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Reimagining Tourism Research through Neuroscience and Artificial Intelligence a Dual-Model Perspective

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ABSTRACT

This study aims to provide a holistic approach to the field by examining the rapidly growing but conceptually fragmented interaction between neuroscience and artificial intelligence in tourism and social sciences literature. In recent years, neuroscientific measurement techniques such as EEG, fMRI, and eye tracking have been widely used in artificial intelligence-supported models to understand tourist behavior and personalize experiences. However, the existing literature is largely limited to a one-way interaction model that positions neuroscience as a data provider and artificial intelligence as a classification and prediction tool. This reductionist approach fails to adequately explain the cultural, social, and emotional dimensions of human behavior. In this study, open-access English articles published between 2020 and 2025 in the Web of Science database were systematically scanned; data obtained from a total of 932 publications were analyzed using Biblioshiny (Bibliometrix) software. Bibliometric analyses revealed annual trends in scientific production, thematic clusters in the conceptual structure, and the temporal evolution of key concepts. The findings show that the field has grown rapidly in recent years but is still in the development stage in terms of theoretical and methodological depth. The bidirectional neuro-AI model proposed in this study contributes to positioning artificial intelligence not only as a data-processing tool but also as a knowledge producer that feeds neuroscientific theories, going beyond reductionist approaches in the social sciences.

Keywords: Artificial Intelligence, Dual-Model, Neuroscience, Neurotourism.

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1 Introduction

The tourism sector has become one of the areas that adapts most quickly to transformations driven by technological innovations. Digitalization, big data, and artificial intelligence-based analyses are widely used to understand tourist behavior, personalize experiences, and make destination management more efficient. Another development accompanying this digital transformation in recent years is the inclusion of neuroscience methods in tourism research. New insights into consumer behavior are being gained by measuring human brain responses through tools such as EEG, fMRI, and eye tracking (Alvino et al., 2020; Khurana et al., 2021). Thus, complex experiences that were previously interpreted only through surveys and observational studies are now supported directly by neural signals. This area of interaction has long been addressed in literature primarily within the framework of a one-way model. In this model, neuroscience is positioned as a source providing raw data to artificial intelligence; neural responses are classified by algorithms to predict consumer satisfaction, emotional state, or behavioral tendencies (Wankhade et al., 2022; Kumar et al., 2020; Zhang et al., 2020). Neuromarketing, emotion recognition, and user experience research provide typical examples of this trend (Azimi & Afshar, 2025; Pei & Li, 2021). However, this approach often fails to provide the contextual and theoretical depth required by the social sciences by reducing human behavior solely to biometric signals. Reductionist data-centricity creates significant limitations, particularly in understanding cultural differences, social interactions, and the multi-layered structure of emotions (Fazlul et al., 2024; Bhandari, 2020). At this point, the bidirectional interaction model that has emerged in recent years offers a noteworthy paradigm shift. In this model, neuroscience does not merely continue to play the role of data provider. At the same time, complex outputs obtained from large-scale neuro-data by artificial intelligence contribute to the reinterpretation of neuroscientific theories (Savage, 2019; Hassabis et al., 2017; Ullman, 2019). Artificial intelligence, in turn, is evolving beyond being merely a technical classifier to become an actor that feeds the conceptual production processes of neuroscience. This two-way flow of information creates a richer theoretical framework for understanding human behavior; it also responds to the need for methodological innovation in the social sciences (Onciul et al., 2025; Uden & Guan, 2022). However, there is no comprehensive framework in the tourism and social sciences literature that systematically addresses this holistic approach and synthesizes existing studies with a proposed conceptual model. Most research is still limited to a one-way data processing logic; the outputs generated by artificial intelligence do not feed back into the development of neuroscientific theories. This situation leads to slow theoretical progress and limited methodological diversity, despite the rapidly growing volume of publications in the field. There is a noticeable lack of studies evaluating the integration of neuroscience and artificial intelligence in the context of tourism from an interdisciplinary perspective.

This research was designed based on this gap. The fundamental problem addressed by the study is why the interaction between neuroscience and artificial intelligence in tourism and social sciences is still mostly reduced to a one-way data flow. The aim is to systematically examine the current state of this field; compare unidirectional and bidirectional usage patterns; and propose a more explanatory, contextual, and methodologically robust bidirectional neuro-AI model for tourism research. This approach aims not only to increase data-driven accuracy but also to enable the theoretical productivity and multi-layered human behavior analysis required by the social sciences. The importance of the study lies in guiding a rapidly growing but conceptually limited literature and presenting a new methodological paradigm in tourism research. Furthermore, this model aims to strengthen interdisciplinary collaboration and support the transformation of neuroscience and artificial intelligence fields not only technically but also at a theoretical level.

2 Literature Review

In recent years, the interaction between artificial intelligence and neuroscience has become a noteworthy research topic not only in technical fields but also in the context of social sciences (Ito et al., 2025; Ribeiro et al., 2025). The literature reveals that this interaction is approached in two distinct ways: unidirectional and bidirectional usage. In the unidirectional approach, neuroscience is considered a data source for artificial intelligence; neurophysiological measurements such as EEG, fMRI, or eye tracking are classified through algorithms and predictive models are generated. This approach has been widely used, particularly in the social sciences; for example, predicting tourist experiences or consumer satisfaction through neural responses using artificial intelligence are common applications. However, a careful examination of this literature reveals the reductive aspects of this model and its inadequacy in understanding the multi-layered human behavior in the social sciences. In contrast, in the approach that can be defined as a two-way model, neuroscience is not limited to providing data to artificial intelligence. At the same time, artificial intelligence also processes large-scale neuro-data, revealing new patterns and using them in the development of neuroscientific theories. Thus, the flow of information ceases to be one-sided and becomes cyclical.

2.1 One-Way Model (Neuroscience → Artificial Intelligence)

Within a one-way relationship framework, neuroscience is considered merely a raw data provider for artificial intelligence; data obtained from devices such as EEG, fMRI, or eye tracking are processed through algorithms and converted into outputs (Akhtar & Rozario, 2025; Bösel et al., 2025). In this approach, neuroscience acts as the data source, while artificial intelligence takes on the role of processor and interpreter. This approach, frequently used in social sciences, is evident in applications such as measuring tourist experiences with EEG data and predicting satisfaction with artificial intelligence. However, this structure reduces neuroscience to merely an auxiliary data provider.

