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A Comparative Study Of Rule-Based Ai Vs. Generative Ai Models In Decision-Making Systems

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Abstract- Decision making systems are using a combination of style rules and new style artificial intelligence to help people make good choices. The old style rules are good because they are clear and easy to understand and they make sure people follow the rules. The old style rules have some problems though. They are hard to scale up. They cost a lot to maintain. Decision making systems that use style rules do not adapt well to new situations. On the hand the new style artificial intelligence like the kind that understands human language can find patterns and help with tough decisions. The style artificial intelligence is really good, at helping people make good choices because it can understand what people are saying and find patterns that the old style rules cannot. The style artificial intelligence is a big help to decision making systems because it can do things that the old style rules cannot. Decision making systems that use the style artificial intelligence can make better choices because they have more information and can understand what people are saying. This kind of intelligence has some problems. Artificial intelligence can make things up. It can be hard to understand intelligence. Also when something goes wrong with intelligence systems like these artificial intelligence systems it is not clear who is responsible, for the artificial intelligence. This paper reviews expert perspectives on both approaches and compares them in terms of interpretability, robustness, data dependence, deployment constraints, and evaluation. Evidence across multiple domains suggests that hybrid architectures integrating explicit rules, structured knowledge, and generative components provide a practical path toward trustworthy and adaptive decision- making.

Keywords – Rule-based systems, expert systems, generative AI, large language models, decision support, explainability, retrieval-augmented generation, neuro-symbolic AI.

I. INTRODUCTION

Decision-making with the help of intelligence is used in many areas where people have to make choices when they are not sure what will happen, when they do not have a lot of time and when they have to follow certain rules or laws. [1] [2]. In the past, people used something called expert systems to help make decisions. These systems were made up of rules that people created, which were then used to make decisions. These rules were often in the form of decision trees or special programs. [2] [3].

The good thing about these systems is that they can explain why they made a decision, and they usually behave in a predictable way. However, they often do not work well in situations that the people who created them did not think about [2] [4].

At the time, a new way of doing things called machine learning had become popular. This method uses statistics and special kinds of computer programs called models to help make decisions. Intelligence and machine learning are changing the way decision-making works [5]. The recent wave of generative AI (e.g., LLMs) extends this trajectory by enabling free-form reasoning, explanation, and interactive dialogue, which are attractive for complex decisions that involve unstructured information. [6] [7] [8]. However, generative models can produce plausible but incorrect outputs, posing safety and governance challenges. [6] [9].

Rule-based AI is a type of intelligence that uses rules to represent knowledge. These rules are like instructions that say if something happens, then something else will happen. For example, in medicine, these rules can be used to help doctors figure out what is wrong with a patient and what treatment they should get. The computer can even explain why it made a suggestion. [10] [4].

II. LITERATURE REVIEW

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Rule-Based AI For Decision-Making

In factories and plants, rule-based systems are still widely used to monitor equipment and raise alarms when something goes wrong. This is because these systems are easy to understand and follow the rules. [2]. The good thing about rule-based AI is that it is transparent, so we can see how it made a decision. It always answers when given the same information, and it is easy to check if it is working correctly when things are not changing. [11]. Rule-based AI is useful when the environment is stable and does not change much. Key limitations include the knowledge acquisition bottleneck, brittleness under distribution shift, and growing maintenance burden as rule sets expand. [2] [4].

Generative AI and Llms For Decision Support

Generative AI models learn to make things like text and pictures from the information they get. When it comes to making decisions, large language models play a crucial role. This is because they can take a lot of information and turn it into possible actions, reasons and summaries. [6] [8]. We have seen that certain ways of asking questions, like thinking step-by-step and taking action, can help these models work better when solving problems. [7]. However, these methods also make us worry about whether the results are reliable, whether we can get the same results again and whether the reasons the models give are true. [6] [7] [12]. Large Language Models and their results need to be looked at. Because LLMs are not inherently grounded, retrieval-augmented generation and tool use have emerged as practical ways to improve factuality and traceability.

