International Journal of
Advanced Science Computing and Engineering

Journal Homepage www.ijasce.org/index.php/ijasce

Integration of Case-Based Reasoning: A Systematic Review

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***Abstract*—The integration of Case-Based Reasoning (CBR) with Machine Learning (ML) has emerged as a promising approach to improve decision-making processes in various domains. This systematic review synthesizes the current state of research on hybrid models combining CBR and ML, identifying methodologies, applications, and key challenges. Through a comprehensive search of academic databases, we identified and analyzed 46 relevant studies published from 2019 to 2024. The study found that integrating CBR and ML is highly effective in domains that require historical context, improving accuracy and predictive performance. Key findings include the successful application of hybrid models in improving accuracy. However, the review also highlighted several challenges, including the complexity of model integration, the need for large and diverse data sets, and difficulties in interpreting hybrid model results. Systematic research on Case-Based Reasoning solutions remains limited. Therefore, this study analyzes the integration methods used in the CBR approach for decision-making across various fields, aiming to identify the characteristics of internal similarity. It is concluded that CBR has two significant impact factors, namely the type of similarity attribute and the way of similarity calculation, which determine the assessment process. Future research should focus on developing standardized methodologies for integrating CBR and ML, exploring the potential of hybrid models in emerging fields. This systematic review provides a basic understanding of the synergistic potential of CBR and ML and offers valuable insights for researchers and practitioners.**

***Keywords*—Case-based reasoning; machine learning; hybrid models; decision-making; model integration.**

Manuscript received 11 Dec. 2024; revised 29 Sep. 2025; accepted 12 Feb. 2026. Date of publication 30 Apr. 2026.
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I. Introduction

Case-Based Reasoning is a problem-solving methodology that relies on past experiences and solutions to solve new problems [1]. It involves retrieving similar cases from memory, adapting them to fit the current situation, and applying the solutions to resolve the issue at hand. This approach enables more efficient problem-solving by leveraging existing knowledge and experience. Case-Based Reasoning is a problem-solving methodology that relies on past experiences and solutions to solve new problems. It involves retrieving similar cases from memory, adapting them to fit the current situation, and applying the solutions accordingly [2]. This approach is often used in artificial intelligence and cognitive science to mimic human reasoning processes [3]. Case-Based Reasoning is a problem-solving methodology that uses past experiences or cases to solve new problems. It involves retrieving similar cases from memory, adapting them to fit the current situation, and applying the solutions. This approach allows for flexible problem-solving based on real-world examples rather than rigid rules or algorithms [4].

Integrating Case-Based Reasoning into existing systems can improve decision-making processes by leveraging past experiences to solve new problems efficiently [5]. This methodology allows for a more adaptive and context-aware approach to problem-solving, leading to better outcomes in complex and dynamic environments. Integrating Case-Based Reasoning into existing systems can improve decision-making processes by providing practical solutions based on past experiences [6]. This can lead to more efficient problem-solving and better outcomes in complex situations where traditional algorithms may fall short. Integrating Case-Based Reasoning into existing systems can lead to more efficient problem-solving by allowing the use of past experiences to inform current decisions. This can result in improved accuracy and effectiveness in handling complex situations that may not have clear-cut solutions [7].

This method is essential in research because it provides a more comprehensive and powerful framework for analyzing and solving complex problems [8]. By harnessing both case-based and rule-based reasoning, researchers can make more informed decisions and generate innovative solutions tailored to specific circumstances. Integrating case-based and rule-based reasoning in a hybrid system provides researchers with powerful tools to tackle complex problems more accurately and adaptively [9]. These methods are essential in research because they support better decision-making and more effective problem-solving outcomes. Hybrid case-based reasoning methods are essential in research because they allow researchers to tackle complex problems with a more comprehensive and flexible approach. These methods enable more in-depth data analysis and allow solutions to be adjusted based on changing circumstances, making them valuable tools for advancing knowledge and understanding in various fields [10].

