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Reviewing The Combination of Case-Based Reasoning and Machine Learning for Improving a Decision Support System

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***Abstract*—This study investigates the integration of case-based reasoning (CBR) with machine learning (ML) to enhance decision support systems. Due to the inadequate synthesis of empirical data in this domain by previous research, we undertook a systematic review of 46 indexed journal articles published between 2019 and 2024. The review adhered to PRISMA principles to ensure a transparent and rigorous selection and analysis procedure. We analyzed integration architectures and documented performance results, application areas, and persistent implementation challenges. The research indicates that hybrid CBR-ML systems typically surpass single-method systems in accuracy, precision, and flexibility, with an average improvement of approximately 7% over CBR-only systems. Sequential and ensemble approaches typically demonstrate effectiveness, though weighted hybrid designs often achieve superior precision and recall, particularly in complex problem domains such as healthcare and finance where accuracy is critical. Researchers based in Asia authored the majority of the reviewed studies, with contributions from Europe and Africa following. These regions concentrated high-impact applications in healthcare, finance, manufacturing, and environmental management. Notwithstanding these developments, several enduring challenges persist, including substantial computational demands, vulnerability to variations in data quality, and the continuing scarcity of clearly articulated evaluation protocols, which hinder the effective implementation of high-impact applications across these regions. Overall, existing findings suggest that integrating reasoning-oriented approaches with learning-based methods can yield a balanced trade-off between predictive accuracy and interpretability.**

***Index Terms*—Combination model, case-based reasoning, machine learning, decision-making study, PRISMA.**

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I. Introduction

A common way to tackle new problems by drawing on experience is called Case-Based Reasoning, or CBR [1]. With CBR, the process usually comes down to three key steps: find an older case that feels similar, tweak the earlier solution to fit what is happening now, and then use that updated solution in the current situation [2]. This approach appears frequently in AI and cognitive science because it mirrors how people often think and decide in everyday life [3]. Unlike strict rule-based methods, CBR remains more flexible by reusing existing knowledge, which can make it quicker and more practical for dealing with complex situations [4].

Bringing CBR into existing systems can also support better decision-making by using lessons learned from past cases to handle new challenges [5]. It encourages more adaptive reasoning that attends to context, which can help systems perform better in fast-changing environments [6]. CBR is also useful when traditional algorithms do not perform well, as it can still provide workable answers for problems that lack a single clear solution [7]. In the end, this can improve accuracy and make it easier to respond to new or uncertain situations.

Lately, combining CBR and Machine Learning (ML) has been seen as a strong, promising hybrid approach [8], [9], [10]. CBR helps by clearly explaining its reasoning, drawing on similar past cases [11], [12], while ML is great at spotting patterns and making predictions when it has access to large amounts of data [13], [14], [15]. Even though more people are interested in combining them, the research remains scattered and poorly organized. Different approaches have been tried, from using ML to improve case retrieval to using CBR to make ML predictions easier to understand [16], [17], [18], [19], [20], [21], [22]. However, to date, no comprehensive study systematically examines these methods across various fields [10], [23], [24]. While studies in health, finance, and manufacturing show positive results, the understanding of the specific integration strategies and success factors in these domains remains limited.

Most earlier researchers have treated CBR and ML as separate topics rather than focusing on integrating them [25],

[26]. Because of that, there are still major gaps in how these combinations are built, how hybrid systems perform compared to using a single approach, how historical data actually contributes, how results differ across domains, and what it all means in real-world use. These missing pieces make it harder for researchers designing new models and for practitioners applying them confidently.

This literature review closes those gaps by pulling together studies on CBR and ML combinations published from 2019 to 2024. It focuses on mapping the main ways researchers combine the two, assessing how well hybrid systems perform, examining how historical data supports these systems, identifying where the approach has worked well in real applications, and comparing how strategies differ across fields. To keep the review focused, five research questions guide it. 1) What methods have been used to combine CBR and ML across different application areas? 2) How do hybrid systems perform compared to systems that use only CBR or only ML? 3) How does historical data improve mixed CBR-ML systems? 4) Which practical applications have successfully used this combination, and what extra value does the integration bring? Moreover, 5) How do these approaches change depending on the domain, such as healthcare, finance, and manufacturing?

