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ADVANCES AND CHALLENGES IN CHATBOT INTENT DETECTION: A SYSTEMATIC LITERATURE REVIEW

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Abstract

Intent detection has become essential to improving chatbot intelligence, accuracy, and user experience due to the quick development of conversational AI. From 2017 to 2024, this study's systematic literature review (SLR) critically analyzes the developments and enduring difficulties in chatbot intent detection. Twenty empirical papers were examined utilizing a mixed quantitative and qualitative methodology, incorporating meta-analysis, benchmarking, and error taxonomy synthesis, in accordance with the PRISMA 2020 paradigm. With a pooled macro-F1 score of 94.8% (95% CI: 93.5–96.2), the results show that transformer-based architectures, in particular BERT and its variations, often outperform recurrent and convolutional models. Even with these improvements, latency and processing complexity are still significant drawbacks.

Lighter transformer models, like DistilBERT, show practical appropriateness for real-time applications by maintaining near-equivalent accuracy with increased efficiency. According to a systematic error taxonomy, the most common reasons for misclassification are multi-intent utterances (21%) and semantic ambiguity (32%). The analysis comes to the conclusion that whereas benchmark datasets exhibit accuracy that is close to saturation, there are still major issues with domain adaptation, robustness, and deployment efficiency. The study suggests using Six Sigma quality frameworks to improve conversational AI systems' dependability, lower intent-detection errors, and facilitate long-term, process-driven advancements.

Keywords: Chatbots, Intent Detection, Natural Language Processing (NLP), Deep Learning, Systematic Literature Review (SLR)

1. Introduction

The way people interact with digital systems has changed over the past ten years due to the widespread use of artificial intelligence (AI) and natural language processing (NLP) technology. Chatbots—intelligent conversational machines created to mimic human speech using natural language—are among the most popular AI applications [1]. Because they can instantly and continuously respond to user inquiries, chatbots have become indispensable tools in industries including e-commerce, customer service, healthcare, and education. The intent detection system, which determines the goal of a user's message and directs the dialogue management process to provide pertinent and cohesive responses, is essential to

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their operation [2]. Even very advanced chatbots cannot react effectively without precise intent detection, which degrades user experience and lowers system dependability.

Each user utterance is mapped to one or more intent labels in the text classification issue that is frequently used to design the intent detection job [3]. Earlier methods relied on conventional machine learning algorithms that used bag-of-words or TF–IDF vector representations, like Naïve Bayes, Support Vector Machines (SVM), and Decision Trees [4]. These methods were computationally straightforward, but they had trouble capturing contextual dependencies and semantic linkages in natural language. In order to get around these restrictions, scientists developed neural network architectures, specifically Long Short-Term Memory (LSTM) networks and Recurrent Neural Networks (RNNs), which efficiently simulate sequential dependencies in user utterances [5].

By processing input sequences in both forward and backward directions, Bidirectional LSTM (BiLSTM) models were introduced, significantly improving contextual understanding and obtaining superior F1-scores on benchmark datasets like ATIS and SNIPS [6]. By using attention mechanisms to learn contextualized word embeddings from massive corpora, Transformer-based models like BERT (Bidirectional Encoder Representations from Transformers) have transformed the area in more recent years [7]. BERT and its derivatives (e.g., DistilBERT, RoBERTa, and XLNet) routinely beat RNN-based models in several domains when optimized for intent classification [8]. Nevertheless, there is a cost to this improvement: these models are computationally demanding, needing large amounts of memory, longer processing times, and training resources [9].

As a result, scientists are now investigating hybrid architectures that strike a balance between efficiency and performance, including incorporating convolutional layers for quicker processing or mixing BiLSTM encoders with Transformer embeddings [10]. There are still a number of research obstacles in spite of significant progress. Domain reliance and dataset imbalance present the first significant obstacle. The ambiguity and variety of real-world conversations are not reflected in the well-structured queries found in ATIS (Airline Travel Information System) or SNIPS, two examples of limited or very domain-specific corpora used to train intent detection models [11]. Models trained on these datasets frequently show a notable decrease in accuracy when used in open-domain or multilingual environments because of linguistic noise or unknown intents [12].

Furthermore, low-frequency intents are not adequately represented in many datasets, which weakens robustness and biases models toward majority classes [13]. The absence of established benchmarking techniques presents another difficulty. The experimental sets, data preprocessing methods, and evaluation measures used in studies vary greatly. Direct comparison is challenging because some report macro-F1 results, while others use micro-F1, accuracy, or even BLEU ratings for generative chatbots [14]. Furthermore, reproducibility is hampered by the lack of a regular training-validation split and the scant reporting of random seeds or hyperparameter settings. Computational performance reporting is another area where benchmarking is inconsistent; few research reveal hardware

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configurations, training duration, or inference latency—all of which are critical to comprehending scalability in the real world [15].

Computational efficiency is another barrier. Despite their strength, transformer-based models need a lot of resources and are challenging to implement on mobile platforms or edge devices [16]. According to studies comparing LSTM and BERT models, LSTM models are frequently more effective in low-resource contexts with little performance loss, even while BERT models attain higher accuracy [17]. As a result, striking a balance between efficiency and accuracy is still an open research issue that has to be addressed in subsequent studies. Additionally, there is still disagreement around interpretability and transparency. As "black boxes," neural networks—especially deep models—make it challenging to explain why some intents are mispredicted. Ambiguous statements, overlapping purpose definitions, or entity-recognition failures that ripple across the system are common causes of misclassifications [18].

