pearson)	P	r (Pearson)	P	r (Pearson)	P
Frontal	Delta	0.142	0.515	-0.022	0.919	-0.231	0.289
	Theta	0.017	0.940	-0.228	0.295	0.346	0.106
	Alpha	-0.015	0.947	0.41	0.853	0.175	0.424
	Beta	-0.192	0.381	-0.158	0.470	-0.148	0.500
	Gamma	-0.344	0.108	-0.145	0.510	0.094	0.671
Parietal	Delta	-0.486*	0.019	0.258	0.234	-0.191	0.382
	Theta	0.122	0.580	-0.130	0.553	-0.015	0.945
	Alpha	-0.130	0.583	-0.232	0.271	0.135	0.540
	Beta	-0.473*	0.023	-0.205	0.347	0.056	0.801
	Gamma	-0.197	0.368	-0.158	0.473	-0.201	0.357
Temporal	Delta	0.147	0.504	0.446*	0.033	0.161	0.462
	Theta	0.154	0.484	-0.121	0.583	-0.017	0.939
	Alpha	-0.046	0.834	-0.334	0.119	-0.157	0.475
	Beta	0.204	0.351	-0.144	0.513	0.166	0.449
	Gamma	0.017	0.937	-0.144	0.512	-0.223	0.207
Central	Delta	-0.090	0.682	-0.128	0.561	-0.202	0.356
	Theta	-0.089	0.686	0.412	0.061	-0.076	0.730
	Alpha	-0.298	0.168	-0.058	0.793	0.107	0.626
	Beta	-0.164	0.454	-0.017	0.940	0.258	0.234
	Gamma	-0.384	0.103	0.123	0.576	-0.228	0.296
Occipital	Delta	0.306	0.155	-0.195	0.374	0.044	0.843
	Theta	0.022	0.919	0.340	0.112	-0.113	0.608
	Alpha	-0.152	0.488	0.414*	0.050	-0.193	0.378
	Beta	0.155	0.481	-0.197	0.367	0.071	0.746
	Gamma	-0.042	0.849	-0.81	0.714	-0.082	0.714

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*Significant correlation at the 0.05 level (2-tailed).

Correlation analyses explored associations between EEG absolute power and behavioral performance measures. Table 4 summarizes the significant correlations observed. Notably, omission errors were positively correlated with occipital alpha power (r=0.414, P=0.050) and temporal delta power (r=0.446, P=0.033). Significant negative associations were found between response times and parietal delta power (r=-0.486, P=0.019) and parietal beta power (r=-0.473, P=0.023).

Discussion

This study aimed to explore the differences in brain activity and cognitive performance between drivers with high CF and those without. Specifically, this study focused on identifying significant differences in cognitive performance during a GNG task, variations in brainwave frequencies (delta, theta, alpha, beta, and gamma), and activity across five brain lobes (frontal, central, parietal, temporal, and occipital) between the two groups. Additionally, the study aimed to pinpoint which brainwave frequency and brain lobe exhibited the most notable changes during CF.

The CF group demonstrated significantly higher CFQ scores than the NCF group (P<0.05). However, no statistically significant differences were found between the CF and NCF groups regarding commission errors, omission errors, inhibitory control, or response times during the GNG task (P>0.05). EEG data during the GNG task showed that the NCF group tended to exhibit higher delta, theta, and alpha power in some regions (notably frontal and occipital). However, these group-level differences were not statistically significant. Only gamma power showed a significant topographical difference between groups. Therefore, trends in other bands should be interpreted cautiously as preliminary and descriptive rather than conclusive. ANOVA results revealed significant differences in delta and gamma power across eye conditions, with the NCF group consistently showing higher gamma activity, which may be associated with stronger cognitive control. EEG thus proved effective in distinguishing cognitive function between groups.

The significantly higher CFQ scores in the CF group validated the group classification, indicating greater vulnerability to attentional lapses and executive dysfunction. Studies have linked self-reported CFs with real-world driving risks. Kazemi et al. (2017) found that increased mental workload among taxi drivers was associated with more frequent cognitive lapses. Similarly, Choi and Feng (2018) reported associations between attentional failures and prior traffic violations in older drivers. Niranjan et al. (2022) showed that CFs mediate the effect of personality traits on distracted driving. These findings underscore the predictive value of CFQ scores in assessing cognitive risk factors relevant to safe driving.