Overall, this study offers a more organized summary of recent work, pointing out the main trends, challenges, and areas worth exploring next. Drawing on 46 studies across multiple academic databases, the review also provides useful guidance for researchers building hybrid models and for practitioners seeking evidence they can trust. The rest of the article goes through the methodology, the review findings, and the discussion, and then wraps up with key takeaways plus ideas for future research.

II. Research Methods

This literature review used the PRISMA method to ensure a clear, methodologically sound process [27]. It followed five key steps: formulating the research questions, planning the literature search strategy, setting the inclusion and exclusion criteria, screening the studies, and extracting the data while checking quality [28].

To begin, the authors developed five Research Questions based on the goals defined in the early stage. These questions shaped how the search and data extraction were done, focusing on the methods used, how performance was evaluated, how historical data was involved, real-world applications, and differences across specific domains.

Second, the study followed a comprehensive and well-organized search strategy to identify papers on combining CBR and ML published in the last five years, from 2019 to 2024. This range was picked to focus on more recent progress and keep the results current and relevant [29]. The authors relied on two major academic databases, Scopus and ScienceDirect, because both provide strong coverage of computer science and engineering research [30].

To ensure they did not miss anything important, the researchers built their search around three keyword groups that covered the entire topic [29]. The first group gathered CBR-focused terms such as Case-Based Reasoning, CBR, case-based reasoning, and analogical reasoning. The second group zoomed in on words that signal a mix of approaches, including integration, hybrid, combined, fusion, and ensemble. The third group pulled in machine learning terms such as Machine Learning, ML, neural networks, deep learning, random forest, support vector machine, K-nearest neighbors, and KNN. On top of that, they added a few more decision-making-focused ML algorithms to widen the net and catch other relevant studies [31].

They used Boolean operators such as AND and OR to connect keywords in a clean, consistent way. The final search string was set up to include at least one term from each keyword category. They first searched the Title or Abstract fields, then followed up by searching the Subject fields to ensure they also captured papers that were properly indexed [32]. Doing it in two rounds helped keep the results both wide-ranging and accurate.

After that, the researchers narrowed everything down using a four-level filtering process to reduce the list without lowering quality [33]. They only kept peer-reviewed journal articles written in English and published between 2019 and 2024. They left out proceedings, reports, books, and theses to keep the review methodologically tight [36]. The emphasis on work published after 2019 was intentional, as CBR and ML have been advancing rapidly in recent years, especially with deep learning and ensemble methods [34]. Anything older than that window was excluded, so the review stayed focused on the most current evidence. Overall, these rules were meant to support a systematic and unbiased selection process [35]. Table 1 summarizes the inclusion and exclusion criteria, and only studies with solid methods and strong relevance were retained.

Table 1.
Research Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Studies focusing on the combination of CBR and ML.	Studies not related to the CBR and ML combination.
Studies employing CBR or ML approaches.	Traditional laboratory or experimental methods without CBR/ML elements.
Peer-reviewed journal articles.	Reports, white papers, or unpublished documents.
Articles with appropriate abstracts and keywords.	Articles with incomplete abstracts or mismatched keywords.
Articles published within the last five years (2019–2024).	Articles published more than five years ago.
Articles written in English.	Articles published in non-English.

The selection process followed the four phases of PRISMA: identification, screening, eligibility, and final inclusion [33]. Figure 1 presents the investigation workflow. The initial search in December 2023 yielded 745 articles from Scopus and ScienceDirect. All data were exported to Mendeley for systematic screening [34]. Duplicate papers were removed, and titles and abstracts were screened based on the inclusion criteria. Articles were excluded if they only discussed CBR or ML separately, lacked combination elements, were unrelated to decision-making, or did not provide clear methodological details. This stage resulted in 156 full-text articles for further

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review [35].