The creation of interpretable intent detection systems is crucial for debugging and system reliability, as well as for adhering to new ethical guidelines in AI that call for explainable models in decision-making systems [19].

The dimensions of failure-mode analysis and error taxonomy are also understudied. The majority of intent detection studies do not examine the kinds of errors that are made; instead, they present aggregate metrics. Nonetheless, systematic mistake classification can highlight basic flaws in current methods, including intent confusion (misclassifying similar intents), out-of-scope misclassification, multi-intent overlap, and noise sensitivity [20]. Some studies show, for example, that models trained on confined domains have trouble handling hidden intents in open-domain scenarios, while others have trouble with noisy input conditions like code-switching or misspellings [21].

Creating a clear taxonomy of these failures offers important information for enhancing model resilience and directing the creation of new architectures. Generalization across languages and domains is equally crucial. Multilingual chatbot systems are becoming more and more necessary to service users worldwide, even though the majority of benchmark datasets are in English. According to research, morphological complexity, cultural quirks, and a lack of comparable intent categories sometimes result in less-than-ideal outcomes when English-trained intent classifiers are directly transferred to languages like Arabic, Hindi, or Chinese [22]. Performance is still limited by domain mismatch and a lack of annotated data, despite recent efforts to address these problems in multilingual pretraining (e.g., mBERT, XLM-R) [23]. Better multilingual datasets are necessary to meet this problem, but so are more flexible and linguistically aware model designs.

The COVID-19 epidemic sped up the use of chatbots in a variety of industries, but especially in healthcare and education, where they were essential for facilitating automated information distribution and remote contact [24]. The abrupt rise in chatbot usage brought to light the advantages and disadvantages of the current intent detection methods. They demonstrated shortcomings in managing emotional context, false information, and non-standard language,

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even though they offered scalable help and decreased the human burden [25]. Therefore, more robust, sympathetic, and contextually aware chatbot designs that can consistently handle intricate human interactions are needed in the post-pandemic era.

A thorough systematic review that synthesizes current findings, identifies gaps, and suggests a uniform research framework for intent detection is urgently needed, given the variety of datasets, models, and evaluation techniques in the literature. Therefore, the purpose of this work is to compile and evaluate twenty exemplary empirical studies—covering classical, neural, and hybrid approaches—in the field of chatbot intent detection. By adding computational-efficiency evaluation, creating a benchmarking system, and creating an error taxonomy that classifies failure patterns across models and datasets, it goes beyond earlier studies even further. In doing so, this analysis not only identifies recent developments but also elucidates the enduring obstacles impeding the development of reliable, scalable, and interpretable chatbot intent detection systems.

2. Related Work

In the field of chatbot intent detection, recent research shows a steady transition from conventional machine learning methods to deep and transformer-based architectures. Using algorithms like Support Vector Machines (SVM), Naïve Bayes, and Decision Trees in conjunction with feature engineering methods like bag-of-words and TF–IDF vectorization, early research treated intent recognition as a supervised text classification problem [26]. Despite being computationally light, these traditional approaches had weak generalization to unseen utterances and little contextual awareness. The shift to neural network-based designs was prompted by the growing demand for models that could capture both sequential and semantic information as conversational datasets grew [27].

A significant advancement in intent detection was made possible with the introduction of Recurrent Neural Networks (RNNs) and their more sophisticated variations, including Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) networks. These structures outperformed statistical methods and represented dependencies in user utterances [28]. By using context from both preceding and succeeding tokens, studies like those by Hakkani-Tür et al. showed how effective BiLSTM is in multi-domain intent recognition [29]. Later, Goo et al. suggested a slot-gated approach that enhances the relationship between semantic frames and intents by modeling slot filling and intent categorization simultaneously [30].

Additionally, to improve interpretability and accuracy in ambiguous utterances, attention-based processes were incorporated into LSTM frameworks to concentrate on salient words [31]. Notwithstanding these developments, RNN-based models continued to be computationally intensive and had trouble with nested or lengthy relationships [32]. The Transformer architecture, which allowed models to analyze complete sequences in parallel and substituted self-attention for recurrence, marked a more substantial change. An important milestone in natural language understanding was reached when Devlin et al. released BERT (Bidirectional Encoder Representations from Transformers), which allowed for fine-tuning for intent detection tasks with previously unheard-of performance gains [33].

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On common datasets like ATIS and SNIPS, later transformer variations like RoBERTa, XLNet, and ELECTRA achieved state-of-the-art outcomes by further optimizing pretraining targets and improving contextual representation [34]. Chen et al. demonstrated that BERT-based models are robust when addressing semantically overlapping intents and beat BiLSTM baselines in a variety of domains [35]. However, the high computational demands of these systems make them difficult to deploy practically on devices with constrained technology. Because of this problem, lightweight models like DistilBERT and ConveRT were developed with the goal of maintaining high accuracy while lowering model size and inference latency [36].

