applied sciences

Review

Brain–Computer Interface (BCI) and Neuroergonomics Applications in Transportation Systems: An Overview of Current Trends and Future Perspectives

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Abstract

A brain–computer interface (BCI) is a complex system that allows humans to interact with physical devices by analysing and interpreting brain signals obtained from neuroimaging modalities (electroencephalography, electrocorticography, magnetoencephalography, intracortical neuron recording, functional magnetic resonance imaging, etc.). BCI applications in robotics and medicine have demonstrated invaluable benefits. The rise of BCI technology and neuroergonomics techniques could also provide promising solutions in transportation systems, particularly in smart roads, vehicles, and traffic regulation systems. This narrative literature review examines how, in the age of smart transportation systems and self-driving vehicles, different far-future applications of BCI systems could be integrated to enhance the safety and capacity of transportation systems.

Keywords: brain–computer interface (BCI); transportation systems; infrastructures; smart roads

1. Introduction

The brain is the most complex organ in the human body. It is a soft mass made up of billions of active neurons. The main portions of the brain are the cerebrum, the cerebellum, and the brain stem. The cerebrum comprises four lobes: frontal, parietal, occipital, and temporal. The frontal lobe, the temporal lobe, the parietal lobe, and the occipital lobe are responsible for reading, learning, thinking, emotions, walking, vision, and hearing (in terms of senses) [1]. The cerebellum is responsible for balance and coordination. The brain stem is liable for the heartbeat, breathing, blood pressure, swallowing, and eye movements [1]. The primary motor cortex in the frontal lobe is usually responsible for limb movement [2]. Brain neurons communicate with each other by emitting tiny electrical signals called impulses. Human factors [3], also known as ergonomics or human factors engineering, is a discipline devoted to understanding the interactions between humans and other system elements. In transportation engineering, human factors are used to design all types of transport vehicles and infrastructures. For example, in roads and highways, the infrastructure design (e.g., vertical and horizontal alignment) is strongly related to users' psychotechnical performance, perception–reaction time, attention levels, and mental workload. Obviously, psychotechnical performance is a manifestation of the users' brain activity. The human brain is amazingly complex, and its processes at every level are chaotic, unstable, nonlinear, non-stationary, non-Gaussian, asynchronous, noisy, and unpredictable [4]. However, there is growing interest in using brain activity for communication and the operation of

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physical devices across various human applications, including transportation systems. A brain–computer interface (BCI), also called a brain–machine interface (BMI), is a complex system that allows humans to interact with the environment by analysing brain signals, primarily via electroencephalography (EEG), without any intermediate intervention from peripheral nerves and muscles. The BCI has already been used in multiple applications, mainly aimed at improving the lives of people with severe disabilities and enabling them to operate technical devices and external medical equipment, such as computers, speech synthesisers, and neural prostheses. BCI systems are particularly attractive for people with severe motor disabilities. In a certain way, a brain interface system (BCI) represents a communication bridge between the brain activity of an individual and a device, completely bypassing the role of nerves and muscles. Therefore, the BCI is a particularly useful system for people with severe motor disabilities or partially or totally affected by neuromuscular or neurological disorders, such as lateral sclerosis, cerebral stroke, or spinal cord injury due to accidents of various types, including road accidents, which cause around 1.19 million deaths each year worldwide. In 2023, road crashes in the member states of the European Union claimed about 20,384 lives and injured more than 1.14 million people.

This study adopts a narrative literature review methodology focused on brain–computer interface (BCI) systems and their speculative applications in transportation engineering and smart mobility systems, along with their limitations and ethical problems.

More specifically, recent innovations in brain–computer interfaces (BCIs) and neuroergonomics are presented, which could be applied to transportation systems in the near future, thereby improving cooperation between humans and vehicles, as well as between physical infrastructures, while also increasing safety, sustainability, and capacity. After examining the most relevant systems for measuring brain activity, we explore potential applications of non-implantable and implantable BCIs in transportation systems. These techniques are already widely employed in certain fields, such as aerospace; therefore, it is reasonable to assume they will also be adopted in road transportation infrastructure, including smart roads, in the near future. These aspects are discussed in the following paragraphs, although the proposed scenarios should be regarded as speculative perspectives and emerging trends.

The remaining article is organised as follows: Section 2 briefly presents the research methodology. Section 3 describes the general aspects of BCIs and the neuroimaging modalities, along with the main brain activity measurement systems and performance metrics. Section 4 explores enabling technologies for smart roads and covers potential neuroergonomics and BCI applications in transportation systems, with a particular focus on smart road systems. Section 5 presents the limitations of this study, the research gap identified from the analysis of previously published papers' results, and future directions. Conclusions are given in Section 6.

2. Research Methodology

This article gives an overview of some recent advances in brain–computer interfaces (BCIs) and neuroergonomics, focusing on their potential applications in future transportation systems. After examining the main techniques for measuring brain activity, both non-implantable and implantable BCIs are considered in the context of smart mobility and road infrastructures. Since these technologies are already widely adopted in fields such as aerospace, they may also enhance human–vehicle interaction, safety, sustainability, and transportation capacity in the near future. Nevertheless, the proposed applications should be regarded as emerging and partly speculative perspectives. The scientific literature was collected from major international databases, including Scopus, Web of Science, IEEE Xplore, and ScienceDirect. The literature search was performed using combinations of the following keywords: "Brain–Computer Interface", "BCI", "Brain–Machine Interface", "Neuroergonomics", "Transportation Systems", "Smart Roads", "Autonomous Vehicles", "Connected and Automated Vehicles", "EEG", "fMRI", "Human Factors", and "Mobility as a Service".

The review mainly considered peer-reviewed journal articles, conference proceedings, and technical reports published in recent years and relevant to neuroscience, transportation engineering, robotics, artificial intelligence, and human–machine interaction in the period 1984–2025. Studies not directly related to BCI technologies or transportation applications were excluded. Overall, several hundred publications were initially identified, while the final selection focused on the most relevant and influential studies concerning neuroimaging modalities, BCI architectures, neuroergonomics, and speculative future applications in smart transportation systems. The analysis was ultimately limited to the 84 most significant scientific documents, grouped by time period as follows: Human Factors (1980–2005); Neuroimaging + EEG (2005–2015); BCI + Robotics (2015–2020); AI + Neuroergonomics + Smart Transport (2020–2023); Neuroscience—AI + Smart Infrastructure + Implantable BCI (2023–2025). Figure 1 shows the co-network map based on the five main clusters considered in the study:

1. BCI;
2. Neuroimaging and Brain Mapping;
3. Human Factors and Driving Neuroscience;
4. Robotics and Autonomous Systems;
5. Smart Systems and Infrastructure.

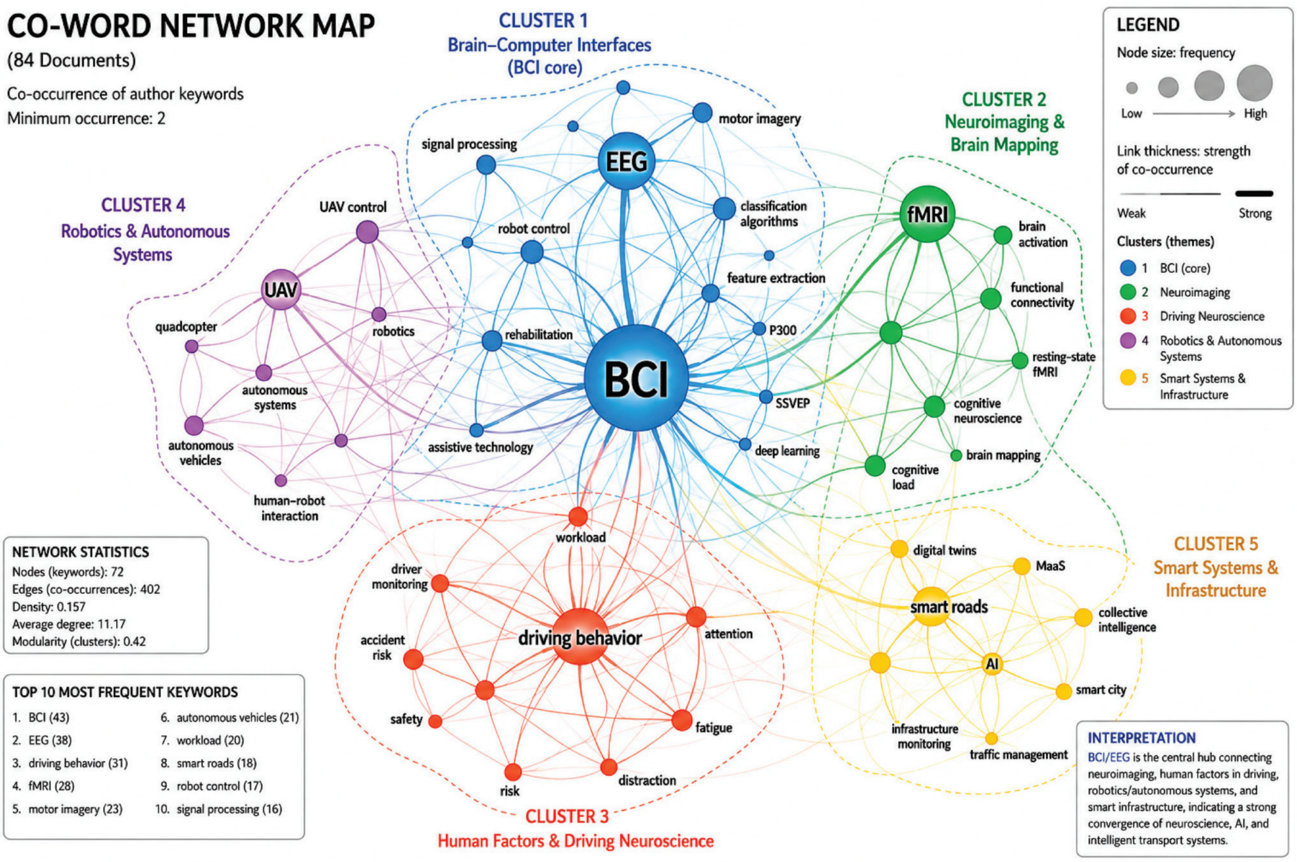


Figure 1. The term co-occurrence maps, obtained for five main clusters (BCI, Neuroimaging and Brain Mapping, Human Factors and Driving Neuroscience, Robotics and Autonomous Systems, Smart Systems and Infrastructure).

