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Ontology-Based Decision Support for Young Agripreneurs in Organic Agriculture Using Semantic Web Rule Language

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Received: 12-12-2025 **Revised:** 01-30-2026 **Accepted:** 02-02-2026

Citation: Chiangnangam, S., Kabmala, M., & Chansanam, W. (2026). Ontology-based decision support for young agripreneurs in organic agriculture using Semantic Web Rule Language. *Org. Farming*, *12*(1), 30–50. https://doi.org/10.56578/of120103.

Abstract: The rapid growth of organic agriculture has created both opportunities and challenges for young agripreneurs, who should navigate certification standards (e.g., Thai Organic and the European Union Organic), compliance requirements, and market-specific documentation for domestic and international trade. This study aims to design and implement an ontology-driven decision support system (DSS) that leverages Semantic Web Rule Language (SWRL) to provide transparent and context-specific recommendations for organic farming. Having adopted a design-and-development approach, the research collected data from 50 agripreneurs and integrated these insights into an ontology framework enriched with rule-based reasoning. Five structured sets of recommendation rules were developed to link organic products, target markets, certification standards, certifying agencies, certification services, and required supporting documents while their performance was evaluated using standard information retrieval metrics. Evaluation based on case-based rule validation indicated that the system returned no false positives across the tested scenarios (100% precision), with an average recall of 93.03% and an overall F-measure of 96.39%, thus demonstrating strong logical correctness and practical applicability within the defined evaluation scope. The study concluded that embedding SWRL-based "IF–THEN" recommendation rules within ontological structures could effectively bridge fragmented regulatory and market knowledge and actionable decision making, in order to offer agripreneurs a scalable and explainable tool to manage certification and market access. The significance of this work lies in its dual contributions: theoretically, it demonstrates how semantic technologies could advance knowledge-to-decision processes in agriculture; practically, it provides structured guidance to support certification compliance and market participation in organic farming.

Keywords: Ontology-based decision support; Semantic Web Rule Language; Organic agriculture; Knowledge representation; Agripreneurs

1. Introduction

Global food systems are under unprecedented pressure: the organic market alone has surpassed $100 billion annually, yet young agripreneurs entering this sector continue to face complex knowledge barriers that undermine sustainable growth (Willer et al., 2023). How can digital technologies help resolve this paradox? Consumers demand environmentally responsible and chemical-free products, but farmers must navigate technical expertise, certification procedures, and market uncertainties (IFOAM, 2024). At the same time, the proliferation of Internet of Things (IoT) devices, semantic frameworks, and infrastructure of digital knowledge has generated vast amounts of data. The critical challenge lies not in generating data, but in translating it into applicable and context-sensitive knowledge that supports long-term sustainability and competitiveness.

Previous research offered partial but important solutions. Early decision support system (DSS) demonstrated the value of computational reasoning in transforming distributed data into structured guidance (Power, 2002; Shim et al., 2002). Ontologies and semantic frameworks further advanced this field, in order to provide standardized vocabularies and rule-based inference for agriculture (Noy & McGuinness, 2001; van Harmelen et al., 2008). Crop-specific models, such as ontology-driven decision support for rice and viticulture, show how domain knowledge could be formalized into machine-readable structures (Afzal & Kasi, 2019; Afzal et al., 2021;

Mouakher et al., 2020). Similarly, semantic frameworks for IoT interoperability and adaptive livestock services highlight the potential for integration across contexts (Kamilaris et al., 2016; Seydoux et al., 2017; Tomic et al., 2014; Tomic et al., 2015). Yet, many of these contributions remain confined to prototypes or narrow domains, often prioritizing feasibility over durability and generalizability.

In parallel, the latest strands of research focus on responsiveness and sustainability. Digital-twin infrastructures, supported by cloud–fog–edge architectures, enable dynamic decision making for crop systems but often under-specify the knowledge representation layer necessary for explainable and auditable recommendations (Kalyani et al., 2024). Continuous learning approaches to information extraction show technical promise but have been insufficiently validated in agricultural practice (Lin et al., 2020). Studies of sustainability provide measurable outcomes, such as soil carbon fractions and reduction of greenhouse gas (Hwang et al., 2022; Kim et al., 2025), but they are rarely integrated with semantic decision frameworks. Meanwhile, case studies about integrated and organic farming emphasizes tacit and context-specific knowledge that ontologies often fail to capture (Dhivya & Karthikeyan, 2021), while knowledge management frameworks highlight the socio-technical factors influencing adoption among emerging farmers (Buitendag & Hattingh, 2024). Collectively, these kinds of research reveal thematic gaps in aspects such as: semantic integration without evaluation of long-term sustainability, operational responsiveness without explainability, and socio-technical frameworks without direct linkage to ontology-driven reasoning.

This study examined how ontology-based decision support, operationalized through the Semantic Web Rule Language (SWRL-based "IF–THEN" recommendation rules), could bridge these gaps by incorporating structured, explainable, and context-aware recommendation rules for organic agripreneurs. By synthesizing insights from semantic interoperability frameworks (Kamilaris et al., 2016; Seydoux et al., 2017), domain-specific ontologies (Afzal & Kasi, 2019; Afzal et al., 2021; Mouakher et al., 2020), and benchmarks of sustainability (Hwang et al., 2022; Kim et al., 2025), the research developed a flexible decision-support approach that is both human-centered and transferable.