Neuro-Symbolic and Hybrid Architectures

Neuro-symbolic AI integrates neural learning with symbolic representations to combine perception and reasoning. [13] [14]. Surveys highlight diverse mechanisms: differentiable logic, knowledge graphs, program induction, and constraint-based decoding. [13] [15]. In practice, hybrid decision systems often implement a pipeline(i) generative model for parsing, summarising, and proposing options; (ii) a retrieval or structured knowledge base for grounding; (iii) symbolic checks, constraints, or policy rules for validation; and (iv) human oversight for high-stakes decisions. [13] [14] [4]

III. METHODOLOGY

We did a study that looked at lots of stories about Artificial Intelligence. First, we decided what we were looking for: we wanted Artificial Intelligence studies that were reviewed by experts or were very popular, discussing how Artificial Intelligence makes decisions using rules, generates new ideas, or a mix of both. Then we put the Artificial Intelligence studies into four groups: Artificial Intelligence in healthcare, Artificial Intelligence in industry and internet-connected things, Artificial Intelligence in computer networking and sharing resources and Artificial Intelligence in business and management. Third, we extracted comparable attributes: decision objective, input type, model class, explanation strategy, evaluation metrics, and governance concerns [12]. Finally, we performed a thematic comparison across five dimensions: interpretability, adaptability, data dependence, robustness/safety, and operational constraints.

IV. RESULTS

COMPARATIVE SUMMARY TABLE

Dimension	Rule-Based AI	Generative AI (LLMs)	Typical Failure Mode	Best Fit Context	Mitigation / Hybrid Pattern
Interpretability	High	Variable	Spurious rationales & hidden shortcuts	Regulated workflows	Grounding, checking rules, and logging
Adaptability	Low–medium	High	Overgeneralization & prompt sensitivity	Dynamic environments	Tool/RAG, calibration
Data requirement	Low data	High pretraining data	Bias propagation	Rich data	Data governance
Robustness	At strong in known cases	Strong in language tasks, weaker under adversarial prompts	Hallucination & inconsistency	Human-facing decision support	Verification, constraints, fallback rules
Maintenance	Rule drift & combinatorial explosion	Model updates & versioning	Regression across versions	Long-lived systems	Continuous eval, change management

Domain Evidence

Healthcare is a field where people are trying to figure out the way to diagnose patients. Some studies have compared ways of doing this to new ways that use something called LLMs. What they found out is that the old way is actually better when doctors are just looking at what they can see and hear from the patient. When they add in test results from labs, the new way starts to work better. So it seems like using both ways together is the best approach for Healthcare. [10] [4] [16]. This is because Healthcare can really benefit from combining the new methods for diagnosing patients.

Industrial Monitoring: Rule-based approaches remain reliable and explainable for alarms; data-driven and generative methods improve anomaly discovery and adaptation [2] [11].
Networking: Empirical comparisons of rule-based heuristics, reinforcement learning, and an LLM-based policy show that an LLM policy can appear competitive on throughput–latency trade-offs and can be adjusted via prompting [17] [8].
Business: Reviews emphasise that generative AI can improve efficiency and pattern discovery, but human judgment remains critical under uncertainty [18, 5] [19].

Figures and Diagrams

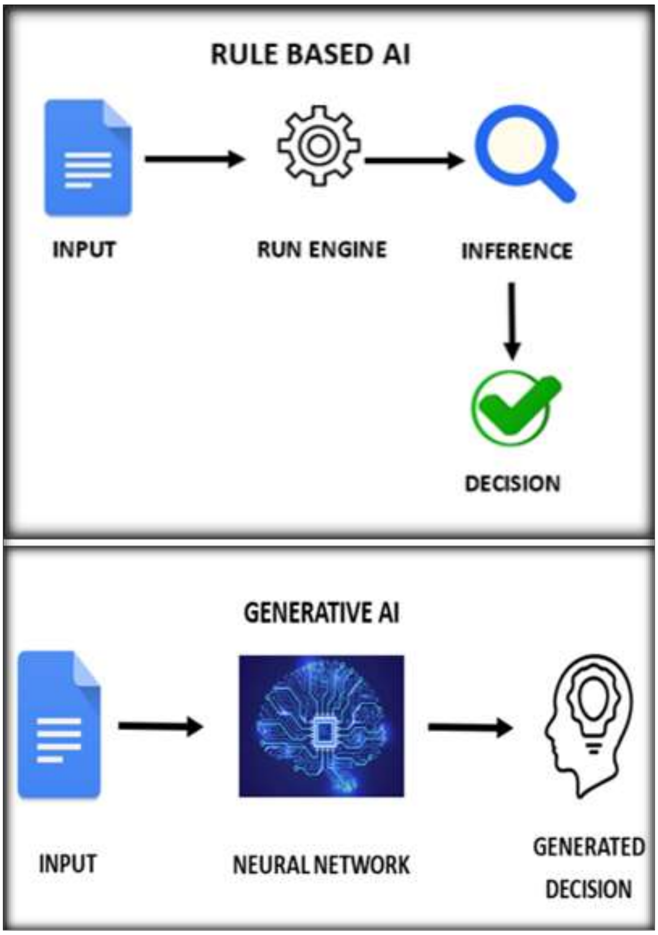

Figure 4.3.1 Architecture comparison (rule-based vs generative).