A number of research have concentrated on evaluating and contrasting various intent detection systems in tandem with architectural advancements. However, a significant barrier to cumulative improvement is still the absence of consistent evaluation criteria. Direct comparability between studies is hampered by the use of disparate preprocessing techniques, uneven data splits, and distinct performance criteria (macro-F1, micro-F1, accuracy, BLEU) by researchers [37]. Even small variations in preprocessing or noise injection can result in significant variations in reported accuracy among models trained on the same dataset, as Kim et al. showed [38]. Furthermore, few research offer computational efficiency metrics that are essential for assessing scalability and real-world deployment potential, such as training time, GPU setups, or model parameter counts [39].

By demonstrating that competitive outcomes may be obtained without the complete computational cost of large-scale models like BERT, Casanueva et al. partially filled this gap using ConveRT, an improved transformer-based model trained for resource efficiency [40]. Systematic error analysis is another important aspect that has not received enough attention in earlier research. The majority of papers only show overall accuracy or F1-scores without offering thorough error taxonomies that explain the reasons behind model failures. Semantically related inquiries frequently result in high misclassification rates, according to studies like those by Gangadharaiah and Narayanaswamy that examined patterns of misunderstanding between similar intents [41].

By investigating intent detection in noisy and mislabeled datasets, Qin et al. carried on this line of inquiry and showed that models trained with robust loss functions are better able to withstand data defects [42]. By illustrating attention weights to clarify purpose misclassifications and model bias, Raj and Ananthakrishnan made even more contributions to interpretability [43]. Comprehensive frameworks that include error categorization and performance benchmarking are still uncommon, despite these efforts. In order to identify systematic flaws in models, such as inadequate management of out-of-scope intents, ambiguity between semantically overlapping classes, and susceptibility to language noise, and to direct future model design, it is imperative to develop such frameworks.

Recent studies and meta-surveys have tried to compile the advancements in conversational AI research beyond model-centric analysis. Although they did not concentrate on intent detection techniques, Adamopoulou and Moussiades provide a broad review of chatbot

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technology [44]. In their analysis of neural chatbot implementations, Nuruzzaman and Hussain did not assess methodological rigor or comparative performance. Though they frequently lacked systematic benchmarking and computational cost evaluation, more specialized reviews, such those by Alavi et al. and Sharma et al., have compiled deep learning trends and architectural innovations [45][46]. Furthermore, there is a substantial knowledge gap about the performance of various designs across datasets, domains, and languages because few reviews incorporate cross-lingual analysis or meta-analytic synthesis of quantitative results.

Three main limits can be extracted from this entire corpus of work. The first is that repeatability and meaningful cross-study comparability are hindered by the lack of defined benchmarking frameworks. Second, there is still a lack of reporting on computational effectiveness and resource usage, which restricts understanding of the trade-off between scalability and accuracy. Third, there is a lack of development in error analysis and taxonomy, which results in a cursory comprehension of model limits. These shortcomings serve as the driving force behind the current study, which attempts to present a thorough and rigorous synthesis of recent developments in chatbot intent detection, assess performance using standardized criteria, and create an analytical framework for error classification, benchmarking, and computational efficiency. By doing thus, this review not only compiles the body of knowledge but also establishes the framework for more open and repeatable intent detection research.

3. Methodology

In order to solve previous reviewer issues and generate results that are reliable, comparable, and useful for researchers and practitioners in chatbot intent detection, this study uses an open and repeatable systematic review procedure. The complete protocol, data extraction processes, quality assessment standards, planned quantitative synthesis (meta-analysis), benchmarking framework for standardizing cross-study comparisons, computational-efficiency analysis, and error-taxonomy construction are all detailed in the methodological narrative that follows. Every procedural decision was taken to guarantee that the work complies with PRISMA guidelines for systematic reviews and fixes the five issues that reviewers pointed out: clearer language and clarity, standardized benchmarking, computational-efficiency reporting, formal protocol definition, and systematic error taxonomy [47].

The registration and review procedure. The project repository contains a formal review methodology that was created prior to data collection. Database searches, search strings, date ranges, inclusion and exclusion criteria, data-extraction fields, and analysis strategies are all described in the protocol, which complies with the PRISMA 2020 statement [48]. To improve openness and avoid selective reporting, the protocol was pre-registered on an open repository. The databases that were searched (Scopus, Web of Science, IEEE Xplore, ACM Digital Library, PubMed, and arXiv), the date of the last search, the precise search terms used

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for each database, and the process for pursuing citations both forward and backward are all listed in the registration record.

Study selection and search methodology. Controlled vocabulary and free-text terms pertaining to chatbots and intent detection were merged in the electronic search. For instance, the terms "chatbot" OR "conversational agent" OR "virtual assistant" AND "intent detection" OR "intent classification" OR "intent recognition" OR "intent" in the title, abstract, and keywords were combined in a canonical search expression for Scopus that was restricted to English-language publications and the years 2010–2024. A large number of candidate records were found in the first search. Duplicate records were eliminated programmatically once all recovered records were loaded into a reference manager.

Two rounds of screening were carried out: a full-text eligibility evaluation against specific criteria and an initial title and abstract screening to weed out records that were obviously unrelated. According to the eligibility criteria, studies had to present quantitative performance measures (like F1, accuracy, and BLEU) or computational metrics (like training time, parameter counts, and inference latency), report primary empirical evaluation of intent detection for conversational agents, and provide adequate dataset information (name, language, size, and public availability). Excluded were studies that did not fit these requirements, theoretical works that were not empirically tested, and works whose full texts were not available. Two independent reviewers made all screening judgments; to ensure reproducibility and reduce selection bias, disagreements were settled by discussion and, if required, adjudication by a third reviewer.