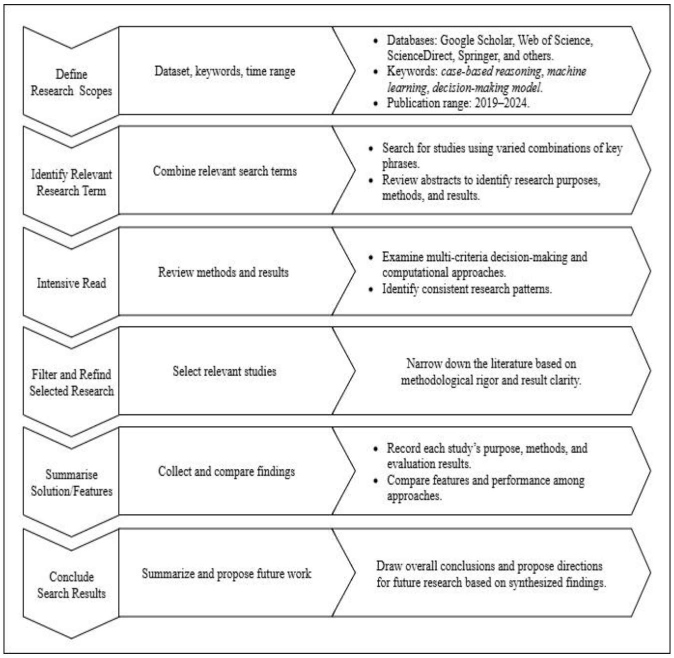

Fig. 1. Investigation workflow of the study.

After that, the researchers reviewed the full text of each article using the inclusion and exclusion rules they had already set. A study was removed if it did not explain its methods clearly enough, did not fit the review focus, did not include meaningful comparisons, or was vague about how the CBR and ML components actually worked together. They also ran a quality check that assessed how detailed the research was, how robust the methods were, whether the data were sufficient to support the claims, how valid the results appeared, and how transparent everything was. To ensure the review's reliability, any paper that did not meet the minimum quality threshold was excluded [36]. In the end, 46 articles were selected as the core set for the analysis. Figure 2 shows the PRISMA flowchart, starting from 745 initial records and narrowing them down to the final 46 studies.

The researchers used a structured data extraction form to capture all key details from each study. They first tested it on five randomly selected articles, then tweaked it so everything remained consistent across the review [20]. The extraction was done independently, and the results were compared; any differences were resolved through discussion until a shared decision was reached.

Next, they sorted everything they pulled from the papers into five clear categories. This step covered the basics, such as the authors, publication year, journal, and research area. They also captured the study details, including the researchers' aims, the domain they worked in, the study design, and the dataset used. Another section zoomed in on how CBR and ML were brought together, including the ML techniques involved, such as Random Forest, Support Vector Machines (SVM), or Neural Networks, the kind of integration approach used, like sequential, parallel, embedded, or ensemble, and what role each part played in the overall system.

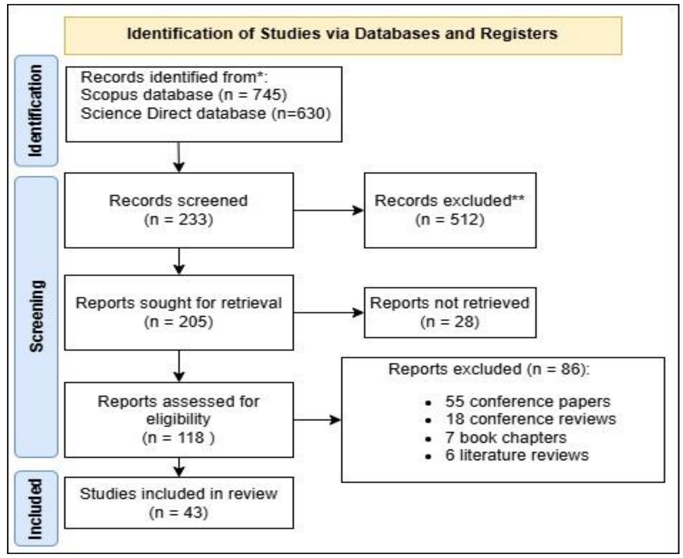

Fig. 2. Result of finding articles using PRISMA.

They also noted how these approaches stacked up against single-method systems, while recording performance metrics such as recall, accuracy, precision, and F1 score. To wrap it up, they pulled together the main takeaways, including strengths, weaknesses, limitations, and what the findings could mean in practice. After that, all the extracted information was gathered into a spreadsheet to support the next stage of analysis.