Since scientific studies have demonstrated that road accidents are closely linked to the human factors of drivers [5,6] and to road design standards and traffic regulation systems [7,8], it can be inferred that technological innovations produced in the field of neuroergonomics and the applications of BCI systems in road transport systems will soon be able to contribute to making the road transportation system safer and more comfortable.

3. Background

Brain–computer interfaces (BCIs) may use specific neuroimaging modalities, including electroencephalography (EEG), electrocorticography (ECoG), magnetoencephalography (MEG), intracortical neuron recording, and functional magnetic resonance imaging (fMRI) (Figure 2). There are two very different neuroimaging categories: structural neuroimaging, which is able to capture the brain structure (skull bone structure, tissues, blood vessels, etc.) and functional neuroimaging, which allows the detection of brain electrical impulses as a reaction to a specific task or stimulus.

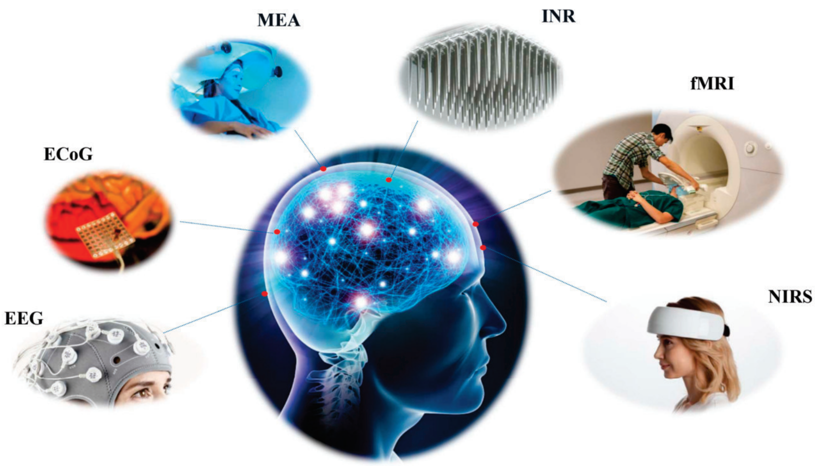


Figure 2. Commonly used methods for recording brain activity.

3.1. BCI Systems: Methods for Recording Brain Activity

The current neuroimaging-based approaches are as follows [1,2]:

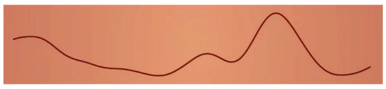
- Electroencephalography (EEG), which uses electrodes (Ag/AgCl, known as nonpolarised electrodes) or disposable electrodes (single-use electrodes called gel-based or bio-potential electrodes) placed on the human scalp to acquire brain electrical signals exported in the form of a polygraph;
- Electrocorticography (ECoG): the brain's electrical signals are obtained through electrodes placed under the skull (either above the epidural or below the subdural);
- Magnetoencephalography (MEG) allows the evaluation of brain activity by measuring the magnetic fields created by charged ions excited within neuron cells. MEG signals are more reliable and provide faster BCI communication than EEG signals because they offer higher temporal resolution (milliseconds). Furthermore, it is a non-invasive technique that does not require the injection of isotopes or exposure to X-rays or magnetic fields;
- Intracortical neuron recording (INR) measures electrical activity inside the grey matter, which is associated with human intelligence and intellect. To achieve this goal, various types of microelectrode arrays implemented inside the brain cortex can be used;
- Functional magnetic resonance imaging (fMRI) employs magnetic resonance imaging (MRI) to investigate the brain activation map correlated with brain activity. An fMRI scan measures blood flow to different regions of the brain. Since brain areas involved in a specific mental process consume more oxygen and therefore require an increased

blood flow compared to other areas of the brain, the measure of blood flow allows indirect investigation of the levels of neural activity;

- Near-infrared spectroscopy (NIRS) uses light in the near-infrared region of the electromagnetic spectrum (780–2500 nm) to penetrate the skull either in the frontal cortex or occipital cortex to measure the haemodynamic alterations accompanying brain activation (oxygenated haemoglobin and deoxygenated haemoglobin levels). More precisely, NIRS provides continuous measures of changes in oxygenated haemoglobin (HbO), deoxygenated haemoglobin (HbR), and total haemoglobin (HbT) concentrations. Compared to fMRI, NIRS appears to be more advantageous because it requires portable measuring devices and is cheaper.

The most commonly used control signal in BCI systems is EEG, a non-invasive technique that uses electrodes placed on the scalp (usually called "scalp EEG") according to the International 10–20 system. EEG tests are characterised by low cost, simplicity, and exceptional time resolution (milliseconds). The output of the EEG is an electrogram in which the frequencies are categorised into different types: alpha (8–13 Hz, with 30–50 µV amplitude), beta (13–35 Hz, voltage between 5 and 30 µV), gamma (35 and 100 Hz), delta (0.5–4 Hz), and theta (4–8 Hz) (Table 1). The detectable rhythms may change depending on the function of the type of action and stimulation. More precisely, alpha waves are detected when a person is in relaxed wakeful conditions and are mostly prominent over the parietal and occipital sites. Beta waves are more prominent in frontal areas and other regions during intense mental activity and when concrete problems must be solved. In contrast, theta and delta waves are not generally observed in wakefulness—if they are, it indicates brain dysfunction. Since the signals are weak, amplifiers must be used to handle the original time signal.

Table 1. Main patterns of neural oscillation in humans.

Frequency Band	Frequency [Hz]	Brain States	Example
Delta (δ)	0.5–4	Sleep	
Theta (θ)	4–8	Deeply relaxed, passive attention	
Alpha (α)	8–12	Very relaxed, passive attention	
Beta (β)	13–35	Anxiety dominant, active, external attention	
Gamma (γ)	35–100	Concentration	

EEG is subjected to a minimal signal-to-noise ratio (SNR) due to a plethora of noise sources, which can be broadly categorised as environmental noise (like power line interference) and biological artefacts like electrooculargraphic activity (EOG, eye activity), electromyographic activity (EMG, movements and muscle activity), and electrocardiographic activity (ECG, heart activity), ballistocardiographic activity, and respiration. Since the primary purpose of a BCI is to convert brain activity into a command for a computer, regression or classification algorithms must be used to analyse EEG data.

Currently, the most widely used procedures for identifying 'patterns' of brain activity rely on classification algorithms that address, and partially solve, the curse of dimensionality and the bias–variance trade-off. Various classification algorithms are generally used, as shown in Table 2. They are divided into five different categories: linear classifiers, neural networks, non-linear Bayesian classifiers, nearest-neighbour classifiers, and combinations of classifiers [9]. Since the application of BCI technologies to transportation systems is a relatively new and rapidly evolving research field, only extensive future deployment will determine which classification algorithms are most effective in terms of both accuracy and real-time data processing performance.

Table 2. Classification algorithms (adapted from [9]).

Classifier	Properties									
	Linear	**Non-Linear**	**Generative**	**Discriminant**	**Dynamic**	**Static**	**Regularised**	**Stable**	**Unstable**	**High-Dimensional Robust**
FLDA	✓			✓		✓		✓		
RFLDA	✓			✓		✓	✓	✓		
Linear-SVM	✓			✓		✓	✓	✓		✓
RBF-SVM		✓		✓		✓	✓	✓		✓
MLP		✓		✓		✓			✓	
BLR NN		✓		✓		✓			✓	
ALN NN		✓		✓		✓			✓	
TDNN		✓		✓	✓				✓	
FIRNN		✓		✓	✓				✓	
GDNN		✓		✓	✓				✓	
Gaussian NN		✓		✓		✓			✓	
LVQ NN		✓		✓		✓			✓	
Perceptron	✓			✓		✓		✓		
RBF-NN		✓		✓		✓			✓	
PeGNC		✓		✓		✓	✓		✓	
Fuzzy ARTMAP NN		✓		✓			✓		✓	
HMM		✓	✓		✓				✓	
IOHMM		✓		✓	✓				✓	
Bayes quadratic		✓	✓			✓			✓	
Bayes graphical network		✓	✓			✓			✓	
kNN		✓		✓		✓			✓	
Mahalanobis distance		✓		✓		✓			✓	

3.2. BCI Systems: Main Brain Activity Measurement Systems and Performance Metrics

Brain–computer interfaces (BCIs) based on neuroimaging-based approaches can offer an invaluable way for humans to communicate and interact physically with the outside world. The BCI is an emerging, innovative discipline that combines AI, computer science, system recognition, pattern recognition, and robotics [10]. The intriguing idea of deciphering brain signals into direct, indirect, and implicit control commands for various devices has been the primary motivation for numerous scientists worldwide to focus their research on developing BCI-based systems. BCIs are currently used in many fields of human activity, including medical rehabilitation, entertainment, education, the military, transportation, aerospace, and space exploration [11]. BCI systems can be classified as exogenous systems, which stimulate the brain with external stimuli to generate specific responses, and endogenous systems, which are based on the self-regulation of brain rhythms and do not require external stimuli but do require the user's attention.

