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Machine Learning in Family Research: A Systematic Review

Aile Araştırmalarında Makine Öğrenmesi: Sistematik Bir Gözden Geçirme

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ABSTRACT

Machine learning is a powerful tool for extracting meaningful patterns from large datasets and performing predictive modeling. In recent years, machine learning methods have been increasingly applied in family sciences, mental health, and educational research. This systematic review aims to evaluate how machine learning methods are used to understand the impact of family dynamics on individuals' mental health, educational attainment, and behavioral outcomes. A comprehensive literature search was conducted in the Web of Science, PubMed, Scopus, Science Direct, Ulakbim, and TRDizin databases, and 11 studies meeting the PICOS criteria were analyzed. The reviewed studies indicate that machine learning algorithms provide strong predictions in areas such as domestic violence, depression, academic achievement, and children's psychosocial development. In particular, Random Forest (RF), Support Vector Machines (SVM), deep learning, and natural language processing (NLP) methods have demonstrated high accuracy in predictive tasks. However, challenges related to model transparency, ethical concerns, and applicability within the family context remain among the limitations of machine learning models. Therefore, future research should focus on enhancing the interpretability of machine learning approaches, integrating them with theoretical models, and supporting their application in family sciences with more empirical studies. By doing so, machine learning techniques can be used more effectively to understand family dynamics and support individuals' mental health.
Keywords: Machine learning, family dynamics, mental health, predictive modeling, artificial intelligence

ÖZ

Makine öğrenmesi, büyük veri setlerinden anlamlı örüntüler çıkarmak ve tahmine dayalı modelleme yapmak için kullanılan güçlü bir araçtır. Son yıllarda, makine öğrenmesi yöntemleri aile bilimleri, ruh sağlığı ve eğitim araştırmalarında giderek daha fazla uygulanmaktadır. Bu sistematik gözden geçirme, makine öğrenmesi yöntemlerinin aile dinamikleri, bireylerin ruh sağlığı, eğitim başarısı ve davranışsal sonuçları üzerindeki etkilerini anlamada nasıl kullanıldığını değerlendirmeyi amaçlamaktadır. Çalışmada, Web of Science, PubMed, Scopus, Science Direct, Ulakbim ve TRDizin veri tabanlarında kapsamlı bir literatür taraması yapılmış ve PICOS kriterlerine uygun 11 çalışma analiz edilmiştir. İncelenen çalışmalar, makine öğrenmesi algoritmalarının aile içi şiddet, depresyon, akademik başarı ve çocukların psikososyal gelişimi gibi konularda güçlü öngörüler sunduğunu ortaya koymaktadır. Özellikle Rasgele Orman (RF), Destek Vektör Makineleri (SVM), derin öğrenme ve doğal dil işleme (NLP) yöntemlerinin yüksek doğruluk oranlarıyla tahmin yapabildiği görülmektedir. Ancak, model şeffaflığı, etik kaygılar ve aile bağlamında uygulanabilirlik gibi konular, makine öğrenmesi modellerinin sınırlılıkları arasında yer almaktadır. Bu nedenle, gelecekteki araştırmalarda, makine öğrenmesi yaklaşımlarının daha açıklanabilir hale getirilmesi, kuramsal modellerle entegre edilmesi ve aile bilimleri alanında daha fazla ampirik araştırma ile desteklenmesi önerilmektedir. Böylece, makine öğrenmesi teknikleri aile içi dinamikleri daha iyi anlamak ve bireylerin ruh sağlığını desteklemek için daha etkin bir şekilde kullanılabilir.
Anahtar sözcükler: Makine öğrenmesi, aile dinamikleri, ruh sağlığı, tahmine dayalı modelleme, yapay zeka

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Introduction

The foundation of machine learning is associated with the work of psychologist Frank Rosenblatt at Cornell University in 1957. Inspired by the working principles of the nervous system, Rosenblatt designed a machine that could recognize the letters of the alphabet. This machine was called a "Perceptron" and was built on a structure that could use analog and digital signals. The Perceptron included a threshold element that converted analog signals into digital signals, and this feature is considered the prototype of modern artificial neural networks (ANNs) (Fradkov 2020). In this context, the Perceptron was an important milestone in developing machine learning and artificial intelligence and laid the foundation for today's deep learning techniques.

Many methods attempt to predict an individual's unknown current and future characteristics (Tversky and Kahneman 1974). Statistical approaches such as classification and regression modeling aim to classify and predict data better using the relationships observed in the data (De'ath and Fabricius 2000). Similarly, machine learning provides a collection of tools for classification and prediction based on patterns observed in data. Recently, machine learning has gained attention for classification and prediction tasks in health research, including family medicine research, due to the increasing availability of large health data stores (e.g., electronic medical record databases) and advances in computing power (Lin 2022).

Machine learning (Mitchell 2010) describes the automated process of identifying patterns in data ("learning") to perform tasks such as classification and prediction. Machine learning is a subfield of artificial intelligence that addresses how computers can "think" or process information "intelligently". Like familiar regression-based techniques, determining the outcome for classification or prediction requires several user decisions, including selecting the data needed to reach the result and defining the variables used for classification or prediction (Black et al. 2023). Machine learning approaches for classification and prediction are supervised learning techniques (Sutton and Barto, 2018). Other subfields include unsupervised and reinforcement learning (Hastie et al. 2009, Sutton and Barto 2018). In unsupervised learning, there is only input data, and the output data is ambiguous. The goal is to find hidden patterns or groups in the data—for example, clustering and dimension reduction. In reinforcement learning, an agent learns according to the reward/punishment it receives from the environment. Reinforcement learning aims to maximize the long-term reward. For example, autonomous vehicles driving safely and avoiding collisions, artificial intelligences playing games, projecting advertisements according to the user (reward: clicking on the ad, punishment: ignoring the ad) (Ongsulee 2018, Sutton and Barto 2018).

Supervised learning learns how to classify and predict unobserved outcomes using outcomes from known data. This is usually achieved by understanding the relationships between known outcomes and predictor variables to classify and predict new outcomes (Black et al. 2023). In other words, at this stage, inputs and outputs are known, and supervised learning aims to learn the relationship between inputs and outputs. For example, email spam filtering or handwriting recognition (Ongsulee 2018). Other approaches of supervised learning techniques are decision trees, random forests (RF, random forest) (Quinlan 1986), support vector machines (SVM, Burges 1998; support vector machines), k-nearest neighbors (Patrick and Fischer 1970), Naive Bayes classifier (James et al. 2021), neural networks, linear and logistic regression (James et al. 2021), neural networks (Bishop 1994).