Although no significant behavioral differences were found between the groups during the GNG task, EEG results—particularly in the gamma band—highlighted neurophysiological distinctions. This discrepancy may indicate that EEG is more sensitive than behavioral tasks at capturing subtle neural changes in cognitive control and attention. Individuals with higher CF may recruit additional brain resources to maintain comparable task performance, reflecting compensatory processes. These findings emphasize the importance of integrating EEG data with behavioral measures to detect latent cognitive differences that may not yet manifest behaviorally.

However, in this study, no significant differences were observed between the CF and NCF groups in commission errors, omission errors, inhibition, or response time during the GNG task. Research has shown a significant link between poor GNG task performance and increased risk-taking in driving, especially among young drivers, with higher commission errors associated with behaviors like speeding and unsafe reactions (Ba et al., 2016; Van Royen et al., 2022). This lack of behavioral distinction may suggest that the task's sensitivity is limited in capturing the broader CFs identified by the CFQ. Alternative methods, such as continuous performance tasks or naturalistic driving simulations, offer greater ecological validity by better reflecting real-world attentional and executive challenges. Balancing experimental control with ecological realism remains an important direction for future research.

Despite the absence of behavioral differences, EEG analyses revealed some neurophysiological variation between groups, particularly in gamma power, which showed a statistically significant AOI × group interaction. Although patterns were observed in the theta, alpha, and beta bands, they did not reach significance and should be viewed as preliminary trends. This suggests that EEG may detect subtle neural modulations that are not yet behaviorally expressed. However, interpretations should be restrained to effects supported by statistical evidence. Previous studies have reported that electrophysiological measures can capture latent inefficiencies or compensatory neural activity, especially in low-demand or overlearned tasks. For example, Di Flumeri et al. (2022) showed that EEG-based indices, such as MDrow index, can detect early signs of driver drowsiness without overt behavioral cues, highlighting EEG's sensitivity to latent cognitive states. Likewise, Di Flumeri et al. (2018) used an EEG workload metric to reveal fluctuations in traffic and road complexity that behavioral measures missed. Saha et al. (2017) also developed a two-stage EEG classifier that identified CFs during simulated driving, even without motor responses. These findings underscore the value of EEG as a complementary tool to behavioral assessments, capable of identifying subclinical cognitive vulnerabilities that remain undetected through performance metrics alone.

In the eyes-open condition of the GNG task, the CF group exhibited higher delta-wave power. When comparing delta activity across different states, a shift is observed: While parietal lobe activity is enhanced during eyes-closed rest, cognitive task engagement leads to increased activity in the frontal and temporal lobes and a gradual reduction in the parietal region. This relationship was further supported by a significant negative correlation between parietal delta power and response time, suggesting that stronger delta activity in this region may facilitate faster motor responses during cognitive engagement. These dynamics align with findings by Liu et al. (2023), who reported that moderate cognitive load enhances frontal lobe activation. However, as task difficulty increases, activity in both frontal and temporal regions rises slightly while parietal activation diminishes. Given the temporal lobe's role in auditory processing and memory, these results indicate a potential association between delta wave activity and memory-related cognitive processes.

Consistent with prior research indicating that theta wave dynamics vary with driving workload (Liu et al., 2023), our findings showed elevated theta activity in the NCF group during the GNG task—particularly in the frontal, temporal, and central regions—relative to the resting state. In contrast, the CF group exhibited increased theta power only in the frontal and central areas. Given the frontal lobe's attention and executive control involvement, this localized increase may reflect greater cognitive effort. However, during the task, the CF group demonstrated a notable reduction in theta power across all brain regions—especially in the temporal lobe—compared to the NCF group. Since the temporal lobe plays a key role in memory and learning, this reduction may indicate compromised neurocognitive processing in individuals with higher CF.

Prior research underscores that the distribution of theta waves varies significantly across brain regions depending on driving conditions and cognitive load. For instance, Li (2023) and Liu (2023) observed that theta activity rises in the frontal and temporal lobes as cognitive demands increase. In contrast, parietal activity weakens—suggesting a functional redistribution of neural resources during task engagement.