Among exogenous BCIs, motor imagery (MI) plays a fundamental role in engineering applications. In general terms, MI is a mental process by which an individual simulates, mentally, in their own brain, a given action. It is widely utilised in sports training as a mental practice of action, in neurological rehabilitation, to assist patients with severe motor disabilities, for the diagnosis of disorders of consciousness, and for entertainment applications. The BCI performance is the capacity to efficiently convert user intentions, as measured by brain activity, into correct actions [12]. The most important metrics used for evaluating the BCI performance are the accuracy, kappa, false-positive rate (FPR), true-positive rate (TPR), and information transfer rate (ITR), obtained through the following relationships [12]:

$$\text{Kappa} = \frac{\text{A} - 1/\text{NC}}{1 - 1/\text{NC}} \tag{1}$$

$$\text{FPR} = \frac{\text{FP}}{\text{TN} + \text{FP}} \tag{2}$$

$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

where A is the observed accuracy (i.e., the percentage of correctly classified commands by the BCI), NC is the number of classes/categories, and FN, TN, FP, and TP denote the numbers of false negatives, true negatives, false positives, and true positives, respectively.

The ITR is a measure of the amount of information transferred per unit of time:

$$\text{ITR} = s\left[\log_2(\text{N}) + \text{A}\log_2(\text{A}) + (1 - \text{A})\log_2\left(\frac{1 - \text{A}}{\text{N} - 1}\right)\right] \tag{4}$$

where N is the number of commands, A is the accuracy value (i.e., classification accuracy), and s is the selection rate (number of decisions per second). It can be observed that, for a fixed number of N commands, the ITR increases with the accuracy A.

3.3. EEG Applications for BCI Systems

During MI, the sensorimotor mu rhythm (i.e., synchronised patterns, usually in the 8–10 Hz range of electrical activity involving large numbers of neurons in the part of the brain that controls voluntary movement) and beta rhythm modify the original frequency components. Consequently, users' real motion intentions can be understood [13]. Brain signal acquisition, signal processing, and output equipment are essential in MI-BCI systems. For brain signal acquisition during brain activities, several techniques are employed, such as (1) electroencephalography (EEG), (2) magnetoencephalography (MEG), (3) functional magnetic resonance imaging (fMRI), (4) functional near-infrared spectroscopy (fNIRS), (5) single-photon emission tomography (SPECT), and (6) proton emission tomography (PET). EEG signals are the most used form of information for BCI applications because, in the case of an intention to move, specific patterns appear in the EEG about 0.5 s to 2 s before the movement. Then, the intention becomes a physical action [14]. However, EEG signals are affected by several problems that cannot be fully overcome. Among these, we can mention the signal's non-linearity and weakness, small frequency range, strong noise, strong randomness, and non-stationarity [4]. Evocation paradigms can be grouped into single-MI and hybrid-MI paradigms. Single MI relies on EEG and therefore suffers from several serious deficits, such as low accuracy and reliability, a low information transfer rate, and poor user acceptability [15]. To eliminate these problems, a hybrid, multimodal control approach has been developed. Hybrid MI combines EEG signals and other signal types, including electromyography, fMRI, NIRS, and electrooculography, or mixes the two features of EEG signals [13]. Traditionally, most BCI applications have been focused on helping people with motor disabilities; however, over the past decade, BCI systems have been used in numerous everyday contexts. Some of the most interesting validated applications of MI-BCI systems to date, as well as their main speculative applications and potential future extensions, fall into the following categories (Figure 3) [13,15,16]:

- Medical rehabilitation (e.g., electric wheelchairs, orthosis, artificial arm and bionic prosthetics, lower limbs, etc.);
- Means of communication for patients (e.g., virtual keyboards and the P300 speller);
- Robots (e.g., humanoid robots, quadruped robots, exoskeleton robots);
- Vehicles (virtual helicopters, quadcopters, hexacopters, drones, radio-control (RC) cars, tractors, aircraft, etc.);
- Mental workload of users [17].

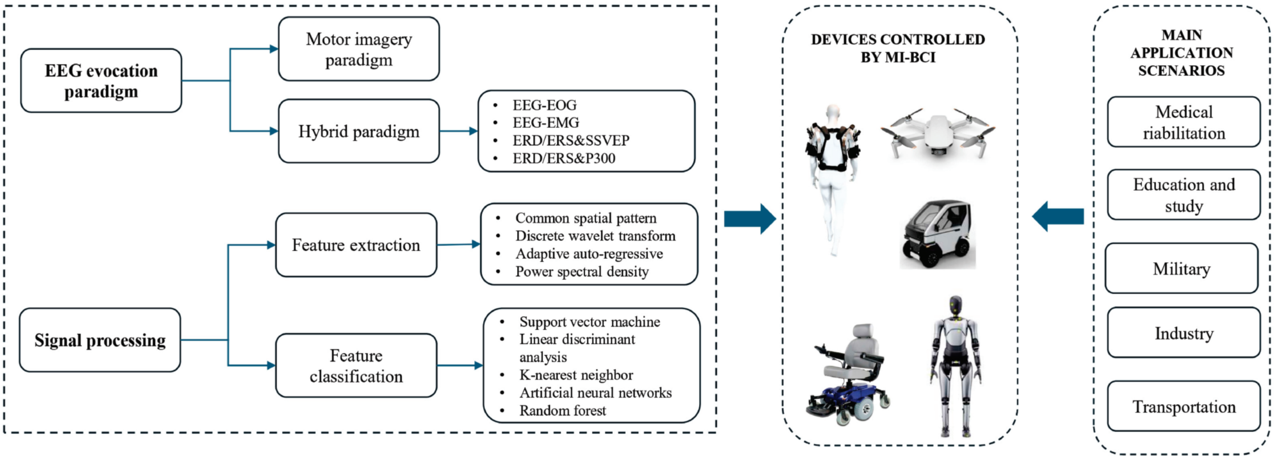


Figure 3. Overview diagram of the main speculative applications and future scenarios based on IM-BCI systems.

It is important to note that, among the BCI applications illustrated in Figure 3, some have already undergone empirical validation (particularly those associated with medical rehabilitation), whereas others are currently supported only by simulation-based evidence or remain conceptual extrapolations, especially within industrial contexts. Regarding transportation systems, empirically validated BCI applications are currently limited primarily to the aerospace sector. In contrast, the implementation of BCI technologies in terrestrial transportation systems, including road and railway networks, should still be regarded as a potential long-term future scenario. In any case, one of the main classification problems in BCI systems based on EEG signals is the bias–variance trade-off [9].

The bias–variance trade-off could be particularly important for BCI applications in transportation systems, as EEG-based control and monitoring require highly reliable classification in dynamic, safety-critical environments. In such contexts, minimising the mean square error (MSE) and classification errors is essential to ensure accurate interpretation of users' cognitive states, thereby reducing the risk of incorrect commands or unsafe decisions in vehicle operation. Moreover, since EEG signals are inherently non-stationary, stabilisation and variance-reduction techniques are crucial for improving the robustness of BCI systems for future transportation applications.

In the classification process, it is required to find the true label y^* of the feature vector x using a mapping f. From the training set T, the mapping f is learnt. Denoting with f^* means the best mapping that has produced the labels is unknown. For these applications, the mean square error (MSE) and classification errors can be subdivided into three different components of errors, namely, noise within the system (irreducible error), bias (divergence between the estimated mapping and the best mapping), and variance (function of the sensitivity of the training set T used). Then, analytically, we have the following [9]:

$$\begin{aligned}\mathrm{MSE} &= \mathrm{E}\left[(\mathrm{y}^* - \mathrm{f}(\mathrm{x}))^2\right] \\ &= \mathrm{E}\left[(\mathrm{y}^* - \mathrm{f}^*(\mathrm{x}) + \mathrm{f}^*(\mathrm{x}) - \mathrm{E}[\mathrm{f}(\mathrm{x})] + \mathrm{E}[\mathrm{f}(\mathrm{x})] - \mathrm{f}(\mathrm{x}))^2\right] \\ &= \mathrm{E}\left[\mathrm{y}^* - \mathrm{f}^*(\mathrm{x}))^2\right] + \mathrm{E}\left[(\mathrm{f}^*(\mathrm{x}) - \mathrm{E}\left[\mathrm{f}(\mathrm{x})\right]^2)\right] + \mathrm{E}\left[(\mathrm{E}[\mathrm{f}(\mathrm{x})] - \mathrm{f}(\mathrm{x}))^2\right] \\ &= \mathrm{Noise}^2 + \mathrm{Bias}(\mathrm{f}(\mathrm{x}))^2 + \mathrm{Var}(\mathrm{f}(\mathrm{x})\Big)\end{aligned} \tag{5}$$

From Equation (5), it is simple to argue that the bias and the variance must be small to achieve an acceptable classification error. In general, stable classifiers tend to have high bias and low variance; conversely, unstable classifiers have low bias and high variance. Since EEG signals are non-stationary, several stabilisation techniques are used in BCIs to reduce variance [4]. Despite the problems mentioned above, EEG was extensively used in several BCI applications, for instance, to control even complex vehicles like quadcopters in 3-D open areas, as shown in [18], where the brain activity was recorded in real-time and patterns discovered to relate it to users' facial expression states with a cheap off-the-shelf electroencephalogram (EEG) headset, the Emotic Epoc device. In the study [18], EEG signals from six electrodes during different facial movements (smile, eyebrow, wink) were examined. A PCA, also known as the Karhunen–Loève transformation [19], which maximises variance reduction and provides an effective method for dimensionality reduction, was then applied. The model is briefly summarised as follows: Consider k samples with n-dimensional input vectors $\mathbf{X_1}, \mathbf{X_2}, \ldots \mathbf{X_k} \in \mathbf{R^n}$. The expected mean vector of the data set is denoted as

$$\boldsymbol{\psi} = \frac{1}{k}\sum\nolimits_{\mathbf{i}=1}^{\mathbf{k}} \mathbf{X_i} \tag{6}$$

The array $[\boldsymbol{\Phi}_1, \boldsymbol{\Phi}_2, \ldots, \boldsymbol{\Phi}\mathbf{k}]$ can be considered, where $\boldsymbol{\Phi}_\mathbf{i}$ is obtained as the difference between $\mathbf{X_i}$ and $\boldsymbol{\psi}$. The covariance matrix is calculated with the relation

$$\mathbf{C} = \frac{1}{\mathbf{k}}\boldsymbol{\Phi}\boldsymbol{\Phi}^\mathbf{T} \tag{7}$$

The first m (m < n) eigenvectors of $\mathbf{C}$ were named as principal components and computed. Different principal components and the covariance matrix were extracted from the EEG during the experiment for different facial expression states. Then, the unknown principal components were compared with those of different facial expression states to indicate which state was displayed.