Decision trees repeatedly partition data into two or more groups with homogeneous outcomes according to predictive characteristics. The data is continued until it reaches a stopping criterion, such as the maximum number of splits to the variable that maximizes the within-group similarity (homogeneity of the groups). The outcome of a new individual is predicted by evaluating the specified splitting rules and assigning the observed outcome to the last group.

The RF is created by modifying the observations and variables included during decision tree development. New classifications and predictions are based on the consensus of forecasts from each component tree.

SVM (Burges 1998) groups data on an n-dimensional plane that partitions the feature space defined by the features. New individuals are assigned to the outcome of the partition in the feature space.

K-nearest neighbors (Patrick and Fischer 1970); the new data are compared with data whose results are known. A new individual's classified or predicted outcome is determined by the results of the k individuals who are most like the new individual.

Neural networks (Bishop 1994) are systems in which interconnected nodes are organized in layers to process information. The nodes receive signals from outside. These signals usually come from data (for example, pixel information from an image). Each node is assigned a weight. These weights determine how significant the incoming signal is. For instance, if a signal has a high weight, it has more impact. The incoming signal is mathematically processed within the node (usually using summation and activation functions). After processing, the node produces an output. This output is transmitted to the next layer. Hidden layers process the information and learn more complex features. Once the output layer is reached, the system produces the result. For example, it can determine whether a picture is a cat or a dog. The main goal of neural networks is to optimize the weights to learn a given task best. This is achieved by reducing the number of errors in the training process.

Linear and logistic regression (James et al. 2021) relate one or more variables to some outcome based on relationships observed in the data. According to mathematical criteria, linear regression finds the line best fits the data. Similarly, logistic regression finds the line that best fits the data after applying the logistic function.

The Naive Bayes classifier (James et al. 2021) is a simple probabilistic classifier that updates an initial prior probability based on the state-related frequencies of features observed in the data. This model assumes that all features are independent; hence the name "naive".

Supervised machine learning (SML) performs classification or prediction by learning the relationships between predictor variables and outcomes and is often closely related to statistics. ML can support statistical analysis, such as understanding possible cause-and-effect relationships or balancing confounding variables, especially in health research. ML goes beyond parametric models, using k-nearest neighbors to make predictions without making assumptions about the data structure. Statistical and ML models can be used together to summarize the relationships between outcomes and predictors (Black et al. 2023).

Machine learning is a subset of artificial intelligence. Deep learning is also a subset of machine learning. Essentially, all deep learning is machine learning, and all machine learning is AI, but not all AI is machine learning (Ongsulee 2018). Deep learning uses artificial neural networks, and the human brain inspires these networks. The difference from other machine learning algorithms is that they automatically perform feature extraction. Deep learning can learn complex relationships in large data sets with its layered structure. It can work with supervised, unsupervised, and reinforcement learning methods (Bengio et al. 2015).

In the digital age, the rapid growth in the size of datasets and easy access to computational power highlight the benefits of machine learning in many fields, especially in the social sciences. It has been observed that machine learning has been utilized in many areas, such as identifying families in need of home visiting services (Ahn et al. 2024); post-traumatic stress disorder risk assessment of family members of individuals in intensive care (Dupont et al. 2024); determining risk factors related to adolescents' witnessing parental conflict (Lopez- Larrosa et al. 2022). Many studies have been carried out in different fields, such as examining the determinants of the lack of continuous access to health services for mothers, children, and newborn babies in East Africa with machine learning (Mlandu et al. 2023); examining the applications in the child welfare review system with machine learning (Schwartz et al. 2017). Many studies have been conducted to reach accurate predictions to target assistance to at-risk children and families, the predictability of one's life course and life outcome, efforts to understand unpredictable differences between social contexts, the possible contribution of scientific discoveries and social policy development, and measuring life outcomes of the family structure consisting of children, parents, and households.

Machine learning in mental health has become a growing area of research in recent years (Le Glaz et al. 2021, Chung and Teo, 2022). Supervised machine learning methods have been tested in various contexts to improve diagnostic accuracy, predict the course of clinical conditions, and identify at-risk individuals early. Promising results have been obtained in areas such as postpartum depression (Zhong et al. 2022), mental health crises derived from electronic health records (Garriga et al. 2022), suicidal behavior (Kusuma et al. 2022), depressive symptoms based on sleep and clinical health indicators (Gomes et al. 2023), adolescent mental health (Rothenberg et al. 2023), and mood swings in bipolar disorder (Sankar et al. 2023). It has also been used to predict treatment response in interventions such as cognitive-behavioral therapy (Vieira et al. 2022), clinical depression treatment (Sajjadian et al. 2021), and cognitive processing therapy for post-traumatic stress disorder (Nixon et al. 2021). These findings suggest that artificial intelligence-based models can both support clinical decision-making processes and contribute to the development of personalized mental health services.

Machine learning algorithms go beyond traditional statistical methods with the capacity to process many variables simultaneously and reveal complex relationships between data (Yarkoni et al. 2017, Ivaskevics and Haller 2022). This is particularly important in family studies because family structure and functioning involve multidimensional patterns of interpersonal interactions. Family-based psychosocial treatments are known to be effective in evidence-based research (Naar-King et al. 2016; Baldwin et al. 2023). Machine learning has the potential to predict which families will benefit more from such interventions and under which conditions. Thus, it can contribute to a more detailed understanding of family dynamics and a more precise adaptation of treatment plans.

The family is a building block where individuals' social, emotional, and behavioral foundations are shaped. Modern data analytics methods, especially machine learning, offer the opportunity to examine these complex dynamics in a previously impossible depth. From the interactions between family members to the effects of social changes on family structure, machine learning has made research on the family more comprehensive and predictive. In this context, machine learning offers a revolutionary way to understand families' critical challenges and develop solutions. Various studies have been conducted on the dynamics of the family and family members studied by machine learning. Machine learning has been applied to family and relationship studies such as child abuse (Chouldechova et al. 2018), the effects of father absence (Liu 2022), teen pregnancy (Harding et al. 2022), and couple relationship quality (Joel et al. 2020).

Previous research has highlighted the challenges of addressing all aspects of machine learning in a single study due to its broad scope and complexity. For example, the failure of the prediction models developed by 160 teams to examine milestones affecting family life (Salganik et al. 2020) and the fact that both the number and categorical abundance of family-related data complicate the modeling process (Hastie et al. 2009) support this. Therefore, given the methodological diversity and the vast opportunities machine learning offers, it is impossible to assess the topic in a single study comprehensively. Thus, this paper aims to discuss machine learning research that has proven helpful in family studies, its usefulness in advancing family science, and illustrate its application through a series of case studies.