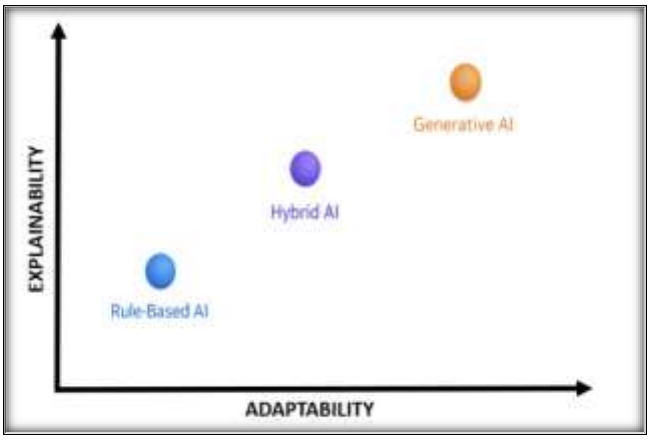

Figure 4.3.2 Explainability vs adaptability trade-off (conceptual).

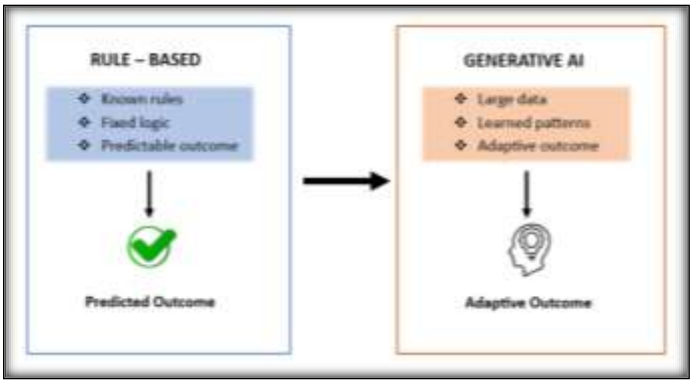

Figure 4.3.3 Decision flow comparison (high-level).

V. DISCUSSION

The evidence shows that there is a pattern. Rule-based systems work well when we need to explain and check the decisions that are made. On the other hand, generative systems are good when the information we are working with is not organised, and the decision process can benefit from being able to understand language flexibly. [7] [4].

However, there are some problems with using Artificial Intelligence. It can make things up; it can be affected by the way it is asked questions. It is not always clear how sure it is about its answers. These problems mean we cannot use Artificial Intelligence on its own to make decisions that have big consequences. [6] [12].

To get around these problems, we can use a combination of approaches. We can use models to do things they are good at, like understanding and summarising information and suggesting ideas. Then we can use tools and methods to make sure the decisions are correct. This idea is in line with some thoughts on how our brains work with symbols. [15]. According to these ideas, it is critical that computers comprehend concepts in a manner similar to constructing with bricks and be able to articulate their reasoning clearly.. This is about neuro-symbolic perspectives. It is really about compositional generalisation and transparent reasoning, in neuro-symbolic perspectives. [13] [14].

Limitations: This review synthesises heterogeneous studies and cannot claim a single unified benchmark. Publication bias may inflate reported gains, and many LLM evaluations depend on prompt design and model version. Future work should standardise reporting (model version, prompts, retrieval corpus, and constraint sets) and adopt stress tests for distribution shift and adversarial inputs. [9].

VI. CONCLUSION

Rule-based artificial intelligence and generative artificial intelligence are two ways to make decisions. Rule-based systems are good because they are clear and easy to control. They have a hard time getting bigger and changing.

Generative models are good because they can think and talk in a way, but they need to be based on real things and have safety measures.

The best way to make decisions is to use a mix of both: combine rules and things we know with language model interfaces, finding the right information using tools, and always checking to make sure everything is working well.

We should use rule-based intelligence and generative artificial intelligence together to make better decisions. For deployment, organisations should implement governance: documentation, audit trails, privacy controls, and human-in-the-loop escalation for uncertain cases. [6] [9] [16].

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