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Review

Deciphering the Mosaic of Therapeutic Potential: A Scoping Review of Neural Network Applications in Psychotherapy Enhancements

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Abstract: Background: Psychotherapy is a component of the therapeutic options accessible in mental health. Along with psychotherapy techniques and indications, there is a body of studies on what are known as psychotherapy's common factors. However, up to 40% of patients do not respond to therapy. Artificial intelligence approaches are hoped to enhance this and with the growing body of evidence of the use of neural networks (NNs) in other areas of medicine, this domain is lacking in the field of psychotherapy. This study aims to identify the different uses of NNs in the field of psychotherapy. Methods: A scoping review was conducted in the electronic databases EMBASE, MEDLINE, APA, and CINAHL. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement influenced this study's design. Studies were included if they applied a neural network algorithm in the context of a psychotherapeutic approach. Results: A total of 157 studies were screened for eligibility, of which 32 were fully assessed. Finally, eight articles were analyzed, and three uses were identified: predicting the therapeutic outcomes, content analysis, and automated categorization of psychotherapeutic interactions. Conclusions: Uses of NNs were identified with limited evidence of their effects. The potential implications of these uses could assist the therapist in providing a more personalized therapeutic approach to their patients. Given the paucity of literature, this study provides a path for future research to better understand the efficacy of such uses.

Keywords: psychotherapy; neural networks; artificial intelligence; mental health; psychology; psychiatry

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1. Introduction

1.1. Psychotherapeutic Interventions

Psychotherapy is an important part of the array of treatments available to help patients suffering from a vast variety of mental illnesses. The evolution of systematized, evidence-based psychotherapeutic approaches in the field of mental illness can be traced back to the early 20th century [1]. Over the years, various psychotherapeutic methods have been developed and widely adopted. The American Psychological Association defines psychotherapy as a collaborative treatment based on the relationship between a person and a psychotherapist [2]. Over the 20th century, three major streams of psychotherapy have emerged. The first originates from Freud's pioneering work, which proposed a coherent approach emphasizing the major influence of the unconscious mind on our daily lives [3]. The second, rooted in scientific observation of human behavior, gave rise to the cognitive behavioral movement. The third revolves around humanistic approaches, prioritizing phenomenological perspectives and self-determination in treatment [4].

Numerous meta-analyses have consistently demonstrated the efficacy of psychotherapy in mental health disorders, in some cases showing comparable outcomes to pharmacological treatments [5]. Psychotherapeutic treatments can benefit individuals of all ages, educational levels, and ethnic and cultural backgrounds [6]. Given the wide range of efficacy of psychotherapy, the choice of psychotherapy type is generally guided by evidence-based validation for specific medical conditions [7]. For instance, cognitive-behavioral therapies, interpersonal therapy, and behavioral activation are considered first-line evidence-based acute and maintenance psychological treatments in depressive disorders [6]. Furthermore, meta-analyses suggest strong evidence for short- and long-term cognitive behavioral approaches to alleviate symptom distress in psychotic disorders [8].

The duration of psychotherapy can vary significantly [9–11]. Meta-analyses on different psychotherapeutic modalities indicate a significant improvement in symptoms in 53% of patients after eight weekly sessions, increasing to over 83% after 52 sessions [11]. There are no formal contraindications for psychotherapy [12]. However, therapeutic modalities must be carefully evaluated and adjusted to each patient's needs, as inappropriate psychotherapy, like other medical treatments, could have adverse effects [13].