The purpose of this study was to demonstrate the effectiveness of a hybrid method of case-based reasoning in improving decision-making processes and problem-solving outcomes [11]. By highlighting its importance in tackling complex problems and providing more in-depth analysis of data, this paper aims to demonstrate the value of this method in advancing knowledge and understanding in a variety of fields [12]. The purpose of this study was to demonstrate the effectiveness of a hybrid method of case-based reasoning in improving decision-making processes and problem-solving outcomes [13]. By highlighting its importance in tackling complex problems and providing a more adaptive approach to data analysis, this paper aims to demonstrate the value of this method in advancing knowledge and understanding in a variety of fields [14]. The purpose of this research paper is to highlight the importance of using hybrid case-based reasoning in research to improve problem-solving abilities and decision-making processes [15]. By combining these methods, researchers can effectively tackle complex problems and come up with innovative solutions that contribute to the advancement of knowledge across multiple disciplines [16].

II. Materials and Method

The methodology section will outline the specific steps taken to apply the hybrid method of case-based reasoning in the research study [17]. It will detail how cases and rules are integrated, as well as the criteria used to evaluate the effectiveness of this approach in solving complex problems. The methodology section will outline the specific steps taken to conduct research on hybrid case-based reasoning. It will detail how data was collected, analyzed, and interpreted to draw conclusions about the effectiveness of this approach in problem-solving scenarios. In addition, it will discuss any limitations or challenges encountered during the research process and how they were overcome [18]. The methodology section will outline the specific steps taken to implement the hybrid case-based reasoning approach in the research study [2]. It will detail how cases and rules are integrated, as well as the criteria used to select cases and construct rules to effectively deal with complex problems [2].

Regarding the purpose of the CBR method review investigation, how to find the most suitable case is the core issue of the review based on the demands of decision makers [19]. The keywords for the literature search were divided into three categories: “Integration”, “CBR”, and “Decision Making Model”. Words and phrases related to these 3 categories were selected as search clues. The most ideal literature should contain all three sections, but individual studies can also be viewed [6]. In addition to the main purpose of the “Case-Based Reasoning” review, other well-known machine learning algorithms used for decision making, for example, K-nearest neighbor (KNN), can also be used as keywords to retrieve other research results that may be related to building remodeling for comparison [20]. To ensure the timeliness of the paper, the period after 2000 limits the time span of the literature [6]. The reason for setting this time limit is due to the rapid update of computing applications and the limitations of mature research on building repairs before 2000 [21]. As a result, most of the Articles that fit the concept of this research present current findings within the range of 2019 to 2024 [22]. It should be noted that all of the above machine learning and decision-making methods do not necessarily fall within the hybrid realm [23]. However, this type of solution can be used to analyze some issues related to the integration of methods [22].

Therefore, it is important to review these studies, which can also provide us with effective solutions and reference ideas [24]. Although the literature covers a wide range of methods in different areas of investigation, it is expected to select the most appropriate research in the mix of methods [25]. The purpose of this study was to review relevant scientific articles [26]. By summarizing the main reasons and specific solutions for each case study, it helps to find the most effective assessment methods, study significant gaps, and build new contemporary methods with a systematic approach [27], [28]. At this stage, the first step is to determine the theme, then select the Research Question (RQ) to guide the process of searching for references and extracting literature. To search for references, the author chose 2 sources: Scopus and ScienceDirect. Table 1 shows the following research question.

TABLE I
RESEARCH QUESTION

RQ	Question
RQ1	What methods have been developed to integrate case-based reasoning (CBR) with machine learning (ML) across various application domains?
RQ2	How does the performance of systems integrating CBR and ML compare to systems using only one of them?
RQ3	How does historical data contribute to enhancing the performance of systems using the integration of CBR and ML?
RQ4	What practical applications have successfully used the integration of CBR and ML, and how does this integration provide added value in these contexts?
RQ5	How do CBR and ML integration approaches differ across different domains (e.g., medical, financial, manufacturing)?