During the data analysis stage, the researchers mixed quantitative analysis with a more thematic approach to answer the research questions [9]. On the quantitative side, they used descriptive statistics to map how studies were distributed across publication years, ML algorithms, research locations, and application areas. When the papers provided enough information, they also compared the accuracy and recall ranges between combined CBR-ML systems and systems that used only one approach.

On the thematic side, they looked for recurring methods, common patterns, and noticeable differences across studies [41]. They grouped the papers by how the combination was implemented: sequential setups in which ML handled case retrieval and CBR handled adaptation; parallel setups in which both worked separately and their results were merged; embedded setups in which ML was integrated into the CBR cycle; and ensemble setups that blended multiple methods. They also compared findings across domains such as healthcare, finance, manufacturing, environmental management, and education to identify context-dependent trends. Finally, they reviewed how historical data was used and whether it helped the systems learn better and improve performance over time.

They pulled together the main challenges that kept recurring, such as heavy computational demands, strong dependence on data quality and availability, and the difficulty of keeping models easy to interpret. At the same time, they examined what worked well across studies, including success factors and practical best practices that could inform future implementations. To bring everything into one clear narrative, they used narrative analysis to summarize findings across all the selected papers [42], structured around the five research questions. When they compared results, they found some patterns that remained consistent, but also noticeable differences across domains.

To keep the review accurate and trustworthy, they built quality checks into the process from start to finish. Every step was carefully recorded, from the exact search strategies to screening choices and the data extraction forms used. They also stuck closely to PRISMA guidelines, using detailed flowcharts and checklists. By clearly reporting their analysis criteria and decision-making process, they made the work easier to reproduce. On top of that, they used a recognized critical appraisal framework to filter out weaker studies, so the final results were backed by stronger evidence and were more reliable overall.

III. Results

A. Results of the Selection Phase

The systematic search and selection process using the PRISMA methodology across Scopus and ScienceDirect initially identified approximately 745 articles. The researchers then applied filters for the publication years 2019–2024 and restricted the search to English-language journal articles. After screening all records, duplicates were removed and titles and abstracts were filtered, leaving 156 articles for full-text review. After evaluating eligibility and assessing quality, the authors obtained 46 studies that met the inclusion criteria for the final synthesis. These studies covered a variety of geographic regions, application fields, and methodological approaches. The following sections outline the main findings regarding algorithmic combination approaches, publication time trends, geographic distribution, and general methods used in combined CBR-ML systems.

B. Combination Based on Algorithms

Looking across the 46 studies that made it into the review, a clear pattern emerges: pairing CBR with ML tends to perform better than relying on a single method. Figure 3 shows which ML algorithms are most often combined with CBR, and Random Forest, SVM, and Neural Networks appear most often. These are commonly used to strengthen things like case retrieval, adaptation, and similarity assessment.

According to the papers, hybrid systems achieved an average accuracy of 92%, which is noticeably higher than that of single CBR-based systems, which averaged 85%. More balanced hybrid setups, where CBR and ML both play meaningful roles, also reported strong results with precision around 88% and recall around 90%. Another interesting point is how well K-Nearest Neighbors fits into a CBR setup, since both naturally rely on similarity to retrieve useful past cases. That match translates into solid performance gains. Overall, these combinations try to get the best of both worlds: the clarity and traceability of CBR plus the stronger predictive power of ML, leading to systems that are not just more accurate and efficient, but also easier to explain.

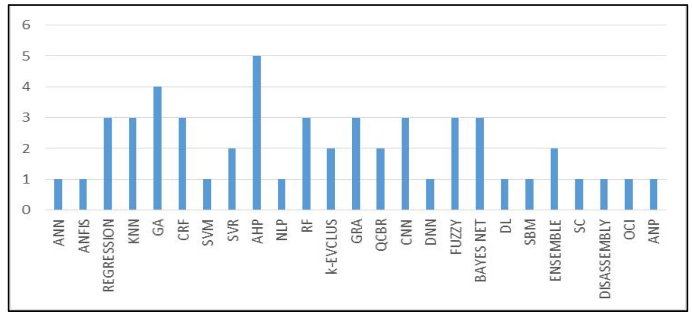

Fig. 3. Integration based on algorithm.

