



HAL
open science

Error-Related Potentials Detection to Enhance Human-Robot Collaboration: A Preliminary Review

David Achanccaray, Aurélie Clodic, Raphaëlle N Roy

► To cite this version:

David Achanccaray, Aurélie Clodic, Raphaëlle N Roy. Error-Related Potentials Detection to Enhance Human-Robot Collaboration: A Preliminary Review. 2025. <hal-05299649>

HAL Id: hal-05299649

<https://hal.science/hal-05299649v1>

Preprint submitted on 7 Oct 2025

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



HAL Authorization

Error-Related Potentials Detection to Enhance Human-Robot Collaboration: A Preliminary Review

Détection des Potentiels d'Erreurs pour Améliorer la Collaboration Humain-Robot : Une Revue Préliminaire

David Achancaray*
david.achancaray@isae-supaero.fr
Fédération ENAC ISAE-SUPAERO
ONERA, Université de Toulouse
Toulouse, France

Aurélie Clodic
LAAS-CNRS, Université de Toulouse,
CNRS
Toulouse, France
aurelie.clodic@laas.fr

Raphaëlle N. Roy
Fédération ENAC ISAE-SUPAERO
ONERA, Université de Toulouse
Toulouse, France
raphaëlle.roy@isae-supaero.fr

Abstract

Error-related potentials (ErrPs) have been studied to evaluate wrong decisions or actions in several contexts. An ErrP is an electrical potential on the scalp generated by the perception of errors and occurs unwittingly. In human-robot collaboration (HRC), ErrP detection can be shown as feedback or trigger an action to adapt the system to the user. This contributes to the improvement of HRC, taking into account user performance. However, to our knowledge, the detection of ErrPs in HRC has not been widely explored, resulting in only a few studies. This preliminary systematic review will present work on ErrP-based interfaces related to adaptation, control, and neuroergonomics for HRC. 11 articles were included after the exclusion criteria of the review stages. The average accuracy of ErrP detection was between 54% and 87.19%. In most cases, the authors simulated the occurrence of unexpected behavior of the robot. The robot mistakes occurred randomly between 25% and 35% of the total trials. Some works focused on the robot learning process and adaptation between humans and robots. The mental model and the robot behavior policy were updated based on the decoded ErrPs during collaborative interactions. ErrPs played a critical role by accelerating the adaptation process. Control-related works have included ErrP detection/features as input inside the control loop or algorithm. The proposed framework enabled the learning algorithm to converge faster than conventional methods. Other studies assessed the influence of mental workload variability in the adaptation process, given that a high mental workload affects the cognitive processes needed to perceive errors. Thus, ErrPs present advantages for enhancing HRC, and this review opens the way to further developments in the robotic domain. We will continue this work by elaborating strategies to take advantage of the ErrP detection to design pipelines and protocols that would be used in future works.

Résumé

Les potentiels d'erreur (ErrPs) ont été étudiés pour évaluer les mauvaises décisions ou actions dans divers contextes. L'ErrP est un

potentiel électrique au niveau du scalp généré par la perception d'erreurs et survient involontairement. Dans la collaboration humain-robot (HRC), la détection d'ErrPs peut être présentée comme un retour d'information ou déclencher une action afin d'adapter le système à l'utilisateur. Cela contribue à l'amélioration de l'HRC, en tenant compte des performances de l'utilisateur. Cependant, à notre connaissance, la détection d'ErrPs dans l'HRC n'a pas été largement explorée, ce qui n'a donné lieu qu'à quelques études. Cette revue systématique préliminaire présentera des travaux sur les interfaces basées sur les ErrPs concernant l'adaptation, le contrôle et la neuroergonomie dans l'HRC. 11 articles ont été inclus après avoir satisfait aux critères d'exclusion des étapes de revue. La précision moyenne de détection d'ErrPs se situait entre 54% et 87,19%. Dans la plupart des cas, les auteurs ont simulé l'apparition d'un comportement inattendu du robot. Les erreurs du robot se sont produites de manière aléatoire entre 25% et 35% du total des essais. Certains travaux se sont concentrés sur le processus d'apprentissage et d'adaptation du robot entre humains et robots. Le modèle mental et la politique comportementale du robot ont été mis à jour en fonction des ErrPs décodés lors des interactions collaboratives. Les ErrPs ont joué un rôle essentiel en accélérant le processus d'adaptation. Les travaux liés au contrôle ont inclus la détection et les caractéristiques des ErrPs comme entrées dans la boucle de contrôle ou l'algorithme. Le cadre proposé a permis à l'algorithme d'apprentissage de converger plus rapidement que les méthodes conventionnelles. D'autres études ont évalué l'influence de la variabilité de la charge mentale sur le processus d'adaptation, sachant qu'une charge mentale élevée affecte les processus cognitifs nécessaires à la perception des erreurs. Ainsi, les ErrPs constituent des avantages pour améliorer l'HRC et cette revue ouvre la voie à de nouveaux développements dans le domaine robotique. Nous poursuivrons ce travail en élaborant des stratégies permettant de tirer parti de la détection des ErrPs pour concevoir des pipelines et des protocoles qui seraient utilisés dans les travaux futurs.