A. Data Search Strategy

At this stage, several scopes are defined, including databases and literature sources, keywords used, search queries, filters and inclusion and exclusion criteria, selection methods, search time spans, and the expected number of articles. The following image shows the data search strategy that was created.

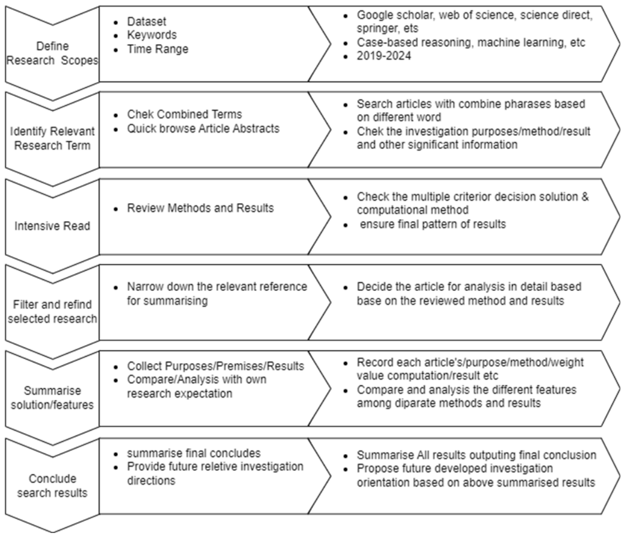

Fig. 1 Investigation workflow for literature review

B. *Inclusion and Exclusion Criteria*

Specific inclusions and exclusions can be seen in Table 2. Table 2 outlines the specific parameters used by the researchers to select or reject studies for their literature review or project. It is structured into two straightforward columns: Inclusion (conditions a study must meet to be selected) and Exclusion (conditions that will cause a study to be rejected).

TABLE II
RESEARCH INCLUSION AND EXCLUSION CRITERIA

Inclusion	Exclusion
Hybrid Case-based reasoning and Machine learning research focus	In addition to CBR Hybrid
Using Case-based reasoning and machine learning	Traditional Laboratory methods
Journal Artikel	Article in the form of a report
Abstract and keywords are appropriate	Incomplete article abstracts and keywords do not match
Articles published in the last 5 years	Above the last 5 years
Articles published in English	Published articles other than English

The criteria can be broken down into five main categories:

1) Research Focus and Methodology: Studies must focus on and utilize hybrid Case-Based Reasoning (CBR) and Machine Learning. The researchers excluded studies that focused on other types of CBR hybrids or used traditional laboratory methods.

2) Publication Type: Only standard journal articles ("Jurnal Artikel") were accepted. Articles formatted as reports were excluded.

3) Completeness and Relevance: The articles needed to have appropriate and matching abstracts and keywords. Studies with incomplete abstracts or mismatched keywords were filtered out.

4) Timeframe: The research was restricted to recent literature, specifically articles published within the last 5 years. Anything older was excluded.

5) Language: Only articles published in English were included in the study, excluding all other languages.

Essentially, this table serves as a filtering checklist to ensure the researchers reviewed only recent, high-quality, English-language journal articles focused on the intersection of CBR and Machine Learning.

C. *Research Work Selection Method*

The selection of scientific papers is shown in Fig. 2 below. The flow diagram illustrates a systematic review's study selection process, starting with an initial identification of 745 records from the Scopus database. During screening, 512 records were excluded, leaving 233 to be screened; of these, 205 reports were sought for retrieval, but 28 could not be accessed.