1.2. Common Factors across Psychotherapeutic Approaches

Alongside the specific psychotherapy modalities and their indications, there exists an extended body of research on what are known as the common factors of psychotherapy. These are a set of characteristics present across all types of therapies that have been defined as early as 1936 and are considered fundamental to achieving positive psychotherapeutic outcomes. The factors that have been highlighted as most contributive to favorable outcomes are the therapeutic alliance, therapist empathy, goal consensus and collaboration, positive regard, mastery, genuineness, mentalization, emotional experience, and client expectations [14]. In a therapeutic dyad or a group setting, it has been found that relationship factors, some of them related to the common factors, are correlated with improved levels of functioning [15]. The outcomes of psychotherapy are conceptualized in a myriad of different ways but can be broadly described on a multidimensional level to include symptom reduction, improvement in functioning and quality of life, achievement of collaboratively articulated therapy goals, and a mature shift in defenses [14]. Moreover, it is important to understand that the common factors are not merely a set of elements that can be identified in all psychotherapies; rather, they 'collectively shape a theoretical model about the mechanisms of change in psychotherapy [16]. It is stipulated that benefits in psychotherapy are produced through three pathways, and these pathways have underlying mechanisms that stem from 'evolved characteristics of humans as social species' [16,17]. According to Wampold, the pathways are (1) the real relationship, (2) the creation of expectations through the explanation of disorder and treatment, and (3) the enactment of health-promoting actions [16].

The most extensively researched common factor is the therapeutic alliance, or the working relationship between patient and therapist. It is composed of the bond between patient and therapist as well as the agreement on therapeutic goals and the tasks of therapy. Its beneficial effect is therefore based on an increase in the mutuality and investment of the patient and the therapist in the therapy, as well as an increase in resilience and tolerance of distressing affects [14]. Another common factor shown to have a major curative effect on therapy is therapist empathy, which is both an inherent quality and learned skill. It is a complex phenomenon that can be subdivided into different factors that include mimicry, emotional and affective sharing, compassion, and sympathy. The therapist that achieves empathy is also able to distinguish the source of emotions in the therapeutic dyad, which refers to an awareness of the countertransference at play. This enables the therapist to adequately identify and reflect on the emotions expressed by the patient; this capacity, combined with the creation of a 'holding environment' in which emotions are validated and overwhelming affects are contained by the therapist, create beneficial outcomes by increasing ego strength. A focus on common factors can not only improve psychotherapy outcomes, but also facilitate an integration of common recommendations for effective psychotherapy training [14,18].

1.3. Artificial Intelligence in the Field of Psychotherapy

The literature on artificial intelligence supports that there are several applications of specialized tools and techniques that could be employed to enhance psychotherapy [19]. As an example, it has been stated that up to 40% of patients do not respond to therapy, and that artificial intelligence is hoped to enhance this number by using close or real-time recommendations [20]. Furthermore, a recent study suggested that artificial intelligence will have a beneficial impact, but that further empirical analysis through data-driven model development is needed [21]. It has therefore been hinted that artificial intelligence, especially the use of deep learning models, might help in personalizing patient treatments [22].

One such approach is known as neural networks (NNs). Algorithms relating to NNs are made up of node layers, each of which has an input layer, one or more hidden layers, and an output layer [23,24]. Each node, or artificial neuron, is linked to another and has its own weight and threshold. If the output of any node exceeds the given threshold value, that node is activated and begins transferring data to the network's next tier [23]. Otherwise, no data are sent to the next network layer. The uses of NNs could provide potential enhancements to psychotherapy, but not such compilation of evidence exists to our knowledge in the current literature.

1.4. Objectives and Hypotheses

The aim of this study is to identify the different uses of NNs in the field of psychotherapy. This will provide a first insight into therapeutic potential in psychotherapy enhancements with the help of this fast-growing and widely used modality that is currently being used in many other areas of medicine. We hypothesize that even though this field is emergent, there will be a wide array of uses such as predictive analysis, intervention delivery, and content analyses. This scoping review will provide a better overview on these different uses and provide details about key areas of future developments in the integration of NNs in the enhancement of psychotherapeutic approaches.

2. Materials and Methods

2.1. Search Strategies

From their inception dates through 2023, a systematic scoping search was conducted in the electronic databases EMBASE, MEDLINE, APA, and CINAHL by the authors. Search strategies included the use of text words and indexing terms (MeSH) containing keywords targeting the area of psychotherapy (e.g., psychotherapy, therapy, intervention, psychotherapeutic approaches, etc.) and the field of neural networks (e.g., machine learning, neural networks, artificial neural networks). These broad phrases were chosen because they better describe the use of neural networks in the context of psychotherapeutic approaches. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement influenced this study's design [25]. The Appendix A contains the main electronic search approach that was used. The search approach was conceptualized and implemented with the assistance of an experienced librarian specializing in mental health. There were no setting or geographical constraints imposed. The search approach used was limited to sources in English or French as to prevent interpretation biases.