While prior studies have demonstrated the potential of ontologies and semantic technologies in agricultural decision support, many existing systems focused primarily on knowledge representation, semantic interoperability, or sensor integration, with limited support for expressive rule-based reasoning and decision logic (Kamilaris et al., 2017; Seydoux et al., 2017). As a result, structured domain knowledge is often not operationalized into actionable recommendations for users, particularly in regulatory and certification-oriented decision contexts (Miller et al., 2024). This study addressed this gap by integrating an ontology-based knowledge model with SWRL to support transparent and context-aware decision-making for young agripreneurs.

2. Literature Review

2.1 Decision Support System in Agriculture

DSS have long been applied in agriculture to support farmers and stakeholders in managing complex decisions related to production, resource allocation, and risk management. Early agricultural DSS primarily targeted operational decisions at the farm level, such as crop planning, irrigation scheduling, pest management, and yield optimization often relying on statistical models, simulation techniques, or sensor-derived data (Janssen & van Ittersum, 2007; Power, 2007). With increased availability of data and computational capacity, more recent systems have incorporated machine learning and data-driven analytics to enable predictive functions, including yield forecasting, disease detection, and assessment of climate impact (Kamilaris et al., 2017). From a data and knowledge management perspective, agricultural DSS are commonly categorized as data-driven, model-driven, or knowledge-based (Power, 2007). Data-driven systems emphasize predictive performance but often function as black boxes with limited explainability, while model-driven systems support scenario exploration yet may struggle to adapt to evolving regulatory and market conditions. Knowledge-based DSS, by contrast, leverage explicit domain knowledge such as rules, standards, and expert knowledge to enable structured and transparent reasoning, rendering them particularly suitable for compliance- and policy-oriented contexts.

Despite these advances, comparatively little attention has been paid to DSS that support regulatory and certification-oriented decision making in agriculture, such as organic certification and market compliance. Existing systems largely prioritize production efficiency, environmental monitoring, or yield optimization whereas the processes of decision remain fragmented and knowledge intensive as they involve certification standards, certifying agencies, documentation requirements, and service workflows. In this context, recommendation-oriented functionalities become relevant with decision logic translated into actionable guidance for users. Recommendation systems are often regarded as a functional component or subclass of DSS in knowledge-intensive domains where users require concrete suggestions (Ricci et al., 2022). While collaborative filtering, content-based filtering, and hybrid approaches have proven effective in domains like e-commerce, they depend heavily on historical behavior or patterns of similarity and offer limited support for explicit reasoning, regulatory constraints, and explainability. In agriculture, recommendation systems have been applied mainly to crop selection, pest management, and market linkage (Chatterjee & Kar, 2018). However, organic agriculture presents additional complexity because agripreneurs should comply with stringent certification rules and documentation requirements (IFOAM, 2020), which cannot be adequately addressed by preference-based or purely statistical approaches.

To address these gaps, this study embedded recommendation mechanisms within an ontology-based DSS architecture that operationalizes certification knowledge through SWRL rules. Rather than prioritizing predictive accuracy, the proposed framework emphasized rule-based reasoning, transparency, and traceability to support compliance-oriented decision making in organic agriculture. By formalizing relationships among standards, agencies, services, and required documentation, the system enabled comprehensible and context-sensitive recommendations grounded in explicit domain knowledge. In doing so, the study contributes a knowledge-driven DSS approach that complements existing data- and model-driven systems and extends agricultural decision support toward regulatory and certification domains where interpretability and justification are essential.

2.2 Ontology-Based Decision Support in Agriculture

This section reviews ontology-based approaches in the context of DSS and clarifies the role of recommendation mechanisms as functional components within such systems. In ontology-driven DSS, ontologies provide a formalized representation of domain knowledge that supports structured reasoning, semantic interoperability, and explainable decision logic. When recommendation mechanisms are embedded within this architecture, they operationalize ontological knowledge into actionable guidance for users. Accordingly, recommendation functionalities in this study were conceptualized not as standalone systems but as decision-support capabilities grounded in ontology-based knowledge modelling and rule-based inference. In computer science, an ontology is defined as a formal and explicit specification of a shared conceptualization of a domain that enables machine-interpretable representation of concepts and relationships (Gruber, 1993). Within agriculture, ontologies have been widely applied to structure domain knowledge, facilitate semantic interoperability, and integrate sources of heterogeneous data across farming activities (Buhl et al., 2024).

Most existing agricultural ontologies have concentrated on production-oriented knowledge, including crops, soil, climate conditions, pests, and farming practices. Examples include crop and soil ontologies for farm management, precision agriculture, and environmental monitoring, as well as semantic models that support integration of sensor data and agricultural data exchange. While these ontologies have demonstrated value for knowledge representation and interoperability, their application often remains descriptive or data-centric, with comparatively limited support for rule-based reasoning and decision support. Web Ontology Language (OWL) alone presents limitations for conditional reasoning when complex logical rules are required. To address this constraint, the SWRL extends OWL by combining Description Logic with Horn Logic, thus enabling the formulation of explicit "IF–THEN" rules that enhance reasoning expressiveness and domain representation (Horrocks et al., 2004). The integration of ontology modelling with rule-based reasoning has been proven to improve the accuracy, transparency, and explainability of recommendation outcomes (Ristoski & Paulheim, 2016).