Similarly, Lin et al. (2011) found that solving cognitively demanding tasks increased frontal theta and beta power, potentially reflecting increased mental load and susceptibility to distraction. Additionally, Diaz-Piedra et al. (2020) reported that the frontal, temporal, and occipital areas' theta EEG power spectrum was higher during the most complex driving scenarios. Conversely, Savage et al. (2013) reported decreased frontal and occipital theta activity under high workload conditions. However, eye-movement artefacts may confound their findings, highlighting the need for methodological rigor in EEG research.

Alpha waves, commonly dominant during rest, typically increase in response to cognitive demands. In this study, the NCF group showed enhanced alpha activity in both the occipital and frontal regions during the GNG task compared to the eyes-closed condition. In contrast, the CF group exhibited increased alpha only in the frontal region and reduced occipital alpha power. Given the occipital lobe's role in visual processing and behavioral monitoring, this pattern could potentially reflect reduced efficiency in visual-cognitive integration among individuals with CF.

Previous research has shown that alpha activity tends to increase in the occipital region as cognitive workload intensifies and decreases in the frontal region. This may indicate a shift in resource allocation toward visual processing under cognitive strain (Liu et al., 2023). Thus, the reduced occipital alpha in the CF group may reflect deficits in visual attention and executive function, consistent with findings linking decreased occipital alpha power to impaired visual monitoring and slower cognitive processing (Arif et al., 2021; Ghojazadeh et al., 2024).

Beta waves, commonly linked to alertness, sustained attention, and complex information processing, generally increase during cognitively demanding tasks. Prior studies have demonstrated that distractions elevate frontal beta activity, while deeper cognitive load enhances beta power in the occipital lobe and reduces it in the parietal area (Liu et al., 2023). However, the CF group showed no significant change in frontal beta activity in our study, while parietal beta activity increased.

The parietal lobe integrates sensory inputs, spatial attention, and executive functions such as planning, decision-making, and attentional control. Some studies have reported decreased parietal beta activity under cognitive overload [16], but our results point to a different pattern. The observed increase in parietal beta activity in the CF group may be related to compensatory cognitive processes, particularly given its significant correlation with faster response times. However, as this interpretation is based on correlational data rather than a formal mediation analysis, it should be regarded as a preliminary hypothesis warranting further testing (Moessinger et al., 2021; Palmiero et al., 2019).

This interpretation is supported by prior research showing that parietal beta oscillations can increase with heightened task effort and may represent compensatory activation during cognitively demanding conditions (Daneshi et al., 2020). Nonetheless, due to inconsistencies in the literature—where beta activity is linked to cognitive engagement and mental overload—we present this interpretation cautiously and recommend further investigation into beta dynamics across varying task complexities.

Additionally, the NCF group exhibited enhanced beta activity in the occipital lobe during the cognitive task, highlighting beta's relevance to visual attention and reinforcing its role in task-related visual processing.

Gamma waves are believed to play a key role in neural synchronization and inter-regional brain communication, especially during cognitively demanding tasks (Leicht et al., 2021). The systematic review by Ghojazadeh et al. (2024) highlights that decreased gamma wave activity in central and temporal brain regions may be a biological marker for detecting fatigue and drowsiness in drivers. However, due to variability in findings across studies, EEG data should be used to identify driver fatigue and drowsiness with caution and careful interpretation. Furthermore, Leicht et al. (2021) demonstrated that gamma-band synchronisation significantly increases between frontal and temporal brain regions during cognitively demanding auditory tasks, reflecting enhanced neural communication and top-down control mechanisms. This supports the notion that gamma oscillations facilitate inter-regional coordination necessary for complex cognitive processing, which may be disrupted in conditions such as driver fatigue.

Although gamma reductions were observed in the CF group, and prior literature links gamma activity to cognitive integration, our data did not reveal a significant correlation between gamma power and behavioral outcomes in the GNG task. These findings may suggest—but do not confirm—a disruption in cognitive efficiency.

