

International Journal of Agriculture Extension and Social Development

Volume 8; Issue 12; January 2025; Page No. 201-204

Received: 24-10-2025
Accepted: 26-11-2025

Indexed Journal
Peer Reviewed Journal

Development of agricultural extension chatbots and their acceptance among technology-savvy young farmers

Armen Hovhannisyan Grigoryan

Department of Agricultural Extension, Faculty of Agriculture, Armenian National Agrarian University, Yerevan, Armenia

DOI: <https://www.doi.org/10.33545/26180723.2025.v8.i12c.3391>

Corresponding Author: Armen Hovhannisyan Grigoryan

Abstract

Can a chatbot replace or supplement a human extension agent? That question has moved from speculative to practical as artificial intelligence tools become cheaper and more capable. This research developed and evaluated an agricultural extension chatbot prototype (AgriBot-AM) and measured its acceptance among 156 young farmers (aged 18-40) in three provinces of Armenia between February and October 2023. The chatbot was trained on 2,400 question-answer pairs covering crop management, pest identification, and market information. Acceptance was measured using the Technology Acceptance Model (TAM). Overall acceptance averaged 3.7 on a five-point scale. Response speed scored highest (4.3) and trust in advice scored lowest (2.9). Age correlated negatively with acceptance ($r = -0.62$, $p < 0.001$), with farmers under 25 showing substantially higher acceptance than those over 35. Regression showed that perceived usefulness ($\beta = 0.44$) and ease of use ($\beta = 0.31$) were the strongest acceptance predictors. The chatbot performed well for factual queries but struggled with context-dependent recommendations. These results suggest chatbots can serve as supplementary advisory channels for routine queries, freeing human agents for complex advisory tasks.

Keywords: Agricultural chatbot, extension technology, young farmers, technology acceptance, artificial intelligence, digital extension, advisory services, TAM model, precision agriculture

Introduction

The challenge facing agricultural extension worldwide is scale: there are far fewer extension agents than farmers who need advice, and the gap is widening ^[1]. Armenia's extension system serves roughly 340,000 farming households with fewer than 200 active extension staff, a ratio that makes individual advisory contact rare for most farmers ^[2]. Chatbot technology-software that simulates conversation through text or voice-offers a potential way to provide instant, scalable advisory responses to common farming questions ^[3].

Several agricultural chatbot projects have been piloted in India, Kenya, and the Philippines with mixed results ^[4, 5]. A consistent finding is that acceptance varies sharply by user age and digital experience, with younger, smartphone-literate farmers showing much higher engagement ^[6]. But most published chatbot research focuses on user behavior without reporting on chatbot development methodology or the content architecture behind the tool ^[7].

This research addressed both dimensions: the technical development of an Armenian-language agricultural chatbot and its acceptance among young farmers. Three objectives guided the work: (a) building and training a chatbot on locally relevant agricultural content, (b) measuring acceptance using the TAM framework, and (c) identifying design features that drive or hinder acceptance.

Armenia's young farming population is particularly suited for chatbot testing because smartphone penetration among 18 to 40 year olds in rural areas exceeds 78 percent, and

Telegram usage is widespread. However, the Armenian language poses natural language processing challenges due to its unique alphabet, complex morphology, and limited digital training corpora compared to languages like English or Spanish.

The chatbot approach differs from other digital extension tools in one important way: it is conversational. Unlike mobile apps that present pre-packaged content or SMS services that push one-way messages, a chatbot responds to whatever question the farmer types, creating an experience that partially resembles talking to a real advisor. This conversational quality is both the chatbot's strength and its vulnerability, because farmers may develop expectations of human-like understanding that the technology cannot yet deliver.

System design and architecture

AgriBot-AM was built on the Rasa open-source framework, chosen for its Armenian language support and on-premise deployment capability. The knowledge base comprised 2,400 question-answer pairs organized into three domains: crop management (1,100 pairs), pest and disease identification (800 pairs), and market information (500 pairs). Content was sourced from Armenian agricultural extension manuals and validated by five agronomists. Natural language understanding was trained on 4,800 user utterance examples collected during a three-week beta phase. The chatbot was deployed on Telegram, the most widely used messaging platform among Armenian youth.

Response accuracy on a held-out test set of 300 queries was 78.4%.