CCS Concepts

• Human-centered computing → Collaborative interaction.

Keywords

Error-related potentials, human-robot collaboration, passive brain-computer interface, adaptation.

*All authors contributed equally to this research.

Mots clés

Potentiels liés aux erreurs, collaboration homme-robot, interface cerveau-ordinateur passive, adaptation.

Reference Format:

David Achancaray, Aurélie Clodic, and Raphaële N. Roy. 2025. Error-Related Potentials Detection to Enhance Human-Robot Collaboration: A Preliminary Review. In *IHM '25 : Actes étendus de la 36^e conférence Francophone sur l'Interaction Humain-Machine, Novembre 3–7, 2025, Toulouse, France.*, 6 pages.

1 Introduction

Human–robot interaction (HRI) occurs in diverse domains such as education, healthcare, domestic environments, and industrial workplaces. Effective collaboration requires that robots adapt to human behavior, cognition, and emotions to optimize teamwork [23]. In human–robot collaboration (HRC), humans and robots share goals and workspaces, coordinating either through physical contact (e.g., forces) or communication (e.g., gestures, voice, gaze, facial expressions). Robust multimodal communication is key to ensuring reliable and resilient collaboration [1].

Identifying errors resulting from wrong decisions or actions can benefit the adaptation process. Error detection can activate feedback, trigger an action, or be part of the robot's control algorithm. Error events evoke neural responses, which are called error-related potentials (ErrPs) when recorded from the scalp using an electroencephalogram (EEG). ErrPs are generated by the perception of errors and occur unintentionally. This perception of errors can occur for errors that are committed by the user themselves (they realize this themselves or are made aware via a given feedback), the system with which it interacts and its environment, or by another agent (human, robot or even artificial intelligence (AI)). These brain potentials can be decoded with a passive brain-computer interface (BCI). A passive BCI monitors brain activity while the user does not control it voluntarily; however, the user has an active role during the human-machine interaction. This determines their engagement level, which can in turn affect error production and perception, and therefore ErrP occurrence [5, 46].

ErrP detection has shown potential to improve adaptation between humans and intelligent systems [28]. However, to our knowledge ErrP detection has not yet been widely explored in HRC, resulting in only a few available studies. In this review, we focused on identifying applications where ErrP detection improved HRC. This review did not consider articles that only aimed at modeling decoders for ErrP detection. This survey answered the following research questions:

- Research question 1 - What type of error is used depending on the HRC application?
- Research question 2 - What type of HRC configurations can be improved with an ErrP-based passive BCI?
- Research question 3 - What approaches can be used to enhance HRC with an ErrP-based passive BCI?

This article proceeds as follows: in section 2, some related research fields to ErrP detection and HRC are overviewed; in section 3, the methods are detailed; in section 4, the results of the analyzed studies are organized according to their approaches and findings;

and finally, section 5, the results and experimental designs are discussed and recommendations for future work are provided.

2 Background

This section will review research fields related to ErrP and HRC to prepare the basis for this review.

2.1 Error-Related Potentials

ErrPs were characterized in the early 90s. This event-related potential showed a negative peak (error-related negativity) in the fronto-central cortex around 80 ms after the error occurrence in a choice task. A larger positive component in the centro-parietal cortex follows the negative peak in the time window of 200-500 ms (Fig. 1) [13, 14, 19]. The error occurrence also elicited frequency modulations, such as an increase in the theta band (4-8 Hz) followed by a decrease in the beta band (12-30 Hz). In addition, connectivity analysis revealed the influence of the anterior cingulate cortex on the prefrontal cortex. A similar response (feedback-related negativity) is generated when feedback is shown to the user to indicate wrong performance and appears in the time window of 200-300 ms after the feedback presentation [5, 21, 46].

2.2 Human-Robot Collaboration

Robots and humans work together as a team in HRC. They share a workspace and task goals while carrying out parallel tasks. Collaboration can involve physical contact through exchange forces or be contactless through gestures, voice commands, motion intentions, facial emotions, or eye gaze to achieve effective communication. Multimodal communication makes the system redundant and more robust to unexpected noise and perturbations [33]. A cognitive model (or architecture) and behavioral block are built by training a machine learning model using the collected data. The robot uses this model to shape its behavior. Machine learning techniques in HRC can be grouped as follows: unsupervised learning, reinforcement learning (RL), and supervised learning. These techniques have been applied to different collaborative tasks, such as collaborative assembly, object handover, object handling, and collaborative manufacturing. Collaborative tasks can be evaluated using metrics categorized as precision of robot movement, robustness, proof of concept, performance improvement, and reduction of physical workload [40].

