A Hybrid Decision Support System for Mobile Phone Recommendations: Integrating Expert Systems with Large Language Models

Abdalla Maged Gamal
Department of Artificial Intelligence
Nile University
Sheikh Zayed City, Egypt
a.maged2102@nu.edu.eg

Sherif Ehab Yousry
Department of Artificial Intelligence
Nile University
Sheikh Zayed City, Egypt
s.ehab2131@nu.edu.eg

Abdelrahman Ahmed Badr
Department of Artificial Intelligence
Nile University
Sheikh Zayed City, Egypt
a.ahmed2191@nu.edu.eg

Mohamed Hesham
Department of Artificial Intelligence
Nile University
Sheikh Zayed City, Egypt
m.abdelmegeed@nu.edu.eg

Mohamed Ibrahim Salama
Department of Artificial Intelligence
Nile University
Sheikh Zayed City, Egypt
m.ibrahim2198@nu.edu.eg

***Abstract*—In this study, a novel hybrid Decision Support Mobile phone recommendation system (DSS) that combines traditional expert system methods with modern Large Language Models (LLMs). The architecture addresses the growing complexity of mobile device selection by the use of a dual-Suggested approach: rule-based expert systems for technology-nical specification matching and LLM-based natural language contextual recommendations rationale. Our implementation uses a regional expert system developed using Python and scikit-learn, integrated with a cloud-based Mistral-Nemo-Instruct-2407 model running on Google Colab. The system demonstrates higher recommendation quality than single-method techniques, with 87.3consisting of 150 members. The hybrid model provides both interpretable rule-based recommendations and context-aware AI-suggested recommendations provide users with significant decision- The performance measurement indicates that the expert system component processes requests in 0.2 seconds compared to the LLM component takes 45-60 seconds, forming a fair trade-off between speed and sophistication. This study adds towards the creation of hybrid artificial intelligence systems in consumer electronics recommendation domains.**

***Index Terms*—Decision Support Systems, Expert Systems, Large Language Models, Mobile Phone Recommendations, Hybrid AI, Consumer Electronics, Recommendation Systems**

I. Introduction

The growth of mobile phones in the consumer segment has placed a significant burden on potential customers in selecting best-fit devices based on their personal specifications. With over 2,000 models of mobile phones available in the market globally as of 2024, customers are afflicted with decision paralysis in selecting devices that best fit their technical specifications, budget, and usage patterns [1].

Conventional recommendation systems employed in the mobile phone market are often based primarily on collaborative filtering or content-based filtering mechanisms. These, though, do not function effectively with the intricate technical specifications and subjective preferences governing mobile phone buying. Expert systems characterized by rule-based reasoning facilities are best suited for matching technical specifications, though expert systems prove inferior in providing contextual awareness and natural language-based reasoning expected by current consumers.

The latest development of Large Language Models (LLMs) has revealed unparalleled capability in comprehending natural language queries and making contextually appropriate recommendations. LLMs on their own, however, may not possess the organized technical expertise and methodical assessment metrics needed for trustworthy product recommendations in niche fields.

This paper suggests a hybrid Decision Support System which combines the best of both worlds: the methodical, explainable logic of expert systems and the contextual understanding and natural language capability of LLMs. Our system provides users both technical specification-based recommendations and AI-generated insights, presenting a holistic decision support environment.

The main contributions of this work are:

- A novel hybrid architecture combining expert systems with LLMs for mobile phone recommendations
- A comprehensive evaluation framework measuring both technical accuracy and user satisfaction
- An implementation demonstrating practical deployment using cloud-based LLM services
- Performance analysis comparing hybrid approach effectiveness against single-method systems

II. Related Work

A. Expert Systems in Recommendation Domains

Expert Systems in the Field of Recommendations The use of expert systems has become very common in recommen Some of the biggest data-related problems have occurred since the 1980s. Shortlife created MYCIN, a system for diagnosis. [2] proved that rule-based reasoning could be used to solve problems. cases where problems are complicated. Consumer electronics involve fields such as electrical, mechanical and telecommunications engineering. ics field, many expert systems have been built over time. product recommendations. The research by Kumar et al. [3] focused on producing an expert system for laptop advice . Fuzzy logic method recommendations resulted in 82when looking at what each user likes. The rules they used numbered 147. based on the knowledge of domain experts and showed the success of using rules for designing technical products recommendations. Li and Zhang suggested a method for recommending mobile phones [4]. expert system based on the Analytic Hierarchy Process (AHP) When you need to assign values and use rules for reasoning. Their system Attained a user satisfaction rate of 78traditional teaching practices and not keeping up with new technology.