Ontology-driven recommendation approaches have been applied to align user profiles with relevant resources of knowledge, such as matching farmer profiles with crop requirements or linking certification standards to supporting documents (Di Noia et al., 2012). Such approaches are particularly valuable in knowledge-intensive domains, such as education, healthcare, and agriculture, where context awareness and explainability are critical (Fernández et al., 2011). Although recent ontology-based systems have increasingly incorporated reasoning to support decisions such as crop selection or resource management, most remain focused on operational or predictive contexts and rarely address regulatory or certification-oriented decisions. Processes of decision related to certification standards, certifying agencies, service workflows, and required documentation are frequently treated as peripheral or handled through non-semantic means. This study addressed that gap by proposing an ontology-based DSS that explicitly modelled certification and market-compliance knowledge and integrated SWRL to enable explainable and rule-based inference. By operationalizing regulatory knowledge into actionable decision logic, the proposed framework positioned ontology-driven reasoning as a central mechanism for compliance-oriented decision support in organic agriculture, in order to integrate ontology modelling, rule-based reasoning, and recommendation output within a unified DSS architecture.

2.3 Reasoning in Ontology-Based Decision Support System

Reasoning mechanisms play a central role in ontology-based DSS by enabling inferred knowledge, consistency checking, and explainable decision logic based on formally represented domain knowledge. SWRL is a logic-based rule language that extends OWL ontologies by incorporating Horn rules to support conditional reasoning and inference (Horrocks et al., 2004). A key strength of SWRL lies in its ability to define conditional rules that operate in conjunction with ontology-based knowledge, particularly in scenarios requiring domain-specific inference. Among available reasoning approaches for ontology-based DSS, rule-based reasoning has been widely adopted to support explicit condition–action logic, particularly in domains where decisions must be justified against formal standards and regulations. Prior studies have demonstrated the utility of SWRL in diverse contexts, such as medical decision support (O'Connor & Das, 2011), smart city energy management (Recent studies have demonstrated the applicability of SWRL-enabled reasoning across multiple domains, including ontology-driven clinical DSS that integrate rule-based inference for healthcare knowledge representation and patient care decision processes (Jing et al., 2023), ontology-based semantic reasoning framework to resolve semantic heterogeneity in Open Platform Communications Unified Architecture (OPC UA)-enabled industrial IoT environments by transforming device information into Resource Description Framework (RDF)-based knowledge structures. The approach demonstrates how ontology-driven inference supports accurate data integration and improves decision-support capabilities in smart manufacturing systems (Bi et al., 2025), and semantic reasoning models in smart learning environments that enable adaptive and context-aware educational decision support (Sarwar et al., 2018). These contemporary applications highlight the flexibility of SWRL in enabling transparent, rule-based inference within ontology-driven decision support environments across heterogeneous domains and adaptive learning systems in education.

Rules in OWL and SWRL significantly extend the expressive power of ontologies by enabling the specification of detailed logical relationships. Typically, rules adopt an "IF–THEN" format: if the antecedent conditions hold, the consequent must also hold (Horrocks et al., 2004; Ponciano et al., 2024). This rule-based paradigm has been widely recognized in recent semantic web and ontology engineering research as an effective mechanism for representing complex logical constraints and enabling inference beyond standard ontology axioms, thereby enhancing reasoning capability and semantic interoperability in knowledge-based systems (Reda et al., 2022). Formally, a rule can be represented as Antecedent ⇒ Consequent, where both components consist of conjunctions of atoms, including class membership assertions, object property relationships, equality or inequality comparisons, and built-in functions. To ensure logical safety and correct execution, SWRL imposes a safety condition requiring that every variable appearing in the consequent must also appear in the antecedent, thereby preventing the introduction of unbound variables and maintaining reasoning consistency within ontology-driven decision support environments.

In agriculture, SWRL has been applied in modelling prediction of plant disease (Alharbi et al., 2024), irrigation management (Nisa et al., 2024), and decision making in farm management. These applications demonstrate the potential of SWRL to connect ontological knowledge with actionable recommendations. However, research focusing on the use of SWRL for organic certification remains limited, thus revealing a notable gap in the current body of knowledge.

Although recommendation systems are increasingly employed in agriculture, most remain grounded in statistical data and lack capabilities of semantic reasoning. Ontology-based systems, while effective for structured knowledge representation, could not fully capture the complexity of organic certification standards without an accompanying rule-based reasoning layer. SWRL addresses this gap by encoding conditional rules that link classes, properties, and requirements of certification, thus allowing systems to automatically generate recommendations aligned with intricate standards and regulations.

This study was grounded in three complementary foundations for ontology-based decision support: (1) DSS for agricultural decision making; (2) ontology-based knowledge representation to formalize and integrate fragmented domain knowledge; and (3) rule-based semantic reasoning to operationalize domain expertise into transparent decision logic. By integrating these foundations, the study developed an ontology-driven DSS that generated explainable recommendations for organic agriculture, specifically supporting young agripreneurs in navigating certification and market-access requirements through structured reasoning over standards, agencies, services, and required documentation. In this architecture, ontological modelling provided a formal structure for representing domain knowledge, while rule-based reasoning enables context-sensitive inference and traceable decision logic.

Prior research has shown that reasoning over agricultural ontologies could enable practical decision support, particularly where expert knowledge could be encoded as explicit rules. For instance, ontology-driven systems have been proposed for crop and plant disease decision support, where OWL combined with SWRL-based reasoning infer diagnoses or management actions from observed symptoms and contextual conditions. Other ontology models support transparent decision making in controlled farming environments, such as aquaponics and vertical farming, where semantic representations of environmental parameters are evaluated through scenario-based reasoning. Beyond agriculture-specific applications, research on explainable ontology-based intelligent DSS highlighted the importance of explicit knowledge structures and reasoning for transparency, traceability, and justification in complex decision principles that were highly relevant to regulatory and compliance-oriented domains.