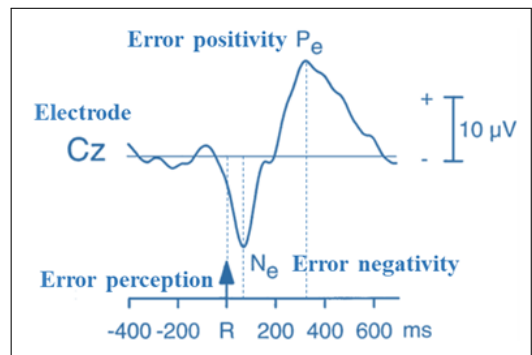


Figure 1: Average of the difference between signals of ErrP and Non-error. Figure modified from [14]

HRC reduces human workload by optimizing the strengths of humans and robots in a specific task. Biofeedback can enhance HRC systems. The robot accesses the human physiological response information and interprets the human state, which can increase awareness within workplaces and HRC efficiency. Biofeedback can be provided from multimodal sources, such as EEG, electrocardiogram, electromyogram, electrodermal activity, skin temperature, and respiration. Biofeedback has been used for different purposes, such as control, mental state assessment, stress level detection, and emotion recognition [36]. The stress level is related to the mental workload, which reflects mental fatigue. It results from carrying out a task under demanding conditions. Automation can generate new stressors for humans by reducing task control and social interaction, and increasing work pace and psychological pressure due to performance monitoring. The complexity of HRC can increase the mental workload. Robot efficiency could cause concern about job security among workers. Another issue is that the robot's proximity to the workers generates fear because it is potentially harmful. However, collaborative robots can alleviate humans from performing heavy or dangerous tasks, which will achieve optimal levels of mental workload and improve task performance [4]. Mental workload is affected by robot-related factors, such as robot features (dimensions and speed), social touching (human-like communication and interaction), and robot movement trajectory (unpredictable possible damage). These factors depend on human perception, which influences the evaluation metrics of collaborative tasks [32].

2.3 BCIs Based on Error-Related Potentials

The most used applications of BCI using ErrPs are Spellers, where ErrPs increased P300-based BCI performance [7, 43, 47]. ErrP detection has been used in other applications, such as cursor control [17, 38], rehabilitation [29, 30, 42], HRI [6, 9, 12, 15, 20, 26, 35, 37, 45], adaptation in HRC [3, 8, 10, 11, 24, 25], control in HRC [2, 16, 39], neuroergonomics in HRC [18, 22], and ErrP decodification in HRI [27, 31, 34, 41]. In this review, we focused on HRC applications, such as adaptation, control, and neuroergonomics. These studies are detailed in section 4. We did not include works about the decodification of ErrPs because they are machine-learning articles.

3 Methods

In the following section, we will detail the methodology adopted (PRISMA protocol [44]) to elaborate this review to answer the research questions. Fig. 2 shows the matic review process.

- **Identification.** The search was conducted in April 2025 in four databases: Web of science, IEEEExplore, Scopus, and Google Scholar. They are the most commonly used to cover the different technological areas involved with this review. Keywords related to HRI, BCI, and HRC features were grouped into three sets (Table 1). The three sets were combined using the Boolean logic operation "AND" between each set and the Boolean logic operation "OR" within each set. Articles only aimed at modeling decoders for ErrP detection were excluded. This search resulted in a total of 39 publications.
- **Screening.** In this stage, all articles were examined by reading the title and abstract. The article's content was also examined when the abstract was not well-detailed. The criteria for including articles in the next stage were as follows. Articles

should be written in English, not review or survey papers, mainly related to HRC, and listed only once.

- **Eligibility.** The whole content of each article was examined in this stage. The criteria for including articles in the next stage were as follows. Articles should be written in English, not review or survey papers, mainly related to HRC, and available in full text.
- **Included.** Parameters were extracted from the included articles to be shown in the next section 4. The parameters were the following: type of error to elicit ErrPs, HRC configuration, ErrP-Based BCI metrics, and Collaborative task metrics.

