

Beyond the Algorithm: Neuroethical Challenges of Artificial Intelligence in Neuroscience and Clinical Decision-Making

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Abstract

The convergence of Artificial Intelligence (AI) and Neuroscience is substantially expanding the possibilities for understanding, predicting, and clinically addressing human brain functions. The increasing use of algorithmic systems, Big Data, neuroimaging, and brain-computer interfaces, however, is creating a new landscape of neuroethical challenges in which technological capability does not necessarily imply ethical acceptability.

This study investigates perceptions of the potential of AI in Neuroscience, the bioethical and neuroethical dilemmas arising from the use of AI algorithms and Big Data, and the role of physicians in algorithmically supported by clinical decision-making.

The study involved 427 participants from different academic disciplines and levels of study. Data were collected using the “AI, Neuroscience and Bio(ethical) Dilemmas” instrument, developed based on the international literature. The instrument explores three interrelated domains: the perceived potential of AI in Neuroscience, emerging neuroethical dilemmas, and the role of physicians in AI-assisted clinical decision-making. Descriptive and implicative statistical methods were employed to analyse the data.

The findings reveal positive perceptions of AI’s potential to influence cognitive and perceptual functions and contribute to the management of psychiatric, neurological, and other brain-related disorders. At the same time, a coherent constellation of neuroethical concerns emerges around individual autonomy, neural-data privacy, human rights, algorithmic bias, transparency, and accountability. The findings further highlight the importance attributed to preserving physicians’ clinical judgment and responsibility rather than transferring therapeutic decision-making exclusively to algorithmic systems.

The integration of AI into Neuroscience should not be understood solely as a technological advancement, but also as a challenge of neuroethical governance. Responsible and sustainable integration requires a human-centred framework in which algorithmic innovation complements rather than displaces human judgment. Such a framework should safeguard autonomy, dignity, privacy, fairness, transparency, and clinical accountability while enabling the benefits of AI-driven neuroscience to be translated responsibly into research and clinical practice.

1. Introduction

The development of brain-computer interfaces (BCIs) using new cutting-edge technologies has revolutionized the field of neuroscience. In brain-computer interfaces (BCIs), artificial intelligence algorithms decode neural activity in real time, allowing paralyzed individuals to control external devices with their thoughts (Brandman et al., 2017).

Today, a large number of non-invasive brain imaging techniques have been developed, which monitor brain activity and can be categorized as follows: a. Metabolic imaging, such as functional magnetic resonance imaging (fMRI), which operates based on fluctuations in blood flow to the brain and aims to identify brain activity as well as its connection to an individual's perceptions and emotions, b. magnetic imaging, such as magnetic resonance imaging (MRI), which focuses on understanding brain function and disorders, c. electroencephalography, known as EEG (Electroencephalography) (Cinel et al., 2019), which records electrical activity via electrodes placed on the head, measuring brain waves by calculating the potential difference between two points, and focuses on detecting disturbances in brain function.

Artificial intelligence's ability to integrate various imaging methods addresses a long-standing challenge in neuroscience: linking structural, functional, and molecular brain data. One application demonstrated how DL models integrate structural MRI with fMRI and PET to predict cognitive decline in preclinical AD models (Warren & Moustafa, 2023).

Today, more than ever, the development of artificial intelligence, deep learning, machine learning, and ontogenetics are contributing to the further advancement of the neurosciences (Gopinath, 2023). It is undeniable that the benefits of artificial intelligence's current capabilities are remarkable, but it is also possible that the capabilities artificial intelligence will possess in the future will be of even greater scientific value. Gopinath (2023) argued that artificial intelligence will essentially unlock the secrets of the human brain.

The convergence of Artificial Intelligence (AI) and neuroscience is shaping a particularly dynamic interdisciplinary field, with significant prospects both for understanding the functioning of the human brain and for advancing medical diagnosis and treatment. The relationship between the two scientific fields is bidirectional: on the one hand, the study of neural mechanisms provides valuable insights for the development of computational models that simulate complex cognitive functions, while, on the other hand, AI methods offer advanced tools for analyzing and interpreting complex neurobiological data (Gopinath, 2023). In particular, AI algorithms can contribute to the investigation of functions such as decision-making, perception, and object recognition, enabling a more comprehensive understanding of the computational principles underlying cognitive function. At the same time, the application of AI in neuroscience facilitates the detection and mapping of changes in the structure, function, and connectivity of brain networks. Utilizing this information can enhance the early identification of neurological or neuropsychiatric disorders, support more accurate diagnostic approaches, and contribute to the development of more personalized treatment strategies (Gopinath, 2023).

In addition, Gundersen & Børøe (2022) emphasized that artificial intelligence, machine learning, and deep learning play a decisive role in enabling more effective and accurate decision-making. The most significant algorithms developed to date are used to diagnose major neurological disorders such as Alzheimer's disease (AD), Parkinson's disease (PD), dementia, depression, schizophrenia, epilepsy, brain tumors, stroke, as well as a host of other diseases associated with the central and peripheral nervous systems.

Functional magnetic resonance imaging (fMRI) and electroencephalography (EEG), in combination with cutting-edge technologies, artificial neural networks (ANNs), machine learning, and deep learning, can bring about major breakthroughs in the field of neuroscience (Sejnowski et al., 2014). According to Ienca & Ignatiadis (2020), the applications of artificial intelligence in clinical neuroscience involve prediction, diagnosis, brain modeling, and neurotechnologies. Artificial neural networks (ANNs), using large-scale data derived from electroencephalograms (EEGs), tend to achieve significant predictive power regarding severe neurological disorders.

At the same time, the use of Artificial Intelligence contributes significantly to the development of neuromarkers through the processing and integration of multidimensional neuroimaging and neurophysiological data derived from techniques such as fMRI, EEG, and MEG. These markers can be used to identify neural patterns associated with specific clinical manifestations or behavioral states, enhancing the ability to predict and evaluate them more objectively. An illustrative application is the Neurologic Pain Signature (NPS), a computational model based on fMRI data that captures characteristic patterns of brain activity associated with physical pain, offering a more objective approach to the study of what is essentially a subjective experience (Badrulhisham et al., 2024).

The convergence of Artificial Intelligence (AI) and neuroscience creates a dynamic interdisciplinary field, expanding the possibilities for understanding brain function, the early diagnosis of neurological disorders, and the development of personalized therapeutic interventions. Through advanced techniques, such as deep learning and neuro-morphic computing, it becomes possible to analyze complex neuroimaging, electrophysiological, and genomic data. At the same time, neuroscience fuels the evolution of AI, inspiring new architectures and learning mechanisms. However, this dynamic interaction is accompanied by challenges related to the interpretability of algorithms, data integration, and ensuring ethically responsible and human-centered applications (Onciul et al., 2025).

Despite the significant prospects arising from the convergence of Artificial Intelligence and neuroscience, the integration of advanced algorithmic systems into neuroscientific research is accompanied by substantial methodological and ethical challenges. Of particular importance is the limited interpretability of AI models, especially in the clinical setting, where the ability to document and understand the reasoning underlying an algorithmic prediction is a fundamental prerequisite for scientific and clinical reliability (Ilan, 2023).

Beyond the neurobiological dimension, human–Artificial Intelligence (AI) interactions may raise additional philosophical and ethical issues and concerns (Rossi et al., 2026). Ethical concerns, issues, and dilemmas are of paramount importance, especially when we refer, among other things, to brain mapping, brain enhancement, and cognitive abilities, which pertain to privacy (Privacy), transparency, and accountability (Cinel et al., 2019), as well as autonomy and agency and discrimination (Ienca & Ignatiadis, 2020).

Furthermore, the inherent complexity, heterogeneity, and noise that characterize neuroscientific data create additional challenges regarding the training, validation, and generalizability of computational models. At the same time, critical ethical and deontological issues arise, primarily concerning the protection of privacy and the confidentiality of sensitive neuroscience data, as well as ensuring equality, impartiality, and equitable access in the development and implementation of AI-based technologies (Jwa & Poldrack, 2022).