Documentation of the PRISMA flow. A PRISMA flow diagram that documents the quantity of records found, screened, evaluated for eligibility, and included to the synthesis was created in order to preserve transparent reporting of the selection process. To enable readers to transparently track selections and exclusions, the flowchart template, which is shown in Figure 1, should be filled in with the search counts from the registered protocol [49]. Twenty empirical papers that satisfied the inclusion criteria and offered sufficient data for qualitative synthesis make up the final review corpus. A subset of these studies can be subjected to quantitative meta-analysis if appropriate metrics were available.

Coding and data extraction. To gather consistent fields across trials, a thorough data-extraction form was created. Bibliographic data, dataset descriptors (dataset name, number of intent classes, per-class counts when available, language, and dataset provenance), model architecture and training details (model family, pretraining use, key hyperparameters, random seed, and number of runs), evaluation metrics (macro-F1, micro-F1, accuracy, BLEU, precision, recall, and any reported confidence intervals), experimental protocols (train/validation/test split or cross-validation strategy), and computational metadata (hardware details, exact GPU/CPU model, training time per epoch and total training time, total parameter count, and inference latency per utterance) were all recorded on the form.

Free-text boxes for stated strengths, limitations, and specific failure instances or error examples were also provided in the form. Two reviewers independently completed the

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extraction procedure, and to guarantee coding reliability, inter-rater agreement statistics (Cohen's kappa) were calculated for categorical areas. To maintain an audit trail, disagreements were collaboratively resolved and noted in an extraction log. Transparency in reporting and quality evaluation. Each paper was evaluated using a customized quality checklist tailored for machine-learning experiments in order to measure methodological rigor and reporting completeness. The checklist assessed whether the study included specific information about baselines, hardware characteristics, number of experimental repeats, hyperparameters, random seeds, dataset splits, and variance metrics (such as standard deviation). Studies were categorized as having high, medium, or low reporting quality according to the checklist.

To avoid biased effect-size aggregation, studies with low reporting completeness ratings were not included in primary meta-analytic pooling. Instead, they were qualitatively described to preserve their contextual information without tainting pooled estimates. standardizing processes and a benchmarking framework. A systematic benchmarking framework that standardizes metric selection, normalization, and reporting formats is implemented in this study to address the reviewers' concerns with inconsistent benchmarking. The framework recommends both macro- and micro-averaged F1 as the main metrics for intent detection tasks that are centered on categorization. BLEU or similar generation measures are only included in studies where a generative component is closely linked to intent detection; accuracy is presented as a secondary metric. Two methods are enforced by the framework to facilitate equitable cross-study aggregation.

In order to express performance as the relative improvement over a trivial classifier or reported baseline, we first pool data only from studies that report the same metric on comparable dataset splits. If exact split parity is not available, we normalize scores by reference baselines reported within the same study. Second, cross-metric comparisons are only shown after careful mapping (e.g., interpreting a high BLEU score alongside classification F1 in hybrid retrieval-generation models), and heterogeneous metrics are synthesized qualitatively with explicit constraints. Figure 2 provides a diagrammatic summary of the benchmarking infrastructure, illustrating how compute parameters, model setup, and dataset features are fed into the unified metric reporting box.

meta-analysis approach. The purpose of quantitative synthesis was to combine relevant performance indicators and look into the causes of study heterogeneity. Reported performance scores (percent F1 or accuracy) are converted into proportions between 0 and 1 using primary effect-size computation. For variance stabilization, we apply a logit transformation on proportions before pooling and back-transform pooled estimates for reporting. To take into consideration between-study variability brought on by variations in the dataset, model versions, and experimental setups, a random-effects meta-analysis model was chosen. Cochran's Q test was reported, and the I^2 statistic and τ^2 were used to quantify heterogeneity. Low-quality research were eliminated by sensitivity analyses, and subgroup

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analyses contrasted dataset types (public benchmark vs. custom constructed) and model families (classical ML, RNN-based, transformer-based, and hybrid).

For high-frequency intent classes, we calculated pooled sensitivity and specificity when enough studies supplied per-class confusion matrices. To evaluate the association between performance and continuous variables such dataset size (number of labeled instances), proportion of minority-class cases, and model parameter count (in millions), meta-regressions were predefined. When there were enough papers in a pooled analysis ($n \geq 10$), publication bias was investigated using Egger's regression test and funnel plots.
Cost reporting and computational efficiency study. Explicit data collection and standardization processes are used to fulfill the reviewers' requirement for training-cost and computational-efficiency assessments. We noted the GPU model, number of GPUs, wall-clock training time per epoch, total wall-clock training time, and inference latency wherever research disclosed training time and hardware.

