AI-Powered Agritourism Chatbot: A Domain-Adapted RAG Chatbot with Transformer NLU for Rural Business Decision Support

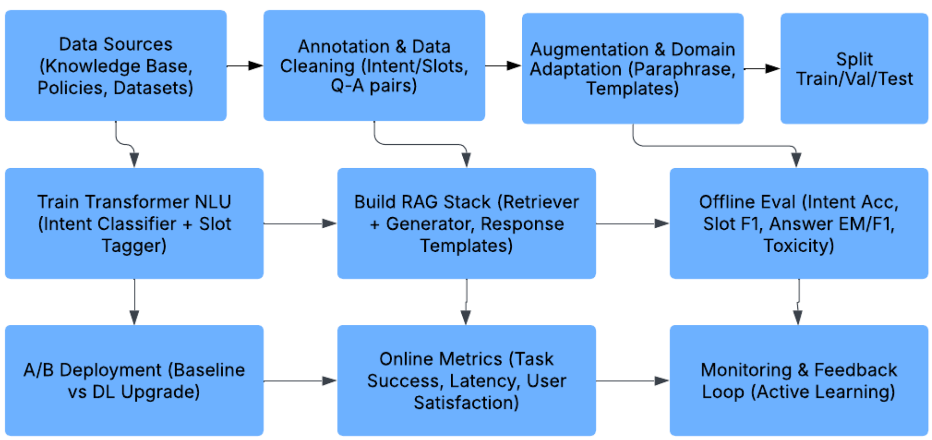
Small and mid-sized agritourism businesses face unique challenges: navigating regulations, planning operations, managing risk, and marketing with limited resources. I developed the AI-Powered Agritourism Toolkit, a decision-support system that delivers actionable, evidence-based guidance to farmers, ranchers, and rural development staff through a domain-adapted chatbot. Stage 1 (completed in summer 2025) integrates a retrieval-augmented generation (RAG) stack over curated agritourism datasets and routes successful queries to five functional modules: Business Planning, Marketing Strategy, Risk Management, Compliance Check, and Impact Assessment (Dong, 2025).

The current, ongoing Stage 2 describes and evaluates a deep-learning upgrade to the chatbot's natural language understanding (NLU) and response planning so it can handle more complex, multi-turn, and compliance-sensitive interactions (Perdana & Adikara, 2025). The upgrade adds: (1) a transformer-based intent classifier and slot tagger for agritourism domains (e.g., "insurance requirements for pumpkin patch with hayrides"), (2) a retrieval controller that composes multi-hop queries across heterogeneous sources, and (3) a policy/safety layer to filter responses for regulatory accuracy and risk-aware guidance (Pokhrel et al., 2025).

To train and adapt the models, I assembled a domain corpus from public regulations, state/county guidance, grant FAQs, and anonymized chat transcripts. I annotated intents and slots, create Q–A pairs, and used light paraphrasing to balance classes. The model stack combines a compact transformer for intents, a token-level tagger with CRF decoding for slots, and an RAG pipeline with dense retrieval and instruction-tuned generation. Figure 1 demonstrates the system and the training/evaluation/deployment workflow.

Figure 1

Training, Evaluation, and Deployment Workflow for the Domain-Adapted Chatbot



Evaluation mixes offline metrics (intent accuracy, slot F1, exact-match/F1 for answers, and toxicity/grounding checks) with field testing in Extension settings (task success rate, latency, user satisfaction from field pilots with agritourism partners). I compared the Stage-1 baseline (rule/NLU-lite + RAG) against the DL upgrade in A/B tests and reported ablations on retrieval depth, policy filters, and prompt templates. Early results indicate faster, more reliable answers on compliance-sensitive queries.

Designed for underserved rural communities, the project packages machine learning into an accessible assistant that shortens time-to-answer and improves decision quality. Although the current deployment centers on agritourism, the architecture is intentionally general: domain-specific NLU, safety-aware RAG, and evaluation tied to real user tasks. This recipe transfers directly to other Extension contexts, including small-business advising, food systems, and outdoor recreation.

References:

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Pokhrel, S., K C, B., & Shah, P.B. (2025). A Practical Application of Retrieval-Augmented Generation for Website-Based Chatbots: Combining Web Scraping, Vectorization, and Semantic Search. *Journal of Trends in Computer Science and Smart Technology*. *6*(4): 424-442