Artificial intelligence-driven Vietnamese-language chatbot for pest diagnosis and pesticide guidance in crop production

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Phát triển chatbot dựa trên trí tuệ nhân tạo hỗ trợ chẩn đoán sâu bệnh và tư vấn thuốc bảo vệ thực vật trong canh tác nông nghiệp

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https://doi.org/10.55250/jo.vnuf.11.1.2026.101-108

Article info:
Received: 02/12/2025
Revised: 05/01/2026
Accepted: 18/03/2026

ABSTRACT

Digital advisory systems have emerged as an important solution for improving crop management in regions where farmers have limited access to timely and reliable technical support. This study developed and evaluated an artificial intelligence-driven chatbot that uses Vietnamese natural language processing and a structured plant protection knowledge base to provide guidance on pest diagnosis, nutrient management, and pesticide use. System requirements were identified through interviews with 30 farmers and 10 agricultural students. A comprehensive knowledge base was constructed from national plant protection guidelines and international technical sources and validated by specialists from provincial plant protection agencies. The chatbot was built on a modular architecture that included an NLP component, a dialogue management module, and image-supported advisory templates, and was deployed on Facebook Messenger. Technical testing over 72 hours showed stable system performance, with an average response time of 1.3 seconds, an intent-recognition accuracy of 85 percent, and an automation rate of 80 percent. Field testing with 30 farmers generated 431 valid queries and demonstrated strong user engagement, particularly for pest diagnosis and pesticide preparation. User evaluations showed high clarity (4.4), usability (4.3), usefulness (4.2), and overall satisfaction (4.3). Qualitative feedback indicated that farmers valued the standardized, stepwise guidance and the absence of commercial pesticide promotion. The system's ability to deliver consistent and scientifically validated information suggests its potential as a practical digital extension tool for Vietnamese agriculture. The findings highlight opportunities to integrate more advanced NLP models, region-specific data, and image-based diagnostic features to further enhance advisory accuracy and usability.

Keywords:
Agricultural chatbot, natural language processing, pest diagnosis, pesticide guidance.

TÓM TẮT

Hệ thống tư vấn số đang trở thành giải pháp quan trọng nhằm nâng cao hiệu quả quản lý cây trồng trong bối cảnh nhiều nông hộ gặp khó khăn trong việc tiếp cận nguồn thông tin kỹ thuật chính xác và kịp thời. Nghiên cứu này xây dựng và đánh giá một chatbot dựa trên trí tuệ nhân tạo, tích hợp xử lý ngôn ngữ tự nhiên tiếng Việt và cơ sở tri thức bảo vệ thực vật nhằm cung cấp hướng dẫn về chẩn đoán sâu bệnh, quản lý dinh dưỡng và sử dụng thuốc bảo vệ thực vật. Yêu cầu hệ thống được xác định thông qua phỏng vấn 30 nông dân và 10 sinh viên nông học. Cơ sở tri thức được xây dựng từ các tài liệu chuyên môn quốc gia và nguồn kỹ thuật quốc tế, sau đó được chuyên gia thuộc các Chi cục Trồng trọt và Bảo vệ thực vật thẩm định. Chatbot được phát triển theo kiến trúc mô-đun gồm xử lý ngôn ngữ tự nhiên (NLP) tiếng Việt, bộ quản lý hội thoại và các mẫu tư vấn có hỗ trợ hình ảnh và được triển khai trên nền tảng Facebook Messenger. Kiểm thử kỹ thuật trong 72 giờ cho thấy chatbot hoạt động ổn định với thời gian đáp ứng trung bình 1,3 giây, độ chính xác nhận diện ý định đạt 85% và tỷ lệ tự động hóa đạt 80%. Thử nghiệm thực địa trên 30 nông dân với 431 truy vấn hợp lệ ghi nhận mức độ tương tác cao, đặc biệt ở các nhóm câu hỏi về sâu bệnh và pha chế thuốc bảo vệ thực vật. Người dùng đánh giá mức độ rõ ràng 4,4; dễ sử dụng 4,3; hữu ích 4,2 và hài lòng chung 4,3 trên thang năm điểm. Phản hồi định tính cho thấy nông dân đánh giá cao tính chuẩn hóa của thông tin, cấu trúc tư vấn theo từng bước và việc không giới thiệu tên thương phẩm. Kết quả chỉ ra rằng hệ thống có khả năng trở thành công cụ hỗ trợ khuyến nông số hiệu quả cho sản xuất nông

Từ khóa:
Chatbot nông nghiệp, chẩn đoán sâu bệnh, hướng dẫn thuốc bảo vệ thực vật, xử lý ngôn ngữ tự nhiên.

nghiệp Việt Nam. Các hướng phát triển tiếp theo bao gồm mở rộng cơ sở triệu chứng, ứng dụng mô hình ngôn ngữ nâng cao và tích hợp chức năng chẩn đoán bằng hình ảnh nhằm tăng độ chính xác và tính cá nhân hóa trong tư vấn.