4 Results

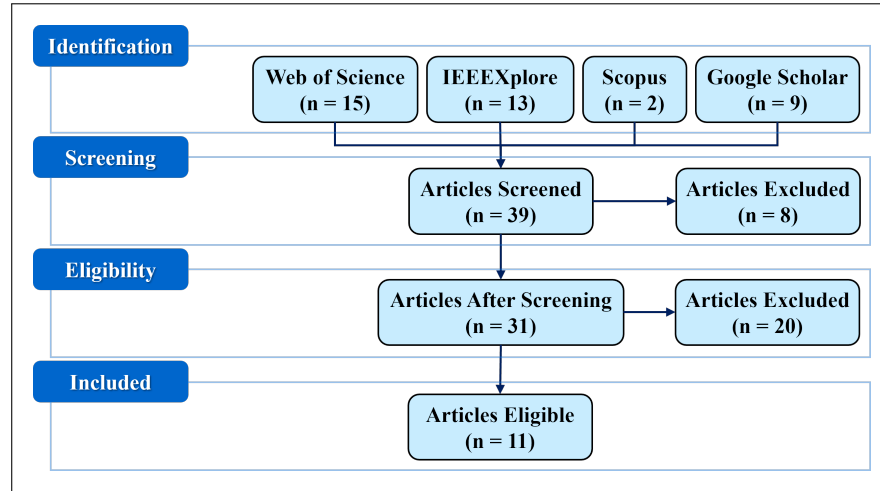
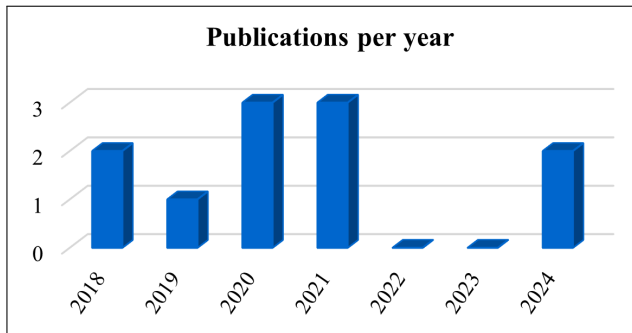
The total number of articles found was 39. After the exclusion criteria in each stage, the articles included in this review were 11. This section presents these articles into three categories: adaptation in HRC, control in HRC, and neuroergonomics in HRC. Fig. 3 shows the number of published articles per year. This figure illustrates the relevance of ErrPs in HRC in recent years.

4.1 Adaptation in HRC

Six articles were found in this category. In a gaming context [10, 11], the robot chose one of three objects, and the human guessed the robot's gaze pattern. The human and robot's behavior policies were updated whenever the human's guess was incorrect. This adaptation was carried out using the ErrP decoded with an average accuracy of ErrP detection of around 81.80%. In addition, the average percentage of right guesses increased from 33% to 70-90% within 10-40 trials. Other studies were focused on robot learning [24, 25], where the human interacted with the robot through gestures. The learning algorithm recognized human gestures and triggered a robot action. If this action did not correspond to the gesture, the evoked ErrP was used to update the robot's behavior policy. The performance of the ErrP detection depended on the human or robot perspectives. The ErrP detection accuracies reached 87.19% and 86.87% for the human and robot perspectives, respectively. This analysis revealed a high correlation (ρ) between robot's learning performance and ErrP detection performance. The ρ values were between 0.897 and 0.934 ($p < 0.01$) for the human perspective, and between 0.869 and 0.965 ($p < 0.01$) for the robot perspective. Other application is the human supervision of robots to correct mistakes during multiple-choice tasks [8]. In this study, the autonomous robot selected targets for a drilling operation. The authors processed multimodal signals (electromyogram and EEG). ErrP detection triggered the correction sequence, which consisted of pattern recognition of left/right hand-gestures of the human supervisor to correct the robot's choice. This hybrid framework presented an average accuracy of around 54% of ErrP detection, while the average accuracy of muscle activity classification for the left hand-gestures was of 65.8% and right hand-gestures was of 85.2%. The EEG signal classification should be improved to ensure a reliable hybrid system. In addition, the feasibility of using ErrP to detect potential emergencies in HRC in a manufacturing context was approached in [3]. The emergencies were generated by simulating errors in the robot's movement execution in an assembly

Table 1: Keywords used in the Systematic Search.

HRI	(AND) BCI	(AND) HRC Features
"human-robot interaction" OR "human-robot collaboration" OR "human-robot cooperation"	"error potential" OR "error-related potential" OR "error-related potentials"	"adaptation" OR "coadaptation" OR "human-centered AI" OR "Control"

**Figure 2: Flow chart of the systematic review process.****Figure 3: Publications per year of articles that applied error-related potentials in human-robot collaboration.**

task. There were three object manipulation cases: crush, drop, and unexpected movement. This study found an optimal time window of 250 ms to process EEG signals. However, the participants had no experience in HRI tasks, which contrasted with real robot operators. This experience difference influences the neural response evoked in emergencies.

4.2 Control in HRC

Three articles were found in this category. A human-in-the-loop approach was applied to correct the path planning of assistive mobile robots in a virtual scenario [16]. The user controlled a smart

wheelchair. The robot control algorithm determined the path planning to reach the target defined by the user. The path was recalculated when an ErrP was evoked by the approach of the robot to the obstacles. The overall ErrP detection accuracy was 78.6%. In addition, human in the loop of robot learning was based on ErrPs detection [39]. ErrP detection evoked by the erroneous robot behavior was an input to update the reward in the RL algorithm during the training stage. This study included feedback conditions, such as visual and visuo-tactile feedback. The ErrP detection average accuracies were 60% and 59% for visual and visuo-tactile feedback, respectively. RL for route learning showed convergence at around nine iterations for both feedback conditions. However, the number of iterations was lower for visuo-tactile feedback than for visual feedback. Regarding more complex control methods, singularity avoidance strategies with complex dynamics in HRC generated detectable ErrP [2]. This study reported that the participants preferred the strategy that produced greater robot predictability (faster response), which reflected a lower power spectral density of the ErrPs.