2.2. Study Eligibility

Studies were considered if they met the following criteria: (1) the study is about (or uses) a type of neural network; (2) the study was conducted in the field of psychiatry or psychology and focuses specifically on mental health; (3) the neural network was used in the context of a psychotherapeutic approach; and (4) the study was focused on a clinical or future clinical intervention. Protocols and proof-of-concept research were excluded as exclusion criteria. There were no unpublished publications (or preprints) included in this review.

2.3. Data Extraction

Data were extracted using a standardized form (in Microsoft Excel, version Microsoft 365, EULA license, USA) and separately counter-verified for consistency and integrity by the authors (A.H., M.A.). NHC addressed any disagreements regarding the inclusion (or exclusion) of a study. The following information was systematically extracted: authors, population, type of neural networks, psychotherapeutic interventions and/or clinical application over a psychotherapeutic approach, psychometric tools (if used) and main outcomes identified.

2.4. Quality Assessment

Criteria derived from the GRADE Checklist were used to assess the quality of the identified studies. As per the GRADE methodology, studies were graded from very low, low, moderate-to-low, moderate, moderate-to-high, and high [26]. Evidence will be evaluated as weaker if it has risks of bias, if there are inconsistencies between the recommendations and the data presented, if it is declined indirectly from the results and if it is imprecise. On the contrary, it will be higher if the reported effect size is large, if there is an identified causality phenomenon, if the analysis of the results correctly identifies the confounding variables or suggests an absence of effect when it is the case. In principle, randomized controlled studies, according to this rating system, can achieve a maximum quality of high, while observational studies can have a quality of low at best. The GRADE system therefore uses eight criteria to critically appraise the quality of evidence: risk of bias or study limitations, inconsistency of results, indirectness of evidence, imprecision, reporting bias, effect size, dose–response gradient, and direction of plausible biases [26].

The author AH rated each studies using the GRADE Checklist. Quality assessment was then reviewed independently by MA to ensure consistent findings. Inconsistencies in the grading were discussed by the authors.

3. Results

3.1. Description of Studies

This scoping review's search strategies enabled the retrieval of 430 potential studies. Across the different databases from which these studies were identified, 273 duplicates were removed with the assistance of the EndNote software (version 20, Clarivate). The remaining 157 studies were summarily screened for eligibility. Amongst these, 123 were excluded as they did not meet the inclusion criteria based on their title and abstract. From the remaining 34 studies, 32 were fully assessed as the full text of two studies could not be accessed. Of these 32 studies, 4 were excluded as they were not about the use of an NN, 7 because they were not in a psychotherapeutic context, 4 because they were not applicable to the field of mental health, and 9 because they were articles of the wrong type. Finally, eight studies were included in this scoping review, with various uses of NNs in the context of psychotherapeutic approaches for the fields of psychiatry, psychology, and mental health. The PRISMA flowchart for the inclusion of studies can be found in Figure 1. The studies identified and their details are presented in Table 1.

Table 1. Scoping review study selection detailed results.

Article	Population	Neural Network	Intervention	Metrics Used	Main Outcome	Quality Assessment
(Gori et al., 2010) [27]	Patients who requested psychotherapeutic treatment (n = 150)	Artificial Neural Networks	Predict treatment outcome	Italian version of the MMPI-2	ANN forecasted 81% of the clinical outcomes (successful/unsuccessful therapy)	Low
(Nitti et al., 2010) [28]	Patient who followed a psychodynamic psychotherapy (n = 1)	Discourse Flow Analysis	Analysis of the verbatim of 43 sessions of therapy	Indexes of discourse network (connectivity, activity, and regulation)	Neural networks allow us the identification of patterns characterizing the psychotherapy process.	Very low