The emergence of Artificial Intelligence in neuroscience and healthcare does not merely mark a technological advancement, but a fundamental shift in the way knowledge about the human brain and health is generated, interpreted, and applied. However, as the capabilities of AI expand, new demands emerge regarding the quality and reliability of data, the transparency of algorithmic decisions, the technical validity of applications, and the ethical management of their consequences. Therefore, the true value of AI does not depend solely on what it can achieve technologically, but also on whether its applications can remain interpretable, safe, fair, and human-centered (Badrulhisham et al., 2024).

Moya-Sanchez (2026) argues that the use of large language models (Large Language Models – LLMs) by individuals with psychiatric disorders is no longer a hypothetical possibility, but an already established and difficult-to-reverse reality of contemporary clinical practice. Increasingly, patients are coming to mental health professionals after having previously interacted with artificial intelligence applications, which they use as informal sources of psychological guidance. Through these apps, they attempt to understand or interpret their symptoms, manage emotional difficulties, and, in some cases, make decisions related to their mental health. However, the use of such systems without professional or clinical supervision carries significant risks (Moya-Sanchez, 2026). These include the potential reinforcement of existing cognitive distortions, the provision of inaccurate or misleading information due to the models' so-called "hallucinations" (hallucinations) of the models, as well as their limited ability to safely recognize and manage mental health crises (Moya-Sanchez, 2026).

Neuroimaging scans, electrophysiological recordings, and clinical datasets are often noisy, inconsistent, and influenced by differing acquisition protocols. These discrepancies can introduce bias and reduce the reliability of artificial intelligence models, especially when applied to diverse populations (Stripelis et al., 2024).

Müller & Rotter (2017) emphasize the principle of "informed consent" with regard to any medical procedure, which is directly linked to a person's personality, dignity, and integrity. A sufficient and necessary condition for any neurotechnological intervention is conscious, explicit consent, given after receiving information, with the aim of protecting the patient's personality and, consequently, their dignity as well as their autonomy, (Müller & Rotter, 2017). It should be noted that the principle of "informed consent" is inextricably linked to personhood (Beauchamp & Childress, 2008).

With regard to transparency in the field of neuroscience (Cinel et al., 2019), where cutting-edge technologies and deep learning algorithms, such as deep neural networks (DNNs), are used, the existence of black boxes raises significant concerns and ethical issues regarding the assignment of responsibility in the event of malfunction and the ability to monitor the system throughout its entire lifecycle (Ienca et al., 2018). The limited interpretability of AI models poses a critical challenge in neuroscience and clinical practice, as even an accurate algorithmic prediction may have limited value when it is unclear how it was derived. The decoding of states of mind, perceptions, intentions, and cognitive abilities in the context of brain mapping raises ethical issues in the field of neuroscience (Müller & Rotter, 2017).

When it comes to algorithmic decisions, issues of censorship arise in the event of an incorrect assessment. It should be added here that these decisions are contested in everyday clinical practice and raise new questions regarding the doctor-patient relationship (Aminololama-Shakeri & Lopez, 2019). The questions raised concern whether decisions will be made by cutting-edge technologies and the doctor will simply follow the decision; To what extent will the doctor depend on the development of artificial intelligence systems and, consequently, need to acquire new skills in these technologies, potentially undermining their own skills as a clinician? What if the physician is unable to understand how the algorithms make decisions? Will the diagnosis and/or treatment remain the exclusive decision, and consequently the responsibility, of the clinician? (Ienca & Ignatiadis, 2020). Finally, is there a risk that the right to human decision-making, that is, the right of the physician or team of physicians to jointly decide with the patient on the treatment and care the patient will receive will be minimized or even eliminated?

Additional challenges arise from evolving regulatory oversight and ambiguity regarding the allocation of responsibility when an algorithmic recommendation contributes to a clinical decision (Hassan et al., 2024).

The integration of artificial intelligence systems into medical practice neither negates nor transfers the physician's professional and ethical responsibility to the technological system. The physician must use AI tools with critical awareness, evaluating the reliability and appropriateness of their results in light of the patient's clinical presentation. Although they may reasonably rely on a properly designed and approved system, they remain responsible for identifying potential indications of error, inconsistency, or risk and, when these arise, for reevaluating the decision proposed by the AI. At the same time, the clinician's responsibility extends to protecting the patient's life, health, and integrity, as well as respecting the patient's autonomy through adequate information and explanation of treatment options. Therefore, EI should function as a tool to support clinical judgment and not as a mechanism to replace human responsibility (Verdicchio & Perin, 2022).

It should be noted that in this paper we examined general issues as well as ethical, bioethical and philosophical in nature, as well as questions related to actual or potential risks, primarily in the fields of artificial intelligence and large-scale data (in the field of neuroscience, we refer to large-scale brain data); for reasons of brevity alone, we will not examine them in detail in the context of neuroscience, as these issues recur either in their original form or as subsets thereof. The most important issues are those related to informed consent, autonomy, personality, dignity, free will, privacy, human rights, and the security of sensitive personal data (Müller & Rotter, 2017).

The risk of bias is very significant in clinical neuroscience, as the training of algorithms may be biased because certain groups of patients with various neurological conditions may be underrepresented or overrepresented, some of which may be rare. The risk of algorithmic discrimination, which can also be characterized as "neurodiscrimination" is also evident, as are privacy concerns, specifically mental privacy, confidentiality, and the manipulation of the human brain.

Issues related to bioenhancement occupy a special place in the field of neuroethics.

Below is a brief overview of the ethical issues related to neuroimaging. Neuroimaging, which is used in neurosciences, raises many ethical issues. These issues concern:

- a. the reliability and validity regarding the objectivity of visualizing the brain in action. Neuroimaging techniques carry the primary risk that courts might use these procedures at an early stage.
- b. The unreliability of predictive neuroimaging raises another ethical issue. This issue relates to the widespread use of neuroimaging techniques to predict psychiatric disorders. There are examples where functional magnetic resonance imaging (fMRI) does not provide reliable diagnoses, and its effectiveness is called into question. This raises the possibility of causing potential harm to the individual.

c. Privacy. There is always the possibility of a privacy breach through technologies that can reveal a person's thoughts. Although accurate prediction could be used for early screening of mental illnesses, greatly benefiting the individual, it nevertheless violates "cognitive freedom," which is a fundamental right pertaining to an individual's autonomy over their brain functions.

With regard to brain enhancement, the (bio)ethical dilemmas that arise are very significant and concern:

- a. safety. Brain enhancement or neuro enhancement may have very serious side effects. Psychostimulants can improve memory. At the same time, they could disrupt their ability to recall past memories.
- b. Competition. When brain enhancement occurs and boosts a person's cognitive abilities, it may raise issues of competition, as the desire for greater achievements increases, either on the part of the person themselves or on the part of others who are competing with them. This will result in an ever-increasing and ongoing need to take such substances. This could also create issues that reflect the inability of individuals with low economic means to meet the costs, thereby placing them at a constant disadvantage compared to those who have the advantage of economic superiority. Consequently, success in school or in one's career is unlikely for low-income individuals.
- c. the transformation of the human condition. A very important ethical issue concerns whether we should seek cognitive enhancement through psychostimulants and intervene in personal cognitive development (Fuchs, 2006). Despite the particularly significant potential that Artificial Intelligence offers in the study of the brain and in the translation of neuroscientific knowledge into clinical practice, its application is not without limitations. The high predictive performance of an algorithm is not, in and of itself, sufficient evidence of scientific or clinical reliability. Limited external validation, methodological weaknesses, and the possibility that models are based on random or spurious correlations can create unrealistic expectations regarding their actual usefulness. Furthermore, when training data do not adequately represent the heterogeneity of the population, the resulting predictions may exhibit systematic biases across different social, demographic, or population groups. Consequently, the future development of neural biomarkers and other AI applications in neuroscience should not be evaluated solely in terms of computational accuracy, but also in terms of generalizability, equitable performance across different subpopulations, neuroscientific validity, and the interpretability of their results (Badrulhisham et al., 2024).