Modeling consumer emotions and thoughts through artificial intelligence has gained momentum with the development of text mining, machine learning, and natural language processing techniques. In the context of one-way models, the categorization of consumer opinions into emotion categories using algorithms is a very common method. In this approach, the individual's experience is not internalized; the focus is solely on the output, and concepts such as emotion, satisfaction, or trust are quantified by artificial systems. Wankhade et al. (2022), in their study discussing methods, applications, and challenges related to sentiment analysis, show that the multi-layered structure of consumer data is often treated in a reductive manner in AI-supported analyses. Kumar et al. (2020) examined the impact of demographic variables such as age and gender on sentiment analysis, revealing the processability of consumer comments through machine learning. Hong and Wang (2021) focused on summarizing customer opinions through topic mining and deep neural network-based models, highlighting the interpretation capacity of artificial intelligence. Kumar et al. (2025a) noted that sentiment analysis could become more comprehensive by integrating multiple data types to increase technical depth, while Bin Wang et al. (2022) offered an important innovation by combining sentiment information and biological signals such as eye movements using the SEMGraph model. However, in all these studies, artificial intelligence continues to play a central interpretive role, while neuroscience is reduced to a secondary data source. Although this provides practical benefits for short-term applications, it is insufficient for understanding the multi-layered human behaviors in the social sciences.

In the context of neuromarketing, the logic of the one-way model also comes to the fore. Signals obtained with neurophysiological tools such as EEG, fNIRS, or eye tracking are used to decipher consumer decision processes, but the interpretation of the data is left to artificial intelligence algorithms.

Alvino et al. (2020), while discussing the contributions of neuromarketing to marketing research, highlighted the capacity of EEG and fMRI tools to capture unconscious responses. Khurana et al. (2021) examined neuromarketing studies based on EEG signals and demonstrated that machine learning algorithms increase accuracy. Fazlul et al. (2024) highlighted the effectiveness of AI-supported classifications in EEG-based neuromarketing techniques, while Bhandari (2020) touched upon the opportunities these technologies offer companies. Azimi and Afshar (2025) systematically compiled the performance of algorithms used in processing EEG data. However, in all these studies, neuroscience has remained merely a data-providing tool; the theoretical contribution has not returned to artificial intelligence.

A similar structure is observed in emotion recognition research. Biometric data such as EEG, facial expressions, voice intonations, and eye movements are classified through machine learning and deep learning algorithms. Zhang et al. (2020) addressed emotion recognition processes using multimodal data and machine learning techniques; Cai et al. (2020) discussed depression diagnosis using multimodal EEG fusion approaches; Kaushik et al. (2019) demonstrated the predictability of individual variables such as age and gender using BLSTM-LSTM architectures. Pillalamarri and Udhaya Kumar et al. (2025) emphasized that EEG-based multimodal learning can improve emotion recognition accuracy; Saleem and Naseem (2023) addressed the optimization of emotional responses with multiple artificial intelligence solutions in the context of e-commerce. However, in all these studies, neuroscientific data has remained merely input, while artificial intelligence has been an output-producing interpreter. This situation ignores the cultural and contextual dimensions of emotion in the social sciences and creates a reductionist framework.

Machine learning applications in marketing research also reveal the limitations of the unidirectional model. Pei and Li (2021) compiled EEG-based emotional information processing techniques in the field of marketing, demonstrating that artificial intelligence models offer high accuracy. Du (2019) examined neural feedback models based on ERP signals; Wang et al. (2024) discussed the modeling of emotional values according to age groups in educational service robots through artificial intelligence. Saban and Dağdevir (2023) compared biomedical signal processing methods, while Azimi and Afshar (2025) systematically addressed machine learning applications based on EEG data. However, a common point among these studies is that the independent explanatory role of neuroscience is left in the background.

Multimodal data integration has a similar structure. Different biosignals such as EEG, eye tracking, or facial expressions are brought together, but the interpretation of this data is left to artificial intelligence. Kumar et al. (2019) predicted customer satisfaction based on EEG responses and product evaluations. Zhu et al. (2022) combined EEG and eye-tracking data to draw conclusions about attention and cognitive load. P'erez et al. (2022) extended multimodal data integration in neuromarketing to include demographic characteristics and life cycle stages. Duan et al. (2023) optimized EEG channel selection using genetic algorithms; He et al. (2024) discussed predicting personal music preferences through EEG analysis. However, in these studies as well, neuroscientific data is viewed solely as a processable signal, not contributing to theoretical production processes.

Overall, within the context of a unidirectional model, the literature positions neuroscientific data solely as a raw data provider, while artificial intelligence becomes the central element that processes, interprets, and converts this data into output. Although this approach provides high accuracy and practical benefits in the short term, it is insufficient for a deep understanding of complex human behavior in the social sciences. At this point, it seems inevitable to turn to the two-way model, which is increasingly being discussed in literature.

2.2 Two-Way Model (Neuroscience ↔ Artificial Intelligence)

A two-way relationship requires neuroscience and artificial intelligence to be approached not merely as supporting disciplines, but as transformative ones. In this approach, artificial intelligence processes large-scale neuro-data sets to reveal complex patterns that the human eye cannot detect; it also facilitates the interpretation of clinical or social behavior data using neuroscientific concepts through methods such as natural language processing (Quinn, 2025; Sola et al., 2025). Neuroscience, in turn, does not merely provide data to artificial intelligence; it also contributes to making algorithms more human-like and adaptable by drawing inspiration from the human brain's learning, attention, and memory processes. This reciprocal cycle provides a much more solid theoretical foundation for models aimed at understanding human behavior in the social sciences.