While psychology often focuses on explanatory models, machine learning offers powerful tools for prediction. This distinction makes it easier to understand the methodological challenges in family research (Yarkoni and Westfall 2017). In family studies, measurement errors, longitudinal analysis difficulties, and minor sample problems are the main methodological challenges limiting the reliability and generalizability of the findings. In psychology and family research, measurement errors limit findings' reliability due to systematic bias and random variance. While traditional statistical methods directly reflect these errors in the model, machine learning algorithms can minimize both systematic error and sampling-dependent variability by optimizing the bias-variance balance (Yarkoni and Westfall 2017). This feature contributes to more consistent and generalizable results in family studies.

Although research to understand family dynamics is often based on longitudinal designs, the complexity of repeated measures and multivariate relationships makes it difficult to analyze with traditional models reliably. Machine learning approaches, primarily through methods such as cross-validation, enable models to be generalizable to existing data and to new samples (Simmons et al. 2011, Yarkoni and Westfall 2017). Thus, it is possible to monitor changes over time more accurately and to reveal the dynamic relationships in family structure more reliably.

Family research is often conducted with limited sample sizes. This situation increases the risk of overfitting in models and reduces the reproducibility of the findings obtained in different samples (Cohen 1962, 1992, Ioannidis 2008, Yarkoni 2009). It is noted in the literature that strong effects obtained from small samples are often lost in larger data sets. Machine learning overcomes this limitation and increases the findings' internal consistency and generalizability, thanks to its structure, which is suitable for working with large-scale data sets and regularization techniques.

Machine learning is a subset of technology that enables computers to learn and develop independently using mathematical algorithms. It can be used to build models with data to identify patterns between health outcomes and predictive factors (e.g., norovirus outbreaks or risk of child abuse) that are important for children and families (Salganik et al. 2020, Syed et al. 2022, Tiyyagura et al. 2022). Although there has been a growing body of work in this area in recent years, there is a limited understanding of the evidence base. Important questions remain unanswered, such as the nature of machine learning tools, the methods applied, the fusion of the results obtained, and their ethical use.

Understanding the evidence base for applied family studies that use machine learning to collect and analyze family data or to provide resources and services to families is crucial. This understanding will allow researchers to consider machine learning as an innovative and applicable tool in the field of applied family science, while also contributing to developing machine learning- supported decision tools for family practitioners and policy makers. Accordingly, the scoping review aims to comprehensively review the empirical literature on applied family science to understand how machine learning is used to examine families' psychological health and risk factors.

Method

The current systematic review was conducted per PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) criteria (Moher et al. 2015). Accordingly, Web of Science (WOS), PubMed, Scopus, Science Direct, Ulakbim, and TRDizin databases were searched without any date criteria due to the current nature of the study topic.

The literature search was conducted between November 2024 and January 2025. Both English and Turkish keywords were used in the searches. The English keywords used were: ("machine learning") AND ("family" OR "parent") AND ("assessment" OR "treatment" OR "screening") AND ("families"); their Turkish equivalents are: ("machine learning") AND ("family" OR "parent") AND ("assessment" OR "treatment" OR "screening") AND ("families"). The keywords were combined through Boolean operators, and different combinations were tried.

As a result of the search, a total of 517 studies were found through PubMed (n=172), Scopus (n=130), Web of Science (n=35), Science Direct (n=91), ULAKBIM (n=90), TRDizin (n=0) databases. When repeated studies (n=210) were excluded, the title and abstract sections of the remaining 307 studies were evaluated in terms of inclusion criteria, and it was concluded that the full text of 48 studies could be examined. Of the 48 studies whose full text was examined with the PICOS criteria, 11 met the requirements and were included in the study.

After removing duplicates from the initial 517 studies, 307 unique records were obtained. In the first stage, titles and abstracts were evaluated, and studies that did not meet the P (Population) and I (Intervention) criteria, i.e., did not include family members, focused only on individuals, or did not include machine learning, were excluded. As a result of this stage, 48 studies were included in the full-text review. O (Outcome) and S (Research Design) criteria were applied in the full-text evaluation; reports that did not examine the protective and risk factors of family structure on the individual, were only economically or legally focused, were in the form of reviews or protocols, and foster family studies were excluded. No restrictions were imposed for criterion C (Comparison). As a result of these steps, 37 studies were eliminated, and 11 studies were included in the systematic review.

Inclusion and Exclusion Criteria

The inclusion criteria of the study were determined within the scope of the PICO (S) (P: Population, I: Intervention, C: Comparator, O: Outcome, S: Study design [PICO (S)]) model (Table 1). Accordingly, (P) family research involving family members, conducted with parents or their children, (I) studies that are affected by the change in family structure or examined with the machine learning technique that affect the family structure, (C) studies that do not use comparison criteria, (O) studies that examine the protective and risk factors of family structure on the individual, and (S) studies that provide comparisons and predictions with the machine learning method were included in the review.

Within the scope of the study, studies that targeted only the individual instead of the family structure, studies that addressed the physical health of a single family member, studies in which family members were in the position of caregivers, studies based on genetic variation related to the family, and studies in which the family was not studied as a protective and risk factor were excluded. Studies that indirectly studied psychological health but only targeted economic or legal developments, incomplete studies (protocols), and studies conducted with foster families were not included in this study. Review articles were excluded. As a result, 11 articles were included in the current study. The process is summarized in Figure 1.