These challenges inevitably shift the discussion from the question "What can AI do for neuroscience?" to the deeper question "Under what conditions should it do so?" The more algorithms gain the ability to analyze brain data, recognize neural patterns, predict behavioral or clinical conditions, and support health-related decisions, the more intensely issues arise that go beyond the technical effectiveness of these systems. The protection of neural data, privacy, individual autonomy, algorithmic bias, equity, transparency, and interpretability of decisions, as well as accountability in the event of an error, are becoming central issues in the relationship between humans, the brain, and AI (Anastasiadou, 2026; Badrulhisham et al., 2024).

At this point, the crucial role of neuroethics becomes evident. The convergence of neuroscience and artificial intelligence does not merely create new possibilities for understanding and intervening in the human brain; it simultaneously creates a new realm of ethical responsibility. Neuroethics is therefore called upon to examine not only the limits of technological intervention but also the conditions under which the use of AI can remain compatible with human autonomy, dignity, privacy, justice, and responsible scientific and clinical practice.

2. Research Questions

The research questions posed in this study are as follows:

RQ1: What are the attitudes toward AI and Big Data, what impact does their development have on issues related to neurosciences, and what is the role of the physician regarding algorithmic decision-making?

RQ2: Is there a statistically significant correlation between the dimensions of ethical issues arising from the use of AI and Big Data algorithms in healthcare and the neurosciences—specifically regarding Privacy, Autonomy, Confidentiality, Bias, Fairness, Safety, Human Rights, and the role of the physician?

RQ3: Do attitudes toward the use of AI algorithms and big data, as well as ethical issues in healthcare and neurosciences, vary according to the demographic characteristics of the respondents?

3. Research Methodology

3.1 Statistical Methodology

In addition to descriptive statistics, inferential statistical analysis was used to evaluate the research data.

Implicative Statistical Analysis (Analyse Statistique Implicative, ASI) is a classification method developed by French professor Régis Gras in 1979 and applied to a wide range of data, such as in statistics, education, psychology, pedagogy, medicine, physics, neuroscience, etc., and is based on the principles of probability theory (Gras, 1979). The original purpose of this methodology is to define an approach capable of addressing the question “if an object has one property, it also has another.” This is not always true, but it is very likely to be the case. In Implicative Statistical Analysis (ASI) (Analyse Statistique Implicative), the goal is to identify these trends across a set of properties (Anastasiadou, 2027). Implicative Statistical Analysis (ASI) essentially generates association rules (Coutourier, 2008). It is regarded as a broad theoretical framework, a theory linked to causality precisely because it addresses the limitations of other multivariate statistical methods and, furthermore, contributes to the development of tools and practices for representing, evaluating, and interpreting data (Anastasiadou, 2019). At this point, it is worth noting that ASI, compared to other association rule methods, stands out because it provides a nonlinear measure that meets certain criteria.

The rules and generalized rules that are developed refer to variables structured in an ordinal manner into nested and oriented classes. However, a rule involving categories of variables truly makes sense only if, within each category of variables whose relationship to others is being examined, there is a specific “coherence” among the variables that comprise it.

To derive the implied association rules, ASI assigns a numerical value between 0 and 1 to each rule in R according to the following scheme. If variable a is observed, then variable b is likely to be observed. Consequently, if variable a takes on a certain value, then variable b is likely to take on a higher value. This measure represents probability, which is called the strength of association. It follows, therefore, that causal and predictive relationships are influenced by the strength of involvement.

The principle of defining the strength of involvement/implication as the probability of a random event is defined as follows: if there were no a priori asymmetric link between variables a and b, the number of counterexamples to rule R would be less than the single random outcome, most likely higher than the number of counterexamples observed in the corpus. Consequently, the method is based on the strength of inferences, which measures the degree of strength inherent in a rule $a \Rightarrow b$.

The strength of the inferences can be enhanced by the degree of validity, which is based on Shannon entropy, selected for this specific classification approach (Couturier, 2008).

The inferential representation of the associations is presented in Figure 1 as a weighted acyclic graph, where each edge represents a rule, and in Figure 2 it is depicted as an ascending hierarchy guided by a set of meta-rules.

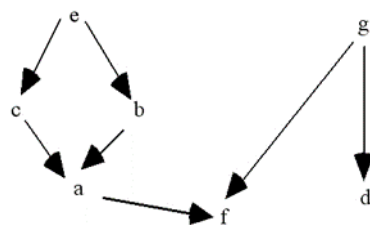


Figure 1

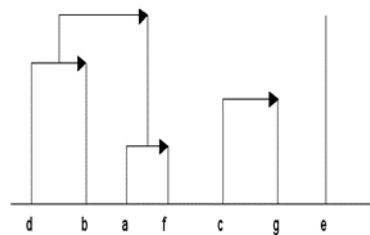


Figure 2

Figure 2 shows the hierarchy artificially derived from 7 variables. The interpretations of such generalized rules are sometimes complex, such as, for example, the rule $(x \Rightarrow (y \Rightarrow z)) \Rightarrow (t \Rightarrow v)$. However, certain rules can be reduced to more easily interpretable sets. For example, the rule $x \Rightarrow (y \Rightarrow z)$ would lead, in the standard case, to $x \wedge y \Rightarrow z$. A qualitative consistency (~ 1) would allow for this semantic extension.

The rule $(d \Rightarrow b) \Rightarrow (a \Rightarrow f)$ or $((db)(af))$ is illustrated in Figure 1 and can be interpreted by the statement: the “theorem” $d \Rightarrow b$ generally leads to the “theorem” $a \Rightarrow f$. This form also shows that the variable e has no proposition or conclusion. Figure 2 is an example of a directed hierarchy.

Similarity (Similarité/Similarity) is a symmetric analysis based on Lerman's algorithm (1981), which groups nearly all items into a large class regardless of their prior taxonomy (Gras & Bodin, 2017).

The similarity dendrogram is based on classification indices defined by Lerman (1981). Similarity indices are commonly used in data analysis to analyze objects described by binary variables and allow for the assessment of similarity between two objects or two variables (Blanchard et al., 2009).

The likelihood index is based on Likelihood Linkage Analysis (LLA) (Learman, 1981) and is defined as follows (Learman, 1993; Blanchard et al., 2009):

Learman's likelihood linkage index is $P(N_{ab} < n_{ab})$, while Grass's inference strength is given as $P(N_{ab}^* > n_{ab}^*)$, (Gras 1996, Gras & Kuntz, 2008), where the hypothesis being tested is H_0 : there is independence between a and b, and N_{ab} and N_{ab}^* are random variables representing the number of counterexamples, and n_{ab} and n_{ab}^* represent the number of counterexamples.

Coherence hierarchy or coherent hierarchy: It is expected that the coherent hierarchy, obtained using the CHIC and RCHIC software packages, successfully structures groups guided by inferences within the classes, while respecting the assumed taxonomic order.

For data analysis, the inferential graph, the hierarchical dendrogram, and the similarity diagram were used via the CHIC (Couturier, 2008) and RCHIC software programs.

3.2 Research Sample

The research sample consisted of 427 participants, of whom 165 (38.6%) were women and 262 (61.4%) were men. Regarding the age of the respondents, 70 (16.4%) were between 18 and 20 years old, 155 (36.3%) were between 20 and 22 years old, 128 (30%) were between 22 and 24 years old, and finally, 74 (17.3%) were over 24 years old.

Regarding place of residence, 330 of the 427 respondents, or 77.3%, reported living in an urban area, 86 (20.1%) in a semi-urban area, and finally, 11 (2.6%) in a rural area.

Regarding their school of study, 128 (30%) were from the School of Engineering, 88 (20.6%) were from the School of Natural Sciences, 47 (11%) were from the School of Health Sciences, 101 (23.7%) were from the School of Economics and Social Sciences, and finally, 63 (14.8%) were from the Schools of Humanities.