This interaction between artificial intelligence and neuroscience is considered a powerful interdisciplinary collaboration that guides the development of information technologies. Algorithms designed with inspiration from the human brain are supported by neuroscientific findings in terms of simulating cognitive processes and enabling artificial intelligence to achieve a more human-like functioning (Hassabis et al., 2017). While mechanisms such as learning, attention, and memory serve as references for artificial intelligence models (Ullman, 2019), AI also contributes to the emergence of previously unobserved patterns by processing large neuro-data (Savage, 2019). In this context, the literature shows that this two-way relationship finds application in a wide range of fields in both health and social sciences. In particular, the reduction of error rates in AI-based models for the diagnosis of neurological disorders (Surianarayanan et al., 2023) and the development of artificial neural networks similar to the human brain (Theotokis, 2025) highlight the clinical and technical dimensions of this two-way interaction. In addition, it is noted that ethical and philosophical debates are intertwined with this process, and that ethical decision support systems based on neuroscientific foundations offer a new paradigm in the context of human-like intelligence production (Gopinath & Gopinath, 2023).

Recent literature argues that neuroscience and artificial intelligence are intertwined not only at the level of technical knowledge exchange but also at the epistemological level. Onciul et al. (2025) reveal that these two fields possess not only data transfer but also theoretical synthesis and transformation capabilities; Uden and Guan (2022) characterize this process as a shared synergy and point to a new, co-evolving research ecosystem. This enables a more comprehensive understanding of human behavior and mental processes, allowing artificial intelligence systems to produce more contextually meaningful outputs. A similar trend is observed in the context of social learning and human-machine interaction. The Social Neuro-AI approach discusses how artificial intelligence can be made more compatible in a social context by addressing not only individual cognitive functions but also the neural foundations of social interactions. Social interaction is seen as a critical dimension that determines the system's capacity for meaning production, yet it is often overlooked in most artificial intelligence models. In this context, integrating social learning theories into artificial intelligence training processes enhances not only algorithmic efficiency but also the quality of relationships established with humans (Bolotta et al., 2022). Savic (2024), in this perspective, suggests that artificial intelligence can acquire the identity of an “artificial companion,” emphasizing that supporting these bonds with neuroscientific evidence is important for social acceptance.

The dual-directional model stands out not only in its technical or social dimensions but also through ethical debates. The development of brain-inspired artificial intelligence systems requires a reassessment of concepts such as responsibility, decision-making, and autonomy. Farisco et al. (2023) argue that ethical analyses should not be limited to algorithmic transparency but should also consider human dignity and social impacts. Chandra et al. (2025) state that explainability goes beyond being a technical tool and forms the basis of ethical responsibility. The use of artificial intelligence applications in neuroscience also demonstrates the practical contributions of the dual-model approach. Zador (2023) emphasizes that neuroscience findings act as a catalyst in shaping the new generation of artificial intelligence through the concept of NeuroAI. Gupta (2025) has demonstrated that neuroscience-inspired continuous learning systems can produce personalized solutions in the context of artificial general intelligence. Thus, artificial intelligence can continuously update its learning capacity not only with static data but also with dynamic environmental inputs. This interaction enables neuroscience to provide artificial intelligence with more human-like, adaptable, and sustainable learning mechanisms; artificial intelligence, in turn, broadens the theoretical and practical horizons of neuroscience. Overall, the two-way model offers a cyclical structure that enriches the relationship between neuroscience and artificial intelligence epistemologically, methodologically, and theoretically. Artificial intelligence is not only nourished by neuroscience, but also advances neuroscience itself. In this context, it is concluded that the two-way model offers a more powerful approach for research in the social sciences aimed at understanding human behavior, emotions, and social context.

The different thematic topics of the unidirectional model examined in the literature reveal significant richness in terms of processing and classifying neuroscientific data with artificial intelligence algorithms, but also highlight the serious methodological and theoretical limitations of this approach. Data such as EEG, eye tracking, or biometric signals can be processed with high accuracy thanks to artificial intelligence; consumer behaviors, emotional responses, or preference patterns can be easily predicted. However, in these processes, neuroscience is often reduced to merely providing data; it has moved away from being a theoretical production mechanism (Usman et al., 2025). Consequently, the flow of information moves unilaterally from neuroscience to artificial intelligence; artificial intelligence, in turn, uses this data solely as a classification and prediction-focused tool. This reductive structure conflicts with the multi-layered nature of human behavior, particularly in the social sciences. Human behavior is too complex to be explained solely by the analysis of neural or biometric signals; when the psychological, cultural, and social contexts of behavior are ignored, the findings obtained cannot go beyond limited technical accuracy (Hao et al., 2025; Malik et al., 2025). This tendency seen in neuromarketing or emotion recognition studies reduces behavior to mere signals, neglecting the meaning of these signals within their context. Therefore, while the one-dimensional model provides practical benefits for short-term applications, it falls short in terms of the epistemological depth of the social sciences.

Table 1: Comparative Framework of One-Way and Two-Way Neuro–AI Integration

Comparison Criteria	One-Way Model (Neuroscience → Artificial Intelligence)	Two-Way Model (Neuroscience ↔ Artificial Intelligence)
Data Flow	Neuroscience devices (EEG, fMRI, etc.) → Analysis, classification, and prediction using artificial intelligence	Neuroscience data → AI analysis → New patterns → Feedback to neuroscience theories and generation of new research questions
Interpreter Role Distribution	Artificial intelligence interprets; neuroscience only provides data	AI analysis transfers the patterns it discovers to the reconstruction of neuroscience theories; neuroscience and AI are interpretive together
Theoretical Contribution Level	Output-oriented, limited theoretical contribution	It enables epistemological transformation; it allows for the development of new theories and interdisciplinary synthesis
Application Examples	Measuring tourist satisfaction with EEG and predicting it with AI (e.g., Wankhade et al., 2022)	New theories from emotional response patterns, ethical decision support systems, social interaction, and artificial companionship models
Structural Depth	Practical and fast, but reductionist	More complex but multi-layered; deeply understands human experience and social context, provides epistemological synthesis
Impact in Social Sciences	Focused on statistical prediction and classification, carries a reductionist tendency	Contributes to a holistic interpretation of behavioral, cognitive, and cultural layers; increases theoretical explanatory power
Theoretical Richness Potential	Low, neuro-data is used as a technical tool	It is high; patterns developed through neuro-data can create new theoretical openings
Processor	Artificial intelligence only	Artificial intelligence and neuroscience are both operative and interpretive
Criticisms	Reductionist, context-free, passivates neuroscience	It is complex but increases theoretical productivity; it is a structure capable of creating interdisciplinary synergy