Table 1. *Cont.*

Article	Population	Neural Network	Intervention	Metrics Used	Main Outcome	Quality Assessment
(Koppe et al., 2019) [29]	Experiences and context specific interventions for psychosis. (*n* = n/a)	Recurrent Neural Networks	Mobile sampling for prediction of symptoms	None	RNNs could be used to forecast individual trajectories and schedule online feedback and interventions.	Very low
(Ewbank et al., 2020) [30]	Patients who followed internet-enabled CBT (*n* = 13,073)	Bidirectional LSTM	Automated categorization of therapist utterances	PHQ-9, GAD-7	The model achieved acceptable categorization and has reached human-level agreement.	Moderate
(Burger et al., 2021) [31]	Healthy participants (*n* = 320)	Recurrent Neural Networks	Identifying schemas (derived from schema therapy) from thought records.	HDAS, BDI-IA, CDS	Schemas can be automatically extracted, and NNs perform better than KNN and support vector approaches.	Low
(Bennemann et al., 2022) [32]	Outpatients treated with CBT (*n* = 2543)	Ensemble modeling using several machine learning algorithms (including artificial neural networks)	Predicting the drop-out rates of patients	PSSI, BSI	Neural networks were identified to be less suited to predict naturalistic data-sets and binary events.	Moderate
(Chen et al., 2022) [33]	Students who followed human–computer interaction psychotherapy (*n* = 120)	Convolutional Neural Networks	Recognizing emotions based on the human–computer interaction	Kaggle facial emotion recognition dataset	Convolutional neural networks are better to recognize student emotions than backpropagation neural network and decision tree algorithms.	Low
(Rodrigo et al., 2022) [34]	Individuals who completed internet-enabled CBT for tinnitus (*n* = 228)	Artificial Neural Networks	Predicting the treatment outcome by determining variables associated with treatment success.	TFI	The best predictive model was achieved by the artificial neural network with an area under the curve with a value of 0.73 over 33 predictor variables.	Low

MMPI-2: Minnesota Multiphasic Personality Inventory-2, PHQ-9: Patient Health Questionnaire-9, GAD-7: General Anxiety Disorder-7, HDAS: Hospital Anxiety and Depression Scale, BDI-IA: Beck Depression Inventory revised, CDS: Cognitive distortions scale, PSSI: Personality Style and Disorder Inventory, BSI: Brief Symptom Inventory, TFI: Tinnitus Functional Index.

3.2. Applications of Neural Networks in Psychotherapy

3.2.1. Predicting Patients' Psychotherapeutic Outcomes

One of the identified uses of NNs in the context of psychotherapy is in the prediction of patient's outcomes. A study by Gori and colleagues conducted on 150 Italian patients requesting psychotherapy used a basic ANN structure to predict patient's psychotherapeutic outcomes based on their MMPI-2 score [27]. The MMPI-2 is a personality questionnaire for diagnostic, descriptive and therapeutic purposes [35]. Each item is calculated using a T score. They used each patient's MMPI-2 individual T scores and attempted to predict their clinical outcome as per the observed change in the T scores. They achieved a mean rate of 81% successful classification in the forecast of successful and unsuccessful treatment. The authors of this study state that such tool should not replace clinical judgement, and are designed to support the psychotherapist in their decision-making process. Such predictive tools could help the therapists in providing the best possible intervention for a specific patient. The authors of this study mention that the limited sample size can impact the result of the ANN and this should be carefully taken into consideration when deriving predictions.