C. Developments over Time in Studies Integrating CBR and ML

Figure 4 suggests that interest in combining CBR and ML has been climbing steadily from 2019 through 2024. The number of studies grows each year starting in 2019, and the largest surge occurs in 2023. In fact, about 35% of the papers analyzed come from 2023 alone. This rise tracks with a few larger shifts in the field, such as the stronger push for Explainable Artificial Intelligence (XAI), the mainstream adoption of deep learning, and the greater ease of working with large-scale datasets. The 2024 research continues in the same direction, with more attention to transfer learning and ensemble-based integration.

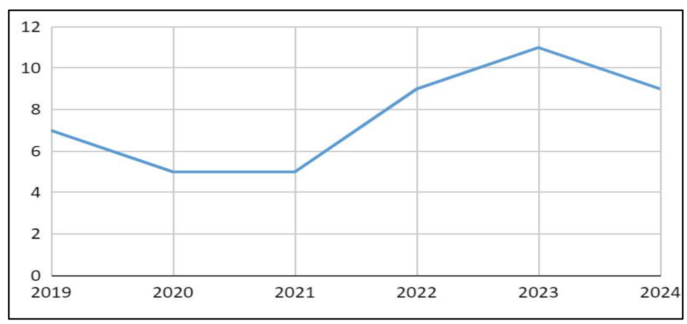

Fig. 4. Integration based on years.

D. Geographic Distribution of Research

Figure 5 highlights the sources of the research based on the authors' affiliations. Most of the work originates in Asia, Europe, and Africa. Asia leads the way, with China, India, and Indonesia accounting for close to 45% of total output. Europe accounts for about 30%, with major contributions from Germany, Spain, France, and the United Kingdom. Africa accounts for roughly 15% of the research, and much of that research focuses on practical areas such as agriculture, healthcare, and infrastructure. North America contributes about 8%, while South America contributes about 2%. Some studies also involve cross-regional collaborations, showing that teams

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are working together across borders.

Table 2.
Summary of Integrated CBR-ML Systems

Algorithm Used	Research Focus	Main Findings
CBR-NN Hybrid	Personalized counseling system in the cosmetic industry.	Suggests a feature-weighted CBR system using Neural Networks to extract weights for symbolic domains, significantly improving retrieval accuracy for personalized recommendations.
Hybrid CBR-DL	Medical report generation (Radiology).	Proposes a framework combining the explainability of CBR with the performance of Deep Learning to generate accurate radiology reports, even with minimal input data.
CBR	Data-driven reactive disassembly planning for the circular economy.	Presents a CBR approach that automatically adapts disassembly plans in response to deviations, ensuring economic profitability and environmental Sustainability.
PC-CBR-E (Ensemble)	Business Failure Prediction (BFP) for Chinese companies.	Develops a Principal Component CBR Ensemble (PC-CBR-E) that outperforms classical CBR and logistic regression in predicting short- and medium-term business failures.
Creativity-driven CBR	Sustainable business model innovation for SMEs.	Introduces a creativity-driven CBR methodology to support companies in systematically designing innovative and sustainable business models.
GNRCS (Neurotrophic Model)	COVID-19 diagnosis using Chest X-ray images.	Proposes a genetic neurotrophic model (GNRCS) that achieves high specificity and sensitivity for COVID-19 recognition, outperforming standard classifiers like SVM and MLP.
XGBoost, RF, SVM, NN	Early identification of Chronic Kidney Disease (CKD).	Identifies optimal classification models for CKD diagnosis using XGBoost for feature selection, demonstrating effective performance in handling dataset limitations
SVM, KNN, HGB	Diabetic Retinopathy (DR) detection using fundus images.	Demonstrates that SVM with transfer learning achieves superior accuracy (96.9%) compared to KNN and HGB for binary DR classification.

Overall, this spread indicates strong global interest in CBR-ML integration, with different regions placing greater emphasis on topics that align with their local needs and priorities.