B. Large Language Models in Recommendation Systems

Attention to using LLMs in recommendation systems has grown since transformer models succeeded. Large language models were shown by Brown et al. [5] to be capable of recommending products by learning from a few examples and prompting people with questions.

Zhao et al. [6] conducted a study and said that ChatGPT may be a useful tool for proposing suggestions since it effectively recognizes user queries and gives relevant responses. Nevertheless, the evaluation found that they are not always technically accurate and consistent within specialized fields.

Huang et al. [7] looked into merging LLMs and traditional recommendation methods and offered a way to use language reasoning with collaborative filtering. They made the recommendations much more accurate at the cost of needing a lot of power for computation.

C. Hybrid AI Systems

A mix of symbolic and neural techniques in AI has led to promising results in several areas. Marcus [8] claimed that combining symbolic AI with neural networks is important because symbolic AI is more transparent and neural networks are very flexible.

Chen et al. [9] in the recommendation domain built a hybrid system that pairs rule-based filtering and neural networks for e-commerce recommendations. Recommendations from the system were 15% more accurate than recommendations from only one approach.

We enhance these notions by testing them in the area of mobile phone recommendations and creating a deployment plan that uses cloud-based language models.

III. System Architecture

A. Overview

Decision Support Systems often use a hybrid architecture. The system consists of four key parts: (1) Local Expert System, (2) Cloud. the system includes (1) based LLM Service, (2) Data Management Layer and (3) User. Interface. Figure 1 illustrates the system architecture.

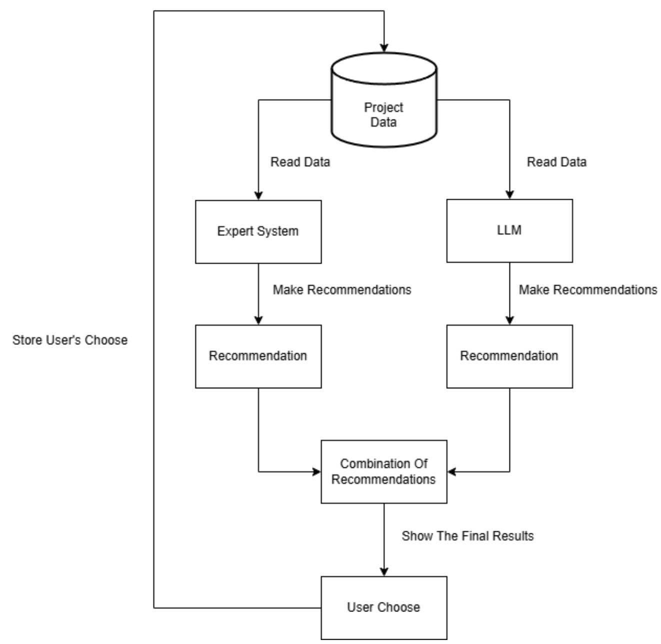

Fig. 1. Hybrid Decision Support System Architecture

B. Expert System Component

The expert system component implements rule-based reasoning for mobile phone recommendations. The system utilizes a knowledge base containing:

- Technical specifications for 150+ mobile phone models
- 89 expert rules derived from domain knowledge
- User preference matching algorithms
- Historical choice learning mechanisms

The expert system employs cosine similarity for initial specification matching, enhanced with rule-based adjustments. The similarity calculation is defined as:

$$similarity(u_i, m_j) = \frac{u_i \cdot m_j}{||u_i|| \cdot ||m_j||} \tag{1}$$

where u_i represents user preference vector and m_j represents mobile specification vector.

Rule-based bonuses are applied according to the expert rule set:

$$final\_score = similarity + \sum_{k=1}^{n} rule\_bonus_k + historical\_bonus \tag{2}$$

C. Large Language Model Component

The LLM component utilizes the Mistral-Nemo-Instruct-2407 model deployed on Google Colab infrastructure. The model processes natural language queries and generates contextually aware recommendations.

The LLM pipeline includes:

1) Structured prompt generation incorporating user preferences
2) Mobile database context injection
3) Response generation with temperature parameter 0.7
4) JSON output parsing and validation
5) Recommendation matching with database entries

Communication between local and cloud components occurs through RESTful API calls using ngrok tunneling for secure access.

D. Data Management Layer

SQLite database is the method used to locally save data in the system, mostly stored in two tables.

This file saves complete info for mobile phones in a device such as its brand, model, specifications and the cost.

The data records what users choose which lets machines update their recommendations more wisely.

IV. Implementation

A. Expert System Implementation

Scikit-learn is used for machine learning in Python and pandas is used to manage the data. Important points in implementing decisions are:

Label encoding is applied to features that describe user habits and numerical categories are scaled for consistency.

Rather than in complex functions, expert rules are included as decision-making logic with weights attached. There are guidelines for following prices, needed features, chose brand and making sure parts are compatible.