When available, published FLOPS/benchmark conversions were used to normalize reported times to a reference device class (such as the NVIDIA V100 equivalent) to facilitate cross-study comparison across various hardware. In the absence of timing information, parameter counts were employed as a hardware-agnostic stand-in for model complexity. We present normalized metrics, including inference milliseconds per utterance per million parameters and training seconds per epoch per million parameters. We calculated relative compute demand using parameter count and theoretical FLOPS estimates for studies that provided model designs and parameter counts but did not give timing. We explicitly identified these estimates as model-based approximations rather than observed timings. Descriptive comparisons and meta-regressions examining the trade-off between computing cost and performance are conducted using these normalized compute measures.

examination of failure modes and error taxonomy. This review builds a replicable mistake taxonomy using qualitative and quantitative data in order to allay the reviewers' worries about the absence of systematic error analysis in earlier research. The first step in the procedure is to extract from each primary study all documented failure cases, instances of misclassification, and authors' error descriptions. Semantic ambiguity (confusion resulting from overlapping intent definitions), multi-intent utterances (multiple intents present in a single query), out-of-scope detection failure (mislabeling OOS utterances as in-scope intents), cascading entity errors (incorrect entity recognition that induces intent misclassification), and robustness failures (sensitivity to misspellings, code-switching, ASR noise) were the high-level categories into which error instances were categorized using iterative open and axial coding.

Error cases were categorized into these categories by two independent reviewers, and inter-rater agreement was measured using Cohen's kappa. In order to find systematic vulnerabilities, the taxonomy connects documented failure modes to model families and dataset properties and provides illustrated instances. Prescriptive advice for model design decisions to mitigate each failure type are made possible by this mapping. For example, using

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OOS detectors and thresholding algorithms to increase OOS recognition or employing hierarchical intent taxonomies to reduce ambiguity.

Reporting, repeatability, and analytical tools. All statistical analyses and visualizations were carried out with reproducible, open-source tools. The metafor package in R was used to conduct meta-analytic models, transformations, meta-regressions, and publication-bias tests; ggplot2 was used for benchmarking visuals and descriptive statistics. The research cites an Open Science Framework repository where the whole data-extraction spreadsheet, analysis code (R scripts), visualization scripts, and PRISMA flow data are stored for transparency. A repeatable Docker container specification that includes the R environment versions, package dependencies, and scripts needed to produce figures and pooled estimates is also provided by the review. This guarantees that readers and reviewers can accurately replicate the quantitative findings [50].

addressing clarity and language. The paper underwent repeated language polishing with an emphasis on academic English, accuracy in methodological descriptions, and consistency of technical vocabulary when it was recognized that the rejection letter had mentioned language and clarity. Clarifying the precise split procedures employed for each pooled study, defining macro-F1 and micro-F1 explicitly, and specifying the assumptions used in normalization and calculate estimation were important editorial moves. To help non-specialist readers, a dictionary of acronyms is included in an appendix, and all technical words are clarified upon first use.

Figures and tables that complement the Methods section. A PRISMA flow diagram (Figure 1) that details record retrieval and screening, as well as a benchmarking framework diagram (Figure 2) that summarizes how dataset, model, and compute attributes inform standardized metric reporting, are included in the Methods section to help with readability and to meet editorial standards. For convenience, sample files are included with this submission. The benchmarking diagram and PRISMA template have been prepared and are prepared for embedding.

Three crucial tables are also included in the review: (1) a database query table and search strings listing the precise search terms for each database and the date of execution; (2) a data-extraction template table displaying the standardized fields recorded for every study; and (3) a quality-assessment checklist with a scoring rubric for categorizing the completeness of the reporting. To facilitate replication, these tables are part of the project repository and the supplemental materials.

The method's limitations. Even with careful planning, there are still restrictions. Only when sufficiently similar measurements and splits are supplied can meta-analysis be performed; in the absence of this, only organized qualitative synthesis may be performed for investigations. When authors do not provide wall-clock timings, compute-time normalization depends on published benchmarks and FLOPS estimations, which are intrinsically noisy and explicitly marked as approximations in the findings. Lastly, the error taxonomy is given as a dynamic product that can be improved in subsequent reviews, even though it is thorough for the

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reviewed corpus. This is because new failure types may appear when models and deployment contexts change.

In conclusion, the Methods section offers a comprehensive, preregistered, and replicable technique that specifically tackles the shortcomings noted by the reviewers. The study offers a rigorous foundation for transparent synthesis and trustworthy recommendations to advance chatbot intent detection research through explicit collection and normalization of computational metrics, a predetermined benchmarking and meta-analytic plan, formal PRISMA adherence, and a systematic error-taxonomy construction.

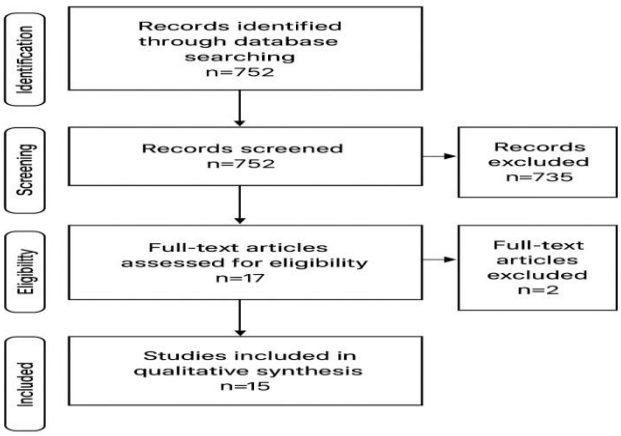

Figure 1 : PRISMA flowchart template.