Regarding their year of study, 60 (14.1%) participants were in their first year, 119 (27.9%) were in their second year, 103 (24.1%) were in their third year, 43 (10.1%) were in their fourth year, 39 (9.1%) were in their fifth year, and 27 (6.3%) were in their sixth year. In addition, 28 (6.6%) participants were at the final stage of their undergraduate studies, while 8 (1.9%) were enrolled in a postgraduate or doctoral program.

3.3. Research Instrument

The "TN, Neurosciences, and Bio(ethical) Dilemmas" instrument: The tool "TN, Neurosciences, and Bio(ethical) Dilemmas" was developed by the author based on the international literature (Cinel et al., 2019; Ineca & Ignatiadis, 2020; Müller & Rotter, 2017).

Specifically, this tool consists of three conceptual constructs. The first, which includes 7 items, is called "AI Capabilities in Neuroscience" (Pos1: Artificial intelligence can transform the brain's cognitive abilities, Pos2: Artificial intelligence can transform the brain's perceptual abilities, Pos3: Artificial intelligence can contribute to the treatment of mental illnesses, Pos4: Artificial intelligence can contribute to the treatment of dementia, Pos5: Artificial intelligence can contribute to the treatment of Alzheimer's disease, Pos6: Artificial intelligence can contribute to the treatment of brain injury, Pos7: Artificial intelligence can contribute to the treatment of brain disease). The second, which includes 14 items, is titled "Neuroscience, AI, and Dilemmas" (Neu1: Applications of artificial intelligence in clinical neuroscience limit intellectual autonomy; Neu2: Applications of artificial intelligence in clinical neuroscience undermine personality, Neu3: Neuroimaging constitutes a violation of human rights, Neu4: In clinical neuroscience, the risk of bias is very significant, Neu5: In clinical neuroscience, the risk of algorithmic discrimination is very significant, Neu6: Brain mapping raises privacy concerns, Neu7: Brain enhancement raises privacy concerns, Neu8: Brain enhancement raises issues of justice, Neu9: Brain mapping raises issues of transparency, Neu10: Brain enhancement raises issues of individual autonomy regarding brain functions,

Neu11: Brain enhancement raises issues of informed consent, Neu12: Brain mapping raises issues of transparency, Neu13: Cutting-edge technologies and deep learning algorithms, such as deep neural networks, and the existence of black boxes raise issues of accountability, Neu14: In algorithmic decision-making in neuroscience, issues of accountability arise in the event of an incorrect assessment. The third section, which includes 4 items, is titled “TN, Neuroscience, and the Role of the Physician,” (Doc1: Algorithmic decision-making in neuroscience raises questions regarding the doctor-patient relationship; Doc2: In algorithmic decision-making in neuroscience, the physician depends on the development of artificial intelligence systems; Doc3: In algorithmic decision-making in neuroscience, the physician must understand how algorithms make these decisions, Doc4: Decisions regarding therapeutic treatment in neuroscience must be the decision and responsibility of the clinician, not an algorithmic one.

4. Analysis of Results

This chapter will present an analysis of the results of the social subjects’ responses to the research instrument and will attempt to answer the research questions that have been posed. The first research question will be analyzed and interpreted using Implicative Statistical Analysis, based on the similarity (similarité) and cohesion (cohésion) indices. We will focus primarily on interpreting the Similarity Diagram. We will then describe the most important inferences and rules derived from the Hierarchical Diagram (or Hierarchy or Cohesion Tree) and the Inductive Diagram (or Inductive Graph). The second research question will be analyzed using Pearson’s correlation coefficient, while the third will be analyzed using the t-test and one-way ANOVA (One-Way Analysis of Variance). The TN tool, “Neurosciences and Bio(ethical) Dilemmas,” consists of three conceptual constructs. The first is called “Potential of TN in the Neurosciences,” the second is called “Neuroscience, AI, and Dilemmas,” and the third is called “Neuroscience and the Role of the Physician.” The first research question will be addressed, which is:

RQ1: What are the attitudes toward AI and Big Data, and what impact does their development have on issues related to neuroscience?

The reliability of the research instrument, in terms of internal consistency, was assessed using Cronbach’s alpha, which amounts to $\alpha = 0.804$ and is satisfactory (Anastasiadou, 2011; Anastasiadou & Anastasiadis, 2019; Taraza & Anastasiadou, 2019).

Potential of TN in the Neurosciences: With regard to the conceptual construct “Attitude toward the Potential of TN in the Neurosciences,” the similarity diagram revealed a distinct group of respondents (Figure 3).

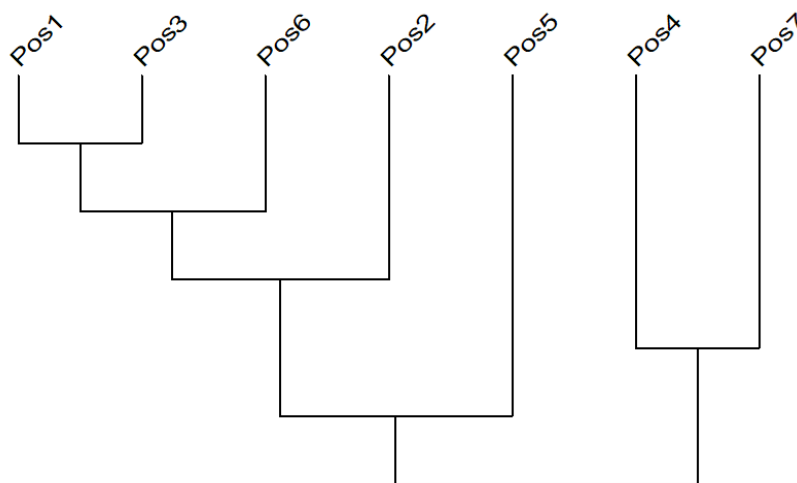


Figure 3: Similarity Tree-Potential Applications of TN in the Neurosciences

This Figure suggests that AI can transform the brain’s cognitive abilities (Pos1) and contribute to both the treatment of mental illnesses (Pos3) and the treatment of brain damage (Pos6). Respondents believe that TN can transform the brain’s perceptual abilities (Pos2) and contribute to the treatment of Alzheimer’s disease (Pos5). There are also respondents who believe that TN can contribute to the treatment of dementia (Pos4) and any other brain disease (Pos7).

From the Hierarchical Diagram, also known as a Hierarchy Tree or Cohesion Diagram, it can be observed that the strongest implication is $\text{Pos3} \Rightarrow \text{Pos2}$, which is extremely significant ((Pos3 Pos2) cohesion: 0.999) (Diagram 2). This rule means that the respondents' view that TN can contribute to the treatment of mental illnesses (Pos3) implies the view that it can transform the brain's perceptual abilities (Pos2). The rule $\text{Pos1} \Rightarrow \text{Pos3} \Rightarrow \text{Pos2}$, with significant cohesion, means that the respondents' view that TN can transform the brain's cognitive abilities implies the rule $\text{Pos3} \Rightarrow \text{Pos2}$. The rule $\text{Pos7} \Rightarrow \text{Pos4}$ is also strong ((Pos7 Pos4) cohesion: 0.973). This rule means that when social subjects believe that AI can contribute to the treatment of brain disease (Pos7), they also believe that it contributes to the treatment of dementia (Pos4).

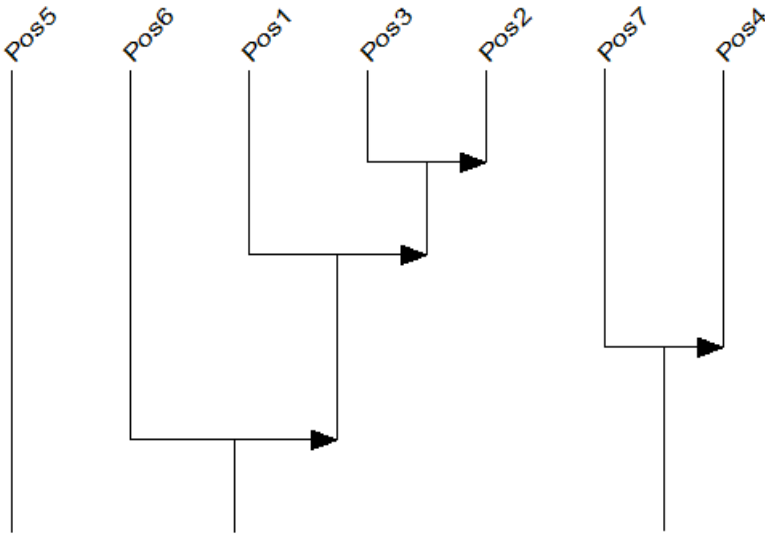


Figure 4: Hierarchical Diagram-TN Capabilities in Neuroscience

In the Implication Graph, the rules $\text{Pos1} \Rightarrow \text{Pos3}$ and $\text{Pos3} \Rightarrow \text{Pos2}$ indicate the strength of implication at a confidence level of 0.99, as they are displayed in red (Figure 5).