4.3 Neuroergonomics in HRC

Two articles were found in this category. Cognitive workload affects the error awareness of a user in HRC [22]. This resulted in reduced ErrP. In this study, the participants evaluated two different workload conditions by performing two tasks. The primary task consisted of interacting with a game by controlling a robot arm end-effector of two degrees of freedom. The secondary task was

a mental calculation with varying difficulty. The ErrP was generated by an unexpected stop of the robot movement in 33% of the trials. A high mental workload mitigated the ErrP amplitude, which evidenced a reduced error awareness. In addition, there was an increase in the theta band power in the frontal cortex and a trend to increase the power of alpha and beta bands in the central cortex after the unexpected stop, compared to the regular stop when the robot reached its target. Another worrying factor is boredom, which negatively influences the performance of collaborative tasks when user engagement is reduced [18]. This work assessed the mental state of participants while they performed an exploration task to reach a target in a large-scale maze in collaboration with a robot in a simulated environment. The robot was programmed to change its direction in 30% of the trials and generated ErrPs. There was an increase in the theta band power and a decrease in the beta band power. In the second half of the task, some participants felt bored, which decreased the ErrP amplitude and the theta band power.

5 Discussion

Regarding ErrPs in HRC studies, an unexpected robot behavior generated errors caused by wrong signal processing or being out of the workspace scope of the robot's sensors. These errors were independent of the application. The average accuracy of ErrP detection was between 54% and 87.19%. In most cases, the robot's mistake was programmed to occur randomly between 25% and 35% of the total trials [3, 8, 16, 18, 22, 39]. In the rest of the cases, the unexpected action occurred naturally during the robot's learning process, or the robot's interaction with the environment in a collaborative task [2, 10, 11, 24, 25]. Although it is easier to provoke or program the robot's error, the error's natural occurrence would be closer to a real case. Usually, the robot's autonomy algorithm is trained to be robust and avoid errors. However, natural errors can occur during the robot's learning in the adaptation stage. It would depend on the experimental design and the application. Thus, it answered the first research question about the type of error. The second research question was about the HRC configuration. HRC studies used ErrPs in several tasks, such as games [10, 11, 22], gesture learning [24, 25], supervision [8], assembly [3], navigation [16, 18], and control [2, 39]. These tasks involved physical and contactless interactions between the human and the robot. The robots were humanoid robots, robot arms, or mobile robots. ErrPs were evoked by visualizing the unexpected robot behavior. In most cases, adaptation was approached in HRC, which was configured as a contactless interaction or manipulation of an object with humanoid robots or robot arms. These adaptation applications in HRC illustrated how human-centered AI of the system updated robot behavior policies based on ErrP detection. An interesting approach for real applications that answered the third research question could be contactless interaction in an exploration or search task, or manipulating an object as an assembly task. These scenarios will provide conditions for the natural occurrence of unexpected robot behavior. An ErrP-based passive BCI would detect these robot errors to enhance adaptation in HRC during the robot learning process. Human-centered AI for the system could use different methodologies for the robot learning process. In addition, a stage of BCI training to detect ErrPs can be included before the robot learning process to avoid the variability

of the average accuracy mentioned in the previous section. BCI training can be based on studies with high average accuracies. This approach gives us a wide spectrum of options to improve HRC.

We will continue this work by elaborating strategies to take advantage of ErrP detection. These strategies will present pipelines and protocols that will be evaluated in future works.

Acknowledgements

This work was supported by the French National Research Agency (ANR) with project EPIIC (grant 21-CE33-0005).