Nevertheless, reasoning-enabled semantic applications in agriculture are predominantly concentrated on production and resource management. Comparatively fewer studies operationalize regulatory knowledge related to organic certification, market linkage, and documentation workflows even though these processes are highly knowledge intensive and critical for agripreneurs. Addressing this gap, the present study contributes a reasoning-centred and ontology-based DSS that explicitly models certification and market-compliance knowledge and translates it into actionable recommendations. By focusing on certification and market-access pathways rather than optimization of production, the proposed framework extended the scope of agricultural semantic DSS and positioned ontology-driven reasoning as a central mechanism for compliance-oriented decision support in organic agriculture.

3. Methodology

This research adopted a design-and-development approach to build a recommendation system grounded in ontology and logical rules. The methodology drew on the principles of Knowledge Representation and Rule-Based Reasoning (Berners-Lee et al., 2001; Noy & McGuinness, 2001), which provide a formal foundation for structuring domain knowledge and enabling logical inference through explicitly defined semantic relationships. In addition, the study was conceptually aligned with the DSS framework (Power, 2002) to ensure that the developed system supports structured decision-making processes among organic agripreneurs. Recent research further underscores the continued relevance of ontology-based knowledge representation combined with rule-based reasoning in enhancing knowledge formalization, semantic interoperability, explainability, and automated reasoning in intelligent decision-support environments (Bi et al., 2025; Jing et al., 2023; Ponciano et al., 2024; Reda et al., 2022). In operational terms, decision logic was implemented through SWRL-based IF–THEN recommendation rules (hereafter referred to as SWRL recommendation rules), which encoded domain-specific conditions and corresponding outcomes to enable ontology-driven inference and generate context-aware recommendations.

3.1 Requirement Analysis and Data Collection

This phase focused on identifying the problems and information needs of young agripreneurs through a user-centred analysis (Norman, 2013). Wilson (1999)'s information-seeking behavior model which emphasized need recognition, information search, use, and access barriers, etc. guided the investigation of how agripreneurs sought and applied knowledge in organic farming contexts. The requirement analysis aimed to ensure that decisions on the system design were grounded in authentic user contexts and real-world decision challenges related to organic certification and market access.

Participants were recruited using a purposive convenience sampling approach that combined purposive selection of information-rich cases with considerations of practical accessibility (Etikan et al., 2016). This strategy is widely used in exploratory and design-oriented research to ensure that respondents possess relevant domain knowledge rather than to achieve statistical representativeness. Recruitment was facilitated through local agricultural networks and extension contacts, targeting young agripreneurs actively engaged in organic farming and related business activities. Using a structured questionnaire, data were collected from 50 organic agripreneurs aged 18 to 45 with 1 to 5 years of business experience; the questions asked included information-seeking behavior, access barriers, and knowledge requirements related to operations of organic farming. The sample size was considered appropriate for requirement analysis, in which the objective is to capture diverse user needs and practical constraints rather than to represent the broader farming population.

The findings from the requirement analysis were used exclusively to inform system design, particularly ontology modelling and the formulation of SWRL recommendation rules that translate domain knowledge into decision logic. Results of the survey guided the identification of core ontology classes such as products, standards, agencies, services, and documents as well as the specification of rule conditions used to generate recommendations under different user contexts. The analysis was not intended to support population-level inference, such as estimating the prevalence of certain needs among all organic farmers. For instance, the data were not used to claim that a given proportion of agripreneurs required a specific certification; instead, they ensured that the ontology and SWRL recommendation rules reflected realistic decision scenarios encountered by practitioners. This design-oriented use of empirical data aligns with the exploratory and knowledge-driven objectives of the study.

3.2 Review of the Developed Ontology

An initial ontology prototype was developed as part of the present research rather than reusing a previously published ontology. The initial prototype was constructed by synthesizing findings from the requirement analysis, relevant literature on organic agriculture and certification, and domain documentation from certification bodies. Core ontology classes such as *Product*, *Market*, *Standard*, *Agency*, *Service*, and *Document* were first identified to capture the main elements of decision faced by young agripreneurs.

The ontology was subsequently refined through iterative analysis to better support rule-based reasoning and generation of recommendations. Refinement involved restructuring class hierarchies, defining object properties, and introducing intermediate classes to support inference. For example, early versions directly linked *Product* and *Standard* classes; however, based on user requirements indicating the need for context-sensitive guidance, an intermediate *Standard Recommendation* class was introduced. This refinement allowed SWRL recommendation rules to infer appropriate standards based on combinations of user-specific conditions, such as target markets and certification services, thereby enabling more flexible and interpretable recommendations. Through this process, the ontology evolved from a conceptual representation into a reasoning-ready knowledge model supporting context-aware decision support.

This stage concentrated on refining and applying SWRL rules to recommend information according to user-specific conditions. The ontology classes, particularly intermediate classes linking user requirements with relevant standards, were reviewed to ensure their suitability (Chansanam & Tuamsuk, 2016). Outcomes of SWRL reasoning were then instantiated in these classes to enable dynamic and rule-driven recommendations. Ontology classes and relationships were iteratively refined based on dominant information needs identified in the user survey, to ensure alignment between empirical findings and semantic modelling decisions. While the ontology was instantiated with individuals during reasoning and querying, the primary contribution of this study lies in the ontology-based knowledge model and its rule-driven inference mechanisms, rather than in the construction of a standalone knowledge graph.