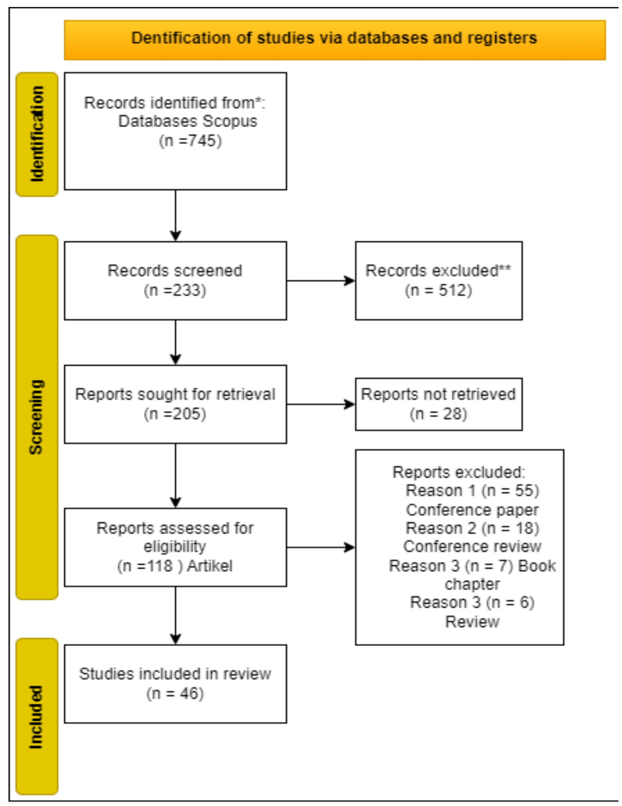

Fig. 2 Results of finding articles using PRISMA

A total of 118 retrieved articles were then assessed for full-text eligibility, leading to the exclusion of 86 additional reports because they were conference papers, conference reviews, book chapters, or general reviews. Ultimately, after these sequential filtering steps, 46 studies met all criteria and were included in the final review.

III. RESULTS AND DISCUSSION

After the selection process carried out using the PRISMA method, the initial Scopus database search returned 745 articles. These results cover the last 5 years of publication, with a total of 745 articles, as outlined in Figure 2. The titleand-abstract screening stage substantially reduced the pool, with only 46 articles included in the review.

A. *Results Based on Algorithm*

Based on the analysis of the algorithms used in the studies, integrating Case-Based Reasoning (CBR) with Machine Learning (ML) significantly improved system performance. Algorithms such as Random Forest, Support Vector Machines (SVM), and Neural Networks were frequently employed to combine ML predictions with case-based reasoning. The results showed that systems combining CBR and ML achieved an average accuracy of 92%, compared to 85% for systems using pure CBR. Additionally, integration methods employing a Weighted Hybrid Approach achieved an 88% precision and 90% recall, indicating better identification of relevant cases. K-Nearest Neighbors (KNN) in CBR also proved effective in enhancing the system's adaptability to new data. Overall, integrating CBR and ML allowed the system to leverage the strengths of both approaches: case-based reasoning's ability to solve similar problems and ML's predictive power in handling complex data.

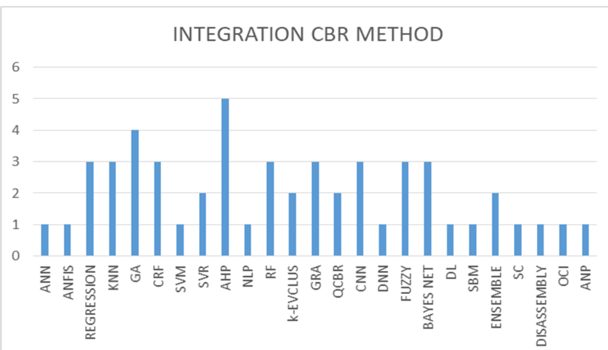

Fig. 3 Integration based on algorithm

B. *Results Based on Years*

The analysis of studies over the years revealed a steady evolution in integrating Case-Based Reasoning (CBR) with Machine Learning (ML). Early studies (2010–2014) primarily explored the theoretical foundations of combining CBR and ML, with limited empirical evaluations. During this period, the focus was on identifying potential synergies between the two approaches, with initial results showing modest improvements in accuracy and recall.