References

- [1] Muneeb Ahmad, Omar Mubin, and Joanne Orlando. 2017. A Systematic Review of Adaptivity in Human-Robot Interaction. *Multimodal Technologies and Interaction* 1, 3 (2017). doi:10.3390/mti1030014
- [2] Stefano Aldini, Avinash K. Singh, Marc Carmichael, Yu-Kai Wang, Dikai Liu, and Chin-Teng Lin. 2021. Prediction-Error Negativity to Assess Singularity Avoidance Strategies in Physical Human-Robot Collaboration. In *2021 IEEE International Conference on Robotics and Automation (ICRA)*. 3241–3247. doi:10.1109/ICRA48506.2021.9561599
- [3] Achim Buerkle, Thomas Bamber, Niels Lohse, and Pedro Ferreira. 2021. Feasibility of Detecting Potential Emergencies in Symbiotic Human-Robot Collaboration with a mobile EEG. *Robotics and Computer-Integrated Manufacturing* 72 (2021), 102179. doi:10.1016/j.rcim.2021.102179
- [4] Claudia Carissoli, Luca Negri, Marta Bassi, Fabio Alexander Storm, and Antonella Delle Fave. 2024. Mental Workload and Human-Robot Interaction in Collaborative Tasks: A Scoping Review. *International Journal of Human-Computer Interaction* 40, 20 (2024), 6458–6477. doi:10.1080/10447318.2023.2254639 arXiv:https://doi.org/10.1080/10447318.2023.2254639
- [5] Ricardo Chavarriaga, Aleksander Sobolewski, and José del R. Millán. 2014. Errare machinale est: the use of error-related potentials in brain-machine interfaces. *Frontiers in Neuroscience* 8 (2014). doi:10.3389/fnins.2014.00208
- [6] Lucio Ciabattini, Francesco Ferracuti, Alessandro Freddi, Sabrina Iarlori, Sauro Longhi, and Andrea Monteriù. 2019. ErrP Signals Detection for Safe Navigation of a Smart Wheelchair. In *2019 IEEE 23rd International Symposium on Consumer Technologies (ISCT)*. 269–272. doi:10.1109/ISCT.2019.8900993
- [7] Aniana Cruz, Gabriel Pires, and Urbano J. Nunes. 2018. Double ErrP Detection for Automatic Error Correction in an ERP-Based BCI Speller. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 26, 1 (2018), 26–36. doi:10.1109/TNSRE.2017.2755018
- [8] Joseph DelPreto, Andres F Salazar-Gomez, Stephanie Gil, Ramin Hasani, Frank H Guenther, and Daniela Rus. 2020. Plug-and-play supervisory control using muscle and brain signals for real-time gesture and error detection. *Autonomous Robots* 44 (2020), 1303–1322.
- [9] Stefan Ehrlich and Gordon Cheng. 2016. A neuro-based method for detecting context-dependent erroneous robot action. In *2016 IEEE-RAS 16th International Conference on Humanoid Robots (Humanoids)*. 477–482. doi:10.1109/HUMANOIDS.2016.7803318
- [10] Stefan K Ehrlich and Gordon Cheng. 2018. Human-agent co-adaptation using error-related potentials. *Journal of Neural Engineering* 15, 6 (sep 2018), 066014. doi:10.1088/1741-2552/aae069
- [11] Stefan K. Ehrlich and Gordon Cheng. 2019. A computational model of human decision making and learning for assessment of co-adaptation in neuro-adaptive human-robot interaction. In *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)*. 264–271. doi:10.1109/SMC.2019.8913872
- [12] Stefan K. Ehrlich and Gordon Cheng. 2019. A Feasibility Study for Validating Robot Actions Using EEG-Based Error-Related Potentials. *International Journal of Social Robotics* 11, 2 (APR 2019), 271–283. doi:10.1007/s12369-018-0501-8
- [13] M. Falkenstein, J. Hohnsbein, J. Hoormann, and L. Blanke. 1991. Effects of crossmodal divided attention on late ERP components. II. Error processing in choice reaction tasks. *Electroencephalography and Clinical Neurophysiology* 78, 6 (1991), 447–455. doi:10.1016/0013-4694(91)90062-9
- [14] Michael Falkenstein, Jörg Hoormann, Stefan Christ, and Joachim Hohnsbein. 2000. ERP components on reaction errors and their functional significance: a tutorial. *Biological Psychology* 51, 2 (2000), 87–107. doi:10.1016/S0301-0511(99)00031-9
- [15] Alessandra Fava, Adriana Lucchese, Roberto Meattini, Gianluca Palli, Valeria Villani, and Lorenzo Sabattini. 2024. Challenges in Detecting and Analyzing EEG Error-Related Potentials: Lessons from a Case Study in HRI. In *2024 33rd IEEE International Conference on Robot and Human Interactive Communication (ROMAN)*. 1618–1623. doi:10.1109/RO-MAN60168.2024.10731468
- [16] Francesco Ferracuti, Alessandro Freddi, Sabrina Iarlori, Sauro Longhi, Andrea Monteriù, and Camillo Porcaro. 2021. Augmenting robot intelligence via EEG signals to avoid trajectory planning mistakes of a smart wheelchair. *Journal of*