3.3 Rule Structuring and Grouping

To enhance flexibility and maintainability, the research employed the concept of modular rule design (van Harmelen et al., 2008). Rules were organized into coherent groups and hierarchies, to create a clear organizational structure that facilitates future management, maintenance, and extension of the rule base. For clarity and consistency, standardized terminology was used throughout the manuscript to refer to ontology components, SWRL recommendation rules, and evaluation metrics, and the same naming conventions were applied across the main text, figures, and tables.

3.4 Rule Formulation

SWRL is a World Wide Web Consortium (W3C)-submitted rule language that extends OWL with Horn-like rules, to enable conditional reasoning over ontology classes, properties, and individuals (Horrocks et al., 2004). SWRL was selected in this study because organic certification and market-access guidance required explicit and explainable “IF–THEN” logic (e.g., mapping product–market conditions to applicable standards, agencies, services, and required documents) that was difficult to express using ontology hierarchies alone. Compared with purely statistical approaches, SWRL supported transparent inference, traceability of recommendations, and direct alignment with regulatory knowledge structures, i.e., features that are essential for decision support in compliance-oriented domains.

Rule formulation was carried out with Rule-Based Reasoning techniques to match user profiles with domain knowledge represented in the ontology. SWRL recommendation rules were encoded using SWRL and executed by an OWL-compatible reasoning engine. Following rule execution, SPARQL queries were used to retrieve inferred knowledge from the ontology for semantic retrieval and evaluation (Russell & Norvig, 2020).

Rule execution and semantic retrieval were supported by a standard Semantic Web software stack. SWRL recommendation rules were executed with an OWL-compatible reasoning engine that supported SWRL inference, specifically Pellet reasoner, within the Protégé environment. Following rule execution and ontology inference, results of recommendation were retrieved using SPARQL Query Aissued against the inferred ontology model. This combination of SWRL-based reasoning and SPARQL-based querying enabled the system to separate logical inference from information retrieval, thereby supporting transparent and reproducible evaluation of recommendation outcomes.

3.5 Rule Testing and Evaluation

To ensure transparency and reproducibility of the evaluation process, each set of recommendation rules was tested with a defined number of case-based scenarios derived from real-world agripreneur contexts. Specifically, Rule Set 1 (*Products*, *Markets*, & *Standards*) was evaluated with 6 test scenarios, Rule Set 2 (*Standards* & *Agencies*) with 11 scenarios, Rule Set 3 (*Condition Types*, *Standards*, & *Conditions*) with 26 scenarios, Rule Set 4 (*Services* & *Agencies*) with 17 scenarios, and Rule Set 5 (*Services* & *Documents*) with 6 scenarios. Each scenario represents a distinct combination of user conditions and information needs commonly encountered by young agripreneurs during certification and market-access decision making. A total of 66 evaluation scenarios were used to assess the logical correctness, coverage, and retrieval effectiveness of the SWRL-based recommendation rules. These scenarios were designed to reflect realistic decision cases rather than synthetic or randomly generated inputs, thereby supporting the practical validity of the evaluation.

The evaluation adopted a case-based validation approach, consistent with prior research on ontology-driven and rule-based DSS. The test scenarios were derived from empirical user data collected during the requirement analysis phase and they could reflect realistic decision situations encountered by young agripreneurs. As the primary objective of this study was to verify the logical correctness, completeness, and practical applicability of the SWRL recommendation rules, the evaluation did not involve an independent hold-out dataset beyond the design cases. Instead, validation focused on confirming that the rules consistently produced correct and interpretable recommendations across a diverse range of scenarios. This approach is appropriate for early-stage semantic system development, where the emphasis lies on the validity of reasoning and knowledge consistency rather than predictive generalization. The reported precision reflects logical correctness within a bounded set of rule-based scenarios rather than statistical generalization performance, and should be interpreted accordingly.

Although the evaluation scenarios were grounded in empirical data collected from young agripreneurs during the requirement analysis phase, the execution of queries and rule testing was conducted by the researchers rather than by the participants themselves. The role of the agripreneurs was limited to providing domain insights and real-world contexts that informed the construction of representative test cases. During the evaluation phase, SPARQL queries were systematically executed against the inferred ontology to verify whether the SWRL recommendation rules produced correct and logically consistent recommendations for each scenario. This separation ensured controlled and repeatable evaluation of rule performance while maintaining alignment with real-world decision contexts.

The formulated rules were tested through real-world case studies involving young agripreneurs. Evaluation followed standard information retrieval metrics, namely Precision and Recall (Cleverdon, 1967) to measure accuracy and completeness of the retrieved recommendations. The F-measure (van Rijsbergen, 1979) was computed as a harmonic mean of these metrics to provide an integrated assessment of system performance. Based on these definitions, the evaluation metrics were calculated using Eqs. (1)–(3).

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100\% \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \tag{2}$$

$$F - \text{measure} = \frac{\text{Precision} \times \text{Recall} \times 2}{\text{Precision} + \text{Recall}} \tag{3}$$

where, TP = the number of retrieved items that are relevant (true positives), FP = the number of retrieved items that are not relevant (false positives), and FN = the number of relevant items that were not retrieved (false negatives).