Although theta and alpha wave patterns differed descriptively across groups, these differences were not statistically significant. Therefore, while such patterns may suggest differential cognitive processing, the present findings do not support robust conclusions regarding their diagnostic utility in distinguishing between CF and NCF groups. A marked reduction in temporal lobe theta activity in the CF group during the GNG task suggests compromised memory and learning functions—capacities that are essential for managing complex driving situations. While both groups exhibited increased frontal theta activity during the task, the CF group's lower engagement may indicate diminished attentional control and reduced cognitive processing efficiency under task-related demands.

Conclusion

The absence of significant behavioral differences between the CF and NCF groups in the GNG task suggests that while this task effectively measures basic inhibitory control, it may lack the sensitivity to detect more subtle cognitive deficits associated with higher CFQ scores. Future research would benefit from incorporating cognitively demanding tasks—such as sustained attention or dual-task paradigms—to better assess real-world cognitive performance.

Among all frequency bands examined, gamma power emerged as the most consistent neural marker distinguishing CF and NCF participants, with a significant group-related topographical difference. While descriptive differences were observed in delta, theta, alpha, and beta bands across regions and conditions, these did not reach statistical significance and should be interpreted as preliminary patterns.

This suggests that EEG, particularly gamma-band activity, may offer sensitive indices of underlying cognitive differences not captured by overt behavior. However, further research with larger samples and task complexity is necessary to validate these trends and clarify their relevance for real-world cognitive performance.

Altogether, these results underscore the value of EEG in revealing cognitive dysfunctions that may not be evident through behavioral measures alone, supporting its application in future efforts to enhance driver assessment and safety strategies.

Limitations and further work

Several limitations should be acknowledged when interpreting the findings of this study.

Gender is an important factor influencing EEG patterns during cognitive tasks, and several studies have reported significant sex-related differences. In the present study, only male taxi drivers were included due to the demographic structure of the study region, where female drivers are virtually absent. As a result, the findings may not be generalizable to female populations, and future studies should address this limitation by including gender-diverse samples.

The GNG task is a well-established tool for assessing neurophysiological correlates of cognitive functions—particularly inhibitory control and attention—; however, it does not fully capture the complexity of real-world driving. Future studies should consider complementing it with driving simulators or more realistic driving scenarios to enhance ecological validity.

Variables such as education, cognitive workload outside driving, and lifestyle factors were not controlled and may influence EEG patterns. Including these covariates in future models would improve interpretive clarity.

As this study focused exclusively on urban drivers, its findings may not extend to individuals operating in non-urban or highway environments, where driving demands differ markedly. Replicating this research in varied driving contexts would help clarify how CFs manifest across road types.

The current analysis did not include traditional event-related potentials (ERPs), as the EEG system and software used (Encephalan-EEGR 121, Medicom MTD Ltd) were primarily optimised for spectral analysis rather than ERP extraction. While spectral power measures provided insights into frequency-specific neural activity associated with CF, future studies employing ERP-based systems could complement these findings by elucidating the temporal dynamics of inhibitory control.

Due to the limited sample size (n=30) and unequal group sizes (20 participants in the CF group and 10 in the NCF group), the analyses may have limited statistical power. Therefore, interpreting statistical results—particularly findings with marginal differences—should be cautiously approached. The use of larger and more balanced samples is recommended for future studies.

Ethical Considerations

Compliance with ethical guidelines

The experimental protocols used in this study were reviewed and approved by the Ethics Committee of Shiraz University of Medical Sciences, Shiraz, Iran (Code: IR.SUMS.SCHEANUT.REC.1402.037). Written informed consent was obtained from all participants. The authors confirm that all procedures followed the Declaration of Helsinki. Also, written informed consent was obtained from the participant depicted in Figure 2 for the use of their photo in an academic publication.

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Authors' contributions

Conceptualization: Zahra Sharifi; Study design and supervision: Reza Kazemi, Seyed Ruhollah Hosseini, and Shohreh Sadeghi; Data collection: Zahra Sharifi and Mohebat Vali; Data analysis: Amir Pour Mohammadi and Mozhgan Seif; Writing the original draft: Zahra Sharifi and Reza Kazemi; Review and editing: Reza Kazemi and Seyed Ruhollah Hosseini; Final approval: All authors.

Conflict of interest

The authors declared no conflict of interest.

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