Some researchers have recently proposed innovative devices based on BCI systems that integrate augmented reality (AR), computer vision, and steady-state visual-evoked potential to control robots or for inspection purposes [20,21]. AR technology enables the creation of a three-dimensional virtual space where users can interact with virtual elements that reproduce physical ones through sight, hearing, touch, and other senses [22]. It is therefore possible to control and manage robots or other technological devices that adopt the BCI system through virtual reality. In this way, what the operator performs in the virtual world is then "projected" into the real world using real robots or other automated devices. This can also lead to a higher level of human–computer interaction.

Moreover, recent studies have combined AR with simultaneous localisation and mapping (SLAM), a technique that enables robots or other vehicles (e.g., drones, self-driving cars) to navigate an unknown environment while simultaneously localising their position within it [22]. To this end, LiDAR sensors, an IMU (Inertial Measurement Unit), and cameras are employed [9].

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3.4. fMRI-Validated Applications in BCI Systems

From the viewpoint of transportation engineering science, driving is a complex task that involves numerous cognitive capacities, including concentration, memory, decision-making, and alertness, to adapt to a rapidly changing, complex environment [23]. Driving performance depends profoundly on how the human brain receives and processes different stimuli from the surrounding environment and the vehicle being driven. Driving ability can be scientifically assessed by neuropsychological tests (NPTs). Many studies on driving activities in virtual reality (VR) or driving software (e.g., STISIM Drive Software) and video games have used fMRI to detect brain areas and neuronal clusters involved in the task and to analyse various neurophysiological aspects [22,24]. In a VR environment, stimuli or tasks that in real contexts could be impractical, dangerous, unethical, or even impossible can be applied. In simple, straight driving, the parietal and occipital regions were observed to be more involved than the others [25]. Different activations of the brain during driving tasks can be considered:

- In driving-only conditions, the frontal region, parietal region, temporal region, occipital region, limbic region, sub-lobar region, and cerebellum;
- During driving with sub-task conditions, the frontal region, parietal region, temporal region, occipital region, limbic region, sub-lobar region, and cerebellum.

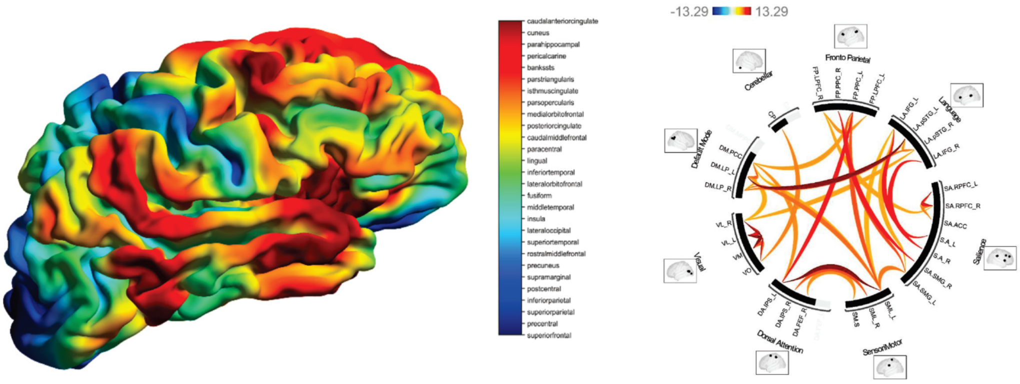
Blood oxygenation level-dependent (BOLD) imaging, as measured by fMRI, can map brain activity via neurovascular coupling, which produces haemodynamic changes in response to neuronal activity. BOLD signal fluctuations of neuronal origin should be mainly located in the grey matter (GM). EEG and fMRI are the two most frequently used non-invasive functional neuroimaging techniques [26] and have substantially complementary properties.

FMRI and fNIRS require real-time mode practice, but they offer high resolution. Conversely, EEG can be used in real time, but it produces lower-resolution information than that obtained with fNIRS and fMRI equipment [14,18]. In the future, fMRI can also be employed as a valuable tool in MI-BCI systems to obtain significant results in real-time systems [14]. Hybrid brain–computer interface (hBCI) systems have been developed to overcome the aforementioned limitations of single BCIs in terms of precision, accuracy, and information transfer rate (ITR) by combining multiple BCIs [27].

EEG-informed fMRI is a multimodal control approach analysis system that combines the high temporal resolution of electroencephalography (EEG) with the high spatial resolution of functional magnetic resonance imaging (fMRI) to study brain activity. This approach uses EEG data to inform fMRI analysis, enabling researchers to investigate brain activity patterns with greater precision and detail. However, also in EEG-informed fMRI, the following steps are required to control a vehicle by using a BCV: (1) preprocessing of bio-signals, (2) feature extraction, (3) optimisation, (4) feature selection, (5) classifiers, (6) statistical analysis, (7) real-time experiments.

The potential of hybrid BCV systems has been demonstrated, for example, in [17,26,27] for quadcopter control. In [28], the possibility of decoding eight commands (four from EEG signal acquisition and four from fNIRS signal acquisition) from the frontal and prefrontal cortices by combining EEG and fNIRS to drive a quadcopter was explored.

fMRI is used to generate activation maps to investigate cooperation among several brain regions (functional integration). fMRI techniques lead to connectivity maps of the brain [29]. In general terms, functional connectivity refers to the statistical dependence between neurophysiological recordings from distinct brain regions and allows the quantification of functional interactions within brain networks [30]. An fMRI data set consists of a time series of volume data sets, so each data point in an fMRI data set has a unique coordinate (x, y, z, t) in 4D space, R^4, where x, y, and z are spatial coordinates and t is time. The results of an fMRI analysis are, for instance, expressed as time series of EPI (echo planar imaging), time series associated with each (3D) voxel [28], and regional homogeneity analysis (ReHo) (i.e., a voxel-based measure of the similarity between the time series of a given voxel and its nearest neighbours [31]). Some interesting results from an fMRI analysis are shown in Figure 4, including volumetric renders and the connectome [32–34]. More specifically, Figure 4a visualises structural and functional neuroimaging data from cross-sectional or longitudinal studies, obtained by processing a sample of brain data using the open-source neuroimaging toolkit of the “FreeSurfer” software.



(**a**) (**b**)

Figure 4. (**a**) Example of brain volumetric renders; (**b**) example of connectome (data from [33]).

3.5. NIRS Applications in BCI Systems

Inferences about brain activity with fMRI are obtained through metabolic feedback, such as indirect responses to neuronal activity. NIRS systems, however, penetrate deeply into the brain tissue, providing both haemodynamic responses and neuronal responses correlated with brain activity. Generally, the hardware used in NIRS techniques is lightweight and portable. In very simplified terms, it consists of a pair of light-emitting and receiving optical fibres and a small unit securely attached to the user’s head. The incident radiation, emanating from the physical device, causes spectral refraction, diffuse reflection, or absorption. fNIRS does not necessitate devices to be inserted into the brain, avoiding potential brain damage. While fMRI requires the subject to maintain a fixed, well-defined spatial position, NIRS systems allow the monitored subject considerable mobility, as the sensor–detector unit can be easily affixed to the skull.

3.6. Implantable Brain–Computer Interface (IBCI)

One of the most fascinating frontiers in neural engineering concerns the implantation of invasive microchips into the human brain. Brain chipping can boost human cognitive capacities while also providing answers to various brain–computer, vehicle, robot, or other external gadget interactions [35]. Possible far-future applications include enhancing memory, learning speed, concentration, and focus, increasing capacity for solving complex problems (e.g., driving a vehicle), creativity, and inventiveness, and increasing intelligence quotient (IQ) [35–37]. Deep brain stimulation (DBS) and responsive neurostimulation (RNS) are among the most studied potential medical applications for improving the quality of life of people with neurological conditions, including epilepsy, paralysis, and Parkinson’s disease. Finally, microchip implants may establish a novel paradigm for a brain–computer interface system, i.e., an implantable brain–computer interface (IBCI). Many such devices are in development. However, in 2023, the Neuralink device received approval from the US FDA to begin human trials, allowing for the control of a computer with thoughts. The first device of Neuralink, called the “N1 Telepathy Implant”, once surgically placed, is cosmetically invisible, and it can record and transmit brain activity to enable humans to communicate with computers [38]. This implant uses 3072 electrodes per array distributed across 96 threads, each thinner than a human hair, to achieve high-density neural recordings [39]. Neuralink also designed a specific robot (R1) with micron-level accuracy for implanting the N1 Implant into brains and a user app (BCI software) that enables individuals to control external devices [40] (Figure 5).