According to the inference $\text{Pos1} \Rightarrow \text{Pos3}$, 74.56% of those who believed that TN can transform the brain's cognitive abilities (Pos1) stated that it can contribute to the treatment of mental illnesses (Pos3). According to the implication $\text{Pos3} \Rightarrow \text{Pos2}$, 77.86% of those who supported the idea that TN can contribute to the treatment of mental illnesses (Pos3) stated that it can transform the brain's perceptual abilities (Pos2).

Two other illustrative examples are the rules $\text{Pos1} \Rightarrow \text{Pos4}$ and $\text{Pos7} \Rightarrow \text{Pos4}$, which show an implication strength between 0.95 and 0.99, as indicated by the green color.

According to the $\text{Pos1} \Rightarrow \text{Pos4}$ rule, 86.84% of respondents who believed that TN can transform the brain's cognitive abilities (Pos1) stated that it can contribute to the treatment of dementia (Pos4).

According to the rule $\text{Pos7} \Rightarrow \text{Pos4}$, 83.33% of respondents who believed that TN can contribute to the treatment of brain disease (Pos7) stated that it can contribute to the treatment of dementia (Pos4). Similarly, all the rules appearing in the implication diagram (Figure 5) can be described in this way.

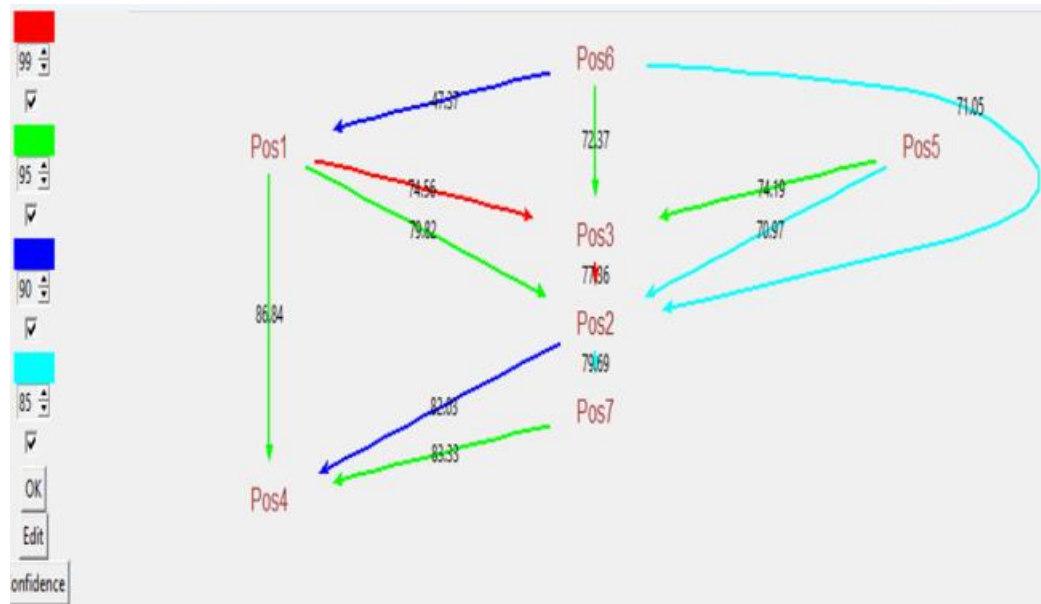


Figure 5: Implication Graph -The Potential of AI in the Neurosciences

Neuroscience, AI, and Dilemmas: With regard to the conceptual construct “Neuroscience, AI, and Dilemmas,” the similarity diagram revealed a distinct group of respondents (Figure 4). This group comprises social actors who argue, among other things, that the applications of artificial intelligence in clinical neuroscience limit intellectual autonomy (Neu1), brain mapping raises transparency issues (Neu9), cutting-edge technologies and deep learning algorithms, such as deep neural networks, and the existence of black boxes raise issues of accountability (Neu13); and finally, brain mapping raises privacy concerns (Neu6), (((Neu1 (Neu9 Neu13)) Neu6) (similarity: 0.980364)). Similarly, they argue that neuroimaging constitutes a violation of human rights (Neu3) and that in clinical neuroscience, the risk of bias is very significant (Neu4) ((Neu3 Neu4) similarity: 0.993145). They strongly support the aforementioned views, as the similarity indices are extremely significant. Similarly, all the similarities shown in Figure 6, which are less significant, can be described in this way.

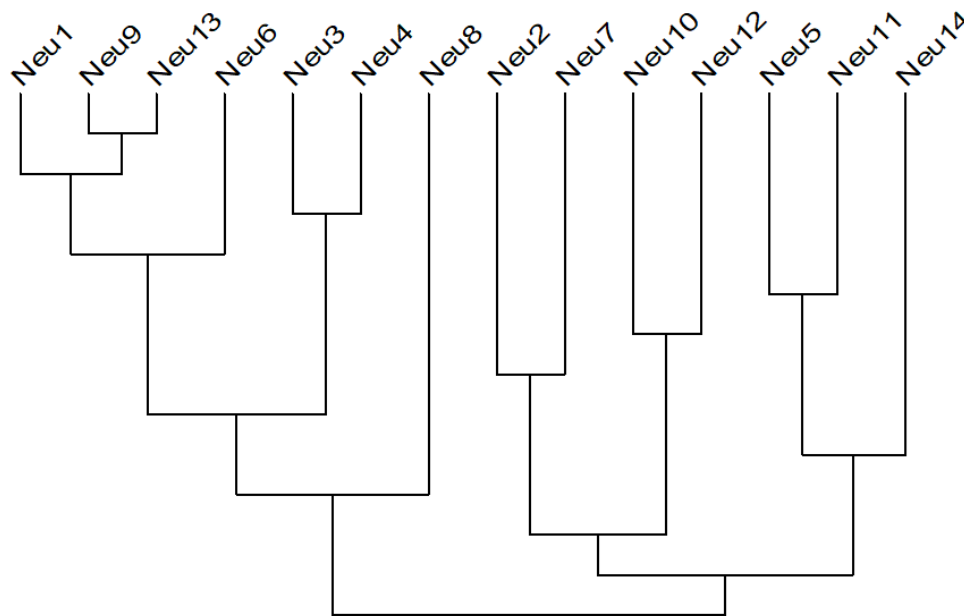


Figure 6: Similarity Dendrogram-Neuroscience, TN, and Dilemmas

From the Hierarchical Diagram, also known as a Hierarchy or Cohesion Dendrogram, it can be observed that the strongest implication is Neu13 $\Rightarrow$ Neu1, ((Neu13 Neu1) cohesion: 0.999) (Figure 7).

The implication $\text{Neu13} \Rightarrow \text{Neu1}$ means that the belief that cutting-edge technologies and deep learning algorithms, such as deep neural networks and the existence of black boxes, raise issues of accountability (Neu13), and implies the belief that applications of artificial intelligence in clinical neuroscience limit intellectual autonomy (Neu1).

As a rule, $\text{Neu11} \Rightarrow \text{Neu10}$ (cohesion: 0.993), the belief that brain enhancement raises issues of informed consent (Neu11) implies the belief that it raises issues of privacy protection (Neu10).