1. INTRODUCTION

Digital transformation in agriculture has accelerated worldwide in recent years, with artificial intelligence, natural language processing (NLP), and knowledge-based systems increasingly applied to improve crop protection, nutrient management, and pesticide decision-making [1]. In countries dominated by smallholder production, timely and reliable advisory services are essential for mitigating yield losses caused by pests and diseases [2]. These challenges affect a significant proportion of global cultivated land each year. Despite the growing availability of digital tools, many farmers, particularly in developing regions, rely on fragmented or unverified information sources, which often leads to incorrect pesticide use, environmental risks, and substantial economic losses.

Recent studies highlight the growing potential of intelligent decision-support technologies in agriculture [3]. It has been reported that machine learning systems can identify crop pests and diseases with high accuracy [4]. A recent study also demonstrated that digital decision-support tools guide farmers toward appropriate pesticide choices and help reduce excessive chemical use [5]. Of particular interest, NLP-based chatbots can deliver accessible advisory services to rural users in several countries. Despite these developments, most existing systems operate primarily in English or other widely used languages and do not fully address regional agronomic practices or regulatory frameworks. In Vietnam, smartphone penetration is high, and Facebook Messenger is widely used in rural communities [6]. However, artificial intelligence- (AI-) based Vietnamese-language chatbots designed for crop protection, nutrient guidance, and pesticide safety remain limited.

This study aimed to develop an AI-based agricultural advisory system integrated with Facebook Messenger to support crop management in a practical and accessible way. This study is distinguished by its integration of a user-centered needs assessment with domain-specific agricultural knowledge on a widely used messaging platform.

2. RESEARCH METHODS

2.1. Requirement analysis and user needs assessment

A needs assessment was conducted through semi-structured interviews with 40 participants, including 30 farmers from different production areas in Hanoi city, Vietnam, and 10 students from the Faculty of Agronomy, Vietnam National University of Agriculture (Hanoi city, Vietnam). Participants were recruited by convenience sampling based on two eligibility criteria, including current involvement in crop production or agronomy training, and willingness to use smartphone-based messaging platforms. Before data collection, all participants were informed of the study objectives and procedures, and verbal informed consent was obtained. Participation was voluntary, and responses were anonymized before analysis. The interviews examined difficulties related to pest identification, nutrient management, pesticide selection, dosage preparation, and safety practices. The analysis identified three main user needs, namely access to verified information on crop symptoms, disease progression, and factors associated with pest outbreaks; clear guidance on pesticide active ingredients, dosage ranges, and mixing procedures; and practical instructions on safe handling and pre-harvest intervals. Non-functional requirements included rapid response time, high accuracy, accessibility via Facebook Messenger, and an interface suitable for older users.

2.2. Construction of the plant protection knowledge base

The knowledge base was developed from authoritative agricultural references and national guidelines, including plant protection textbooks from the Vietnam National University of Agriculture (Hanoi city, Vietnam), the National Integrated Pest Management Handbook, and national pesticide regulations, supplemented by technical documents from the Food and Agriculture Organization of the United Nations and the International Rice Research Institute. To capture crop production conditions in Vietnam, the dataset was expanded to include 18 major crop species selected from national production statistics and farmer interviews, including rice (32%), vegetables (24%), fruit crops (18%), maize (10%), industrial crops such as coffee and pepper (8%), and other minor crops (8%). The knowledge base covered 152 plant health problems, including 87 diseases, 52 insect pests, and 13 physiological or nutrient-related disorders, with coverage prioritized according to the frequency of farmer-reported problems. A nutrient management module was also included, covering 13 groups of essential nutrient deficiencies and toxicities across major crop groups, with recommendations expressed by active ingredient and supported by guidance on dosage, application timing, and safety considerations. In addition, the system incorporated 108 pesticide active ingredients commonly registered in Vietnam, selected according to national regulations and expert consultation, and linked to specific crops and pest groups to support accurate and compliant recommendations. The final architecture comprised 150 standardized response templates, 56 dialogue pathways, 108 pesticide active ingredients, 87 diseases, 52 insect pests, 13 nutrient disorder groups, and 40 preparation instructions adapted to common commercial formulations. All content was reviewed by plant protection specialists from provincial Crop Production and Plant Protection Sub-Departments.