Figure 5. Neuralink IBCI system (source: [40]).

According to some scholars, the use of ICBI systems could, in the future, improve quality of life and expand human capabilities, both in terms of intellectual capacity and interaction with the physical environment and various types of devices, including vehicles and transportation infrastructure. More precisely, potential non-therapeutic IBCI applications can be inferred from Neuralink's stated goal to "unlock human potential" [41]. As in the more conventional, non-implantable BCI systems, a few machine learning and deep learning algorithms have been proposed to correctly decode movement intentions in real time. However, numerous bioethical, neuroethical, and philosophical–psychological debates about the long-term stability and safety, ethics, and personal and collective risks of using IBCIs are currently underway in academia and the media [42,43]. More precisely, the use of IBCIs in transportation systems raises significant ethical concerns, particularly regarding privacy and security. Because these technologies can access neural data directly from the brain, sensitive information related to thoughts, intentions, and emotions could be exposed, misused, or manipulated. When integrated into vehicles or intelligent transport networks, IBCIs may also become vulnerable to cyberattacks or unauthorised access, potentially affecting users' decisions and safety. In addition, continuous brain monitoring may threaten mental privacy, individual autonomy, and informed consent, while system failures or interference could create complex issues relating to responsibility and liability in the event of accidents. Finally, unequal access to such technologies may contribute to new forms of social inequality in future mobility systems.

4. Neuroergonomics and BCI Speculative Applications in Transportation Systems

Neuroergonomics is the scientific discipline that explores how brain activity relates to human performance in everyday settings, specifically during work tasks. As stated in [44], "*Neuroergonomics focuses on investigations of the neural bases of mental functions and physical performance in relation to technology, work, leisure, transportation, health care and other settings in the real world*". It embraces scientific and practical principles from neuroscience, ergonomics, human factors, and engineering to plan and design innovative, efficient, and safer systems, devices, technologies, and working conditions.

It should be emphasised at this point that human capabilities and their psychophysical specificities, as well as human factors, have always been at the core of the design of infrastructure and transport vehicles for both civilian and military purposes. Modern transport vehicles and their infrastructure constitute a robotic system as a whole; they can, to varying degrees of independence, carry out work in place of humans. Studies, technologies, and applications relating to human–robot interactions could be usefully employed for the new transportation system paradigm here denoted as the "Human–Transportation System Interface" (HTSI). In fact, given recent innovations in transport systems, smart infrastructure, telecommunications technologies, and autonomous driving systems, it is possible to infer that, soon, a close union between smart mobility, neuroergonomics, and BCIs will become a concrete human reality. Some speculative technical applications are briefly examined below. First, it is useful to consider that, in transportation engineering, techniques such as fMRI have proven to be valuable tools in several research and practical applications, including the following:

- Brain activation analysis during driving tasks with an fMRI-compatible driving simulator;
- Measuring the brain activity and mental workload of professional and inexperienced drivers [45,46];
- Evaluating the effect of training on different body parts after a stroke in road users [46];
- Examining the neural substrates of primary driving-like behaviour with and without cellular conversation [40];
- Exploring the changes in spontaneous regional activity in post-traumatic stress disorder (PTSD) and abnormal neuronal activity in road users who experienced severe traffic accidents [47];
- Studying the chronic pain symptoms after motor vehicle crashes [48];
- Suitable tools for pre-implantation cortical mapping and electrode target localisation for pre-implantation localisation of BCIs in children and adults [49];
- Analysing the accident risk during car-following driving tasks with and without additional language and auditory tasks [50];
- Analysing the performance of professional pilots employed in civil aviation [51];
- Studying the spatial perception of users of vehicles and transportation infrastructures;
- The analysis of the effect of the horizontal and vertical alignment of road infrastructures on users' behaviours and brain activities, and how a monotonous environment (e.g., empty and decorated sidewalls) may result in a propensity of driving errors (distraction, speed and trajectory faults), both in open cross-sections and tunnels [52];
- Applying neuroergonomics techniques [44] able to combine psychological and neuroscientific models of users' behaviours in transportation systems to better understand the mutual correlation between users, vehicles, infrastructure, and environment [53];
- Meeting the new challenges posed by automation in transportation systems (e.g., self-driving cars [54] and partially automated driving tasks [55,56]);
- Analysing drivers' cerebral areas engaged when being alerted by a specific vehicle auditory warning system (e.g., a lane departure warning system, LDWS) [57].

4.1. Aerospace Transportation Systems

Human anatomy and physiology are the consequence of evolution on Earth. Thus, the space environment is inherently hostile and dangerous to the human body and psyche for many reasons, including extreme temperatures, lack of orientation, vacuums, radiation, and microgravity.

For this reason, astronauts' extravehicular activity (EVA), like exploration, must be kept to a minimum and conducted as safely as possible; therefore, where astronauts' presence is not strictly necessary, robotic systems are preferred. For both EVAs and robots, there are numerous concrete advantages to using BCI systems. For example, technical tasks can be performed via teleoperation to control machines, either by individual astronauts or by multiple astronauts simultaneously. BCI-controlled robotic aids could also be used to assist astronauts weakened after many months in microgravity, as demonstrated in some validated applications and simulator-based studies.

Another advantage is so-called shared control, in which there are essentially two intelligent agents: the human user (astronaut) and the robot [4,58]. The user simply transmits their intentions to the robot via BCI systems, and the robot then autonomously performs the requested task. BCIs have been envisioned to enable human augmentation and improve astronaut performance. Spaceships and space stations have limited space for astronauts to move around, and therefore intravehicular activities (IVA) generate many problems. Within these vehicles, BCI systems could help control the spacecraft's robotic systems and semi-automated devices through a single wearable interface. BCI systems can enable the monitoring of brain activity and physiological responses, and the detection of emergency situations, which can be analysed and resolved promptly [58] (Figure 6). Finally, the capabilities of astronauts could be improved thanks to BCIs' potential to augment human performance.

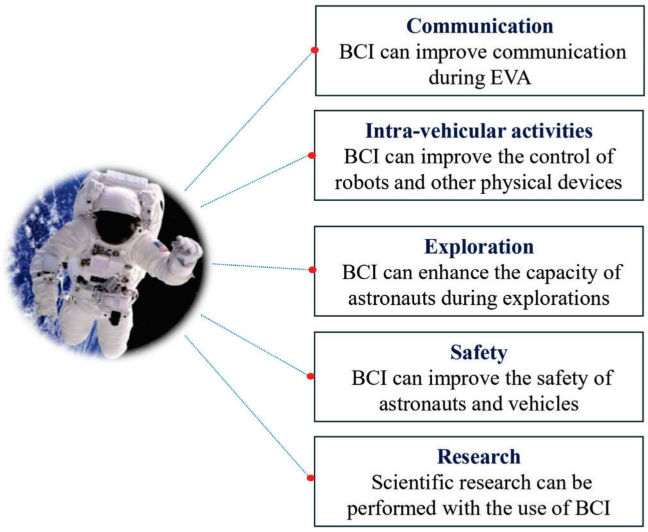


Figure 6. Examples of BCI applications in aerospace.

4.2. Smart Roads, Smart Intersections, and MaaS

Over time, the transport system has evolved. Soon, the mobility sector will undergo a radical transformation to fully realise the potential of AI and new digital and telecommunications technologies, making users' travel experiences as comfortable, safe, and accessible as possible. The first interesting topic is brain-controlled vehicle (BCV) systems. In the field of human–vehicle cooperation, several types of brain-controlled vehicle (BCV) (or mind-controlled vehicle, MCV) have been proposed in the last decade and tested in some experiments. An MCV is an embedded system that combines hardware, software, and bio-signals [13,14,59]. A BCV aims to perform tasks related to vehicle navigation and manoeuvring, such as keeping in lane, passing and following other vehicles, turning, avoiding obstacles, and braking.

The most commonly used patterns for identifying drivers' intentions to perform a given manoeuvre are event-related potentials (ERPs), steady-state visually evoked potentials (SSVEPs), desynchronisation/event-related synchronisation (ERD/ERS), readiness potentials (RPs), and local evoked potentials (LEPs). As summarised in Figure 7, the BCI systems for a transportation vehicle involve four main components: (1) sensors for recording brain activity; (2) decoders for translating neural recordings into control signals; (3) application modules; and (4) feedback to the user after executing the commands from the external device. Among the mobility revolution systems that have assumed pivotal roles are the concepts of Mobility as a Service (MaaS) [60] and the smart road. In light of this evolution in the digital age, BCIs and ICBIs can serve as an invaluable source of additional information to improve the safety and efficiency of transportation systems. Smart roads are innovative and digitalised road infrastructures created with the main goal of being more sustainable and safer than roads in the past, transforming the relationship between vehicles, users, and physical infrastructures. Smart roads are also designed to achieve full compatibility with automated vehicles (AVs) and connected and automated vehicles (CAVs), but also with driver-assisted vehicles, and automation levels that are lower than in CAVs. Smart roads use technologies typical of cooperative intelligent transport systems (C-ITS) and communication (Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), Vehicle-to-Pedestrian (V2P), Vehicle-to-Everything (V2X)) to enable communication and cooperation between all vehicles, as well as between them and road infrastructures, and to provide users, thanks to on-board computers in vehicles or mobile apps, with information on traffic conditions (e.g., congestion, accidents, etc.), environmental conditions, and behavioural requirements (e.g., speed limits). Furthermore, the integration of next-generation communication technologies (e.g., 5G, 6G, satellite) could further improve intelligent road systems. More precisely, 6G is expected to offer significantly higher speeds, lower latency, and greater capacity than 5G. 6G is also expected to integrate various technologies like AI, IoT, and cloud computing, enabling new applications and use cases in smart roads and other transportation systems.