In the rule, $\text{Neu5} \Rightarrow \text{Neu2}$ (cohesion: 0.986), the belief that in clinical neuroscience the risk of algorithmic discrimination is very significant (Neu5) implies the view that applications of artificial intelligence in clinical neuroscience undermine personality (Neu2).

In the rule, $\text{Neu4} \Rightarrow \text{Neu3}$, (cohesion: 0.984), the belief that the risk of bias in clinical neuroscience is very significant (Neu4) implies the view that neuroimaging constitutes a violation of human rights (Neu3).

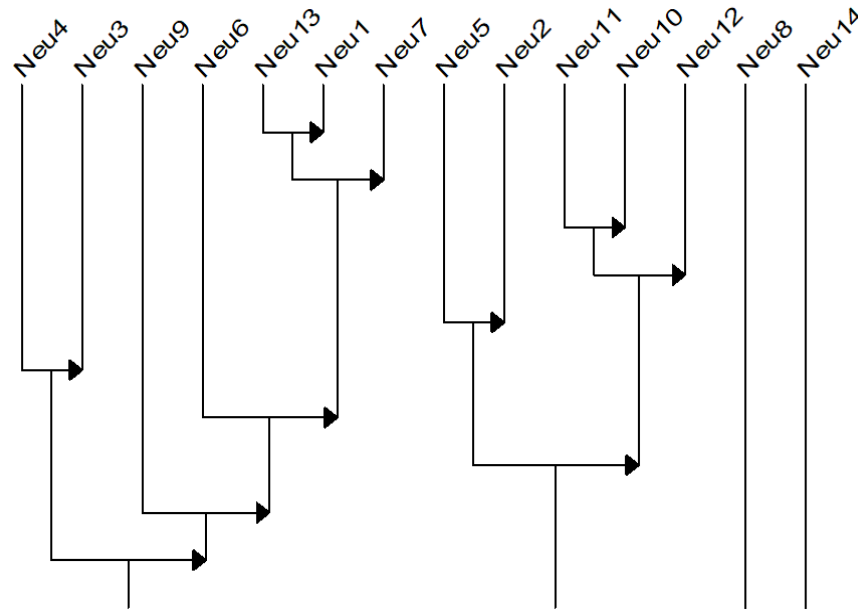


Figure 7: Hierarchical Diagram-Neuroscience, TN, and Dilemmas

Similarly, all the rules shown from the Implication Graph, in Figure 8 can be described.

The rules $\text{Neu6} \Rightarrow \text{Neu1}$ and $\text{Neu13} \Rightarrow \text{Neu1}$ indicate a strong inference at a confidence level of 0.99, as shown in red (Figure 6). According to the rule $\text{Neu6} \Rightarrow \text{Neu1}$, 64.04% of those who believed that brain mapping raises privacy concerns (Neu6) stated that artificial intelligence applications in clinical neuroscience limit intellectual autonomy (Neu1).

According to the rule $\text{Neu13} \Rightarrow \text{Neu1}$, 65.67% of respondents argued that cutting-edge technologies, deep learning algorithms (Neu13), as well as deep neural networks, the existence of black boxes raises issues of accountability, stated that applications of artificial intelligence in clinical neuroscience limit intellectual autonomy (Neu1).

Two other illustrative examples are the rules $\text{Neu11} \Rightarrow \text{Neu12}$ and $\text{Neu12} \Rightarrow \text{Neu10}$, which show an inference strength between 0.95 and 0.99, as indicated by the green color.

According to the $\text{Neu11} \Rightarrow \text{Neu12}$ rule, the 81.85% who argued that brain enhancement raises issues of informed consent (Neu11) stated that brain mapping raises issues of transparency (Neu12).

According to the rule $\text{Neu12} \Rightarrow \text{Neu10}$, 82.03% of respondents who argued that brain mapping raises issues of transparency (Neu12) also argued that brain enhancement raises issues of privacy protection (Neu10).

Similarly, all the rules appearing in the Implication Graph (Diagram 8) can be described in this way.

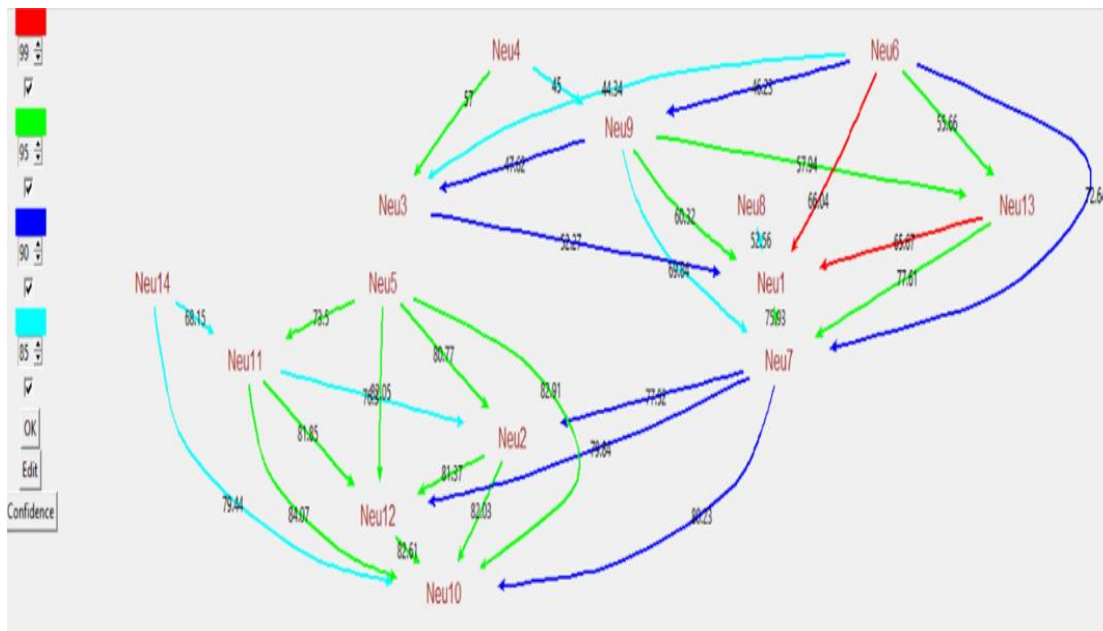


Figure 8: Implication Graph-Neuroscience, TN, and Dilemmas

AI, Neuroscience, and the Role of the Physician: With regard to the conceptual construct “AI, Neuroscience, and the Role of the Physician,” the similarity diagram revealed a distinct group of respondents (Figure 7). This group consists of social actors who argue that algorithmic decisions in neuroscience raise questions regarding the doctor-patient relationship (Doc1) and believe that decisions regarding therapeutic treatment in neuroscience should be the decision and responsibility of the clinician, not an algorithmic one (Doc4). Furthermore, they believe that in algorithmic decision-making in the neurosciences, the physician is dependent on the development of artificial intelligence systems (Doc2) and must understand how the algorithms make these decisions (Doc3) (Figure 9).