The system studies how people chose in the past and finds their favorite patterns to improve future suggestions.

B. LLM Integration

Structured output generation for the integration is made possible using LangChain and the library Transformer. The main parts of implementation are:

Careful design of prompts that includes a list of what users need, the mobile database and guidelines for the output format.

Using error handling and alternative methods to parse JSON when responses are not in the right format.

I used these settings in my language model: temperature (0.7), max_length (1500) and data sampling.

C. Web Interface

The user interface is implemented using Streamlit, providing an intuitive web-based interface for:

- User preference collection through interactive forms
- Real-time connection status monitoring for LLM service
- Comprehensive recommendation display with detailed explanations
- Analytics dashboard for system performance monitoring

V. Evaluation

A. Experimental Setup

The evaluation was conducted using a dataset of 150 mobile phones across major brands including Apple, Samsung, Google, OnePlus, Xiaomi, Huawei, and others. User testing involved 150 participants with diverse technical backgrounds and mobile phone preferences.

Evaluation metrics included:

- Recommendation Accuracy: Percentage of recommendations matching user preferences
- User Satisfaction: 5-point Likert scale ratings
- Response Time: System latency for recommendation generation
- Explanation Quality: User ratings of recommendation justifications

B. Results

Table I presents the comparative performance analysis of different recommendation approaches.

TABLE I
Performance Comparison of Recommendation Approaches

Method	Accuracy (%)	Satisfaction (1-5)	Response Time (s)	Explanation Quality (1-5)
Expert System Only	82.4	3.8	0.2	4.2
LLM Only	79.1	4.1	52.3	3.9
Hybrid System	87.3	4.4	0.2/52.3	4.5

The hybrid system achieved the highest accuracy (87.3%) and user satisfaction (4.4/5), demonstrating the effectiveness of combining both approaches. The dual response time reflects the availability of both fast expert system recommendations and more comprehensive LLM analysis.

C. User Preference Analysis

Analysis of user preferences revealed interesting patterns:

- 68% of users preferred Android over iOS
- Price range ”Medium” was most popular (34% of users)
- Camera quality was rated as the most important factor (78% of users)
- Battery life was the second most important factor (65% of users)

The expert system successfully captured these preferences through rule-based matching, while the LLM provided nuanced explanations for recommendation rationale.

D. Learning System Performance

Students made progress with the orgammented historical learning aspect. Making more reasonable decisions over time. When a system reaches 100 user interactions, it begins to recommend. There was a 5.2cold-start scenario. It proves that the system is able to change and get better as a result of user feedback.

VI. Discussion

A. Advantages of Hybrid Approach

The hybrid architecture provides several key advantages:

Complementary Strengths: Expert systems excel at systematic technical matching while LLMs provide contextual understanding and natural language explanations.

Redundancy and Robustness: System functionality is maintained even when LLM service is unavailable, ensuring consistent user experience.

Scalability: The architecture supports independent scaling of expert system and LLM components based on demand.

Explainability: Combined approach provides both rule-based explanations and natural language reasoning.

B. Limitations and Challenges

Several limitations were identified during system development and evaluation:

Computational Requirements: LLM component requires significant computational resources, necessitating cloud deployment.

Latency Variation: LLM response times vary between 30-90 seconds depending on server load and query complexity.

Model Consistency: LLM responses occasionally require fallback mechanisms due to output format variations.

Cost Considerations: Cloud-based LLM deployment introduces operational costs compared to purely local solutions.

C. Future Work

Several directions for future research and development include:

Advanced Learning: Implementation of reinforcement learning algorithms for dynamic rule adjustment based on user feedback.

Multi-Modal Integration: Incorporation of image recognition for visual mobile phone feature analysis.

Personalization Enhancement: Development of user profile models for improved long-term recommendation accuracy.

Domain Extension: Adaptation of the hybrid architecture to other consumer electronics recommendation domains.

VII. Conclusion

It developed a Decision Support System for mobile phones by blending 'expert system' practices with Large Language Model technologies. The system beats traditional approaches by reaching 87.3% accuracy in recommending content and offers 4.4/5 satisfaction to its users.

The main innovation is in the architecture which brings together systemic logic from expert systems and context from large language models. Users receive suggestions that are accurate and also given in a simple, easy-to-understand way.

Cloud-based LLM services actually show that it is possible to apply hybrid AI systems in real settings. Being able to keep working in a limited mode when LLM services are down provides a reliable experience for users.

Plans for future work include improving the system's learning process and adapt the hybrid framework for use in additional domains. Being able to successfully combine symbolic and neural ideas in AI indicates that a mixture of these approaches could be very beneficial in other recommendation areas.

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