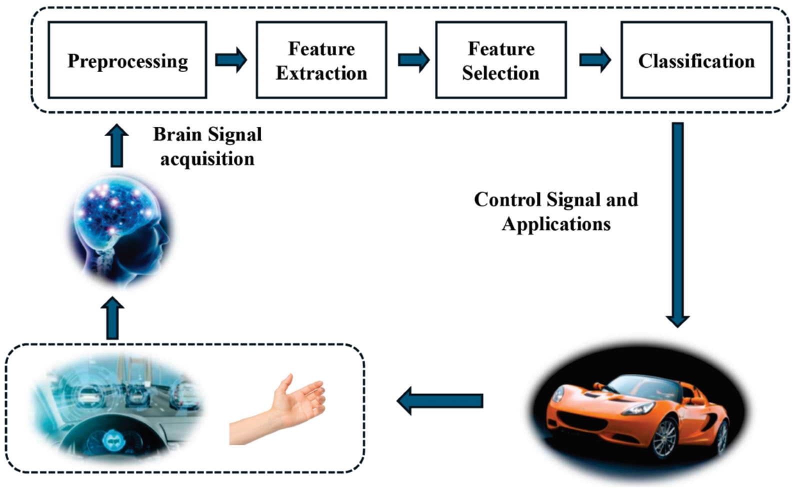


Figure 7. Simplified BCI system for a brain-controlled vehicle (BCV).

The Italian guideline subdivides smart roads into Smart Road Type I and Smart Road Type II categories, depending on the functional specifications and infomobility services (i.e., C-ITS “Day-1” and C-ITS “Day-1.5”) [61]. Considering different levels of automation for vehicle guidance systems, the World Road Association (PIARC) suggests the following taxonomy based on the degree of readiness of the road to host CAVs [62]: Humanway (HU); Assistedway (AS); Automatedway (AT); Full Automatedway (FA); Autonomousway (AU). Both CAVs and smart roads are equipped with advanced sensors that enable them to perceive one another. However, the role of physical infrastructure is pivotal in facilitating the seamless operation of CAVs.

Beyond C-ITS and CAVs, in smart roads, numerous devices and traffic regulation systems exist, including the following ones [63]:

- Reserved lanes for AVs and CAVs;
- Advanced intrusive or non-intrusive sensors and microelectromechanical systems (MEMS) for monitoring traffic (inductive loop detectors, video detection systems, magnetometers, microwaves, magnetic sensors, passive infrared sensors, LiDAR,

radar, ultrasonic, etc.), structures (e.g., bridges, viaducts, tunnels), road pavement, weather conditions, and air pollutant levels;
- Ramp-metering, hard shoulder-running (HSR), and variable speed limit (VSL) systems;
- Green islands (GIs) equipped with drone areas for landing and take-off used to survey the traffic streams and deliver first-aid kits, such as portable defibrillators;
- Electric priority lanes and charge vehicle systems (e.g., dynamic wireless power transfer systems (WPTSs));
- Piezoelectric devices to generate electrical energy;
- Programmable wireless digital traffic sign systems and smart crosswalks;
- Static weighing, weigh-in-motion (WIM), virtual WIM, and high-speed weigh-in-motion (HS-WIM);
- Smart intersections that allow for reducing fatal collisions and enhancing safety at road intersections. Using intelligent cameras, object recognition, and V2X, connected vehicles can warn the driver of a pedestrian crossing, even when they are not directly within the line of sight;
- Smart streetlights and road safety barriers equipped with an accident monitoring system (AMS);
- Smart motorway toll booths equipped with ATPMs (automatic toll payment machines).

Interest in using CAVs in road transport is closely linked to the potential benefits achievable in terms of safety and transport system capacity.

Several closed-form models are available in the literature for estimating the operational conditions of roads under flow conditions subjected to different percentages of CAVs [64–66]. In this regard, it should be considered that, on motorways, under the so-called basic conditions specified in the HCM 7th edition manual [67], the capacity C of each lane can be primarily related to the free-flow speed (FFS).

The capacity of the lanes in the real operative conditions of use of the infrastructure, if these differ from the basic conditions, is estimated with the following relationship [67]:

$$C_{adj} = C \cdot CAF_s \tag{8}$$

where

- C_{adj} = the correct lane capacity to take into account the actual characteristics of the infrastructure (pc/h);
- C = lane capacity under basic conditions (pc/h);
- CAF_s = capacity correction factors.

Among the various capacity correction factors (CAF_s), only CAFCAV is included here, which allows us to evaluate the effect of CAVs on a lane's capacity based on their percentage impact in the flow stream [67]. A similar approach is suggested for smart road intersections, where traffic streams will be partially or totally composed of CAVs [68].

BCIs could be integrated into CAVs' environment as an additional human-in-the-loop communication layer, enabling direct transmission of user intent to both the vehicle and the broader traffic network. This enhanced human–vehicle interface may improve decision synchronisation in mixed-autonomy environments, reducing the latency and coordination uncertainty that limit road throughput. At the system level, BCIs can also act as adaptive demand-modulation mechanisms, enabling real-time prioritisation of navigation objectives (e.g., route changes or cooperative merging) within the cooperative CAV control framework. By increasing precision and reducing the delay in intent sharing between humans and autonomous agents, BCI–CAV integration could further reduce required safety margins and enhance effective road capacity beyond conventional connected-vehicle coordination.

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Consequently, in a potential BCI–CAV integrated system, capacity values may exceed those obtained from Equation (8).

In these fields, human brain activation analysis with non-invasive or invasive techniques can be quite impactful, able to investigate and improve the human–transportation system interface (HTSI) by analysing and affecting the neural processes of any individual interacting with a smart road device (signals, infomobility, traffic regulation systems, etc.) that can work as a collaborator, tool, or even extension of the road users.

From this perspective, ergonomics measures related to visual attention and oculomotor control may support the assessment of the effects of road vertical and horizontal alignment, as well as traffic signs, on transportation system users, thereby contributing to the design of more effective smart road infrastructures. In particular, the integration of BCI systems could further enhance the functionality and safety of road infrastructures under mixed-traffic conditions, characterised by the simultaneous presence of human-driven vehicles, autonomous vehicles, and CAVs, especially during the intermediate transition phase toward fully automated mobility. In addition, the BCI and innovative ICBI systems, by analysing the brain activity of every user, at a certain time instant and in a given road section, may help to implement specific artificial intelligence (AI), swarm intelligence (SI), and other collective intelligence (CI) algorithms [69] to process the single intention and optimise and self-organise in a smarter manner the traffic regulation systems and devices (e.g., traffic lights, smart crosswalks, HSR and VSL systems, etc.). CI refers to the potential enhanced capacity that arises when a group of users in the road systems cooperate and share information and insights to solve traffic or safety problems. In CI systems, the collective intelligence of a group exceeds the sum of its individual intelligences [44]. In this regard, the CI paradigm should be considered as a useful approach to increase the capacity of the transportation system [70]. As a matter of fact, in traditional roads, users make autonomous choices that are independent of each other (e.g., choice of trajectory, speed, lane changes, etc.), thus leading to problems of flow instability and congestion that could instead be attenuated by optimising their driving behaviour after having defined their needs from their brain activity. Also, the driver model and software of CAVs and other driving assistance systems could be used to design systems more efficiently by analysing the responses of brain structures during travel across different behavioural and traffic conditions. This approach may help develop more comfortable and safer vehicles and also serves as the basis for communication between the human brain and the smart sensors used in modern vehicles (accelerometers, gyroscopes, LiDAR cameras, radar, etc.).

Additionally, neuroergonomics measures could be unconventional but useful variables for investigating the real effect of accelerations on the human brain during vehicle impacts against guardrails and other type of vehicle restraint systems (VRS) and for designing new types of smart road safety barriers [71,72], the designs of which are traditionally related to physical variables like the Acceleration Severity Index (ASI), the Head Injury Criterion (HIC), the Theoretical Head Impact Velocity ($THIV_{man}$), Real Head Impact Velocity (RHIV), and the Neck Injury Risk (N_{ij}) [73]. The limits of these measures are correlated with the Abbreviated Injury Scale (AIS), which describes the injuries in the head, brain, and neck area of occupants of vehicles involved in collisions [74], as summarised in Table 3.

In general terms, the ASI assesses the severity of a vehicle impact. The general criterion is that the higher the ASI level, the greater the risk of injury to the vehicle's users. Given that, when the ASI exceeds 1.0 or 1.4, the consequences for passengers are considered

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dangerous or even lethal, these values are considered the standard for designing safety barriers [75]. The ASI is calculated with the following relations:

$$\mathrm{ASI(t)} = \sqrt{\left(\frac{\bar{a}_x(t)}{a_x^*}\right)^2 + \left(\frac{\bar{a}_y(t)}{a_y^*}\right)^2 + \left(\frac{\bar{a}_z(t)}{a_z^*}\right)^2} \tag{9}$$

in which

$$a_j(t) = \frac{1}{\delta}\int_t^{t+\delta t} a_j(t)\cdot\delta t \qquad j = x, y, z \tag{10}$$

and

- x, y, z: longitudinal, lateral, and vertical directions in the vehicle, respectively;
- t: time variable;
- $\bar{a}_x(t)$; $\bar{a}_v(t)$; $\bar{a}_z(t)$: acceleration components related to the car's centre of gravity (CG) (values averaged over a moving time interval δ = 50 ms);
- $a_x^* = 12$ g; $a_y^* = 9$ g; $a_z^* = 10$ g: limits of acceleration components in x, y, z directions;
- g = 9.81 m/s^2: gravity acceleration.