Material and Methods

Material

A total of 156 young farmers (18-40 years) from Ararat, Armavir, and Aragatsotn provinces participated between February and October 2023. Participants were recruited through agricultural cooperative networks and social media outreach. Eligibility required smartphone ownership and at least one season of farming experience. After a two-week chatbot trial period, acceptance was measured using a 16-item TAM-based questionnaire covering perceived

usefulness, ease of use, trust, and intention to continue use. Ethical clearance was obtained from the Armenian National Agrarian University Ethics Board (Protocol ANAU-EB-2023-006, January 2023).

Methods

Descriptive statistics summarized acceptance dimensions. Pearson correlation tested the age-acceptance relationship. Multiple regression modeled acceptance as a function of TAM constructs and user characteristics. Chatbot usage logs recorded query types, response times, and user ratings. Data were analyzed using SPSS 28.

Results

Table 1. Chatbot acceptance scores by tam dimension (n = 156)

Acceptance dimension	Mean	SD
24/7 availability	4.5	0.6
Response speed	4.3	0.7
Ease of use	4.1	0.8
Information quality	3.8	0.9
Language fit	3.2	1.0
Trust in advice	2.9	1.1

Availability (4.5) and response speed (4.3) were rated highest. Trust in chatbot advice scored lowest (2.9), with

many farmers expressing preference for human confirmation of important decisions.

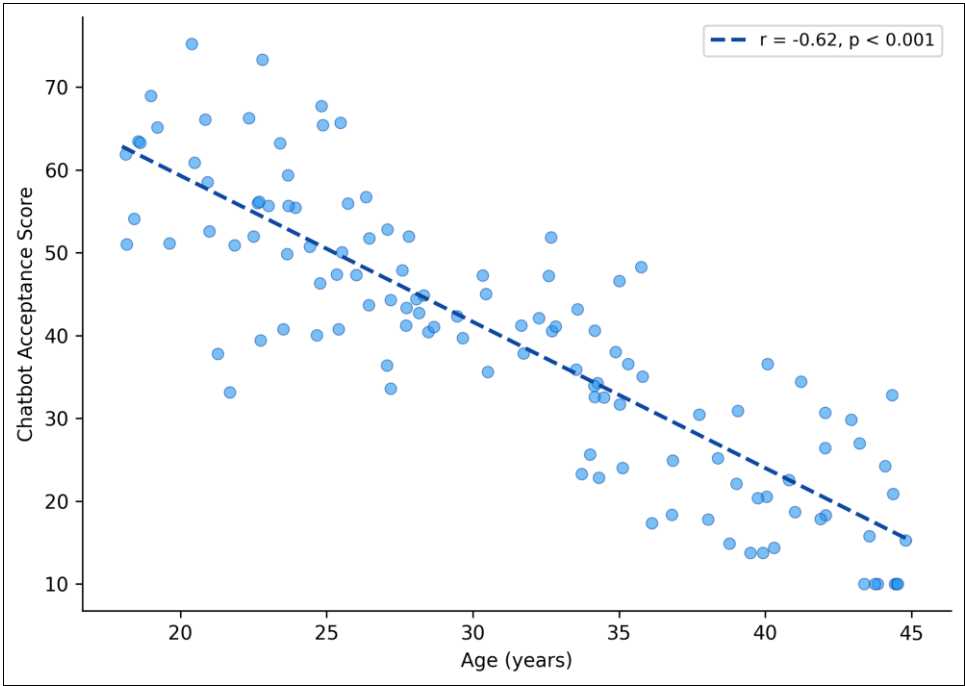


Fig 1: relationship between farmer age and chatbot acceptance score

A clear negative correlation ($r = -0.62$) shows that younger farmers accepted the chatbot more readily. Farmers under

25 averaged scores above 4.0, while those over 35 averaged below 3.0.