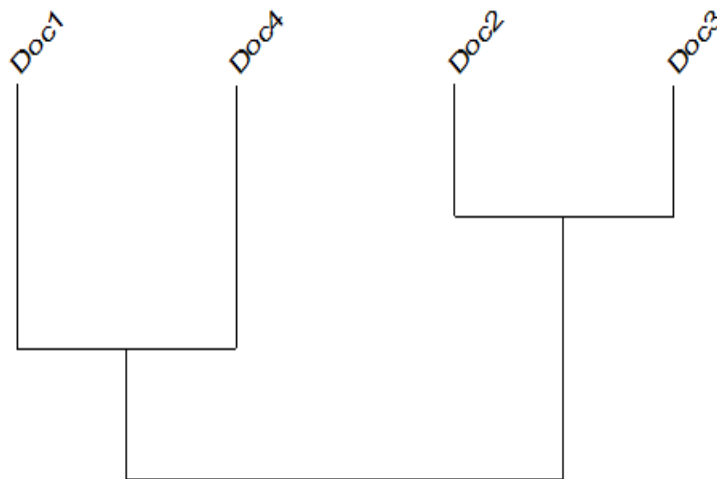
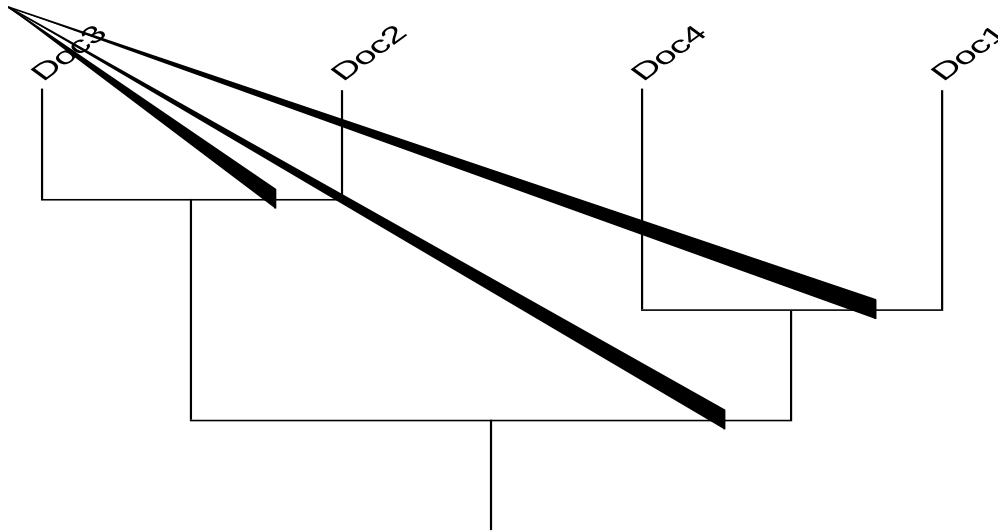


Figure 9: Similarity-TN Tree Diagram, Neuroscience, and the Role of the Physician

The Hierarchical Diagram, also known as a Hierarchy Tree Diagram or Cohesion Diagram (10), is fully consistent with the Similarity Tree Diagram (Figure 9). From the Hierarchical Diagram, Hierarchy Tree Diagram, or Cohesion Diagram, it can be observed that the strongest implication is $\text{Doc3} \Rightarrow \text{Doc2}$, with a cohesion of 0.778. According to this, the belief that in algorithmic decision-making in neuroscience, the physician must understand how algorithms make these decisions, leads to the belief (Doc3), which implies the view that in these decisions, the physician depends on the development of artificial intelligence systems (Doc2).

In the rule $\text{Doc4} \Rightarrow \text{Doc1}$, which exhibits relatively high cohesion (cohesion: 0.503), the perception that treatment decisions in neuroscience must be the decision and responsibility of the clinician and not an algorithmic one (Doc4), implies the belief that algorithmic decisions in the neurosciences raise questions regarding the doctor-patient relationship (Doc1) (Figure 10).



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Figure 10: Hierarchical Diagram-TN, Neuroscience, and the Role of the Physician

In the Implication Graph, the rules $\text{Doc4} \Rightarrow \text{Doc1}$ and $\text{Doc3} \Rightarrow \text{Doc2}$ show an implication strength between 0.70 and 0.90, as indicated by the turquoise color.

According to the rule $\text{Doc4} \Rightarrow \text{Doc1}$, the 36.46% who argued that treatment decisions in neuroscience should be the decision and responsibility of the clinician rather than an algorithmic one, argued that algorithmic decisions in neuroscience raise questions regarding the doctor-patient relationship.

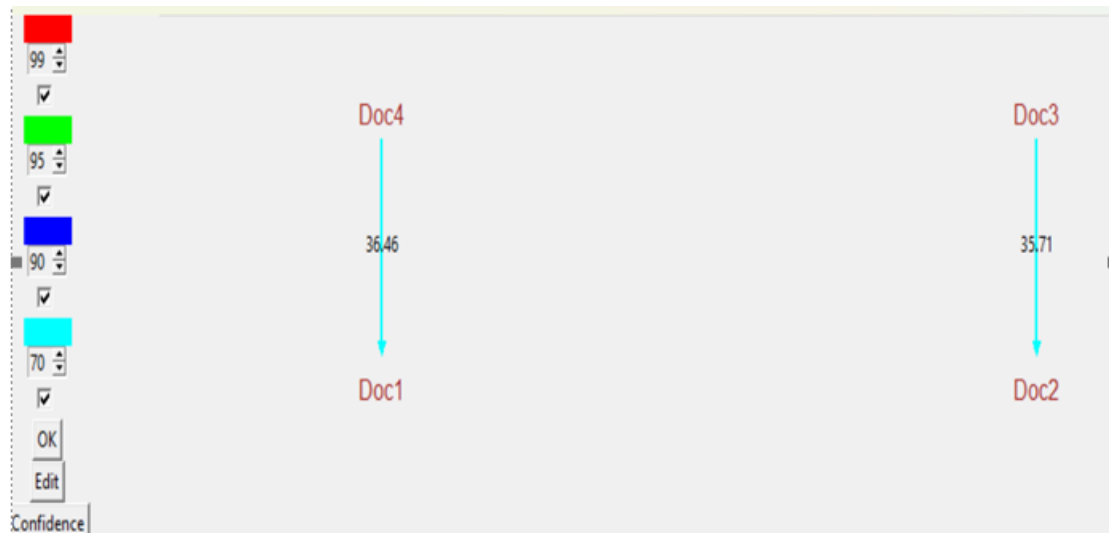


Figure 11: Implication Graph -TN, Neuroscience, and the Role of the Physician

According to the rule $\text{Doc3} \Rightarrow \text{Doc2}$, the 35.71% who argued that in algorithmic decision-making in neuroscience, the physician must understand how algorithms make these decisions, argued that in these algorithmic decisions in neuroscience, the physician is dependent on the development of artificial intelligence systems.

The study of the impact of demographic variables on the conceptual frameworks of research tools is addressed in the second question, which investigates the extent to which attitudes toward the use of AI algorithms, Big Data, and ethical issues based on the demographic characteristics of the respondents (Q2).

- a. Regarding the study of the effect of the demographic variable “Gender,” the t-test for the instrument “AI, Neuroscience, and Bio (Ethical) Dilemmas” showed that gender is not a differentiating factor for the conceptual construct “Potential of TN in Neuroscience” ($t=0.193$, $df=109$, $p=0.848$), “Neuroscience, TN, and Dilemmas” ($t=0.109$, $df=109$, $p=0.914$), and “Neuroscience and the Role of the Physician” ($t=-1.144$, $df=109$, $p=0.255$).
- b. Regarding the study of the effect of the demographic variable “Age,” the ANOVA test for the “TN, Neurosciences, and Bio(ethics) Dilemmas” showed that age is not a differentiating factor for the conceptual construct “Potential of TN in the Neurosciences” ($F=0.480$, $p=0.697$), “Neurosciences, TN, and Dilemmas” ($F=0.783$, $p=0.506$), and “Neuroscience and the Role of the Physician” ($F=0.598$, $p=0.617$).
- c. Regarding the study of the effect of the demographic variable “Place of Residence,” the ANOVA test for the construct “TN, Neurosciences, and Bio (Ethical) Dilemmas,” that place of residence is not a differentiating factor for the conceptual construct “Potential of TN in Neuroscience” ($F=0.167$, $p=0.847$), the conceptual construct “Neuroscience, TN, and Dilemmas” ($F=0.200$, $p=0.819$), and “Neuroscience and the Role of the Physician” ($F=0.328$, $p=0.721$).
- d. Regarding the study of the effect of the demographic variable “School of Enrollment,” the ANOVA test for the “TN, Neurosciences, and Bio (Ethical) Dilemmas,” showed that the School of Study is not a differentiating factor for the conceptual construct “Potential of TN in the Neurosciences” ($F=0.078$, $p=0.989$), the construct “Neuroscience, TN, and Dilemmas” ($F=0.103$, $p=0.981$), and the construct “Neuroscience and the Role of the Physician” ($F=0.851$, $p=0.496$).
- e. Regarding the study of the effect of the demographic variable “Year of Study,” the ANOVA test for the “TN, Neurosciences, and Bio (Ethical) Dilemmas,” that the year of study is not a differentiating factor for the conceptual construct “Potential of TN in the Neurosciences” ($F=0.391$, $p=0.906$), the construct “Neuroscience, TN, and Dilemmas” ($F=0.229$, $p=0.978$), and the construct “Neuroscience and the Role of the Physician” ($F=1.164$, $p=0.330$).