Table 3. Abbreviated Injury Scale (AIS).

AIS	Category	Injuries
1	minor	Light brain injuries with headache, vertigo, no loss of consciousness, light cervical injuries, whiplash, abrasion, contusion
2	moderate	Concussion with or without skull fracture, less than 15 min unconsciousness, corneal tiny cracks, detachment of retina, face or nose fracture without shifting
3	serious	Concussion with or without skull fracture, more than 15 min unconsciousness without severe neurological damage, closed and shifted or impressed skull fracture without unconsciousness or other injury indications in skull, loss of vision, shifted and/or open facial bone fracture with antral or orbital implications, cervical fracture without damage to the spinal cord
4	severe	Closed and shifted or impressed skull fracture with severe neurological injuries
5	critical	Concussion with or without skull fracture, with more than 12 h of unconsciousness, with haemorrhage in the skull and/or critical neurological indications
6	Survival not sure	Death, partial or full damage to the brainstem or the upper part of the cervical due to pressure or disruption, fracture and/or wrench of the upper part of the cervical with injuries to the spinal cord

The ASI is defined as the maximum value of ASI(t) during the crash event. Acceleration limits that can lead to brain damage, abnormalities, or other problems related to brain activity, in the short or long term, should be redefined using new neuroergonomics techniques and medical instruments such as ECG and NIRS, or other devices capable of measuring brain activity with precision. This would lead to increased safety provided by safety barriers and, therefore, by roads with varying percentages of human-driver vehicles (HDVs), AVs, and CAVs.

Another area in which BCI and IBCI systems could be used in a smart road environment is that of UAV drone control. In fact, although UAVs in particular are created with the aim of operating in autonomous mode (i.e., they do not require human intervention to function), the use of a BCI as a new interface for their control introduces unique advantages that could not be obtained otherwise, such as automatic detection between vehicle and pilot [76]. In the smart road environment, drones and UAVs controlled or assisted by BCI and ICBI systems would enable monitoring of traffic conditions within the infrastructure, prevent terrorist acts, and quickly reach accident sites to provide immediate assistance by bringing defibrillators to the scene. The smart road could then be connected with medical personnel in hospitals who could immediately follow and direct first aid, exploiting Digital Twin (DT) and virtual reality technologies [77]. In the field of MaaS, smart roads and intersections play a pivotal role [68]. They can integrate adaptive AI in traffic signal control to reduce urban congestion and enhance pedestrian safety. From an operational point of view, public transportation vehicles can be prioritised in smart intersections, improving their reliability and reducing delays. The convergence of DT technology, CBI virtual reality (VR), and augmented reality (AR) can create a metaverse transportation system (MTS) capable of replicating real-world infrastructure, vehicles, and logistics facilities. In the age of Maas, an MTS could offer efficient mobility options such as virtual taxis, trains, and buses, optimised routes, and personalised services. V2X communication systems can reduce accident risks. In addition, multi-sensor fusion techniques combining LiDAR, radar, and cameras enable accurate tracking of pedestrians and vehicles [78]. Therefore, smart intersections may implement BCI and IBCI systems to control intersections or pedestrian crosswalks, so that pedestrians can reserve green light time in advance to cross the road and facilitate disabled people (e.g., blind people). A similar optimisation benefit could result from the advent of public or private vehicles controlled remotely and in virtual reality using BCI and IBCI systems (Figure 8).

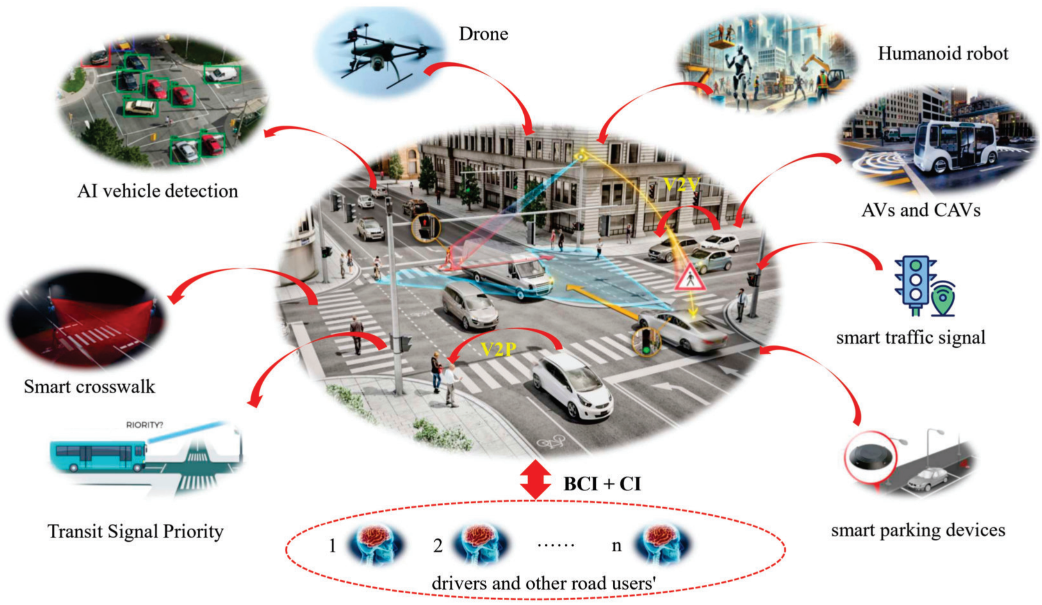

Figure 8. Examples of speculative future scenarios for brain–computer interface (BCI) and collective intelligence (CI) integration into a smart road environment.

Through the combined use of DT technology, infrastructure building information modelling (I-BIM) [79], and neuroergonomics techniques, in the future, it will be possible to remotely control construction and maintenance sites on smart roads, thus ensuring greater safety for operators thanks to the precision, reactivity, and repeatability of autonomous systems. This is similar to what is already being experimented with in the field of telerobotics [80]. With BCI systems, users could also request information from the infrastructure's infomobility devices.

The absence of human drivers in fully autonomous vehicles (AVs and CAVs) means that traditional communication strategies between drivers and other road users, such as eye contact and gestures, are no longer necessary [81]. For this reason, several studies are focused on developing new systems that allow autonomous vehicles (AVs and CAVs) to convey their intentions to road users, particularly pedestrians, cyclists, and micro-mobility users, through external human–machine interfaces (eHMIs). These systems use different modalities, such as light patterns or on-road projections, to communicate the intent and awareness of AVs and CAVs. In the next few decades, BCIs and ICBIs could be implemented in eHMIs to enhance communication among different road users, thereby improving the safety and efficiency of urban transportation systems [80]. Another area of application for BCI systems is the future use of humanoid robots for construction, maintenance, inspection, and surveillance tasks in transportation infrastructure (roads, railways, airports, subways, etc.). Humanoids are collaborative robots that resemble a human body with a head, arms, and legs. The potential benefits of using humanoids in civil construction are significant. Among the most important aspects are [80] enhanced profits, improved safety on site, improved working conditions, increased quality of construction products, reduced operational costs and waste, reduced numbers of injuries to human workers, reduced project delivery time, and increased task efficiency.

As for autonomy, the BCI autonomy levels in smart roads and intersections can be understood as a combination of human and machine/vehicle/robot decision-making, with the influence of control commands weighted across all components. Therefore, if we indicate with the symbol m the generic machine (vehicles, AVs, robots, or other physical devices of the transportation systems), the following relationship can be used for modelling the BCI control level [82]:

$$k = \omega \cdot k_m + (1 - \omega) \cdot k_b \tag{11}$$

in which k stands for the actual decision of the system control (BCI), ω is the control weight of the machine end, whose value is in the range 0–1. k_m, and k_b are the control commands of the machine end and the human brain end, respectively.

In the case in which a human operator dominates the decision-making process ($k = k_b$), different BCI control modalities can be considered [82]:

- The pre-programmed control of the vehicle/robot ($\omega = 0$, the human operator determines and programs the machine's strategies and actions in advance) and the full teleoperation control obtained by the BCI, hBCI, or IBCI;
- Traded control: the human brain and machines take turns in fully controlling the requested tasks ($\omega = 1$ or 0, depending on the requests);
- Shared control: the human brain and machines work together; the machine has independent decision-making capabilities, but the human brain can intervene to provide additional commands or modify the machine's operating modes ($0 < \omega < 1$);
- Supervisory control: humans monitor the machine performing the tasks, and the BCI does not transmit commands. Humans only occasionally intervene to compensate for the machine's possible errors or capabilities ($0 \leq \omega < 1$);
- Full autonomy: the machine makes full decisions and is able to carry out tasks autonomously without any human intervention ($\omega = 1$).

Table 4 summarises the BCI control modes described above. At a lower level of control (L0) is the pre-programmed system, in which decisions are made by humans through the analysis of their brain activity with non-implantable or implantable BCIs. At the highest level is full autonomy (L5), in which machines are enabled to perform the tasks assigned to them autonomously and intelligently without any human intervention, whether physical or deduced from the brain analysis.

Regarding CAVs for traditional roads, smart roads, and smart intersections, $\omega = 1$. However, a possible future scenario is that, with the advancement of BCI systems, shared control or supervisory control ($0 < \omega < 1$) could be preferred in different conditions of transport infrastructure use, for instance, in urban contexts, to better understand and communicate with users that cannot be integrated into automated transportation systems (e.g., pedestrians, children, etc.) and therefore cannot be well analysed by full-autonomy vehicles.

Table 4. Autonomy levels in BCI decision-making.