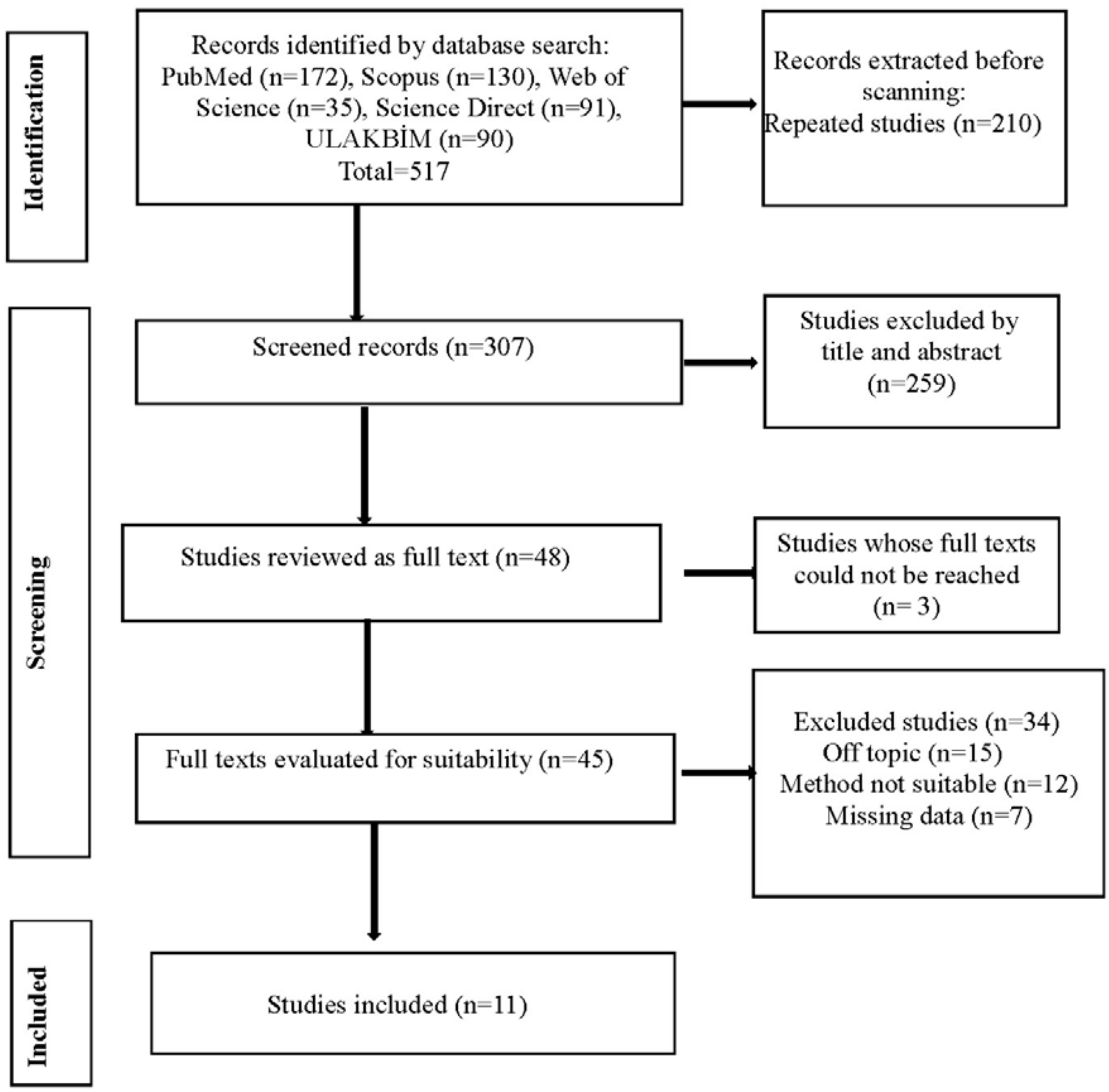

Figure 1. PRISMA flow chart

Table 1. PICOS criteria

Criteria	Inclusion	Exclusion
P(Population)	Covering family members; Family research conducted with parents or children	Targeting only the individual; addressing only the physical health of a single family member; Limited work with family members in the position of caregiver
I (Intervention)	Studies affected by change in family structure or affecting family structure and examined with machine learning technique	Studies based on genetic change related to the family and do not consider the family as a protective/risk factor
C (Comparator-Comparison)	Studies conducted without using comparison criteria were accepted.	–
O (Outcome)	Studies examining the protective and risk factors of family structure on the individual	Although it indirectly studies psychological health, studies that only target economic or legal developments
S(Study Design)	Original research that provides comparisons and predictions using machine learning	Incomplete studies (protocols), studies with foster families, review articles

Results

The articles included in the systematic review were analyzed in terms of sample characteristics, main measurement tools, research design, intervention characteristics, and effects. The relevant table is summarized in Table 2.

Sample Characteristics

The sample characteristics of the studies using machine learning methodology are variable. Sample sizes ranged from 61 people (Zheng and Ye 2022) to 1.16 million users (Li et al. 2021). In 45.45% of the studies conducted (Sun et al. 2020, Lopez-Larrosa et al. 2022, Zheng and Ye 2022, Wang et al. 2023, Zhou et al. 2024), family data were collected through adolescent participants. In 36.36% of the studies (Li et al. 2021, Gil et al. 2022, Berkel et al. 2023, Zhou et al. 2024), data were collected through the child and the primary caregiver. The systematic review included two studies that studied family variables through children's data (Schwartz et al. 2017, Gao et al. 2024). Only two of the studies provided detailed demographic information of the participants (Lopez-Larrosa et al. 2022; Sun and Sayer 2024).

Machine Learning Methods

Regarding machine learning methods, Natural Language Processing (NLP), RF, Logistic Regression, and Deep Learning techniques stand out among the most widely used methods. Berkel et al. (2023) used TF-IDF and BERT models from NLP methods. In Gil et al. (2022), Sparse Logistic Regression (SLR), SVM, and RF methods were compared, and the RF model gave the most successful results with an 86% accuracy rate. In Zhou et al. (2024), Logistic Regression and Random Forest algorithms were compared, and it was reported that both methods provided high accuracy. On the other hand, Schwartz et al. (2017) found that machine learning models were successful in judgment guidance processes with an accuracy rate of 93%.Among the most preferred machine learning methods in the studies, RF stands out and has a prevalence of around 30% as one of the most used methods. This is followed by Decision Trees and Logistic Regression, each with a utilization rate of around 20%. Deep Learning methods also play an essential role, but their usage is around 15%. Regularized Logistic Regression and Regression methods were preferred at lower rates (10%). In addition, supervised machine learning methods (Association Rule Mining and Supervised ML), which are used less frequently but found a place in some studies, have a share of 5%.

Table 2. Characteristics of the studies examined

	Source	Sample	Purpose	Measure	Variable	Interv	Interv detail	Result	
1	Berkel et al. 2023	113 families (130 parents, 92% female)	To examine the evaluation of family-based control programs with machine learning	(TF-IDF and BERT) COACH	Various indicators such as the quality of implementation of the program, the level of parental involvement, the ability to implement it at home, and parental motivation.	Yes	Family Check-Up 4 Health programı	NLP methods (TF-IDF and BERT) have been found to be valid and effective for monitoring the quality of implementation of the program.	NLP
2	Gao et al. 2024	141,356 children	Creating an ADHD management model in which the community, family and hospital participate together		Personal health -Social and family factors and Parent-child interaction patterns	No	No	An algorithm for the diagnosis of ADHD was established based on 13 independent determinants.	Logistic regression
3	Gil et al. 2022	171 family data (171 fathers, mothers and university students)	Developing machine learning to predict depression risk in college students and identify important family and individual factors	SPS STS CES-D BFI-10 FACES IV KMSS PBI	Family harmony Depression level Personality Traits	No	No	Family harmony and maternal depression have been explained among the predictors of depression.	-RF -SLR -SVM
4	Li et al. 2021	Public data of 1.16 million active users	To examine whether there is a change in the personalities of individuals who are exposed to domestic violence	Big Five Inventory	The personality changes of the group that was subjected to violence and those who were not subjected to violence were compared.	No	No	It has shown that after experiencing domestic violence, the victims' neuroticism increases and responsibility decreases.	Linguistic Inquiry and Word Counting
5	López-Larrosa ve ark. 2022	251 Spanish adolescents (Mage = 15.59, SD = 1.74).	To examine the participation of family adolescents in conflict and those who do not live with their families	-CPIC -SIFS - HFBWAQ -CV -MOVQ	They examined the variables that predict participation in family conflict.	No	No	It was able to predict adolescent involvement in family conflicts with a 65% accuracy rate.	-K-Nearest Neighbor, Naive Bayes -SVM -Decision Trees (C5.0), -RF
6	Schwartz et al. 2017	78.394 Individual child case	More accurate detection of low, medium and high risk cases	-	Referrals at the Child Protection Service	No		It shows that it will significantly improve the accuracy and utility of the child welfare risk assessment tool	Decision Tree Regression