E. Common Methods Used for Decision Support

Pulling together the 46 studies, the researchers found four main ways CBR and ML are usually combined. The most popular was the sequential setup, where ML assists with certain steps in the CBR process, such as case retrieval or adaptation, which appeared in about 40% of the studies. Next was the parallel approach, used in about 25% of the papers, in which CBR and ML run separately and their outputs are merged afterward. Embedded integration accounted for roughly 20%, with ML placed directly within the CBR cycle itself. The remaining 15% used ensemble or hybrid models that combine multiple integration methods.

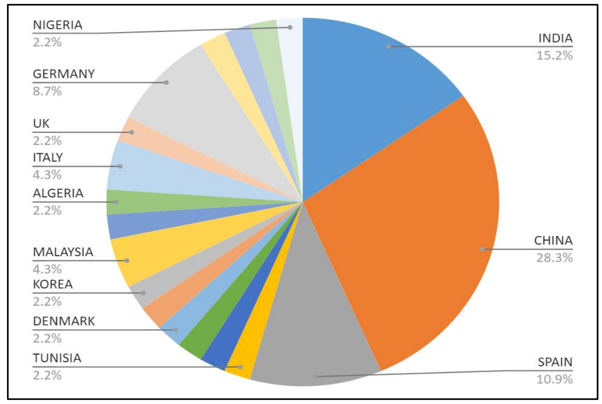

Fig. 5. Distribution of Articles Based on Author Nationality

Table 2 pulls these systems together, showing the integration type, the focus of each study, and the main takeaways. Overall, the findings suggest that good integration is not just about picking a strong algorithm. It also depends on how well the integration design fits the data and what the application domain actually needs. Studies that spelled out exactly what CBR and ML do in the system tended to report improvements that were more stable and consistent.

IV. Discussion

Pulling insights from the 46 studies, the takeaway is pretty straightforward: bringing Case-Based Reasoning together with Machine Learning tends to boost performance across many domains. Hybrid systems often beat single-method approaches because they mix the strengths of both. CBR offers flexibility and easy-to-trace reasoning, while ML offers stronger predictive power and the ability to generalize. It also aligns with where AI is headed right now, as people increasingly want systems that deliver high performance while still explaining their decisions, especially when the choices are complex or high-stakes.

Looking at the algorithms used, Random Forests, SVMs, and Neural Networks appear most often when paired with CBR. Most of the time, these combinations are used to improve accuracy in key CBR steps, such as case retrieval and adaptation. The studies also suggest that weighted hybrid setups and ensemble-style architectures are the most reliable, which points to an important takeaway: the best results usually come from keeping CBR and ML in balance, rather than letting one side completely dominate. On a similar note, K-Nearest Neighbors inside CBR frameworks work especially well, since both approaches rely heavily on the same core idea of similarity.

Looking at the research trends, it is clear that activity has increased significantly since 2019. The spike in papers from 2020 to 2023 aligns with rapid progress in deep learning and the ease of access to large-scale datasets. With more data and stronger models available, researchers have been able to train ML components within CBR-based systems more effectively, thereby improving retrieval precision and making the overall systems more flexible. The momentum continues into 2024, suggesting that CBR and ML integration is no longer just a niche idea but a more established and growing subfield within hybrid AI.

In terms of where the work is happening, Asia produces the most publications, followed by Europe and Africa. The strong output from Asian institutions points to significant investment in AI research, especially for real-world applications in areas such as healthcare, manufacturing, and agriculture. Meanwhile, European studies tend to focus more on environmental management and industrial decision support, while research from Africa often targets practical, efficient solutions that work well even with limited resources. Taken together, this mix shows how adaptable CBR and ML integration can be, since it can be shaped around different data realities and regional priorities.

Hybrid CBR and ML systems are being used across a range of areas, especially healthcare, finance, manufacturing, and environmental management. In healthcare, they have been shown to improve diagnostic accuracy in conditions such as COVID-19 [35], chronic kidney disease [36], diabetic retinopathy [37], and cardiovascular disorders [31]. By combining ML-based pattern recognition with the reasoning logic of CBR, these systems provide robust support for clinical decision-making [9]. In the financial sector, CBR-ML models are utilized for credit risk assessment [38], financial distress prediction [17], [21], and stock price forecasting [14]. This combination improves risk and fraud detection by merging historical data with predictive models, resulting in higher accuracy than single methods. In manufacturing, the integration has been successfully applied to automated fault diagnosis [39] and predictive maintenance [22], supporting operational efficiency without compromising interpretability.