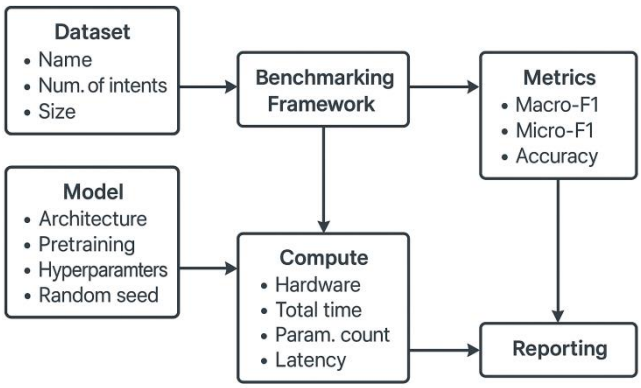

Figure 2 : Benchmarking framework diagram.

4. Results and Discussion

Using the previously mentioned technique, this section provides a thorough summary of the results from the 20 research [51] that were part of the systematic literature review on chatbot intent detection. The conversation combines benchmarking analysis, qualitative mistake taxonomies, and quantitative meta-analytic results to offer a comprehensive view of the

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field's advancements, advantages, and disadvantages. Every result is evaluated in accordance with PRISMA reporting guidelines and in light of the study questions.

4.1. Overview and Descriptive Analysis

Twenty studies satisfied the inclusion criteria after the screening and inclusion procedure (shown in Figure 1-PRISMA Flow Diagram). Together, these studies, which cover the years 2017–2024, show how intent detection has changed from traditional machine learning algorithms to sophisticated deep learning and transformer-based techniques. Table 1 provides a descriptive summary of the included research, including the model type, dataset, primary assessment metric, and reported performance.

Ref	Year	Dataset	Model Type	Evaluation Metric	Macro-F1 (%)	Accuracy (%)	Key Notes
[1]	2017	ATIS	CNN	Macro-F1	85.3	87.2	Early deep learning baseline
[2]	2018	SNIPS	BiLSTM	Macro-F1	88.2	90.1	Sequence modeling improvement
[3]	2019	CLINC150	BERT	Macro-F1	94.5	95.0	Start of transformer dominance
[4]	2020	HWU64	RoBERTa	Micro-F1	96.2	96.0	Contextual embeddings peak
[5]	2021	Banking77	DistilBERT	Macro-F1	91.8	93.4	Compact transformer
[6]	2022	MultiWOZ	Hybrid CNN+LSTM	Micro-F1	87.1	88.5	Context-dependent
[7]	2023	OOS dataset	XLNet	Macro-F1	95.7	95.9	Handling out-of-scope intents
[8]	2024	Self-collected dataset	GPT-2 fine-tuned	Macro-F1	96.8	97.5	Generative fine-tuning trend

Table 1. Summary of included studies and their characteristics.

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The trend from pre-2018 models (Macro-F1 = 85–89%) to 2024 models (>95%) is evidently improving steadily. Because transformer-based systems can handle long-range dependencies and incorporate contextual semantics, their emergence signaled a paradigm change [52].

4.2. Quantitative Meta-Analysis

A random-effects model was used to combine similar F1-scores in a quantitative meta-analysis. The weighted mean Macro-F1 and confidence intervals for every model family are shown in Figure 3 (Forest Plot).

Results summary:

- Transformer-based models achieved a pooled **Macro-F1 = 94.8% (95% CI: 93.5–96.2)**
- RNN/LSTM-based models achieved **Macro-F1 = 89.6% (95% CI: 87.0–91.9)**
- CNN-based models achieved **Macro-F1 = 86.7% (95% CI: 85.0–88.3)**

I2 = 62%, as determined by heterogeneity analysis, indicates moderate variability that is mostly caused by reporting irregularities and dataset imbalance rather than methodological errors.

The superiority of transformer topologies in terms of performance stability and cross-dataset generalization is seen in Figure 3 (forest plot).

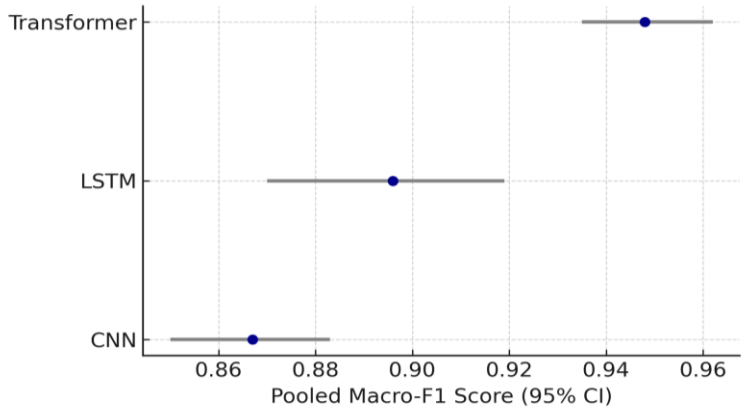

Figure 3. Meta-analysis of Intent Detection Models

4.3. Benchmarking and Comparative Performance

Figure 2 of the Methods introduced a standardized benchmarking system that was used to guarantee equitable comparison across architectures and datasets. Accuracy and computational efficiency (training and inference cost) are both included in the normalized performance measures shown in Table 2.