2.3. Chatbot architecture and system development

The chatbot was developed with a modular architecture that consisted of four major components: a user interface layer, a Vietnamese NLP module, a dialogue management module, and the plant protection knowledge base. Chatfuel served as the development platform, as previously described [7]. The NLP component classified user messages into predefined intent categories such as pest diagnosis, pesticide dosage, nutrient disorder, or safety requirement (Figure 1). The dialogue management module connected user inputs to relevant templates in the knowledge base and produced structured responses across multiple steps.

2.4. System deployment and user interface design

The system was deployed on Facebook Messenger as recently described [8]. Features included quick-reply buttons, image-based symptom descriptions, and multi-step guidance for pesticide preparation. Dialogue flows followed a hierarchical structure with options that allowed users to select symptoms, choose crop stages, or request more detail (Figure 2). The deployment process also included the configuration of logging tools that recorded user queries and system performance. These logs supported iterative improvements during the testing process.

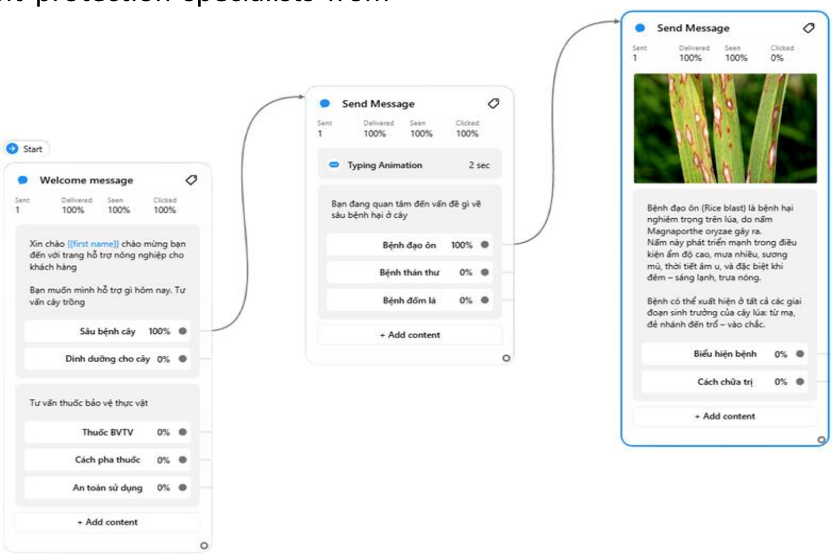

Figure 1. Dialogue pathway for pest diagnosis within the chatbot system

Figure 2. Interface design and dialogue flow of the agricultural advisory chatbot developed in this study

2.5. Technical evaluation procedures

Technical performance was assessed during a continuous 72-hour test period. Key metrics included response time, intent recognition accuracy, automation rate, and system stability. Response time was measured as the interval between user message input and chatbot output. Intent accuracy was calculated as the proportion of correctly classified user queries within a test set that included standard Vietnamese text, regional terminology, and queries without diacritics. Automation rate was defined as the proportion of queries that received a complete and correct response without human oversight. The evaluation also included a manual review of misclassified cases to identify error patterns.

2.6. Field testing with farmers

Field testing was conducted with 30 farmers who represented a range of agricultural production systems. Testing took place over two weeks and generated 431 valid queries. Farmers were instructed to use the chatbot for common tasks such as pest identification, pesticide mixing, nutrient management, and safety guidance. After each interaction session, participants recorded their evaluations on a five-point Likert scale that measured clarity, usability, usefulness, and overall satisfaction. Additional qualitative feedback was collected through follow-up discussions with the same participants (Figure 3).