Table 2. Characteristics of the studies examined

	Source	Sample	Purpose	Measure	Variable	Interv	Interv detail	Result	
7	Sun & Sayer 2024	5114 adolescents (Mage = 15) Parents (N = 4548; 92.71% mothers, Myaş=41.51, SD=6.35)	To examine the relationship between family experience variables measured in adolescence and educational achievement	-	Exploring predictors of school success with family experience variables	No		14 family variables related to school success were reached.	WMO, RF
8	Sun et al. 2020	5114 adolescents (Mage = 15)	To examine the predictive variables of adolescence family experience factors in educational achievement	Family variables and attending or enrolling in college	They tried to measure the consistency of family experience variables that affect school success.	No	No	Family experiences have predicted the success of young adults with an accuracy of 72.33-79.10%.	Regularized logistic regression RF
9	Wang et al. 2023	2455 students (Regardless of age group)	To examine the combined effects of risk/protective factors of depression in family and school areas	DBF	-Family structure -Parental divorce -Parent education -Family unity -Family conflict -School variables	No	No	Family adjustment, family conflict, peer support, and teacher support have been shown to emerge as the strongest factors associated with adolescent depression.	Relationship Rule mining
10	Zheng & Ye 2022	61 adolescents with social anxiety	Evaluate the effectiveness of CBT with deep learning in the treatment of social anxiety in adolescents	-Social anxiety scale -Emotional regulation -Self-efficacy scale	Adolescents' social anxiety levels and emotional regulation self-efficacy.	Yes	CIS	An exploratory algorithm has been created to be used in the treatment and diagnosis phase with the deep learning method.	Deep Learning
11	Zhou et al. 2024	7967 students and their primary caregivers	Non-suicidal self-injury in adolescence It is aimed to examine the accuracy of risk estimation at the family level.	-PHQ-9 -HEAT -Family APGAR -NMHLQ	Sociodemographic information -Family structure -Adolescent and parental depression -Family functionality -Perceived stigma	No	No	With the RF method, family functioning, family conflict and parental depression were explained as risk factors.	RF Logistic Regression

BERT = Bidirectional Encoder Representations from Transformers, BFI-10 = Big Five Personality Inventory, CES-D = Center for Epidemiologic Studies Depression Scale, COACH = Cognitive Oriented Approach to Child Health, CPIC = Children's Perception of Interparental Conflict Scale Conflict Perception Scale), CV = Conflict Vignette, DBF = Demographic Information Form, DMS = Supervised Machine Learning, DSRSC = Depression Self-Rating Scale for Children, FA = Family APGAR (Family Functioning Scale), FACES-II = Family Adaptation and Cohesion Evaluation Scales II – Family Version II, FACES-IV = Family Adaptability and Cohesion Evaluation Scale IV Association Assessment Scale IV), FES = Family Environment Scale, HFBWAQ = How Does My Family Behave When We Have Argument Questionnaire), ISI = Insomnia Severity Index, KMSS = Kansas Marital Satisfaction Scale, MOVQ = My Opinion About the Video Questionnaire, NLP = Natural Language Processing, NMHQ = National Mental Health Literacy Questionnaire, PBI = Parental Bonding Instrument, PDD = Perceived Discrimination and Devaluation Scale, PHQ-9 = Patient Health Questionnaire, RF = Random Forest, SIFS = Security in the Family System Scale, SPS = Spiritual Perspective Scale, STS = Self-Transcendence Scale, SVM = Support Vector Machine, SLR = Stepwise Logistic Regression, TF-IDF = Term Frequency – Inverse Document Frequency; Interv: Intervention

Mental Health of Family Members with Machine Learning

Within the scope of the systematic review, there are four studies aiming to predict family variables on individuals' mental health (Gil et al. 2022, Wang et al. 2023, Gao et al. 2024, Zhou et al. 2024). Gao et al. (2024) aimed to estimate individual, familial and social factors with individuals experiencing attention deficit hyperactivity disorder (ADHD) and associated family-related risk factors such as poor parent-child interaction patterns (parents often show impatience with their children or get angry frequently), premature birth and parental divorce or separation with an increased risk of ADHD (Gao et al. 2024). A predictive model including social and familial factors has been developed to improve the understanding and management

of ADHD in the family context. Gil et al. (2022) stated that family cohesion and maternal depression level were the strongest predictors in their study, in which they aimed to predict individual and familial variables of depression risk with family data consisting of 171 mothers, fathers, and university students (Gil et al. 2022). In addition, it was explained that depression in the mother, respiratory diseases, and cancer in the father were determined as three significant family factors in predicting the risk of depression in university students. (2024); 7967 students and their primary caregivers, the findings revealed that family function, family conflict, left- behind experience, experience of death of a family member, family history of mental illness, parental depression, parental insomnia, help-seeking behaviors for mental distress from parents or other family members, and mother's education level below high school were important familial predictive factors for non-suicidal self-harm behavior in adolescence (Zhou et al. 2024). Wang et al. (2023) conducted a study with a total of 2455 adolescents studying in primary and secondary schools. They showed that family cohesion, family conflict, peer support, and teacher support emerged as the strongest factors associated with adolescent depression (Wang et al. 2023). Low family cohesion and high family conflict emerged as the most influential predictive risk factors among family factors, independent of gender, age group, and left-behind status.