On the other hand, advanced artificial intelligence applications developed in recent years point to a new research ecosystem that could transcend the limitations of the unidirectional model. Deep learning, natural language processing, and multimodal data analysis techniques not only process neuro-data but also lay the groundwork for reinterpreting neuroscientific theories (Istace, 2025). By revealing complex patterns in large-scale neuro-data sets that go beyond human observational power, artificial intelligence enables the emergence of new questions that neuroscience cannot formulate with its own methods. For example, linking patterns extracted from EEG signals to social behavior or correlating eye-tracking data with cultural representations only gains explanatory power within such a bidirectional interaction model (Onciul et al., 2025). In this context, neuroscience is not merely a data provider; it is transforming into an active discipline that reconstructs its own theoretical foundation based on the findings produced by artificial intelligence. Artificial intelligence, meanwhile, is moving beyond being merely a data-processing tool to become an interpretive actor that expands the conceptual boundaries of neuroscience (Akhtar et al., 2025; Pelosi et al., 2025). Thus, both fields are integrating epistemologically and methodologically within a cyclical structure that feeds off each other. This is precisely where the critical transition point emerges. Although the unidirectional model provides technical accuracy, it fails to produce the contextual and theoretical depth required in the social sciences. The two-way model, on the other hand, overcomes this limitation by proposing a holistic network of interaction that incorporates neuroscience and artificial intelligence into each other's knowledge production processes (Kumar et al., 2025b; Prabha, 2025). This transition is not merely a technical choice but also a necessary step toward understanding human behavior in a multi-layered way in the social sciences (Guerrero et al., 2025; Onciul et al., 2025). Table 1 compares a one-way model, in which neuroscience data is only transferred to artificial intelligence, with a two-way integration model that establishes mutual interaction between neuroscience and artificial intelligence in terms of data flow, theoretical contribution, application examples, and impacts on the social sciences.

3 Research Methodology

This research was designed to examine the interaction between neuroscience and artificial intelligence in the tourism and social sciences literature and to develop a comprehensive, two-way conceptual model based on current trends. The study is based on exploratory bibliometric research and conceptual synthesis approach. This method was chosen to map a rapidly growing but theoretically fragmented field of knowledge using objective indicators and to propose a new theoretical framework based on the thematic findings obtained. Research data were systematically collected from the Web of Science database. The search strategy was designed to broadly cover the conceptual boundaries of the field. The basic query string used is “neurotourism” OR “tourism” OR “social science” AND “artificial intelligence” OR ‘AI’ OR “machine learning” AND “neuroscience”. The bibliometric analysis was conducted using the Biblioshiny interface of the R package Bibliometrix. Core analytical functions such as biblioAnalysis, thematicMap, and trendTopics were applied to identify thematic evolution, research trends, and intellectual structure.

The search was limited to articles published between 2020 and 2025, in English, open access, and of the document type article. To preserve the interdisciplinary nature of the studies, the WoS categories Social Sciences Interdisciplinary, Neurosciences, Social Work, and Computer Science Artificial Intelligence were selected. These criteria resulted in a total of 932 publications. The search process was completed in September 2025. The resulting bibliographic dataset was analyzed using Biblioshiny (Bibliometrix R-package). Three basic steps were followed in the bibliometric analysis. These were: examining annual scientific production trends, thematic mapping to reveal the conceptual structure of the literature, and temporal analysis of keyword frequency to track the development process of concepts. These analyses determined the themes around which the literature clustered, which concepts were central or peripheral, and how the field evolved over time. In particular, thematic mapping and concept frequency analysis systematically revealed which aspects of the field had matured, where methodological gaps existed, and which topics had become emerging research agendas. These bibliometric outputs formed the conceptual basis for the proposed dual-directional neuro-AI model in the study. The methodological design of the research was planned in a transparent and reproducible manner. The search string, selection criteria, and time frame were clearly defined; attention was paid to the principle of ethical access by including only open-access English studies in the form of articles and reviews. All visuals and metrics used for bibliometric analysis were generated using the open-source Biblioshiny tool, ensuring the methodological reproducibility of the study (Aria & Cuccurullo, 2017).

4 Results and Discussion

4.1 Bibliometric Analysis Findings

Annual scientific output (Figure 1) shows that the field had an extremely limited volume in the 2020–2022 period, experienced a significant structural break as of 2023, and reached its peak in 2024. The limited decline in 2025, considering that the data cut-off was in September and indexing delays, indicates not that the field's momentum has weakened, but most likely that the full year is not reflected.

This pattern reveals that the integration of neuroscience and artificial intelligence has become a young but rapidly maturing line of research in tourism and social science literature. The trend observed in the post-leap period points to a phase where, going beyond classification/prediction-focused unidirectional applications, the patterns revealed by AI are fed back into neuroscientific theories, thus making the necessity of a bidirectional epistemological framework apparent. The findings empirically support the motivation to develop a comprehensive, bidirectional neuro-AI model, both methodologically and theoretically. Furthermore, since the analysis is limited to open-access publications, the actual production volume may be higher; however, the annual pattern is preserved when the OA constraint is removed.