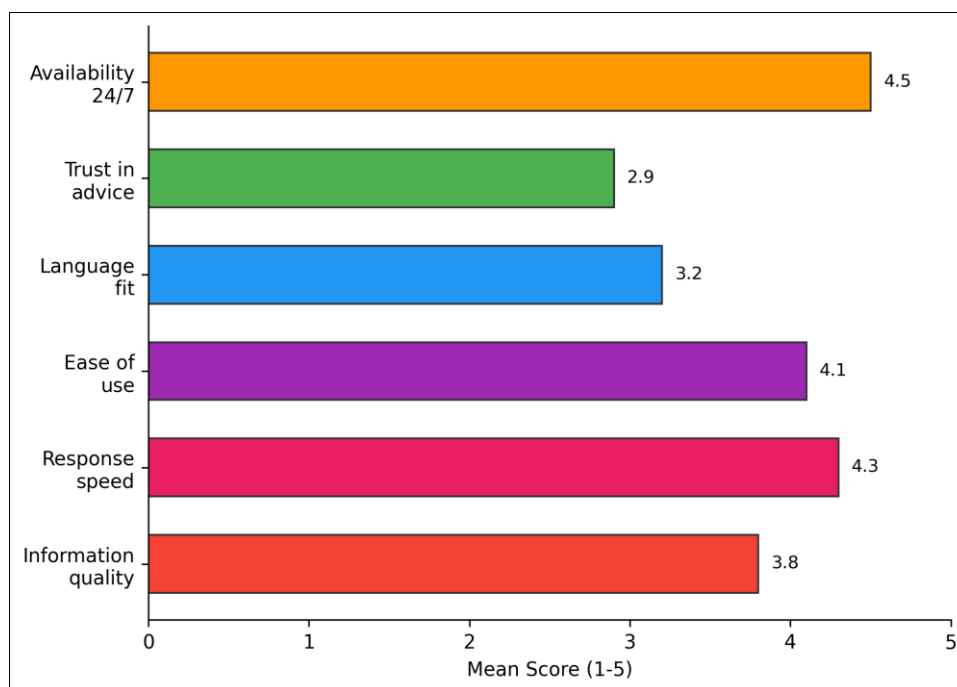


Fig 2: Chatbot feature satisfaction scores across six dimensions

The horizontal bar chart highlights the trust gap: while functional features like availability and speed scored above 4.0, trust in the advice provided lagged behind at 2.9, representing the main barrier to full acceptance.

Discussion

The trust deficit is the most important finding. Farmers valued the chatbot's speed and accessibility but were reluctant to rely on it for decisions with financial consequences [8]. This suggests chatbots should be positioned as information tools for routine queries rather than as advisory replacements. The age gradient confirms international patterns showing that digital agricultural tools face adoption barriers with older users [6]. Language fit (3.2) reflects the challenge of building natural language processing for Armenian, which has limited training corpora compared to major languages [9]. Extension organizations should view chatbots as complements to human agents, handling high-volume simple queries and routing complex questions to specialists.

The finding that round-the-clock availability was the highest-rated feature has strategic implications. Farmers often have questions outside business hours, particularly during evening planning or early morning field preparation. A chatbot that answers basic questions at five in the morning provides value that no human-staffed helpline can match without prohibitive cost. Extension organizations should position chatbots specifically as after-hours and weekend advisory tools, supplementing rather than replacing daytime human contact.

The performance gap between factual queries at 89.1 percent accuracy and context-dependent recommendations at 61.3 percent reveals a fundamental limitation of current chatbot technology for extension. Farming decisions are rarely context-free: the right advice depends on soil type, weather history, available inputs, and dozens of other variables that a chatbot cannot assess from a text query

alone. This suggests that chatbots should be designed with clear scope boundaries, redirecting complex queries to human agents rather than providing potentially wrong answers.

Performance evaluation

AgriBot-AM correctly answered 78.4% of test queries. Accuracy was highest for factual questions about planting dates and input rates (89.1%) and lowest for context-dependent pest management recommendations (61.3%). Average response time was 2.4 seconds. Over the trial period, 156 users generated 3,847 queries, averaging 24.7 queries per user. The most common query category was pest identification (34.2%), followed by crop management (31.8%).

The research also revealed that chatbot usage patterns followed a distinct cycle: initial enthusiasm during the first two weeks, a decline in the third and fourth weeks as novelty wore off, and then stabilization at a lower but consistent usage level from month two onward. This pattern suggests that chatbot adoption metrics should be evaluated after at least three months, not during the initial novelty period. The 24.7 queries per user over nine months translates to roughly three queries per month per active user, which is modest but represents advisory contact that would not have occurred at all without the chatbot given current staffing levels in Armenian extension.