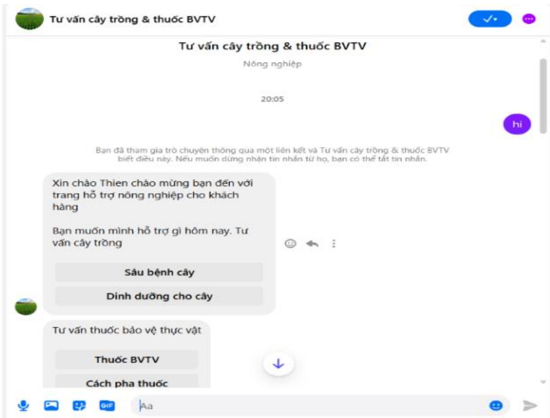

Figure 3. Example of chatbot interaction on Facebook Messenger during user testing

3. RESULTS AND DISCUSSION

3.1. System development and knowledge base validation

The development process resulted in a fully operational chatbot designed to provide multidimensional advisory support for crop protection, nutrient management, and pesticide use in Vietnamese farming systems. The system was constructed with a modular architecture that incorporates a user interface layer, a Vietnamese NLP component, a dialogue management module, and a structured agricultural knowledge base. Chatfuel served as the implementation platform because its block-based dialogue design, Application Programming Interface integration capability, and compatibility with Facebook Messenger aligned well with the communication habits of Vietnamese farmers. The use of predefined dialogue blocks ensured consistent responses and simplified the processing of common agricultural queries related to pests, diseases, nutrient disorders, and pesticide applications.

The knowledge base was organized into thematic groups covering diagnostic features of major pests and diseases, environmental and biological factors influencing pathogen development, integrated pest management (IPM) strategies, indicators of nutrient imbalance, pesticide active ingredients, dosage recommendations, safety precautions, and pre-harvest intervals. The resulting repository comprised 150 standardized response templates, 56 dialogue pathways, 108 pesticide active ingredients, 87 crop diseases, 52 insect pests, 13 nutrient disorder groups, and 40 mixing instructions adapted to commonly used pesticide formulations.

Validation of the knowledge base was carried out with the participation of plant protection specialists working in provincial Crop Production and Plant Protection Sub-Departments. These experts reviewed the scientific accuracy, clarity, and practical relevance of each content category, with particular focus on pesticide-related information and safety procedures. Their evaluation confirmed that the knowledge base aligned with national technical standards, exhibited IPM principles, and avoided the promotion of commercial pesticide products. The expert assessment also highlighted the accessibility of the content for farmers with varying levels of agricultural experience. Through this process, the knowledge base achieved a high level of reliability and suitability for integration into an AI-supported advisory system for crop production in Vietnam.

The development and validation of the chatbot system demonstrate that an AI-assisted advisory tool grounded in Vietnamese-language NLP and a structured plant protection knowledge base can effectively address the long-standing challenge of inconsistent and inaccessible agricultural guidance for smallholder farmers. The modular architecture, supported by a block-based dialogue design on Chatfuel, aligns with recent findings that emphasize the importance of predictable response structures for users with limited digital literacy, as recently noted [9]. These development and validation results indicate that combining Vietnamese NLP with a specialist-validated knowledge base can deliver standardized advisory content for farmer-facing applications. The modular design also provides a foundation for future extensions such as region-specific knowledge updates and image-supported diagnosis.

3.2. Technical performance and system functionality

The technical evaluation provided clear quantitative evidence of stable and efficient system performance. During a continuous 72-hour test period, the chatbot operated without any recorded interruption, error message, or system restart. The average response time reached 1.3 seconds for each query and consistently remained below the target threshold of 2 seconds. The intent recognition accuracy reached 85 percent and showed the highest performance in queries that used complete Vietnamese diacritics and crop protection terms familiar to extension officers. The lowest accuracy appeared in queries that contained missing accents or informal local expressions.

Automation performance also reached a level that exceeded the predefined requirement. Out of all chatbot interactions in the technical test set, 80 percent received complete and correct responses without any human intervention. This value was above the minimum target of 75 percent. The remaining 20 percent required manual review and belonged mainly to multi-symptom queries. Examples included combinations such as yellowing leaves with wilted stems, blackened roots with poor grain filling in rice, or questions that combined pest and nutrient issues in a single input message. These complex scenarios reduced the system's ability to match queries to predefined templates.