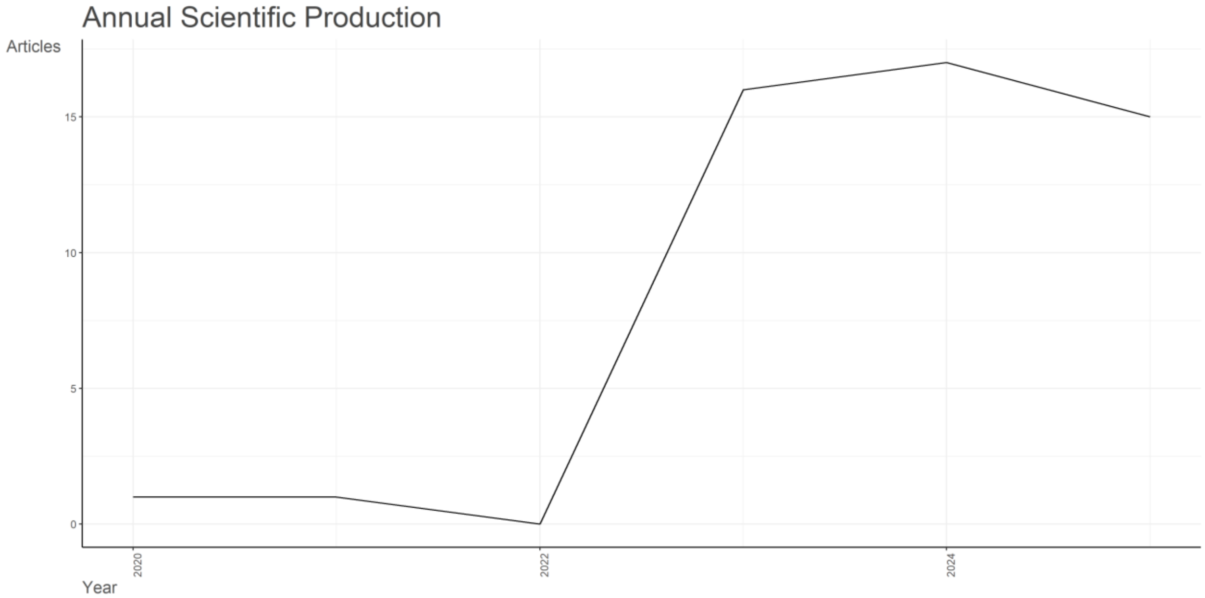

Figure 1: Annual Scientific Production

Thematic mapping (Figure 2) reveals the conceptual structure of the field through four fundamental axes. Among the motor themes are the clusters of culture–tourism–bibliometric analysis and social science–risk–COVID-19; this indicates that tourism and social science studies are still concentrated on the axes of cultural context and post-COVID-19 risk management. Within niche themes, the model–agent-based modeling–behavior and artificial intelligence–politics clusters stand out; this finding indicates that methodological modeling and behavioral simulation approaches are powerful but not yet fully integrated into the core of the literature. The prominence of the concepts of knowledge–framework–critique–explanation–epistemology among fundamental but developing themes indicates that the field is moving beyond technically application-oriented studies toward theoretical and epistemological discussions. The bidirectional neuro-AI model proposed in our study aims to fill this thematic gap and offer a holistic conceptual framework beyond reductionist unidirectional approaches. Furthermore, the concepts of values, social theory, research ethics, and psychology, which are located in the rising/declining themes area, indicate that the field may undergo an ethical and social theory-focused transformation in the future; this supports the necessity of referring to ethical and social dimensions in addition to the methodological contribution of our model.

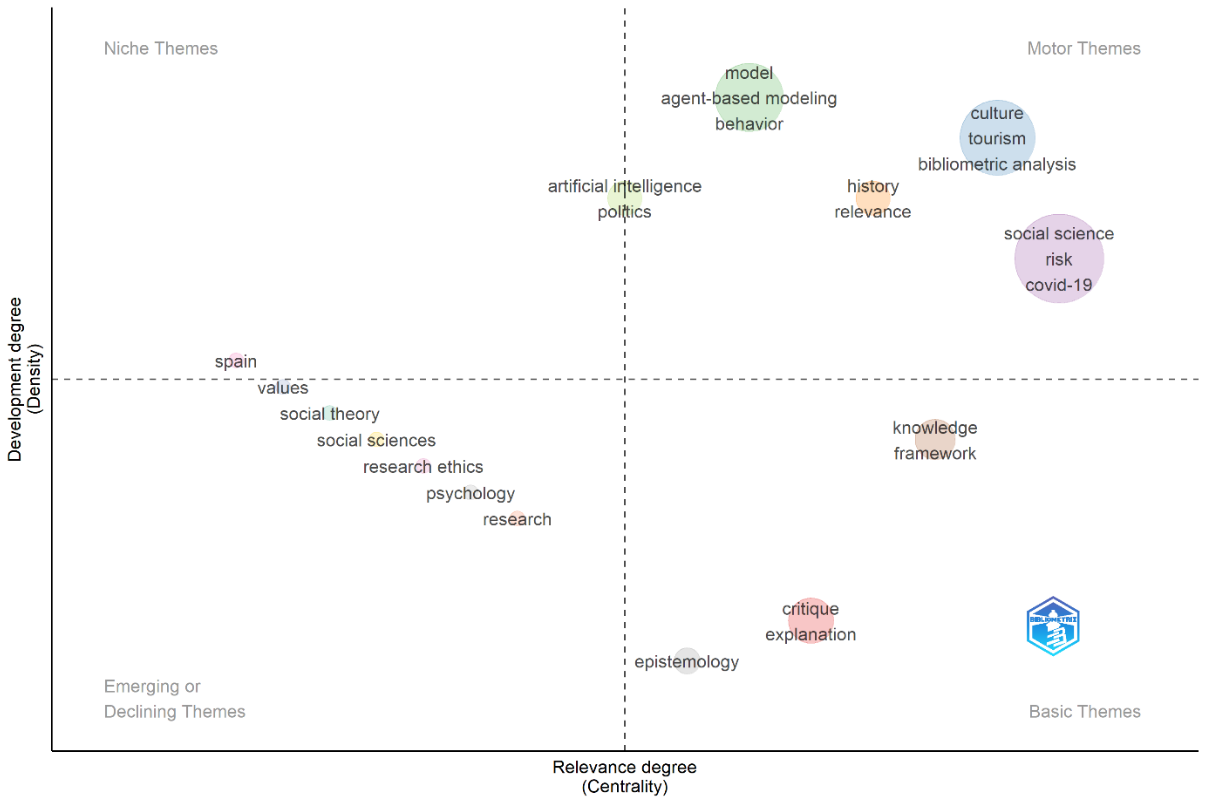

Figure 2: Thematic Map

When examining the frequency of use of key concepts over the years (Figure 3), it is evident that the field was conceptually quite limited between 2020 and 2022. As of 2023, concepts such as ‘COVID-19’, ‘social science’, and ‘culture’ have come to the fore, indicating that neuroscience and artificial intelligence-focused research in tourism and social sciences began to increase rapidly after the pandemic. In the 2024–2025 period, the visibility of theoretical and methodological terms such as ‘epistemology’, ‘critique’, ‘explanation’, ‘framework’, ‘model’, and ‘methods’ has increased. This trend shows that the field has evolved from an initial phase focused on technical application and crisis management to epistemological and conceptual deepening. The dual-directional neuro-AI model developed in our study conceptualizes this transformation and offers a theoretical alternative