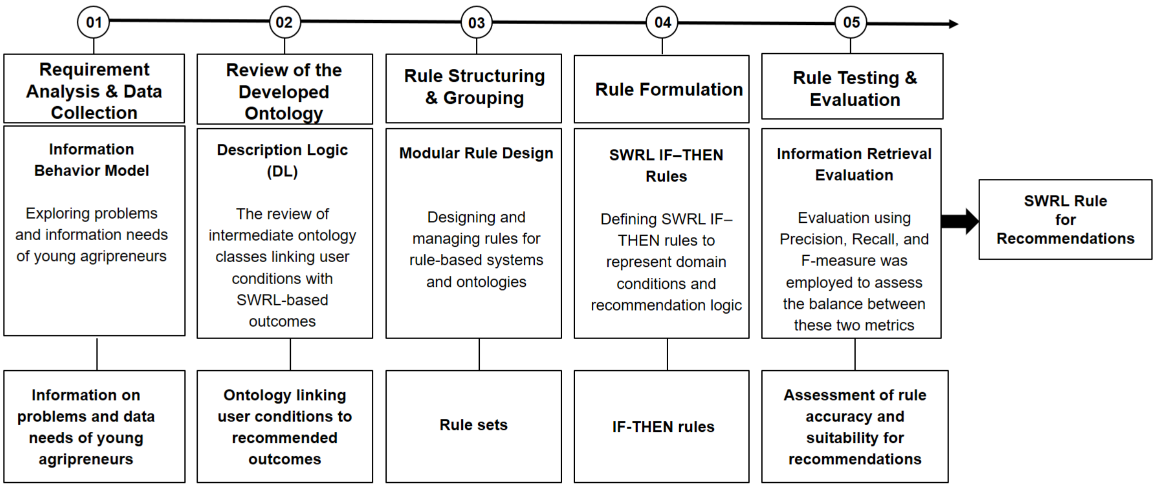

Figure 1. Research conceptual framework

Figure 1 illustrates a five-phase conceptual framework for developing SWRL-based recommendation rules for young agripreneurs, progressing from requirement analysis to final rule evaluation. The process includes requirement analysis and data collection, ontology review using Description Logic, modular rule structuring and grouping, and formal rule formulation as SWRL IF–THEN rules. The final phase evaluates the rules using precision, recall, and F-measure, alongside suitability checks, culminating in validated SWRL recommendation rules. The workflow is informed by prior studies (Cleverdon, 1967; van Harmelen et al., 2008; van Rijsbergen, 1979; Wilson, 1999).

3.6 Implementation of Environment and Experimental Setup

The ontology was implemented via the OWL and developed in the Protégé ontology editor (v5.5), which supported ontology modelling, SWRL rule authoring, and integration of reasoning. SWRL recommendation rules were encoded directly within the ontology using Protégé's SWRLTab, which enabled rule-based inference over class hierarchies, object properties, and individual instances. The implementation adopted a standard Semantic Web software stack that deliberately separated logical inference from the retrieval of information. SWRL recommendation rules were executed using an OWL-compatible reasoning engine that supported SWRL inference, specifically Pellet reasoner, integrated within the Protégé environment. Once the ontology was instantiated, the reasoning process was triggered to infer new relationships and generate recommendation outcomes based on user-defined conditions and formal domain rules.

Following rule execution and ontology inference, SPARQL queries were applied to the inferred ontology model to retrieve recommendation results in a structured and verifiable manner. This design reflected the complementary roles of SWRL and SPARQL: SWRL generated inferred knowledge through rule-based reasoning whereas SPARQL was optimized for querying and inspecting ontology states. By decoupling reasoning from retrieval, the system enhanced transparency, facilitated debugging and evaluation of inferred results, and supported reproducible assessment of recommendation outcomes without embedding retrieval logic directly into definitions of rules. The reasoning and querying components were selected to ensure compatibility with OWL and SWRL standards and to support reproducible semantic inference workflows.

The experimental setup employed a case-based evaluation design in which each test case represented a realistic decision scenario derived from agripreneur profiles, including specified products, target markets, certification services, and regulatory conditions. For each scenario, SPARQL queries were issued against the inferred ontology to retrieve recommended standards, agencies, services, and supporting documents. The retrieved results were compared with expected outcomes defined by domain knowledge and certification guidelines to determine true positives, false positives, and false negatives. This implementation and evaluation strategy ensured that system performance reflected logical correctness and semantic consistency rather than statistical prediction accuracy, which was appropriate for ontology-driven and rule-based DSS focused on transparent and explainable reasoning. To support transparency and reproducibility, the implementation environment and evaluation procedure were explicitly documented. The ontology developed in this study was maintained by the authors and available upon reasonable request for verification of the research, with plans for public repository release in future work.

4. Results

This section presents results at multiple levels, encompassing user requirement analysis, semantic rule design, and system performance evaluation, in order to provide a comprehensive view of both conceptual and technical outcomes.

4.1 Analysis of User Needs and Data Collection

The study of user problems and information needs aimed to analyze and understand the extent to which knowledge regarding organic agriculture and organic standards was accessed, as well as the essential information requirements for conducting organic agricultural business. The researcher collected data from a sample of 50 young agripreneurs. The results of analysis are presented according to the items in the questionnaire as follows.

4.1.1 General information of the respondents

The results indicated that the majority of young agripreneurs were in adolescence to early working age, demonstrating readiness to pursue stability in career. Most respondents held a bachelor degree, which might influence their ability to adopt new knowledge, technologies, and innovations in organic agriculture. The majority of young agripreneurs operated as individual farmers, reflecting that organic farming in the sample was predominantly carried out independently rather than collectively. Most engaged in plant-based organic production, with the majority obtaining certification within 1–5 years (70%) and some not yet certified (14%) as illustrated in Figure 2. This indicated that most young agripreneurs were in the early stages of entering the certification system. Furthermore, all respondents primarily marketed their products within Thailand and this might reflect constraints in export standards, production costs, and international market channels.