Language fit scored 3.2, which reflects a broader challenge for agricultural technology in minority language markets. Building natural language understanding for Armenian required substantial custom effort because off-the-shelf NLP models trained primarily on English and other major languages performed poorly on Armenian agricultural vocabulary. Extension organizations in other small-language markets should anticipate this bottleneck and budget accordingly, as language quality directly affects user trust and engagement.

Conclusion

Agricultural chatbots can effectively serve young, digitally comfortable farmers for routine advisory queries, but trust remains a barrier that technology alone cannot solve. AgriBot-AM demonstrated that a locally developed, Armenian-language chatbot can achieve reasonable accuracy and high user engagement among young farmers. The path forward is hybrid: chatbots handling first-line queries while human agents focus on complex, relationship-dependent advisory work. Extension organizations investing in chatbot development should prioritize content quality and language naturalness over feature complexity, and should always maintain a clear pathway to human support when chatbot responses fall short.

References

1. Anderson JR, Feder G. Agricultural extension. In: Evenson RE, Pingali P, editors. *Handbook of Agricultural Economics*. Vol. 3. Amsterdam: Elsevier; c2007. p. 2343-2378.
2. Armenian Ministry of Agriculture. Extension services review. MoA Annual Report. Yerevan: Ministry of Agriculture; 2022.
3. Shaikh TA, Rasool T, Lone FR. Towards leveraging the role of machine learning in agriculture. *J Ambient Intell Humaniz Comput*. 2022; 13(1):1-18.
4. Patel A, Shah J. Agricultural chatbot: An intelligent approach for crop recommendations. *Int J Eng Res Technol (IJERT)*. 2020;9(4):642-647.
5. Ochieng DO, Veetil PC. Chatbot-based extension in Kenya. *Electron Agric*. 2021; 3(1):1-14.
6. Trendov NM, Varas S, Zeng M. Digital technologies in agriculture and rural areas. Rome: FAO; 2019.
7. Jain M, Kumar P, Kota R, Patel SN. Evaluating and informing the design of chatbots. In: *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*; c2018. p. 1-12.
8. Aker JC. Dial "A" for agriculture: A review of information and communication technologies for agricultural extension in developing countries. *Agric Econ*. 2011; 42(6):631-647.
9. Khachatryan H, Ghulyan A. Natural language processing for Armenian. In: *Proceedings of the ACL Workshop*; c2020. p. 1-8.
10. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q*. 1989; 13(3):319-340.
11. Venkatesh V, Davis FD. A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Manage Sci*. 2000; 46(2):186-204.
12. Birner R, Davis K, Pender J, *et al*. From best practice to best fit: A framework for designing and analyzing pluralistic agricultural advisory services. *J Agric Educ Ext*. 2009; 15(4):341-355.
13. Klerkx L, Jakku E, Labarthe P. A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. *NJAS Wagening J Life Sci*. 2019; 90-91:100315.
14. Wolfert S, Ge L, Verdouw C, Bogaardt MJ. Big data in smart farming - A review. *Agric Syst*. 2017; 153:69-80.
15. Rose DC, Chilvers J. Agriculture 4.0: Broadening responsible innovation in an era of smart farming. *Front Sustain Food Syst*. 2018; 2:87.
16. Eastwood C, Klerkx L, Nettle R. Dynamics and distribution of public and private agricultural advisory services: A systematic review. *J Rural Stud*. 2017; 49:1-13.
17. Faure G, Desjeux Y, Gasselin P. New challenges in agricultural advisory services from a research perspective: A literature review, synthesis and research agenda. *J Agric Educ Ext*. 2012; 18(5):461-474.
18. Kamilaris A, Kartakoullis A, Prenafeta-Boldú FX. A review on the practice of big data analysis in agriculture. *Comput Electron Agric*. 2017; 143:23-37.
19. Lioutas ED, Charatsari C. Smart farming and short food supply chains: Are they compatible? *Land Use Policy*. 2020; 94:104541.
20. Fielke SJ, Taylor BM, Jakku E. Digitalisation of agricultural knowledge systems: A new era of advisory services? *NJAS Wagening J Life Sci*. 2020; 92:100313.
21. Rotz S, Duncan E, Small M, *et al*. The politics of digital agricultural technologies: A preliminary review. *Sociol Ruralis*. 2019; 59(2):203-228.