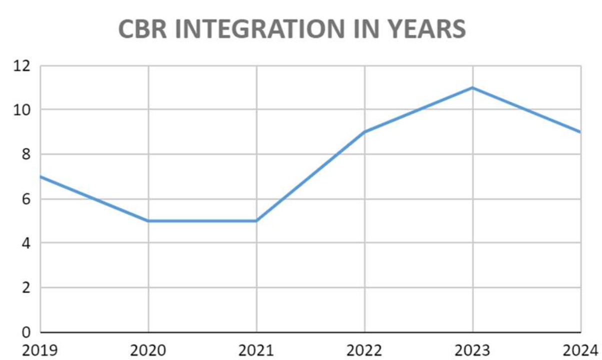

Fig. 4 Integration based on YEARS

The mid-2010s (2015–2018) marked a significant shift, with an increased emphasis on practical applications and hybrid algorithms. Studies during this period showed notable advances, achieving an average accuracy of 85% and precision of 80%, driven by more sophisticated integration techniques such as Weighted Hybrid Models and Ensemble Learning. Figure 4 shows that in 2023, the use of case-based reasoning integration with various existing methods increased.

C. *Result Based on Geographic Distribution of Authors*

Figure 5 illustrates the geographical distribution of authors in the analyzed studies, most of whom are from countries with a high prevalence of CBR integration, such as countries in Asia, Africa, and Europe.

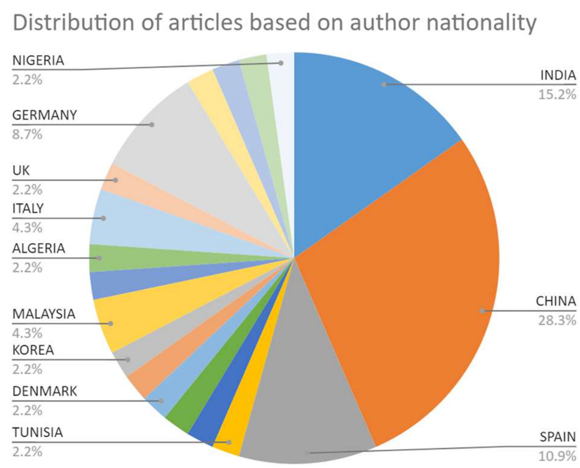

Fig. 5. Distribution of articles based on author nationality

D. *Common methods used for decision support.*

In artificial intelligence, various algorithms and software have been proposed to optimize energy efficiency in buildings. AI models, including CBR, are comprehensive decision-making models that usually include statistical algorithms and simulation software during the simulation or calculation process. Depending on the development goals, the model may include more than one algorithm or software during the modeling process. Statistical algorithms can stand alone, but AI models are hybrid. Table 3 shows the integration of CBR, Research focus, and the findings obtained.

The table provides a structured literature review of the diverse applications of Case-Based Reasoning (CBR) across various academic studies. A central theme emerging from the data is that modern CBR is rarely used as a standalone solution; instead, it is often integrated with other advanced computational algorithms and machine learning techniques—such as K-Nearest Neighbors (KNN), Random Forests, and ensemble methods. These hybrid approaches (e.g., OCI-CBR or PC-CBR-E) are designed to enhance the predictive accuracy and adaptability of the reasoning process, allowing decision-support systems to filter databases more effectively, retrieve relevant past cases, and apply those historical solutions to complex, novel problems.