- Ambient Intelligence and Humanized Computing* (2021 MAY 3 2021). doi:10.1007/s12652-021-03286-7
- [17] Pierre W. Ferrez and José del R. Millán. 2008. Error-Related EEG Potentials Generated During Simulated Brain–Computer Interaction. *IEEE Transactions on Biomedical Engineering* 55, 3 (2008), 923–929. doi:10.1109/TBME.2007.908083
- [18] Takumi Fuji and Kiyohisa Natsume. 2024. Error-Related Potential During Cooperative Exploration by Humans and Robots in a Large-Scale Maze and the Effect of Boredom on It. In *2024 15th International Conference on Information and Communication Technology Convergence (ICTC)*. 1833–1837. doi:10.1109/ICTC62082.2024.10827196
- [19] William J. Gehring, Brian Goss, Michael G. H. Coles, David E. Meyer, and Emanuel Donchin. 1993. A Neural System for Error Detection and Compensation. *Psychological Science* 4, 6 (1993), 385–390. doi:10.1111/j.1467-9280.1993.tb00586.x arXiv:https://doi.org/10.1111/j.1467-9280.1993.tb00586.x
- [20] Fumiaki Iwane, Aude Billard, and José del R Millán. 2023. Inferring individual evaluation criteria for reaching trajectories with obstacle avoidance from EEG signals. *Scientific Reports* 13, 1 (2023), 20163.
- [21] Fumiaki Iwane, Aleksander Sobolewski, Ricardo Chavarriaga, and José del R. Millán. 2023. EEG error-related potentials encode magnitude of errors and individual perceptual thresholds. *iScience* 26, 9 (2023), 107524. doi:10.1016/j.isci.2023.107524
- [22] Alka Rachel John, Avinash K Singh, Klaus Gramann, Dikai Liu, and Chin-Teng Lin. 2024. Prediction of cognitive conflict during unexpected robot behavior under different mental workload conditions in a physical human–robot collaboration. *Journal of Neural Engineering* 21, 2 (mar 2024), 026010. doi:10.1088/1741-2552/ad2494
- [23] Lionel P. Robert Jr., Rasha Alahmad, Connor Esterwood, Sangmi Kim, Sangseok You, and Qiaoning Zhang. 2020. A Review of Personality in Human–Robot Interactions. *Foundations and Trends® in Information Systems* 4, 2 (2020), 107–212. doi:10.1561/29000000018
- [24] Su Kyoung Kim, Elsa Andrea Kirchner, and Frank Kirchner. 2020. Flexible online adaptation of learning strategy using EEG-based reinforcement signals in real-world robotic applications. In *2020 IEEE International Conference on Robotics and Automation (ICRA)*. 4885–4891. doi:10.1109/ICRA40945.2020.9197538
- [25] Su Kyoung Kim, Elsa Andrea Kirchner, Lukas Schloßmüller, and Frank Kirchner. 2020. Errors in Human-Robot Interactions and Their Effects on Robot Learning. *Frontiers in Robotics and AI* 7 (2020). doi:10.3389/frobt.2020.558531
- [26] Su Kyoung Kim, Elsa Andrea Kirchner, Arne Stefes, and Frank Kirchner. 2017. Intrinsic interactive reinforcement learning - Using error-related potentials for real world human-robot interaction. *Scientific Reports* 7 (DEC 14 2017). doi:10.1038/s41598-017-17682-7
- [27] Su Kyoung Kim, Julian Liersch, and Elsa Andrea Kirchner. 2023. Classification of Error-Related Potentials Evoked During Observation of Human Motion Sequences. In *Augmented Cognition*, Dylan D. Schmorow and Cali M. Fidopiastis (Eds.). Springer Nature Switzerland, Cham, 142–152.
- [28] Oliver W Klaproth, Emmanuelle Dietz, Juliane Pawlitzki, Laurens R Krol, Thorsten O Zander, and Nele Russwinkel. 2024. Modeling of anticipation using instance-based learning: application to automation surprise in aviation using passive BCI and eye-tracking data. *User Modeling and User-Adapted Interaction* (2024), 1–31.
- [29] Akshay Kumar, Lin Gao, Elena Pirogova, and Qiang Fang. 2019. A Review of Error-Related Potential-Based Brain–Computer Interfaces for Motor Impaired People. *IEEE Access* 7 (2019), 142451–142466. doi:10.1109/ACCESS.2019.2944067
- [30] Akshay Kumar, Elena Pirogova, Seedahmed S Mahmoud, and Qiang Fang. 2021. Classification of error-related potentials evoked during stroke rehabilitation training. *Journal of Neural Engineering* 18, 5 (sep 2021), 056022. doi:10.1088/1741-2552/ac1d32
- [31] Catarina Lopes-Dias, Andreea Ioana Sburlea, GR Müller-Putz, et al. 2019. Asynchronous detection of error-related potentials using a generic classifier. In *Proceedings of the 8th Graz Brain-Computer Interface Conference*, Vol. 10. 978–3.
- [32] Lu Lu, Ziyang Xie, Hanwen Wang, Li Li, and Xu Xu. 2022. Mental stress and safety awareness during human-robot collaboration - Review. *Applied Ergonomics* 105 (2022), 103832. doi:10.1016/j.apergo.2022.103832