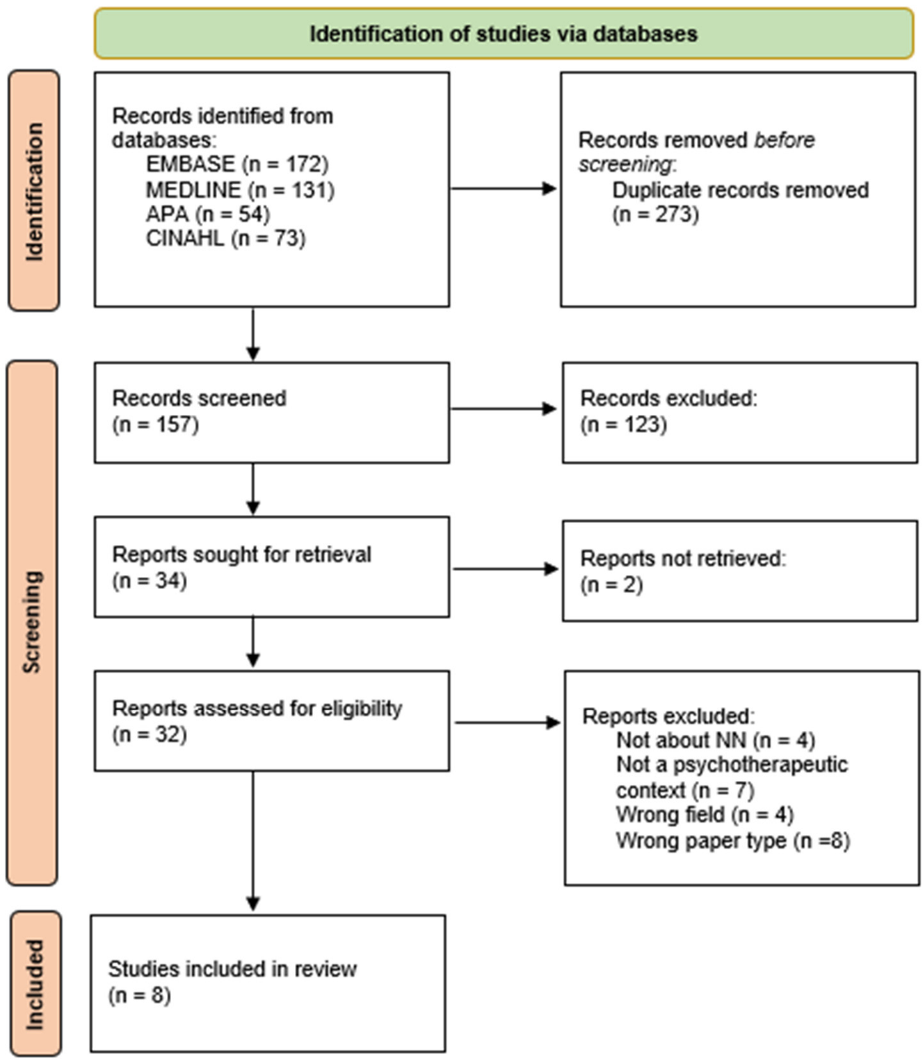

Figure 1. PRISMA flowchart for the inclusion of studies.

In Koppe's study of 2019, the authors conducted an analysis of different studies from the literature about the use of recurrent NNs in mobile sampling [29]. This is evaluated in the context of patients suffering from psychosis. They support that the use of such NNs could be used to forecast individual trajectories and schedule online feedback and interventions, and this should be further studied. As an example, a patient suffering from schizophrenia could have their trajectory predicted as per a mobile device, which is dynamically updated as time elapses, and different interventions could be conducted in response to the predicted trajectory to avoid a psychotic episode. Small datasets and varying data distributions are reported to be the main dangers of such NNs, and this should be considered when inferring a prediction.

As part of therapeutic outcomes, there is the notion of drop-out rates, which is of interest. The 2022 study by Bennemann and his colleagues compared the use of an ensemble of machine learning algorithms to a generalized linear model using neural network modeling [32]. With the data (per the Personality Style and Disorder Inventory and the Brief Symptom Inventory) of 2543 outpatients who were treated with CBT, they used several types of artificial NNs such as a feed-forward NN, an averaged feed-forward NN, and a monotone multi-layer perceptron NN, as well as other machine learning techniques. They demonstrated that for this dataset, NNs were identified to be less suited to predicting naturalistic datasets and binary events. Ensemble modeling comprising Random Forest algorithms and nearest-neighbor modelling performed best, by correctly identifying 63.4%

of cases of patients who dropped out [32]. The quality of the data is reported to be poor, and might have hindered the results.

For patients suffering from tinnitus and following an internet-enabled cognitive behavioral therapy, artificial NNs and support vector machines were studied to predict their therapeutic outcomes. In a 2022 from Rodrigo and colleagues, 228 patients suffering from tinnitus who follow internet-enabled cognitive behavioral therapy had to complete the Tinnitus Functional Index (TFI) at the beginning of their treatment and at the end to determine if their therapy was successful (or not) [34]. The authors implemented two types of machine learning models: an artificial NN and a support vector machine, over 33 predictor variables including 7 demographic variables, 15 tinnitus and hearing-related variables, 4 treatment-related variables, 9 different types of tinnitus, and 7 clinical factors. The artificial NN performed best, with a predictive accuracy represented by an area under the curve of 0.73, as compared to the SVM, which achieved an area under the curve of 0.69 [34]. The authors state that his study was limited to the predictive variables, and other models could yield other results if encompassing other variables.