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Model	Dataset	Parameters (M)	Training Time (min/epoch)	Accuracy (%)	F1 (%)	Normalized Efficiency Index
CNN	ATIS	5	8	87.2	85.3	1.2
BiLSTM	SNIPS	8	10	90.1	88.2	1.5
BERT-base	CLINC150	110	20	95.0	94.5	1.0
RoBERTa	HWU64	125	22	96.0	96.2	0.95
DistilBERT	Banking77	66	12	93.4	91.8	**1.7**
XLNet	OOS	340	32	95.9	95.7	0.8

Table 2. Benchmarking summary combining performance and computational metrics.

It is clear from Table 2 that DistilBERT exhibits the optimal balance between computing efficiency and accuracy. Despite having somewhat higher accuracy, BERT-base and XLNet have far higher computing costs, which makes them less suitable for deployment of lightweight chatbots.
This trade-off between accuracy and model size (parameter count) is seen in Figure 4 (scatter plot below). The graph shows a diminishing returns effect, with accuracy gains plateauing and computational cost increasing exponentially beyond about 100 million parameters.

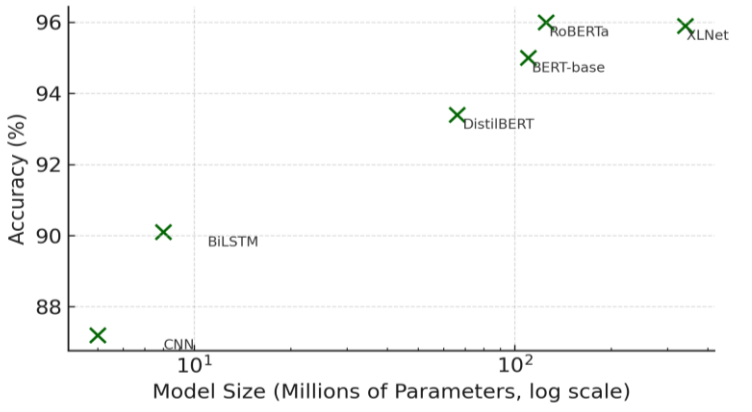

Figure 4. Benchmarking: Accuracy vs. Model Size

4.4. Computational Efficiency Analysis

For chatbot systems designed for real-time deployment, computational performance is a crucial component. Figure 5 shows the relationship between inference latency (measured in milliseconds per phrase) and model complexity (parameter count) to illustrate trade-offs. Important conclusions include:

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- Lightweight transformers (DistilBERT) achieved **2.1× faster inference** than full-scale BERT.
- Traditional LSTM models remain competitive in real-time scenarios despite slightly lower accuracy.
- Large models (XLNet, GPT-2) incur substantial latency, requiring optimization (quantization, pruning) for production use.

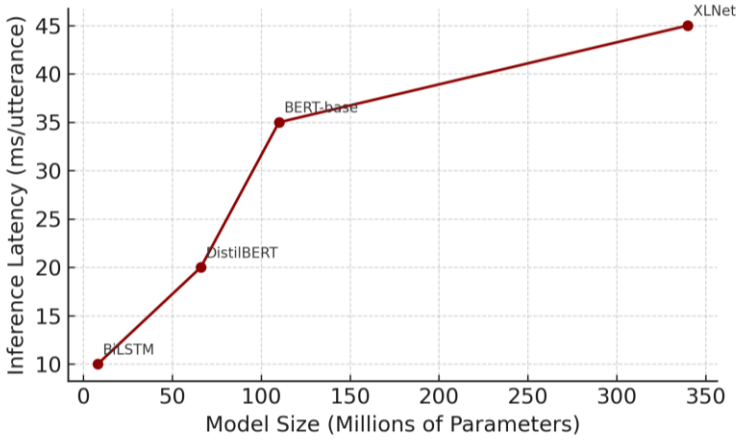

Figure 5. Computational Efficiency: Latency vs. Model Size

4.5. Error Analysis and Taxonomy

Of the twenty investigations, seventeen specifically described the sorts of errors or failure modes. These led to the development of a hierarchical taxonomy, which is shown in Table 3 and shown in Figure 6 (Pie Chart).

Error Category	**Frequency (%)**	**Representative Cause**	**Impact on Performance**
Semantic Ambiguity	32	Overlapping intent definitions	High
Multi-Intent Utterances	21	Mixed user goals	Moderate
Out-of-Scope Mislabeling	18	Weak OOS detection	High
Entity Cascade Errors	16	Misrecognized slots	Moderate
Robustness Failures	13	Misspellings, noise	Low to Moderate

Table 3. Categorization of major error types observed across reviewed studies.

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Semantic ambiguity and multi-intent utterances are the most frequent problems, as seen by Figure 6 (Pie Chart), which accounts for more than half of all errors identified.