Family Intervention and Support Systems with Machine Learning

Studies aiming to increase the effectiveness of interventions for families and family members (Schwartz et al. 2017, Zheng and Ye 2022, Berkel et al. 2023) are discussed in this context. Berkel et al. (2023) aimed to use machine learning methods such as NLP to evaluate the implementation process of evidence-based parenting programs. The study evaluated the Family Check-Up 4 Health (FCU4Health) program on 116 English and 81 Spanish transcripts obtained from 113 families. Term Frequency-Inverse Document Frequency (TF-IDF) and Bidirectional Transformations from Coding Representations (BERT) models were trained, and the validity of the models was tested by comparing them to the COACH (the program's system for evaluating implementers) criteria used for implementer evaluation (Berkel et al., 2023). The results revealed that both models showed a significant relationship with COACH observer ratings. This study evaluated the Checkup Program for Families' Health (FCU4Health) using machine learning methods (TF-IDF and BERT). These methods were shown to provide significantly better agreement when compared to the COACH measures used by practitioners. The findings suggest that machine learning methods can be an effective tool for evaluating parenting programs and can contribute to practitioner evaluations. However, it is not clear whether the methods are fully equivalent to practitioner evaluations.

Furthermore, these models were found to be successful in predicting domains such as in-session attendance, parenting session attendance, home practice competence, and motivation to change. Zheng and colleagues (2022) aimed to conduct an in-depth study on the diagnosis and treatment processes of Cognitive Behavior Therapy (CBT) application based on deep learning in adolescents (Zheng and Ye 2022). In this context, the correlation prediction model between CBT and adolescent social anxiety was built based on a multi-objective evolutionary algorithm. It was stated that risk and protective factors in teenage growth will help individuals reduce social anxiety by screening from the perspectives of people, family, school, and society. Schwartz et al. (2017) studied the referral criteria of 78,394 child cases examined between 2010 and 2015 using machine learning to direct individual child cases in the child protection center towards the judiciary (Schwartz et al. 2017). It was explained that the model identified 93% of the cases that should be referred to the judiciary. When an algorithm is not used, it is explained that 40% of the cases are misdirected with the model. As an interesting finding of the study, the reliability of the referral and adjudication processes was discovered through the designed model and added to the predictive variables of the process. Evidence of abuse and/or neglect, including injuries, death, and/or previous reports; uncooperative caregiver behavior, including restricting their access during the investigation process; caregiver violence and/or criminal history; unsafe/hazardous housing conditions, lack of food; and unrelated persons living in the home have been described as predictors of cases referred for adjudication (Schwartz et al., 2017).

Domestic Violence Risk Analysis and Machine Learning Methods

There are two studies (Li et al. 2021, Lopez-Larrosa et al. 2022) that aim to predict the changes of domestic violence on individuals in the family and related predictive factors. In their study, Li et al. (2021) aimed to predict the changes of domestic violence on personality traits by creating two separate samples based on the posts of 1.6 million participants about family violence on Weibo (Li et al., 2021). In their study, it was shown that there were statistically significant differences in the areas of agreeableness (agreeableness), neuroticism (emotional stability), and conscientiousness (conscientiousness) of those who experienced domestic violence compared to those who did not. In the second sample group, consisting of people who experienced domestic violence for the first time in their lives, it was shown that neuroticism increased after experiencing domestic violence, and the conscientiousness sub-dimension decreased. Within the scope of the study, it was explained that there was no differentiation between domestic violence, childhood abuse, witnessing domestic violence, physical violence, and non-physical violence types. Lopez-Larrosa et al. (2022) aimed to predict the predictors of adolescents' involvement in domestic conflict if they lived with their families (Lopez-Larrosa et al. 2022). An interesting finding of the study was that participants' reactions to hypothetical videos predicted their responses to real-life conflicts. The study's results showed that age, gender, or family type were not the most important predictors of involvement in family conflict. The sociodemographic variable, which refers to adolescents attending schools in rural or urban areas, was shown to be the highest predictor of involvement in conflict between parents.

Family and Educational Achievement: Association Analyses with Machine Learning

Two ongoing studies (Sun et al. 2020; Sun and Sayer 2024) have examined family variables that predict young adults' education to explore family predictors of educational achievement. In their study, Sun et al. (2020) studied the predictive loadings of family experience variables that affect the academic achievement of young adults. Accordingly, variables related to family experience were family structure (9 variables), socioeconomic characteristics (10 variables), family relationships and parenting (12 variables), parental involvement in education (7 variables), socio-cultural characteristics (5 variables), family health resources and behaviors (11 variables), parental and family relationship history (4 variables) and negative family experiences (4 variables) (Sun et al. 2020) as the best family predictors of university enrollment and university graduation outcomes; socioeconomic characteristics of the family and educational expectations of the parents were shown. The 14 family-related predictor variables obtained within the scope of the study; maternal education (positive effect), family income (positive effect), paternal education (positive effect), being in parent-teacher association (positive effect), maternal educational expectations (positive effect), intergenerational rapprochement (positive effect), parental age (positive effect), maternal professional prestige (positive effect), parental control (adverse effect) and having dinner with parents (positive effect). Sun and Sayer (2024) aimed to discover family variables that predict educational achievement from 143 articles conducted through the National Longitudinal Study of Adolescent Health data with supervised machine learning. In the study's findings, 14 family variables were identified, and while family socioeconomics was the highest predictor variable, negative family experiences were the least influential variable in predicting educational achievement (Sun and Sayer 2024).

Machine Learning and Results of Family-Related Variables

Machine learning methods and NLP techniques have been found effective in predicting the effects of family, individual, and social factors on mental health and education. Berkel et al. (2023) found that TF-IDF and BERT models agreed highly with COACH measures and predicted important areas such as parental involvement. (2024) developed a nomogram that predicts attention deficit hyperactivity disorder with 95.9% accuracy. Gil et al. (2022) reported that the RF model performed best in predicting depression risk with 86% accuracy and emphasized that family cohesion is essential to depression risk. Li et al. (2021) showed that compatibility and responsibility scores were 5-10% lower, and emotional instability scores were higher in victims of domestic violence compared to the control group. Lopez-Larrosa et al. (2022) predicted the risk of adolescents' participation in family conflicts with 65% accuracy. Sun and Sayer (2024) showed that 29% of the educational level of young adults was associated with the family's socioeconomic status. (2023) examined the relationship of depression with family and school factors and reported that family cohesion and peer support were protective factors, while family conflict was a risk factor. Zheng and Ye (2022) found that cognitive behavioral therapy was effective in reducing social anxiety in adolescents and that anxiety decreased significantly after treatment. Zhou et al. (2024) predicted non-suicidal self-harm behavior with 85.2% accuracy and revealed that factors such as family functioning and parental depression are essential. These findings show that machine learning methods have predictive power with high accuracy rates in understanding individuals' psychological and social states.

Discussion

The current systematic review aims to evaluate the use of machine learning methods in studying the health and well-being of families and family members. It was aimed to understand how machine learning techniques are used to predict the effects of family dynamics on individuals' mental health, educational achievement, and behavioral outcomes. As a result of the review, 11 studies determined to meet the PICOS inclusion criteria were examined regarding sample characteristics, study designs, assessment tools, characteristics of intervention approaches, and the effects of interventions. As a result of the review, it is seen that machine learning methods can be an effective tool in identifying risk and protective factors within the family and evaluating the effectiveness of intervention programs.