The technical assessment identified several recurrent error patterns that guide future system refinement. Queries lacking diacritics caused approximately 30 percent of the misclassified cases within the 15 percent intent-recognition error segment. Queries that used local terminology accounted for another 25 percent of misclassification. Cases involving rare diseases or overlapping symptoms produced the remainder. Despite these limitations, the system maintained consistent dialogue flow across all evaluated scenarios, and no contradictory instructions were detected in sections related to pesticide dosage, mixing procedures, or IPM guidance. These quantitative results indicate that the system can support real-time agricultural advisory functions with a high level of stability, a fast response rate, and an automation level that meets practical field requirements.

The technical performance outcomes indicate that the chatbot is capable of supporting real-time advisory needs in crop production, and they highlight several strengths that align with findings from recent research on AI-based agricultural systems. The stable operation throughout the 72-hour test period and the average response time of 1.3 seconds show that the system can function reliably under continuous use, a characteristic that earlier studies identified as essential for farmer-facing digital tools in rural environments with inconsistent connectivity [10]. The intent-recognition accuracy of 85 percent matches performance ranges confirmed by a previous report [11]. It has also been noted that NLP models in agriculture often face accuracy reductions when users employ informal language or local dialects [12]. The error patterns observed in this study, especially the effects of missing Vietnamese diacritics and region-specific crop protection terms, support those observations and suggest that linguistic variation remains a major challenge for NLP systems deployed in multilingual agricultural landscapes. The automation rate of 80 percent also aligns with the expectations outlined in similar chatbot applications, and it demonstrates that knowledge-based design can handle a large portion of routine queries without human oversight. The remaining errors involved multi-symptom descriptions or ambiguous conditions, and these cases underline the complexity of agricultural diagnosis when farmers describe multiple issues in a single message [13]. Overall, the technical evaluation indicates that the system can support real-time advisory tasks with stable operation, fast response, and practical automation. The main failure cases were associated with linguistic variation (missing diacritics and regional terms) and multi-symptom descriptions, which suggests that future work should focus on more robust language modeling and adaptive diagnostic strategies.

3.3. User testing and field evaluation with farmers

Field testing with 30 farmers produced clear evidence of the chatbot's practical value in real production settings. Over a two-week period, the system processed 431 valid queries. Questions related to pests and disease symptoms accounted for 38 percent of all interactions, questions related to pesticide dilution and mixing accounted for 32 percent, questions related to nutrient disorders and crop care accounted for 20 percent, and questions related to safety requirements and pre-harvest intervals accounted for the remaining 10 percent. The high frequency of pesticide-mixing queries showed that farmers often require precise operational guidance. Figure 4 presents an example of the system's output for pesticide dosage, spraying instructions, and safety notes and demonstrates the level of detail required by farmers during daily production activities.

User satisfaction results indicated positive experiences across several aspects of the system. The clarity of chatbot responses reached an average score of 4.4 on a five-point Likert scale. Usability reached 4.3, perceived usefulness reached 4.2, and overall satisfaction reached 4.3. Many participants described the stepwise structure as easy to follow and noted that the replies avoided conflicting information that they often encounter from informal sources. Disease-related queries produced the highest engagement. Figure 5 shows an example of the diagnostic output for rice blast, which includes image-based symptom cues and buttons that allow users to request additional explanations on disease expression and control measures. The ability to view images and select follow-up steps supported user comprehension, especially for farmers who preferred guided navigation rather than free-text queries.

Qualitative feedback revealed several consistent themes. Many farmers described the system as a reliable and convenient source of technical information and stated that the absence of commercial pesticide names increased their confidence in the recommendations [14]. Users also reported that the structured buttons and predefined options reduced the risk of entering incorrect information. The primary limitations involved situations where farmers described multiple overlapping symptoms in one query or asked questions that required region-specific interpretation [15]. These cases reduced the system's ability to provide a single definitive response. However, farmers indicated that the follow-up questions generated by the chatbot made it easier to refine their inputs. Our results showed that the system can address common information gaps in plant protection and that it offers a practical and accessible tool for farmers who require immediate and consistent technical guidance.