3.2.2. Content Analysis

One application of NNs is content analysis. In Nitti et al. (2010) study, a discourse flow analysis was conducted over verbatim from psychodynamic therapy interventions [28]. In their work, they illustrate that the role of the discourse in psychotherapy is to generate new meanings through time, and this can be demonstrated by a discourse network. They created a discourse flow network and used it over the verbatim of a patient who went through 43 sessions of psychodynamic therapy. Using different metrics such as connectivity (density of the association among nodes), activity (global network ability to extend the spectrum of associations among nodes through time), and regulation (via super nodes, which are particular nodes carrying out the function of super-ordered meaning working as taken-for-granted assumptions), they concluded that NNs allow for the identification of patterns characterizing the psychotherapy process. It is mentioned that the redundancy of the language could potentially impact the validity of the model.

Another interesting approach was identified in Burger's study of 2021. They used though records and data from 320 healthy participants over depressive, anxious, and cognitive distortions scales to verify the possibility of using machine learning to extract schemas from their thought records [31]). Schemas are cognitive structures that make up our view of the world, and such schemas can be maladaptive, which is makes it interesting to be able to identify them. This is used in several therapeutic approaches. One of the machine learning approaches used is recurrent NNs, which were found to outperform the use of other algorithms such as k-nearest-neighbor and support vector machine for such a task. A larger set of schemas is suggested so that better content analysis can be achieved.

As part of psychotherapeutic content, emotions play an important role in the therapeutic relationship. A 2022 study by Chen and colleagues assessed the use of convolutional NNs for the recognition of emotions in students using human-interactive psychotherapy [33]. Their results demonstrate that deep learning convolutional NNs have better (accuracy of 81.86%) student emotion recognition ability than backpropagation neural networks (BPNNs) and decision tree algorithms (below 80%). They also conducted an acceptability analysis to identify the students' thoughts about emotional recognition and classification, conducted via artificial intelligence, and this methodology was found acceptable by the students. The limitations of the study are not mentioned in the manuscript.

3.2.3. Automated Categorization of Psychotherapeutic Interactions

A study conducted on the interactions of 13,073 patients demonstrated that recurrent NNa can perform well and achieve human-level agreement when categorizing therapist utterances [30]. This study was conducted with the use of a bidirectional long–short-term memory algorithm, which is a form of natural language processing using recurrent neural networks. It requires a large amount of data in order to achieve acceptable performances.

Therefore, the authors used data from patients who followed internet-enabled CBT. Categorization of over 24 potential categories of utterances was achieved with acceptable performance (as characterized by precision) and recall of interactions classified in each of the categories [30]. The authors state that it is hard to know if a therapeutic intervention was conducted in the appropriate manner, and the model does not consider the quality of these interventions.

3.2.4. Quality of the Evidence

As can be observed, most studies achieved a low quality of evidence at best. Considering that most of the identified studies are conducted with a low sample size in the context of descriptive analysis, the quality of the evidence is therefore limited, per the GRADE system [26]. Further studies should be conducted on larger sample sets to confirm the effectiveness of the identified uses of NNs in the context of psychotherapy.

4. Discussion

4.1. Main Findings

The aim of this study was to identify the different use of NNs in the field of psychotherapy. A scoping review strategy was employed, considering the limited amount of literature on the subject. A total of eight articles were analyzed, and three main uses were identified: predicting therapeutic outcomes, content analysis, and automated categorization of psychotherapeutic interactions. While the number of studies identified were limited, this study provided a few examples of practical implication of NN for psychotherapeutic approaches and patient care.