Machine learning is essential in identifying risk indicators and basic predictive variables that individuals experience in the family. The studies reviewed in this systematic review show that machine learning algorithms have a strong potential to analyze and understand the complex relationships between family dynamics and outcomes of family members (Gil et al. 2022, Wang et al. 2023, Berkel et al. 2023, Gao et al. 2024). Methods such as RF, SVM, and deep learning have demonstrated high accuracy rates in identifying and predicting risk and protective factors at the family and member level (Gil et al. 2022, Zhou et al. 2024, Gao et al. 2024). Family socioeconomic status is one of the strongest predictors of young adults' educational achievement (Sun et al. 2020, Sun and Sayer 2024). It has been explained that variables such as parents' education level, family income level, and social support mechanisms have direct relationships with individuals' academic achievement. In addition, family conflict, parental depression, and low family functioning are shown to be among the important risk factors that increase depression and non-suicidal self-harm behaviors in adolescents (Gil et al., 2022; Wang et al., 2023; Zhou et al., 2024). Such negative family experiences may weaken the psychological resilience of individuals and pave the way for mental health problems. Therefore, it is essential that machine learning can detect risk in these areas.

On the other hand, parental involvement and supportive family approaches protect children's mental health and development (Naar-King et al. 2016, Berkel et al. 2023). Parents' sensitivity to their children's psychological needs, seeking psychological support, and positive family interactions protect individuals from adverse outcomes. This situation emphasizes the importance of family-based interventions and reveals that parents should be encouraged to participate actively in their children's developmental processes. Machine learning algorithms have great potential to understand the relationships between these complex variables better, identify risk factors early, and develop protective measures. It is noteworthy that the theoretical background of the models used in most of the studies examined in the review and explanations of variable selection are limited (Gil et al. 2022, Lopez-Larrosa et al. 2022, Wang et al. 2023, Ahn et al. 2024, Zhou et al. 2024).

The sample characteristics were quite diverse within the scope of the systematic review studies reviewed. The studies generally focused on children, adolescents, and family members (parents and primary caregivers). For example, Zheng and Ye (2022) included 61 adolescent participants, while Li et al. (2021) analyzed data from 1.16 million social media users. In 45.45% of the articles included in the systematic review, family data were collected through adolescent participants (Lopez-Larrosa et al. 2022, Zheng and Ye 2022, Wang et al. 2023, Sun and Sayer 2024, Zhou et al. 2024). In 36.36% of the studies (Smith et al. 2018, Gil et al. 2022, Zhou et al. 2024), data were collected from both children and primary caregivers. The studies of Gao et al. (2024) and Schwartz et al. (2017), in which family variables were examined through child data, are also noteworthy. In only two of the studies, demographic information of the participants was provided in detail (Lopez-Larrosa et al. 2022; Sun and Sayer 2024).

Given the size of the data accessed through data mining in the studies and the diversity of the sociodemographic information of the number of participants, the difficulty of sharing this data is apparent. Compared to other fields, this is an aspect that needs to be improved to increase confidence in the results of studies in social services and health, given the significant impact of the results on the well-being of individuals.

Studies have generally addressed family-related issues such as domestic violence (Li et al. 2021, Lopez-Larrosa et al. 2022), children's mental health, depression risk (Gil et al. 2022, Wang et al. 2023, Zhou et al. 2024), attention deficit hyperactivity disorder (ADHD) (Gao et al. 2024), social anxiety in adolescents (Zheng and Ye 2022), and educational achievement (Sun et al. 2020, Sun and Sayer 2024). Li et al. (2021) investigated the effects of domestic violence on personality traits of individuals, while Gao et al. (2024) examined familial risk factors of ADHD. Gil et al. (2022) examined the risk of depression in university students, and Sun and Sayer (2024) investigated family factors affecting the educational success of young adults. This distribution reflects a comprehensive approach to understanding the effects of family dynamics on individuals' psychological health and development. Given that the nature of individuals is complex and can be influenced by many different variables, different variables may operate in each situation. In addition, the data used in the studies are old (Schwartz et al. 2017); the possibility that the predictor variables may have changed over time may jeopardize the reliability of the results, with the inclusion of many confounding variables. These limitations may also cast doubt on the external validity of the studies and findings discussed in the current review. These limitations suggest that machine learning applications should be based on more solid theoretical foundations. Furthermore, more work is needed on model transparency and interpretability. While there are ethical permissions regarding the reliability of the data used in the studies, the challenges related to the application and practical use of machine learning modeling in the context of very large-scale cases and social media studies (Li et al. 2021) require more resources.

Jacob Cohen's (1994) critique of null hypothesis testing (NHST) in The Earth Is Round ($p < .05$) provides a critical perspective that emphasizes the importance of AI and machine learning approaches in scientific research. Cohen (1994) argued that misinterpretation of p-values and over-dependence on significance in statistical results limit scientific progress. In this context, traditional NHST methods are limited, especially when working with large data sets, because the p-value does not measure the truth of a hypothesis, but rather the probability of the random occurrence of observed data. In contrast, machine learning algorithms can make effective predictions with their data-driven approach and evaluate model performance with various validation techniques (e.g., cross-validation, ROC curves, AUC, F1 score). In this respect, machine learning overlaps with statistical approaches such as effect size and confidence intervals proposed by Cohen (1994), enabling more in-depth and meaningful analysis of the results.

Machine learning methods contribute to obtaining more reliable and interpretable results in scientific research by overcoming the limitations of NHST, criticized by Cohen (1994). Especially in predictive modeling and analysis of complex data relationships, machine learning is based on model accuracy and generalizability beyond p-values. This supports the importance of scientific replication and effect size emphasized by Cohen (1994) in research processes. Moreover, the flexible nature of machine learning algorithms allows for discovering complex relationships in large and diverse datasets regardless of the theoretical framework. Therefore, Cohen's criticisms of NHST may justify the adoption of artificial intelligence and machine learning techniques as more effective and innovative methods in scientific research. These methods contribute significantly to the scientific literature by enabling researchers to reach more meaningful and reliable results in both theoretical and practical terms.