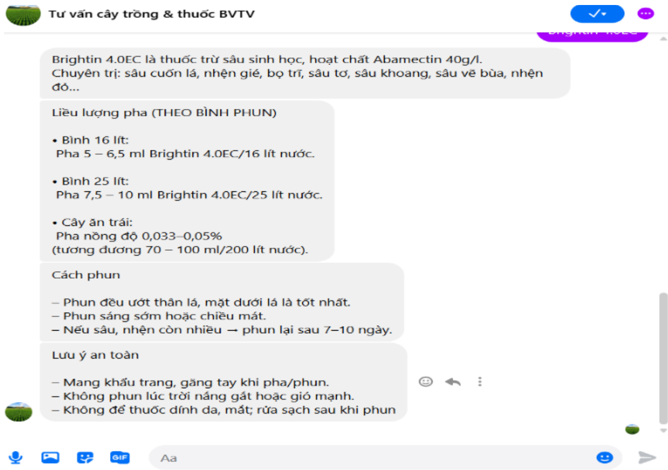

Figure 4. Example of chatbot output for pesticide dosage, application method, and safety instructions

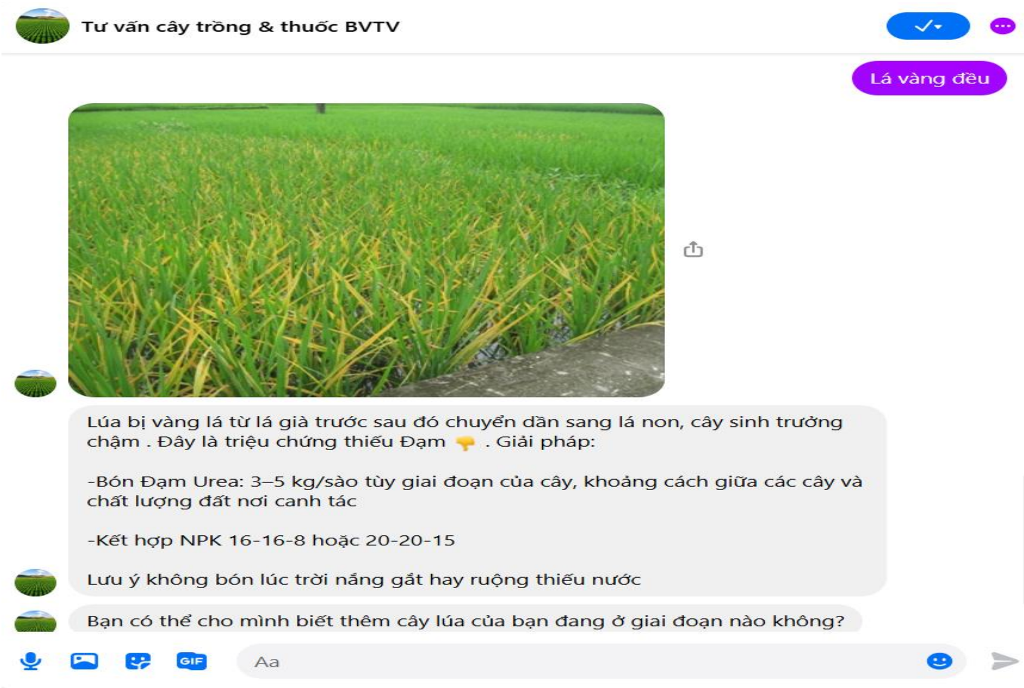

Figure 5. Detailed disease description and follow-up options generated by the chatbot during rice blast diagnosis

4. CONCLUSIONS

This study developed and evaluated an AI-supported chatbot designed to provide reliable guidance on pest diagnosis, nutrient management, and pesticide use within Vietnamese crop production systems. The system integrated Vietnamese natural language processing with a structured and expert-validated plant protection knowledge base. Technical evaluation showed that the chatbot reached an average response time of 1.3 seconds, an intent-recognition accuracy of 85 percent, and an automation rate of 80 percent, which demonstrates that the system can handle a large portion of routine agricultural queries with consistent performance. Field testing with 30 farmers and 431 queries confirmed that the chatbot addresses key information needs, particularly in pest identification and pesticide preparation, and that users report high levels of clarity, usability, and overall satisfaction.

The findings indicated that the chatbot can serve as a practical and accessible digital extension tool that supports farmers who require rapid and standardized technical information. The system also reduces reliance on informal sources that often provide conflicting or inaccurate guidance. Several limitations remain, particularly the difficulty of interpreting multi-symptom descriptions, region-specific terminology, and ambiguous input messages. These constraints point to areas where future development can focus on expanded symptom databases, more advanced language models, and image-based diagnostic tools. The study contributes a scalable framework for AI-assisted crop protection services in Vietnam and provides a foundation for the integration of more advanced capabilities that support sustainable and knowledge-based agricultural practices.

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