The demographic and background data were collected through a structured questionnaire administered to 50 young agripreneurs. Responses to survey were compiled and analyzed using descriptive statistical techniques, including distributions of frequency, percentages, means, and standard deviation (SD), to summarize respondents' age, education level, and business experience. The purpose of this analysis was not inferential testing, but to characterize the profiles of participants and provide contextual grounding for the subsequent requirement analysis that informed ontology modelling and SWRL rule formulation. The survey dataset was maintained by the authors and was available upon reasonable request for verification and research purposes.

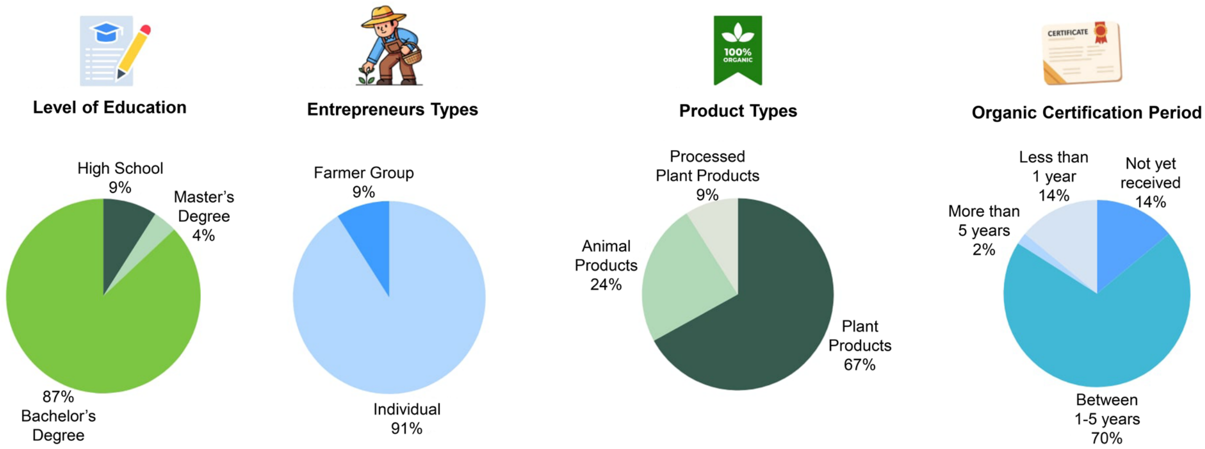

Figure 2. General information of the respondents

4.1.2 Analysis of access to knowledge on organic agriculture for young agripreneurs

As shown in Table 1, in this study, knowledge on organic agriculture as production processes in accordance with organic standards, organic production practices required for certification, management of organic agricultural outputs, and the linkage of organic products to market channels. The analysis of respondents' perceptions was conducted using a Likert scale to determine the level of access to knowledge across these dimensions. As shown in Table 1, the mean scores regarding access to knowledge on organic agriculture ranged from 3.36 to 3.72, indicating a medium to high level. The SD ranged from 0.76 to 0.95, reflecting moderate variation in respondents' perceptions. Specifically, item 1.2, concerning knowledge and understanding of the production processes according to organic standards, had a mean of 3.36 (SD = 0.90), while item 2.2 regarding information on promoting organic agriculture according to international standards had a mean of 3.40 (SD = 0.95). These results suggested that some young agripreneurs felt adequately informed by relevant agencies (e.g., the Department of Agricultural Extension, the Department of Agriculture, the National Bureau of Agricultural Commodity and Food Standards, and organic certification bodies such as Organic Agriculture Certification Thailand) whereas others perceived information access as insufficient, resulting in significant differences in opinions. This highlighted inconsistencies in knowledge transfer and accessibility of information, as certain regions or groups might have more opportunities for training and guidance from public or private agencies, while others remained underserved. Such disparities in information access should be addressed to ensure equitable capacity development among young agripreneurs.

4.1.3 Analysis of information needs related to organic agriculture for young agripreneurs

The analysis indicated that young agripreneurs expressed high to very high information needs in relation to the organic market. As shown in Table 1, the mean scores for this dimension ranged from 4.18 to 4.39, with SD values between 0.52 and 0.68, indicating relatively high agreement among respondents. The highest mean score was found for information on networking and linkages among organic agricultural stakeholders at all levels (Mean = 4.39, SD = 0.62), followed by information on the development of distribution channels and marketing of organic agricultural products (Mean = 4.32, SD = 0.68). Information on value-added processing of organic agricultural products also received a high level of demand (Mean = 4.18, SD = 0.52).

These findings suggest that market-related information is particularly important for young agripreneurs, especially with regard to distribution, networking, and value creation. Such information is essential for business planning, market participation, and improving competitiveness in the organic agriculture sector. The survey findings also provided practical guidance for ontology design. In this study, the ontology was structured using standard Semantic Web components, including classes, properties, and individuals. In particular, the relatively high levels of information need related to market access, organic standards, and institutional support, as reflected in Table 1, suggested that young agripreneurs required integrated guidance across regulatory, procedural, and market-related dimensions. In response, the ontology was designed to represent concepts such as *Market*, *Standard*, *Service*, and *Document* as core classes rather than as simple data attributes. The relationships among these concepts were modelled through object properties, such as *requiresDocument*, *regulatedByStandard*, and *providedByAgency*, while specific entities, such as particular standards or documents, were represented as individuals. This modelling approach enabled rule-based reasoning over structured semantic relationships and supported more explainable and context-aware decision support.