In environmental management, these systems facilitate sustainable agriculture [15], [40], water-quality assessment [41], and resource allocation [42]. They work especially well in settings where data is limited or the situation changes quickly, because the mix of learning from data and reasoning from past cases helps the system stay practical and adaptable.

Even with the strong results, a few recurring issues keep coming up. One is that the computational load can become heavy when ML is tightly integrated into the CBR cycle, especially with high-dimensional data or deep learning models. Another is that the system is only as good as the data and the case base behind it, so weak data quality or poorly structured cases can seriously hurt accuracy and reliability. A third challenge is interpretability. These hybrids are usually easier to explain than pure black-box ML, but as the architecture gets more complex, that transparency can start to fade. Addressing this requires more standardized data preprocessing, clearer design guidelines for hybrids, and shared reference datasets to evaluate results more consistently.

The studies with the strongest outcomes have a few things in common. They assign CBR and ML roles that complement each other, use well-organized case bases with rich features, and tune the approach to the specific domain so it balances fast search with strong predictive accuracy. Overall, this suggests that how the hybrid is designed matters more than simply choosing a particular algorithm.

Going forward, the research highlights three main areas worth focusing on. First, the field needs more standardized methods for evaluating hybrid systems so that results can be compared fairly across studies and domains. Second, explainable integration should be further developed by examining how ML-learned features shape case retrieval and adaptation, not only the final output. Third, there should be more work on hybrids designed for low-data situations or real-time needs, since these conditions are common in real deployments and require systems that can adapt quickly.

In the end, this review reinforces that blending CBR with ML is a strong approach for making decision support systems both more accurate and easier to interpret. The findings show real momentum in hybrid reasoning research and point toward clear next steps for both future studies and practical applications.

V. Conclusion

A systematic review of 46 studies published from 2019 to 2024 indicates that integrating case-based reasoning and machine learning yields substantially better system performance than deploying either method alone. Hybrid case-based reasoning and machine learning systems provide decision support that is more accurate, more efficient in data use, and more readily interpreted. This improvement arises from combining the contextual responsiveness of case-based reasoning with the pattern-learning capabilities of machine learning, enabling solutions that are better aligned with diverse operational settings and domain-specific constraints.

The effectiveness of this integration depends on careful algorithm selection and on ensuring functional coherence between the case-based reasoning and machine learning components. Sequential, parallel, embedded, and ensemble designs each offer distinct strengths, yet the most reliable outcomes are achieved when component responsibilities are explicitly specified, and information flows are systematically organized. These results highlight the importance of principled architectural design practices explicitly tailored to the characteristics and demands of the target application domain.

Analyses across time and region also suggest expanding international attention to hybrid case-based reasoning and machine learning approaches, with Asia, Europe, and Africa contributing prominently to research output. Since 2019, research output has been increasing, driven by fast advances in deep learning and growing attention to XAI. These methods have also been applied in real-world use cases across healthcare, finance, manufacturing, and environmental management, highlighting their ability to handle complex problems that rely heavily on data and context. That said, there are still persistent challenges, such as uneven data quality, high computational costs, and a lack of shared standards. Moving forward, the field will benefit from common reference datasets, broadly accepted evaluation methods, and more transparent hybrid system designs that make results easier to reproduce and scale. This kind of transparency matters even more in high-sensitivity areas, where trust is critical.

In general, combining case-based reasoning with machine learning provides a solid foundation for building the next generation of decision support systems. It blends the flexible, experience-driven nature of case-based reasoning with the predictive power of machine learning, helping strike a good balance between strong results and clearer reasoning. Future research should focus on shared evaluation standards, greater transparency, and wider adoption across newer and growing application areas. Ongoing improvements in methods will also be important to ensure these hybrid systems remain practical, reliable, and impactful over the long run.

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