Level	Control Mode	Authority Allocation	Explanation
L0 (Human dominant)	Pre-programmed	Human	The machine performs a predetermined task through human programming.
L1	Teleoperation	Human	The human interacts with the machine while receiving sensory feedback from the machine itself.
L2	Traded control	Human/Machine	Control authority alternates between humans and machines, manually or automatically, based on scheduled processes or triggering events.
L3	Shared control	Human and Machine	Humans and machines work together to perform a specific task.
L4	Supervisory control	Machine/Human	The human monitors and, when necessary, intervenes in the machine's activities to modify, correct, or set a new task.
L5 (Machine dominant)	Full autonomy	Machine	The machine autonomously performs the assigned task without human intervention.

It is worth noting that future studies should also investigate the dynamic interactions among driver attention, fatigue, stress, and trust calibration in adaptive and neuroadaptive transportation systems, particularly under mixed-traffic conditions involving human-driven vehicles, AVs, and CAVs [83,84].

5. Discussion

This narrative review highlights the growing convergence among brain–computer interface (BCI) technologies, neuroergonomics, and intelligent transportation systems. The literature suggests that BCI-based approaches may significantly contribute to future smart mobility paradigms by improving human–vehicle–infrastructure interaction, traffic safety, and adaptive transportation management.

However, despite the rapid technological evolution observed in recent years, several important limitations and research gaps still remain. First, most of the currently available studies are experimental, small-scale, or conducted in highly controlled laboratory environments, often relying on virtual reality simulators rather than real-world transportation scenarios. Consequently, the ecological validity and operational reliability of many proposed BCI applications in complex traffic environments remain uncertain. In addition, EEG-based systems, although non-invasive and relatively inexpensive, are still affected by low signal-to-noise ratio, non-stationarity, motion artefacts, and limited classification accuracy, particularly during dynamic driving conditions. The main limitations, ethical issues, and research perspectives are summarised below.

5.1. Main Limitations and Ethical Issues

At present, numerous limitations still emerge in the use of these technologies. These are primarily due to the limited number of experiments carried out to date and, in some cases, to ethical issues associated with the use of BCI systems. More precisely, the development of implantable brain–computer interfaces (IBCs) raises significant ethical concerns, particularly regarding privacy and security. Since these technologies can collect neural data directly from the brain, there is a risk that highly sensitive information about thoughts, intentions, or emotions could be exposed or misused. When BCI systems are applied to transportation environments, such as connected vehicles or intelligent infrastructures, additional cybersecurity risks emerge, including the possibility of external interference with neural control signals. Another critical issue is the preservation of human autonomy and responsibility. In semi-autonomous transportation systems based on BCI technologies, it may become difficult to clearly distinguish between human decisions and machine-driven actions. This also creates legal and ethical uncertainty in the event of accidents or system failures. Furthermore, unequal access to advanced neurotechnologies could increase social disparities, limiting the benefits of smart mobility systems to only a privileged part of the population. For these reasons, many researchers argue that integrating IBCIs into transportation systems should be accompanied by strict ethical regulations that protect safety, cognitive freedom, and fundamental human rights.

5.2. Research Perspectives

Future research in BCI-based transportation systems should adopt comprehensive neuroergonomic and system-level evaluation frameworks that go beyond traditional metrics such as signal processing performance and classification accuracy, incorporating cognitive, behavioural, and operational dimensions relevant to real-world driving environments. In particular, factors such as mental workload, fatigue, distraction, sustained attention, stress, and situation awareness play a critical role in shaping both the quality of neural signal acquisition and the stability of human–machine interaction in dynamic and safety-critical traffic conditions. These cognitive states become even more relevant in semi-autonomous and highly automated driving contexts, where variations in driver engagement and vigilance may directly affect response capability and overall system safety. At the same time, trust in automation and user acceptance remain central determinants of effective deployment, influencing reliance on automated functions, behavioural adaptation, and willingness to interact with wearable or implantable BCI technologies, which may raise additional concerns related to usability, comfort, privacy, cybersecurity, and ethical acceptability. From a system perspective, future developments should prioritise secure and privacy-preserving neural data management frameworks supported by advanced encryption techniques, decentralised architectures, and real-time cybersecurity monitoring to mitigate the risks of unauthorised access or signal manipulation. In parallel, robust shared-control paradigms should be further investigated to ensure an optimal balance between human intent and autonomous system decision-making in critical driving scenarios, while explainable artificial intelligence methods should be integrated to enhance transparency and support calibrated trust in automation. Finally, long-term interdisciplinary studies are required to assess the neurological, psychological, and behavioural impacts of prolonged BCI usage, including effects on cognitive autonomy and decision-making processes, while establishing international standards for accountability, informed consent, neural data ownership, and equitable access. Overall, interdisciplinary collaboration among neuroscience, transportation engineering, artificial intelligence, ethics, and cybersecurity will be essential to ensure the safe, transparent, and socially acceptable integration of BCI technologies into future intelligent transportation systems.

6. Conclusions

The challenge facing many road operators and institutions is knowing how to leverage emerging technologies such as self-driving vehicles, advanced sensors, and smart traffic management devices to enhance the safety and capacity of transportation systems while reconciling and integrating these innovations with traditional infrastructure. In recent years, BCI systems have made enormous, previously unthinkable progress and have already been used in several technical applications designed to facilitate the lives of people with severe disabilities and enable them to operate technical devices and external medical equipment, such as computers, speech synthesisers, and neural prostheses. Moreover, BCI systems are studied and applied across numerous disciplines, including robotics, aerospace, and all fields where potential human mental enhancement is required. From this point of view, it is possible that brain monitoring with non-invasive, invasive, and partially invasive BCIs could also assume a pivotal role in transport systems. Principal applications may include:

- Control of humanoid robots in construction, maintenance, inspection, and surveillance tasks in transportation infrastructures, above all, in critical or dangerous contexts (e.g., viaducts, tunnels, etc.);
- Shared control or supervisory control of AVs and CAVs in specific complex traffic conditions;
- Interaction between the human brain and smart road devices (smart signals, infomobility equipment, traffic regulation systems, etc.) that can work as collaborators, tools, or even as a sort of digital extension of the road users;
- Creation of metaverse transportation systems (MTS) to replicate real-world infrastructures, vehicles, and logistic facilities for different traffic and safety purposes;
- Design of better road safety barriers taking into account the real brain response during the impact of vehicles;
- New design criteria of road and highway infrastructures, intersections, and interchanges founded on the users' behaviours and brain activities to increase safety and comfort conditions;
- Implementation of sophisticated collective intelligence algorithms to increase the transportation system's capacity by optimising the traffic regulation systems after having defined the collective needs of users assessed from their brain activity.

In conclusion, this article advocates using the frontiers of neuroergonomics and BCI techniques as valuable and essential tools to improve the far-future efficiency and safety of transportation systems and to enhance human–vehicle and smart road cooperation. However, current BCI technologies present several limitations, mainly due to the limited number of experimental studies and ongoing technical constraints. Significant ethical concerns arise, particularly regarding privacy, security, and the protection of sensitive neural data in implantable brain–computer interfaces. When applied to transportation systems, additional cybersecurity risks and uncertainties regarding human autonomy and responsibility become critical issues. Moreover, unequal access to BCI technologies may exacerbate social inequalities and limit fair distribution of their benefits. For these reasons, strict ethical regulations are required to ensure safety, cognitive freedom, and the protection of fundamental human rights in future applications.

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Abbreviations

AI	Artificial intelligence
AIS	Abbreviated Injury Scale
AVs	Autonomous Vehicles
ATPM	Automatic Toll Payment Machine
ASI	Acceleration Severity Index
EVA	Extravehicular Activity
BMI	Brain–Machine Interface
BCI	Brain–Computer interface
BOLD	Blood Oxygenation Level-Dependent
BCV	Brain-Controlled Vehicle
CAVs	Connected Autonomous Vehicles
CI	Collective Intelligence
DBS	Deep Brain Stimulation
DT	Digital Twin
DWPT	Dynamic Wireless Power Transfer
eHMIs	External Human–Machine Interfaces
ECoG	Electrocorticography
EEG	Electroencephalography
EMG	Electromyography
EOG	Electrooculography
ERD/ERS	Desynchronisation/Event-Related Synchronisation
ERPs	Event-Related Potentials
EPI	Echo Planar Imaging
fMRI	Functional Magnetic Resonance Imaging
GM	Grey Matter
HDV	Human-Driver Vehicles
HIC	Head Injury Criterion
hBCI	Hybrid Brain–Computer Interface
HTSI	Human–Transportation System Interface
I-BIM	Infrastructure Building Information Modelling
IBCI	Implantable Brain–Computer Interface
ITR	Information Transfer Rate
IVA	Intravehicular Activities
IQ	Intelligence Quotient
LDWS	Lane Departure Warning System
LEP	Local Evoked Potentials
MI	Motor Imagery
MI-BCI	Motor Imagery-Brain–Computer interface
MEMS	Microelectromechanical System
MaaS	Mobility as a Service
Nij	Neck Injury Risk
NPTs	Neuropsychological Tests
ReHo	Regional Homogeneity Analysis
RHIV	Real Head Impact Velocity
RNS	Responsive Neurostimulation
RP	Readiness Potentials
SPECT	Single-Photon Emission Tomography

SI	Swarm Intelligence
SNR	Signal-to-Noise Ratio
VRS	Vehicle Restraint Systems
VR	Virtual Reality
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
V2P	Vehicle-to-Pedestrian
V2X	Vehicle-to-Everything
SLAM	Simultaneous Localisation and Mapping
SVEP	Steady-State Visually Evoked Potentials
$THIV_{man}$	Theoretical Head Impact Velocity
UAV	Unmanned Aerial Vehicle
PTSD	Post-Traumatic Stress Disorder
HSR	Hard Shoulder-Running
VSL	Variable Speed Limits
GIs	Green Islands

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