- [33] Debasmita Mukherjee, Kashish Gupta, Li Hsin Chang, and Homayoun Najjaran. 2022. A Survey of Robot Learning Strategies for Human-Robot Collaboration in Industrial Settings. *Robotics and Computer-Integrated Manufacturing* 73 (2022), 102231. doi:10.1016/j.rcim.2021.102231
- [34] Karameldeen Omer, Francesco Ferracuti, Alessandro Freddi, Sabrina Iarlori, Andrea Monterù, and Camillo Porcaro. 2022. Human-in-the-Loop Approach for Enhanced Mobile Robot Navigation. In *2022 IEEE International Conference on Metrology for Extended Reality, Artificial Intelligence and Neural Engineering (MetroXR/AINe)*. 416–421. doi:10.1109/MetroXR/AINe54828.2022.9967516
- [35] Xavier Perrin, Ricardo Chavarriaga, Francis Colas, Roland Siegwart, and José del R. Millán. 2010. Brain-coupled interaction for semi-autonomous navigation of an assistive robot. *Robotics and Autonomous Systems* 58, 12 (2010), 1246–1255. doi:10.1016/j.robot.2010.05.010 Intelligent Robotics and Neuroscience.
- [36] Patrick Rückert, Hannah Wallmeier, and Kirsten Tracht. 2023. Biofeedback for human-robot interaction in the context of collaborative assembly. *Procedia CIRP* 118 (2023), 952–957. doi:10.1016/j.procir.2023.06.164 16th CIRP Conference on Intelligent Computation in Manufacturing Engineering.
- [37] Andres F. Salazar-Gomez, Joseph DelPreto, Stephanie Gil, Frank H. Guenther, and Daniela Rus. 2017. Correcting robot mistakes in real time using EEG signals. In *2017 IEEE International Conference on Robotics and Automation (ICRA)*. 6570–6577. doi:10.1109/ICRA.2017.7989777
- [38] Gerwin Schalk, Jonathan R Wolpaw, Dennis J McFarland, and Gert Pfurtscheller. 2000. EEG-based communication: presence of an error potential. *Clinical Neurophysiology* 111, 12 (2000), 2138–2144. doi:10.1016/S1388-2457(00)00457-0
- [39] Lucia Schiatti, Jacopo Tessadori, Nikhil Deshpande, Giacinto Barresi, Louis C. King, and Leonardo S. Mattos. 2018. Human in the Loop of Robot Learning: EEG-Based Reward Signal for Target Identification and Reaching Task. In *2018 IEEE International Conference on Robotics and Automation (ICRA)*. 4473–4480. doi:10.1109/ICRA.2018.8460551
- [40] Francesco Semeraro, Alexander Griffiths, and Angelo Cangelosi. 2023. Human-robot collaboration and machine learning: A systematic review of recent research. *Robotics and Computer-Integrated Manufacturing* 79 (2023), 102432. doi:10.1016/j.rcim.2022.102432
- [41] Avinash Kumar Singh, Stefano Aldini, Daniel Leong, Yu-Kai Wang, Marc G. Carmichael, Dikai Liu, and Chin-Teng Lin. 2020. Prediction Error Negativity in Physical Human-Robot Collaboration. In *2020 8th International Winter Conference on Brain-Computer Interface (BCI)*. 1–6. doi:10.1109/BCI48061.2020.9061616
- [42] P. Soriano-Segura, M. Ortiz, E. Iáñez, and J.M. Azorín. 2024. Design of a brain-machine interface for reducing false activations of a lower-limb exoskeleton based on error related potential. *Computer Methods and Programs in Biomedicine* 255 (2024), 108332. doi:10.1016/j.cmpb.2024.108332
- [43] Martin Spüler, Michael Bensch, Sonja Kleih, Wolfgang Rosenstiel, Martin Bogdan, and Andrea Kübler. 2012. Online use of error-related potentials in healthy users and people with severe motor impairment increases performance of a P300-BCI. *Clinical Neurophysiology* 123, 7 (2012), 1328–1337. doi:10.1016/j.clinph.2011.11.082
- [44] Andrea C. Tricco, Erin Lillie, Wasifa Zarin, and et al. 2018. PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. *Annals of Internal Medicine* 169, 7 (2018), 467–473. doi:10.7326/M18-0850 arXiv:https://doi.org/10.7326/M18-0850 PMID: 30178033.
- [45] Xiaofei Wang, Hsiang-Ting Chen, Yu-Kai Wang, and Chin-Teng Lin. 2023. Implicit Robot Control Using Error-Related Potential-Based Brain–Computer Interface. *IEEE Transactions on Cognitive and Developmental Systems* 15, 1 (2023), 198–209. doi:10.1109/TCDS.2022.3151860
- [46] Mine Yasemin, Aniana Cruz, Urbano J Nunes, and Gabriel Pires. 2023. Single trial detection of error-related potentials in brain–machine interfaces: a survey and comparison of methods. *Journal of Neural Engineering* 20, 1 (jan 2023), 016015. doi:10.1088/1741-2552/acabe9
- [47] Timothy Zeyl, Erwei Yin, Michelle Keightley, and Tom Chau. 2016. Adding Real-Time Bayesian Ranks to Error-Related Potential Scores Improves Error Detection and Auto-Correction in a P300 Speller. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 24, 1 (2016), 46–56. doi:10.1109/TNSRE.2015.2461495