The findings obtained in this review significantly overlap with Cohen's criticisms of the NHST (Cohen 1962, Cohen 1992, Cohen 1994). The studies included in the review have shown that machine learning algorithms (RF, SVM, Deep Learning, etc.) offer more powerful and flexible prediction capabilities compared to traditional methods when examining the effects on family dynamics and individuals' psychological health (Yarkoni and Westfall 2017, Gil et al. 2022, Wang et al. 2023, Black et al. 2023, Gao et al. 2024, Sun and Sayer 2024, Zhou et al. 2024). For example, in Sun and Sayer (2024), the effect of family socioeconomic status in predicting educational achievement of young adults was limited by traditional regression models, while machine learning models (Lasso, Decision Trees, RF) produced more detailed and robust results with higher accuracy rates. This aligns with Cohen's (1994) criticism that one should not focus only on the p-value for effective results. On the other hand, in some respects, the present findings differ from Cohen's criticisms. While Cohen emphasizes the inadequacies of NHST, he focuses on the classification accuracy and performance measures of machine learning models. It has been observed that some of the studies in the review (e.g., Gil et al. 2022) present results that are disconnected from the theoretical basis and far from interpretability when using machine learning algorithms. In line with Cohen's (1994) criticisms, instead of focusing only on model performance (accuracy, AUC), how the predictive variables of the models are related to the theoretical framework should also be considered. This suggests that machine learning models should be better integrated with the theoretical background to produce stronger and valid results, as indicated by Cohen.

The machine learning methods used in the reviewed studies stand out in different areas (see Table 3). For example, RF models have demonstrated high accuracy rates in predicting domestic risk factors thanks to their ability to handle a large number of variables simultaneously and to rank risk/protective factors hierarchically (Gil et al. 2022, Zhou et al. 2024). Conversely, SVM showed powerful performance on classification problems (e.g., binary outputs such as whether adolescents are at risk of depression) (Gil et al. 2022). Deep learning algorithms provided strong predictions on large and complex datasets (e.g., social media data, multidimensional psychosocial data), but were limited in interpretability (Zheng and Ye 2022). While NLP methods have made novel contributions in analyzing verbal data such as family communication, social media content, or parent-child interaction texts, they have faced limitations such as data cleaning and sensitivity to linguistic context (Berkel et al. 2023). More traditional methods, such as logistic regression, while advantageous in simplicity and interpretability, have been limited compared to other methods in explaining complex multivariate relationships (Zhou et al. 2024).

Table 3. Machine learning methods

Method	Studies	Conclusion
RF	Gil et al. 2022, Zhou et al. 2024, Sun and Sayer 2024	High accuracy in risk/protective factors
SVM	Gil et al. 2022	Strong performance in binary classifications
Deep Learning	Zheng & Ye 2022	High predictive power in complex data, low interpretability
NLP	Berkel et al. 2023	Verbal data analysis, parenting program evaluation
Logistic Regression	Gil et al. 2022, Zhou et al. 2024	Simple, interpretable; Limited in complex relationships
Nomogram	Gao et al. 2024	95.9% accuracy in ADHD prediction

DL = Deep Learning, NLP = Natural Language Processing, RF = Random Forest, SVM = Support Vector Machine

When these findings are evaluated in terms of family sciences research, it can be said that methods such as RF and SVM offer powerful tools for identifying risk and protective factors, while deep learning and NLP approaches are promising especially in large-scale and text-based data sets (Gil et al. 2022, Zheng and Ye 2022, Berkel et al. 2023, Zhou et al. 2024). However, the models used in family sciences must be highly predictive, interpretable, sensitive to ethical principles, and understandable for practitioners (Ivaskevics and Haller 2022, Ahn et al. 2024). Further research should emphasize that RF and NLP-based methods will be especially prominent in understanding the dynamics of family relationships. Still, these models should be supported by the principles of transparency and explainability.

While most of the reviewed studies focus on the accuracy and predictive power of machine learning models, transparency, interpretability, and ethical dimensions of the models have been addressed to a limited extent (Ivaskevics and Haller 2022, Ahn et al. 2024). The quality of the data used in the family context, the confidentiality of personal and sensitive information, the risk of algorithmic bias, and the explainability of the decision processes of the models are among the issues that need to be considered more in the future in this field. As the applicability of machine learning in family research increases, integrating ethical concerns and transparency principles into the research processes, in addition to model performance, will strengthen the reliability and applicability of the findings.

One of the limitations of this systematic review is that only studies conducted in English and in a limited number of databases were included. The lack of an exclusion criterion regarding the statistical values of the research results can be shown as a limitation. The lack of a detailed evaluation of the quality of the research in the studies included in this review is also seen as a limitation. Possible publication bias was not evaluated in the studies included in this study. As the PRISMA guideline recommends, examining publication bias is necessary for the findings' generalizability (Page et al. 2021). However, since this analysis was not performed in the current review, it should be considered that the results obtained may carry a bias in favor of studies with positive findings. Methodological quality assessment of the included studies was not performed systematically. The PRISMA checklist recommends assessing study quality and reporting the methodology used. This shortcoming is a limitation that should be noted alongside the review's strengths. Furthermore, the absence or incomplete AUC (Area Under the Curve) criteria in the articles makes it difficult to interpret the available findings comprehensively. This can be explained by the fact that studies in this field are relatively new, and methodological standards have not yet been fully established (Yarkoni and Westfall 2017).

Research using machine learning techniques was included in the family research discussed in this study. Increasing the number of studies in this context can be recommended for developments in psychology. Although there are machine learning techniques in Turkey, there is no study in which family variables are studied with machine learning techniques. In the context of our country, to develop machine learning studies on family dynamics, comprehensive data sets reflecting the cultural and social structure are needed. In this context, longitudinal data sets that include family communication, parenting styles, socioeconomic status, education level, mental health indicators, and social support mechanisms can be created. Systematic collection of the results of family-based interventions will help machine learning algorithms predict risk and protective factors more accurately. For example, observing parent-child interactions in the natural environment and recording them through digital tools can be analyzed with natural language processing and deep learning methods. Moreover, multidimensional datasets combining socioeconomic indicators and psychological variables can help predict family well-being and guide policymakers. The development of such datasets will bring a new methodological dimension to family-based research in Turkey and make original contributions to the international literature.

Conclusion

The review highlighted the following areas where machine learning can be used in family research: identifying risk and protective factors within the family, predicting the effects of family structure on the individual, and evaluating the effectiveness of family-based interventions. The reviewed studies show that RF, SVM, and deep learning methods have a strong potential in understanding family dynamics with high accuracy rates. Machine learning methods can detect risk indicators related to the psychological health and well-being of family members at an early stage and guide intervention processes by revealing protective factors. In this context, variables such as parental involvement, socioeconomic status, family conflict, and social support mechanisms were found to have risk and protective effects.

The findings suggest that machine learning algorithms are becoming an increasing focus of interest for social science research and professionals providing clinical services. Future studies must base these methods on more solid theoretical foundations and strengthen methodological standards. In addition, the insufficiency of studies examining family variables with machine learning techniques in Turkey reveals that new research in this field will provide valuable contributions at both academic and applied levels.

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