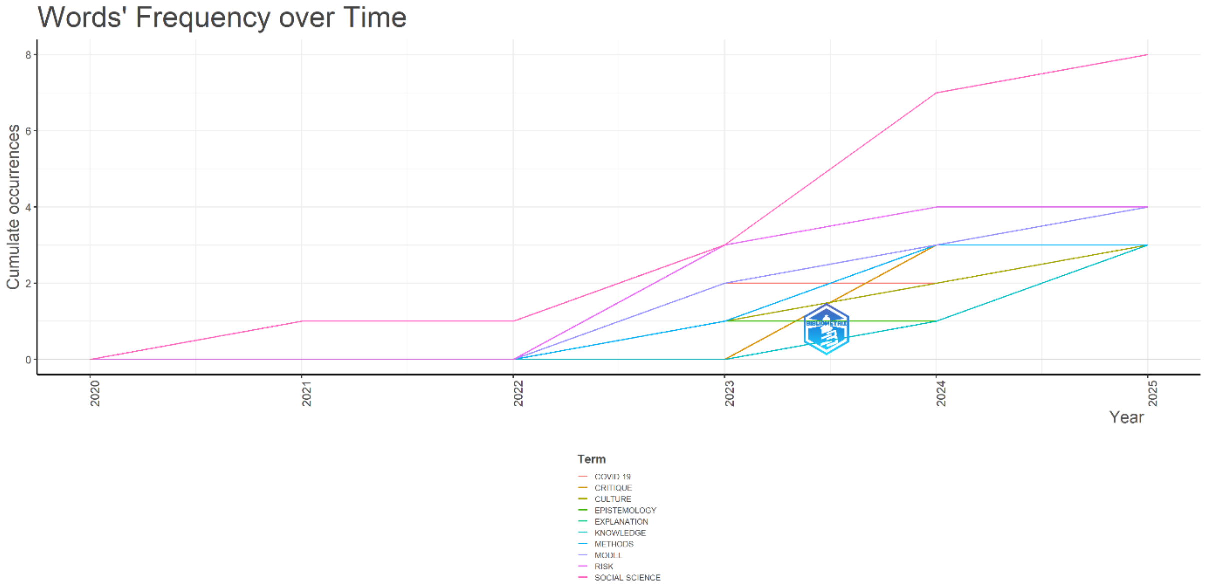

Figure 3 Words' Frequency Over Time

4.2 The Necessity of the Proposed Two-Way Model from the Perspective of Social Sciences

The one-way approach (neuroscience → artificial intelligence) is quite common in current research practices and is extremely practical in terms of application. Outcomes such as the high-accuracy classification of neurophysiological data, the development of decision support systems, and the optimization of marketing applications at the individual level make this model effective in the short term. However, when considering the multi-layered structure inherent in social sciences, the clear limitations of this approach become apparent. This is because interpreting human behavior solely through neural responses; reducing emotions, experiences, and social contexts to mere data representations leads to a reductionist epistemological perspective. The proposed model here is a two-way relationship structure based on mutual interaction between neuroscience and artificial intelligence. This structure involves not only the analysis of neuroscientific data by AI, but also the use of patterns revealed by AI in the reinterpretation of neuroscientific theories. In other words, artificial intelligence here is not merely a "data processor" but also becomes an actor that "contributes to theory." This approach has the potential to increase interpretive depth in the social sciences. For example, using EEG data not only for emotion classification but also for understanding an individual's behavioral patterns in a social context; or examining eye-tracking data in relation to cultural representations, is only possible within such a two-way model. Furthermore, the insights emerging from AI-supported analyses can also pave the way for new neuroscientific questions. Such a feedback mechanism not only makes theoretical production possible but also strengthens the contextual explanatory power in the social sciences. Ultimately, the bidirectional model not only provides a platform for interdisciplinary collaboration but also aims to bridge the gap between data and theory in the social sciences. In this way, artificial intelligence becomes more human-like and contextual, while neuroscience finds opportunities to develop explanatory models suited to the complex nature of the social sciences. Such an interaction model offers a framework that can respond not only to today's technical needs but also to the methodological orientations of the future.

The schematic model presented in Figure 4 structures the two-way interaction process between neuroscience and artificial intelligence as a sustainable knowledge production cycle. The starting point of the model consists of neuroscientific inputs such as EEG, fMRI, and eye tracking. These data are analyzed through artificial intelligence modules such as machine learning, deep learning, natural language processing, and multimodal integration, and the outputs are reproduced in the form of predictions or patterns (Wankhade et al., 2022; Zhang et al., 2020). At this stage, artificial intelligence contributes to the reinterpretation of neuroscientific theories by revealing complex patterns in large-scale neuro-data sets that are imperceptible to the human eye (Savage, 2019; Surianarayanan et al., 2023). The outputs generated enable the reinterpretation of neural patterns in behavioral, emotional, and social contexts, paving the way for the definition of new neuroscientific questions (Bolotta et al., 2022; Khurana et al., 2021). These questions trigger new experimental designs and data collection processes within the scope of current neuroscientific research; thus, knowledge production progresses based on a continuous feedback loop rather than a one-way transfer. Ultimately, this model reveals that neuroscience and artificial intelligence are not only mutually supportive but also mutually transformative fields, providing a robust methodological framework for developing multi-layered explanations of human behavior in the social sciences (Hassabis et al., 2017; Theotokis, 2025).

The methodological path that a researcher wishing to conduct research based on a two-way neuro-AI interaction should follow suggests a multi-layered structure that goes beyond classical data processing routines. In this model, neuroscientific data is not only collected for analysis; outputs obtained through artificial intelligence are also interpreted backwards in a way that contributes to the development of neuroscientific theories. Therefore, the research process is designed as a cyclical system that progresses with continuous feedback rather than a linear flow.