5. Conclusions

The findings of the present study reveal a complex relationship between the perceived potential of Artificial Intelligence (AI) in Neuroscience and the ethical concerns associated with its application. Participants did not appear to perceive technological advancement and neuroethical risk as mutually exclusive. Rather, their responses indicate that recognition of AI's potential in the study and treatment of brain-related conditions coexists with substantial concerns regarding autonomy, privacy, human rights, algorithmic bias, transparency, and accountability.

With regard to the perceived potential of AI in Neuroscience, the findings indicate meaningful associations among participants' views of their different applications. The strongest implicative relationship ($\text{Pos3} \Rightarrow \text{Pos2}$; cohesion = 0.999) shows that the belief that AI can contribute to the treatment of psychiatric disorders strongly implies the perception that it can transform perceptual capacities of the brain. Furthermore, the rule $\text{Pos1} \Rightarrow \text{Pos3} \Rightarrow \text{Pos2}$ suggests an interconnected pattern linking perceived transformations in cognitive abilities with the treatment of psychiatric disorders and changes in perceptual capacities. A further strong relationship ($\text{Pos7} \Rightarrow \text{Pos4}$; cohesion = 0.973) connects the broader perceived contribution of AI to the treatment of brain disorders with its potential contribution to dementia treatment. These findings suggest that participants conceptualise AI's role in Neuroscience as a network of interrelated cognitive and therapeutic possibilities rather than as a set of isolated applications.

At the same time, the analysis of the "Neuroscience, AI and Dilemmas" construct identified a distinct and highly coherent pattern of neuroethical concerns. Participants who associated AI applications in clinical Neuroscience with limitations on intellectual autonomy also tended to associate brain mapping with transparency concerns, black-box deep-learning systems with accountability issues, and brain mapping with threats to privacy (similarity = 0.980364). An even stronger association was identified between concerns that neuroimaging may affect human rights and perceptions of algorithmic bias as a significant risk in clinical Neuroscience (similarity = 0.993145). Thus, the reported findings indicate that participants do not perceive autonomy, privacy, transparency, accountability, human rights, and bias as independent ethical problems, but as closely interconnected dimensions of AI-enabled Neuroscience.

The findings concerning the role of physicians further reinforce this pattern. Participants associated algorithmic decision-making in Neuroscience with changes in the physician-patient relationship and expressed the view that therapeutic decisions should remain under the responsibility of the clinician rather than being transferred exclusively to an algorithm. They also emphasised that physicians should understand how algorithmic systems generate their decisions. These results point to a model in which AI supports, rather than replaces, clinical judgment and in which human oversight remains central to the use of algorithmic systems in healthcare.

Taken together, the findings suggest that the challenge posed by AI in Neuroscience is not simply whether increasingly sophisticated algorithms can analyse brain data or support diagnosis and treatment. The more fundamental issue concerns how these capabilities can be integrated into clinical and neuroscientific practice while preserving human agency, professional responsibility, privacy, and fundamental rights. In this respect, Neuroethics provides an important conceptual framework for examining the boundaries between technological capability and ethically responsible application.

Importantly, the present findings should be interpreted as evidence of participants' perceptions and patterns of association, rather than as evidence that AI itself causes particular therapeutic outcomes or necessarily produces specific ethical harm. The implicative and similarity relationships identified in the analysis reveal how these issues are cognitively and ethically connected within the surveyed population; they do not establish causal relationships or demonstrate the clinical effectiveness of AI-based interventions.

Overall, the study highlights a central tension in contemporary AI-enabled Neuroscience: the same technologies that are perceived as opening new possibilities for understanding and addressing brain-related disorders are also associated with concerns about autonomy, privacy, human rights, bias, transparency, and accountability. The findings therefore support the importance of a human-centred approach in which technological innovation is accompanied by meaningful human oversight and clearly defined clinical responsibility.

The central question emerging from the study is consequently not only what AI can contribute to Neuroscience, but under what ethical conditions these contributions should be pursued. As AI becomes increasingly involved in analysing brain-related data and supporting clinical decisions, the findings underscore the importance of ensuring that technological advancement remains compatible with human autonomy, rights, privacy, and physician responsibility.

6. Implications

The findings of the present study have several theoretical, clinical, ethical, and educational implications for the emerging intersection of Artificial Intelligence, Neuroscience, and Neuroethics.

From a theoretical perspective, the results suggest that perceptions of AI in Neuroscience should not be conceptualised exclusively in terms of technological acceptance or anticipated clinical utility. Participants simultaneously associated AI with cognitive and therapeutic possibilities and with concerns related to autonomy, privacy, human rights, bias, transparency, and accountability. The strong similarity relationships observed among these ethical dimensions indicate that they may constitute an interconnected neuroethical framework rather than a collection of isolated concerns. Future conceptual models of AI adoption in Neuroscience may therefore benefit from integrating ethical perceptions alongside technological and clinical factors.

From a clinical and professional perspective, the findings emphasise the continuing importance of the physician in AI-supported decision-making. Participants' views that therapeutic decisions should remain under clinical responsibility, together with their emphasis on physicians understanding how algorithmic decisions are generated, support a human-in-the-loop approach to AI implementation. AI may therefore be most appropriately positioned as a tool for augmenting clinical reasoning rather than replacing professional judgment. This has practical implications for the design of clinical AI systems, which should facilitate meaningful physician oversight and provide information that clinicians can critically evaluate before incorporating algorithmic recommendations into patient care.

The findings also have important neuroethical and governance implications. The observed associations among intellectual autonomy, brain mapping, privacy, transparency, accountability, human rights, and algorithmic bias suggest that governance mechanisms should address these concerns collectively. Protecting neural and other sensitive health-related data requires more than conventional data-security measures; attention should also be directed toward how such data are collected, interpreted, reused, and incorporated into algorithmic decision-making. Particular consideration should be given to informed consent, transparency of data use, algorithmic explainability, bias assessment, and clearly defined lines of responsibility when AI contributes to clinically consequential decisions.

The strong association between perceived threats to human rights and concerns about algorithmic bias further highlights the importance of fairness and representativeness in AI development. Training and validating algorithms on insufficiently representative populations may result in unequal performance across patient groups. Accordingly, developers and healthcare institutions should consider systematic evaluation of datasets and algorithmic performance across relevant demographic and clinical populations, including groups that may be underrepresented in available datasets.

An additional implication concerns AI and algorithmic literacy among healthcare professionals. If physicians are expected to retain meaningful responsibility for AI-supported clinical decisions, they require sufficient knowledge to critically assess algorithmic recommendations, recognise potential limitations and biases, and communicate the role of AI to patients. Education in AI-supported healthcare should therefore extend beyond technical competence to include explainability, data ethics, bias, privacy, accountability, and Neuroethics.

More broadly, the results suggest that Neuroethics should be incorporated at an early stage of AI development and implementation rather than applied retrospectively after technological deployment. Ethical reflection should accompany the entire lifecycle of AI-enabled neuroscientific applications, from data collection and model development to validation, clinical implementation, monitoring, and subsequent reuse of data. Such an approach may contribute to aligning technological innovation with respect for autonomy, privacy, human rights, fairness, and professional responsibility.

Overall, the practical implication of the study is not that AI development in Neuroscience should be restricted, but that technological advancement and neuroethical safeguards should evolve together. The findings point toward a model of responsible AI-enabled Neuroscience in which algorithmic capability, human oversight, protection of fundamental rights, and clinical accountability are treated as complementary rather than competing requirements.

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