In several areas of medicine, predictive approaches are being employed to select the best treatment for the patient. Prediction of patients' clinical trajectories, especially in the field of psychosis, is an eminent avenue of research in psychiatry. Such approaches could lead to more personalized treatments [36]. As identified in this scoping review, the use of NNs for predicting outcomes was brought up in Gori's study of 2010, which stated that such use of NNs could help the therapist with their decision making, and help in selecting the appropriate treatment for the patients [27]. However, the literature is currently hinting at the potential limitations of such uses, considering that models are dependent on the data they are provided; therefore, the transparency of such models should be made available to the clinicians to highlight their potential limitations [37]. Complex evaluations, such as posing a diagnosis, can cause predictive models to achieve poor performances, and can therefore limit their usability in assisting the clinician in their decision-making. The application of such models in the day-to-day work of psychologists and psychiatrists could also pose several ethical challenges, which should be addressed prior to broad usage [38]. In the field of psychotherapy, emerging randomized controlled trials using personalized prediction and adaptation tools for treatment outcomes are hoped to provide further information on the role of prediction tools in assisting therapists [39].

Machine learning has been used for content analysis in many domains of medicine [40]. For example, a recent literature review identified that text processing and text mining can be conducted using different kinds of artificial NN, recurrent NN, convolutional NN and linear short-term memory algorithms [41]. Different types of content can be analyzed in the context of psychotherapy, such as the content of the interactions, the emotions, and the relationship (therapeutic alliance). Content analysis in psychotherapy has been studied for several years, and the use of computational techniques to enhance this approach has been forecasted since over two decades ago [42]. However, it was found that limited data are available on the use of NNs for this context. While emotional recognition was found acceptable per Chen and colleagues, other work in the field of facial recognition demonstrates the superiority of NNs compared with other algorithms in recognizing facial traits [33,43].

In psychotherapy, implementation of supervised algorithms to categorize patient's interactions have been employed, but are often limited by small datasets [44]. However, when such datasets are available, NNs offer acceptable performance, as was observed in Ewbank and colleagues' study for a large array of categories [30]. When large datasets are not available, support vector machines are preferred, especially when the interactions are linearly separable [45]. One major concern for such applications, notably for NNs, is when data are imbalanced. Depending on the training data available, machine learning algorithms including NNs can perform poorly on some categories, which can lead to classification anomalies [46]. This limitation must be taken into account when conducting analyses on verbatims or other therapeutic corpora that have been automatically annotated.

4.2. Limitations

This scoping review focused only on the different uses of neural networks in the context of psychotherapy. The current search strategies highlight the use of NNs in the context of psychotherapy; however, certain studies might have used ensemble modeling comprising NNs. These might have been overlooked, considering it is difficult to estimate the role and effect of NNs when they are contained in an ensemble model. Furthermore, the small number of studies identified makes it difficult to derive significant conclusions as to the effects of the different uses of NNs in psychotherapy.

5. Conclusions

Psychotherapy is an important form of treatment for patients suffering from mental illness. To better understand psychotherapeutic processes and approaches, computational techniques have emerged across the years. This scoping review focused on the use of NNs in the context of psychotherapeutic approaches. From the eight studies analyzed, three main uses were identified: predicting therapeutic outcomes, content analysis, and automated categorization of psychotherapeutic interactions. The potential implications of these uses could assist the therapist in providing a more personalized therapeutic approach with their patients. Considering the limited amount of literature on the subject, this study paves the way for future research to better understand the effectiveness of such uses. Integration of NNs in the clinical aspects of psychotherapeutic approaches should be further studied, and their impact on clinical outcomes should also be studied.

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Appendix A

Table A1. Electronic search planification strategy for the systematic review conducted.

	Neural Networks	Psychotherapy
EMBASE	X	psychotherapy/OR psychology
MEDLINE	X	Psychology Services, Psychology/or Psychotherapy, Psychiatric
APA	Neural networks/artificial intelligence	psychotherapy/or psychiatry/or mental health/

Table A1. *Cont.*

	Neural Networks	Psychotherapy
CINHAL	X	
Free vocabulary	(Neural networks OR machine learning OR deep learning OR artificial intelligence) N3 (Neural OR neuron OR networks OR computer science OR deep OR natural language processing)	(psychotherapy OR psychology) N2 (interventions* OR treatment* OR psychoed* OR psychology* OR psychiatry* OR psych*)

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