In the first step, the researcher is expected to identify the neuroscientific data that will form the basis of the study. These data may be neural or physiological measurements such as EEG, fNIRS, eye tracking, or emotional responses based on facial expressions. The goal at this stage is to establish a structure that provides measurable and multidimensional data. Subsequently, the collected data must be structured in a way that contributes to theoretical meaning production, not just for technical analysis.

This structuring process is expanded in the second stage with the introduction of artificial intelligence analysis modules. Here, instead of a single algorithm, the researcher should use systems capable of multimodal analysis (e.g., CNN, LSTM, NLP-based classifiers, or data fusion approaches) to reveal patterns, trends, and predictions in the data set. The important point is not to focus solely on the statistical accuracy of these patterns; it is also to contribute to the meaning production process by considering the neuroscientific counterpart of each output. In the next stage, these patterns and predictions generated by artificial intelligence are compared with neuroscientific theories. For example, it is evaluated whether a specific emotional response matches a signal pattern observed in the EEG, or whether the attention regions tracked by eye movement show consistency with predefined neuropsychological processes. This interpretation process is a critical stage where the researcher combines their knowledge of neuroscientific literature with the results of artificial intelligence. The unique aspect of the model is that this comparison is not an end but a new beginning. In other words, researchers should develop new neuroscientific questions that have not been formulated before, based on the AI outputs. These questions should not remain within the confines of existing data; they should also lead to the establishment of new experimental setups, the application of different data collection strategies, and even the construction of alternative theoretical approaches. Thus, the research process not only responds to the existing literature but also becomes a candidate for transforming it. In this approach, the analysis process and theoretical interpretations are not separate; rather, the results obtained from data analysis directly feed back into the theory and are reinterpreted through theoretical assumptions, completing the research cycle. When researchers adopt this method, they use their artificial intelligence tools not only for analysis but also as partners in theory production. This shifts them from the position of the classical researcher to that of a transformative scientist who acts as a dynamic intermediary between data and theory. The methodological journey of a researcher working with a two-way model continues in a cycle that begins with data collection, returns to theory, and then triggers new data production with new questions. While this approach serves the process of developing data-driven theory in the social sciences, it also activates the theoretical production capacity of artificial intelligence, not just its technical capacity.

The fundamental advantage of the bidirectional interaction model is that it allows the disciplines of neuroscience and artificial intelligence to be conceived not only as supporting each other but as structures that transform each other. This model prevents neuroscientific data from being reduced to a data set solely for analysis; instead, it ensures that artificial intelligence outputs return to neuroscientific conceptualizations. This approach aims not only for the researcher to be satisfied with technical accuracy, but also to increase the power of theoretical explanation. Thus, a bridge is built between data-driven decision-making processes and theory-based interpretive explanations. The application of the two-way model enables a more holistic analysis of multi-layered human behavior in the social sciences. It ensures that emotions, attention processes, decision-making patterns, and cognitive tendencies are understood not only as neural representations but also in conjunction with contextual, cultural, and individual differences. This model also encourages interdisciplinary work, as artificial intelligence experts, neuroscientists, and social science researchers can all play an active role in different dimensions of the model. The ability to produce theory not only based on literature but also based on data creates an important opportunity, especially for researchers who want to develop original contributions in innovative academic work. One of the most important contributions of the bidirectional model is that it ensures sustainable knowledge production, because the output of one study can become the starting question for another study.

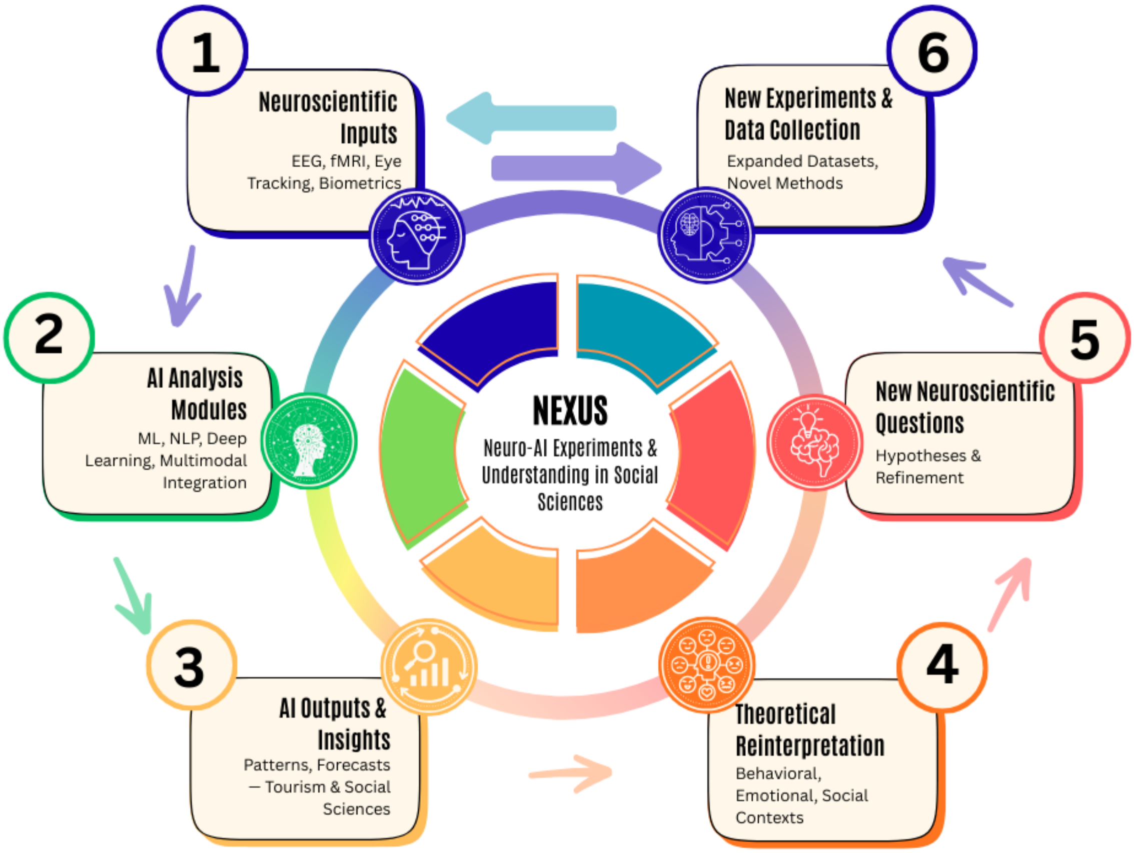

Figure 4: A Dual Model of Neuro-AI Interaction in Social Sciences

Source: Created by the author.