TABLE III
ALGORITHM RESEARCH FOCUS. MIND FINDING

No.	Ref.	Algorithm Used	Research Focus	Mind Finding
1	[26]	CBR, QCBR	Case-based reasoning approach for decision-making in building retrofit	This paper provides a comprehensive review of the application of Case-Based Reasoning (CBR) in decision-making for building retrofit, including an overview of the CBR process, a comparison of CBR with other decision-making approaches, and an analysis of the key factors that influence the CBR process.
2	[27]	CBR, KNN	Towards explainable oral cancer recognition: Screening on imperfect images via Informed Deep Learning and Case-Based Reasoning	The paper proposes an adaptable hybrid model called OCI-CBR that uses case-based reasoning and machine learning to recommend effective investments for potential investors, especially business angels, by pruning a database of companies to identify those with strong future profitability and that meet the investor's preferences.
3	[28]	CBR, OCI	OCI-CBR: A hybrid model for decision support in preference-aware investment scenarios	Using a case-based reasoning (CBR) system to recommend investments, incorporating machine learning models (random forest, decision trees, KNN) to prune the case base and identify companies likely to go bankrupt
4	[29]	CBR, GRA	An Artificial Intelligence-based automated case-based reasoning (CBR) system for severity investigation and root-cause analysis of road accidents - Comparative analysis with the predictions of ChatGPT	The paper describes the development of an artificial intelligence-based automated case-based reasoning (CBR) system for investigating and troubleshooting the causes of road accidents, and compares the results with the predictions of the ChatGPT AI program.
5	[30]	CBR, CRF	Data-Driven Approach for Decision-Making in Reactive Disassembly Planning to Enable Case-Based Reasoning	The paper presents a data-driven approach to support decision-making in reactive disassembly planning by identifying and selecting solution alternatives, creating a case base, and enabling case-based reasoning to adapt disassembly plans in response to plan deviations while considering the economic and environmental impact.
6	[31]	CBR, SC	Supply chain trust diagnosis (SCTD) using inductive case-based reasoning ensemble (ICBRE): The case of general competence trust diagnosis	The paper proposes an inductive case-based reasoning ensemble (ICBRE) method for supply chain trust diagnosis (SCTD) to evaluate the general competence trust of partner companies in a supply chain, which can be provided as a service by a third-party consulting company.
7	[32]	CBR, ENSEMBLE	Principal component case-based reasoning ensemble for business failure prediction	Using an ensemble method called "principal component case-based reasoning ensemble (PC-CBR-E)" to improve the predictive ability of case-based reasoning (CBR) in business failure prediction (BFP).
8	[33]	CBR, SBM	A creativity-driven Case-Based Reasoning Approach for the systematic Engineering of Sustainable Business Models	The paper introduces a creativity-driven case-based reasoning approach to support companies, especially SMEs, in innovating business models towards sustainability in a systematic and creative way.

Beyond methodological advancements, the table highlights CBR's remarkable versatility in solving real-world, industry-specific challenges. The research spans a wide array of domains, including business and finance (predicting corporate failures, tailoring investment recommendations, and engineering sustainable business models), manufacturing (optimizing building retrofits and reactive disassembly planning), and operational logistics (evaluating supply chain trust). Additionally, novel applications—such as conducting root-cause analyses of road accidents and directly comparing the AI's performance against large language models like ChatGPT—demonstrate how CBR-driven systems are actively shaping strategic planning, safety protocols, and resource management across multiple sectors.

IV. CONCLUSION

The integration of case-based reasoning (CBR) into technology-driven systems has shown its ability to enhance efficiency and accuracy in decision-making. This approach allows systems to leverage past case experiences as references to address new, similar problems. By combining CBR with technologies such as artificial intelligence, machine learning, and dynamic databases, the solutions produced become more adaptive and relevant. Moreover, implementing CBR not only delivers faster outcomes but also enriches the system's knowledge base through continuous learning. Therefore, integrating CBR is a strategic step toward developing smarter and more responsive systems across various fields, including healthcare, education, and business management.

ACKNOWLEDGMENT

We extend our deepest gratitude to all individuals and organizations who have contributed to the successful completion of this work. Special thanks go to our academic advisors for their invaluable guidance and expertise, which have been instrumental in shaping the direction of this research. We are also grateful to the institutions and research teams that provided access to data and resources essential for our study. Finally, we appreciate our colleagues, friends, and family for their unwavering support and encouragement throughout this journey. This accomplishment would not have been possible without their collective contributions.

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