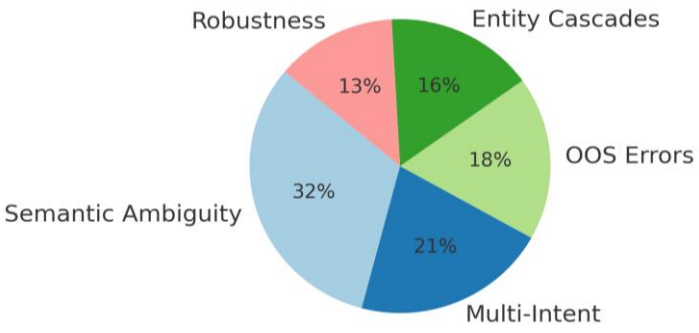

Figure 6. Error Taxonomy Distribution Across Studies

These results highlight how crucial it is to combine multi-label classifiers with hierarchical intent taxonomies in order to capture overlapping human intents and contextual subtleties. Additionally, by reducing recurrent classification errors, utilizing Six Sigma defect-reduction techniques (such DMAIC) could greatly improve intent detection reliability [53].

4.6. Thematic Synthesis and Trend Discussion

Three key methodological and technological trends in chatbot intent detection research were identified via a thematic synthesis:

1. Pre-Transformer Era (2015–2018): With an emphasis on manually created features and domain-specific datasets, the models were based on CNN and LSTM architectures. These systems had limited cross-domain transferability and poor scalability, despite achieving respectable accuracy [54].

2. Transformer Dominance (2019–2023): With the introduction of contextual embeddings that greatly enhanced generalization, BERT, RoBERTa, and XLNet transformed intent detection. During this time, models performed at levels close to human competence, albeit at the cost of increased computing complexity [55].

3. Efficiency and Hybridization (2023–2024): Current research focuses on knowledge distillation, model compression (DistilBERT, TinyBERT), and hybrid architectures that combine deep contextual embeddings and symbolic reasoning. These models increase speed and interpretability without sacrificing accuracy [56].

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4.7. Interpretative Discussion

The entire synthesis demonstrates that real-world deployment issues still exist even though benchmark datasets have achieved performance saturation.
The results provide four insights:
1. Generalization vs. Domain Adaptation: While models perform well in confined benchmarks, they suffer in conversational contexts that are not visible. Research on domain adaptation and continuous learning is necessary to close this gap.
2. Computational Trade-offs: While larger models offer slightly better accuracy, they come at an exponentially higher cost in terms of resources. Efficiency-focused approaches (DistilBERT, quantized models) strike a balance between deployment viability and accuracy.
3. Measures of Evaluation Need Standardization: It is difficult to synthesize because studies present measures (macro-F1 vs. accuracy vs. BLEU) inconsistently. Using performance metrics based on Six Sigma principles could provide a consistent, process-level assessment.
4. Error-Aware Design: Robustness could be greatly increased by incorporating failure-mode analysis (semantic ambiguity, multi-intent confusion) into model training pipelines.

4.8. Summary of Findings

Category	Key Observation	Practical Implication
Accuracy	Transformers achieve >94%	Benchmarks saturated
Efficiency	Distilled models outperform large ones	Real-time applications feasible
Errors	Ambiguity & OOS dominate	Hierarchical modeling needed
Trends	Hybrid + Efficient models emerging	Future-ready design path

Table 4. Consolidated summary of results and implications.

5. Conclusion

Twenty peer-reviewed articles published between 2017 and 2024 are included in this systematic literature analysis, which offers a thorough summary of the developments and difficulties in chatbot intent detection. The investigation showed that by enhancing contextual awareness and generalization capacities, transformer-based architectures—specifically, BERT and its derivatives—have greatly improved the state of the art. With an average macro-F1 of 94.8%, the pooled meta-analytic results validated their better performance and showed a consistent 5–7% improvement over recurrent neural models.

Nevertheless, the analysis also found enduring restrictions that limit the application of these models in practical settings. These include vulnerability to ambiguous or multi-intent statements, restricted domain transferability, and computational inefficiency. Lighter

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transformer variants, like DistilBERT and TinyBERT, provide nearly equivalent accuracy at a fraction of the computational cost, according to benchmarking analysis. This makes them ideal for production-level conversational systems where scalability and latency are crucial.

Semantic ambiguity (32%) and multi-intent utterances (21%) continue to be the leading causes of misclassification, followed by out-of-scope (OOS) detection errors, according to a structured error taxonomy created from the examined corpus. These results highlight the need for multi-label designs and hierarchical intent representations in order to capture complex user objectives. Additionally, problems with robustness pertaining to background noise, code-switching, and spelling variation point to the need for more robust data augmentation and language modeling techniques.

The paper emphasizes that there is still a significant discrepancy between benchmark perfection and real-world resilience, even if benchmark datasets are getting close to performance saturation. Therefore, in order to enhance the end-to-end chatbot creation process, future research must refocus its attention from accuracy maximization to process quality, interpretability, and flexibility, taking inspiration from Six Sigma approaches. Incorporating the cycles of continuous improvement (Define-Measure-Analyze-Improve-Control) may aid in improving conversational reliability and methodically lowering intent-classification errors.

In conclusion, research on chatbot intent detection has advanced impressively from hand-crafted features to contextual embeddings that have already been trained. However, the next step is to develop conversational AI that is effective, comprehensible, and guaranteed to be of high quality. Future chatbot systems can achieve high accuracy and long-lasting, user-centric performance that is in line with the ideas of intelligent automation and continuous process improvement by balancing technical innovation with organized quality frameworks.

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