This model has a wide range of applications. In neurotourism, neural and behavioral data related to tourists' experiences can be analyzed together to make destination planning more meaningful. In neuromarketing studies, consumers' attention, preferences, and purchasing decisions can be comprehensively evaluated using both neurophysiological and digital tracking data. In educational technologies, students' attention and learning processes can be monitored with AI-supported analysis and restructured with neuropedagogical approaches. In digital behavior analysis, users' emotional interactions and responses can be monitored with multimodal data processing, enabling the development of more personalized and ethically grounded systems. Furthermore, in creative industries such as emotional content development, cinema, media, and game design, real-time interpretation of audience or player reactions and shaping content accordingly can also be made possible within the framework provided by this model. Ultimately, the two-way interaction model is a structure that can have a profound impact not only in academic research but also in creative and commercial applications.

5 Conclusions

This research comprehensively examines the current state of neuroscience and artificial intelligence interaction in tourism and social sciences literature, revealing the conceptual and methodological gaps in the field. Bibliometric analyses reveal that the number of publications, which was extremely limited between 2020 and 2022, showed a rapid increase as of 2023, peaked in 2024, and experienced relative stagnation in 2025. This dynamic indicates that the field is still in its early stages and that there is a continuing need for robust theoretical frameworks. Thematic mapping results reveal that the literature is still concentrated around social science-focused driving themes such as culture, tourism, and risk management, while methodological modeling and behavioral simulation approaches remain niche and peripheral. At the same time, the appearance of concepts such as “epistemology, critique, framework, explanation” among the fundamental but developing themes indicates that the field is evolving from a reductive data processing logic towards methodological and theoretical deepening. The frequency of use of key concepts over the years also supports this transformation: interest, which began with COVID-19 and risk-focused applications, shifted towards methodology, theoretical framework, and epistemology in the 2024–2025 period. These findings point to the limitations of the unidirectional interaction model that has long dominated the literature (Wankhade et al., 2022; Kumar et al., 2020; Zhang et al., 2020). This model reduces neuroscientific data to classification and prediction through artificial intelligence algorithms, often neglecting the social and cultural contexts of human behavior (Azimi & Afshar, 2025; Pei & Li, 2021). However, recent studies from various fields argue that artificial intelligence is not only a technical tool but also a knowledge producer that can contribute to the reformulation of neuroscientific theories (Hassabis et al., 2017; Savage, 2019; Ullman, 2019). This research is the first to systematically model this idea of a two-way interaction within the context of tourism and social sciences, bringing together scattered trends in the literature into a comprehensive framework. The findings show that AI should be positioned not only as a technology that analyzes data but also as an intellectual tool that feeds theoretical production processes, in line with the calls for interdisciplinary method development by Onciul et al. (2025) and Uden & Guan (2022).

Consequently, the research offers both methodological and conceptual contributions. First, a systematic bibliometric search and thematic analysis were conducted to map the current state of knowledge in the field, establishing a transparent methodological framework. More importantly, an alternative paradigm has been developed against reductive unidirectional approaches with the proposed bidirectional neuroscience-artificial intelligence model. This paradigm aims to support the contextual and explanatory depth required by the social sciences by not only measuring tourist behavior but also ensuring that the obtained neurodata and artificial intelligence outputs are fed back into theoretical knowledge production. In this context, the study offers a new methodological paradigm in tourism research by guiding a rapidly growing but still theoretically fragmented literature; it also demonstrates that the interaction between neuroscience and artificial intelligence has the potential for not only technical but also epistemological transformation.

5.1 Theoretical Implications

This study reveals that the interaction between neuroscience and artificial intelligence in tourism and social science literature is still mostly reduced to a one-way data flow and proposes a two-way theoretical model as an alternative. The findings show that despite the field's rapid growth, particularly after 2023, it lacks a comprehensive conceptual and methodological framework. The study emphasizes that artificial intelligence can be positioned not only as a technical tool that processes neurodata but also as an epistemic actor that can contribute to the reshaping of neuroscientific theories. In this regard, the research offers a critical perspective on technological reductionism in the social sciences; it develops a new theoretical paradigm that does not ignore cultural, social, and emotional dimensions in understanding human behavior. It also suggests that tourism research should evaluate the integration of neuroscience and artificial intelligence not only as a tool that produces practical benefits but also as an interdisciplinary platform that contributes to the knowledge production process.

5.2 Practical Implications

The research offers various practical recommendations for academics, destination managers, marketing experts, and technology developers working in the field of tourism. First, it emphasizes that artificial intelligence-based systems used to understand tourist experiences should be designed not only to classify behavioral outputs but also to theoretically inform neuroscientific insights. This approach enables deeper user insights across different areas, from destination planning to experience design. Furthermore, it is recommended that ethical frameworks and social context be considered when developing AI-supported neuro-measurement applications, and that data privacy and user consent processes be conducted transparently. The research can contribute to tourism businesses and policymakers using technology-based decision support systems not only for prediction and classification purposes, but also as a tool for strategic information production that considers cultural diversity and social factors. Consequently, the study paves the way for the innovative and human-centered application of artificial intelligence and neuroscience integration in the tourism sector.

6 Declarations

6.1 Study Limitations

This study is limited to open-access English-language publications indexed in Scopus, which may lead to potential database or language bias. Future studies could extend the analysis by incorporating multiple databases and non-English sources.

6.2 Competing Interests

There is no conflict of interest in this study.

6.3 Ethical Approval

Since the study is based on open-access secondary data, ethical committee approval is not required.

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