Table 1. Survey of access to knowledge and information needs on organic agriculture among young agripreneurs

Items		Standard Deviation (SD)	Mean	Level
1. Knowledge on organic agriculture	1.1 Acquisition of knowledge on organic agriculture from relevant agencies	0.93	3.46	High
	1.2 Acquisition of knowledge on production processes according to organic standards	0.90	3.36	Medium
	1.3 Acquisition of knowledge on enhancing production capacity for organic certification	0.83	3.38	Medium
	1.4 Acquisition of knowledge on management of organic produce	0.76	3.50	High
	1.5 Acquisition of knowledge on market access for organic products	1.01	3.44	High
2. Knowledge on organic standard	2.1 Acquisition of information on promotion of organic farming according to domestic standards in Thailand	0.88	3.44	High
	2.2 Acquisition of information on promotion of organic farming according to international standards	0.95	3.40	Medium
	2.3 Acquisition of knowledge on Participatory Guarantee Systems (PGS) and its application in organic farming production	0.78	3.72	High
3. Knowledge on organic market	3.1 Information on the development of distribution channels and marketing of organic agricultural products at all levels	0.68	4.32	Very high
	3.2 Information on value-added processing of organic agricultural products	0.52	4.18	High
	3.3 Information on networking and linkages among organic agricultural stakeholders at all levels	0.62	4.39	Very high

Note: Mean values represent the average score for each item across respondents (N = 50).

4.2 Evaluation of the Author-Developed Ontology

The ontology evaluated in this section was developed by the authors as part of the present study and constituted a core research contribution. It was designed to formally represent certification, regulatory, and market-access knowledge in organic agriculture and to support rule-based and explainable decision support for young agripreneurs. Unlike existing agricultural ontologies that primarily focused on production or environmental data, the proposed ontology explicitly modeled standards, agencies, services, and documentation workflows to enable semantic reasoning over compliance-oriented decision scenarios. The following evaluation examined the structural adequacy, reasoning support, and suitability of the ontology for generating context-aware recommendations.

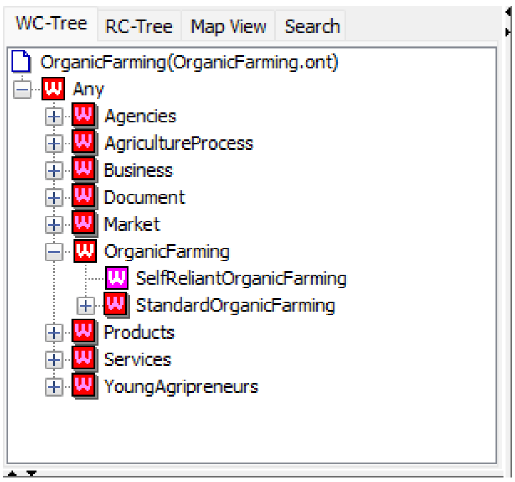

Figure 3. Core classes and hierarchy of the Web Ontology Language (OWL)-based organic agriculture ontology for young agripreneurs (HOZO visualization)

The ontology is situated in the primary domain of organic agriculture, with a specific focus on standardized organic farming practices and certification-related decision support for agripreneurs. The classes of the ontology were defined based on conceptual frameworks and arranged hierarchically, with each class representing a core concept within the domain. The ontology comprised a total of 127 classes, including 9 principal classes, as illustrated in Figure 3 and detailed in Table 2.

Although Figure 3 is referred to as showing core classes, it represents a formal OWL ontology fragment visualized via the HOZO Ontology Editor rather than a high-level conceptual diagram. The term "core" was used to indicate the main domain classes relevant to certification-oriented decision support.

The ontology summarized in Table 2 was developed by the authors during the course of this study through an iterative ontology engineering process informed by requirement analysis, domain literature, and certification documentation, and was refined to support SWRL-based reasoning and decision support.

Table 2. Detailed descriptions of the core classes in the author-developed organic agriculture ontology for young agripreneurs

No.	Class	Description
1	Young agripreneurs	Individuals or groups engaged in organic agriculture, categorized into types by entrepreneur and property characteristics.
2	Organic farming	Types of organic farming, categorized into self-reliant (uncertified) and standard (certified with domestic and international market access).
3	Products	Types of organic products in Thailand, including domestic, imported, and exported items.
4	Businesses	Types and names of organic agricultural businesses and operational focus.
5	Markets	Types and names of organic agricultural markets, representing distribution channels with domestic and international market access.
6	Agricultural processes	Types of organic farming processes, including annual crop, perennial crop, ruminant livestock, poultry, and aquaculture.
7	Agencies	Types of agencies, categorized by type and role, including governmental, private, and certification bodies.
8	Service	Types of services and certification request cases, categorized by service and case.
9	Document	Types of documents, categorized by application submission and assessment inspection.

To support rule-based semantic reasoning and inference, the authors introduced a new class, *Standard Recommendation*, as illustrated in Figure 4. This class served as an intermediate reasoning construct that captured inferred recommendation outcomes generated through SWRL recommendation rules based on user-specific conditions. A "part-of" relationship was assigned to the class representing agripreneurs, as shown in Figure 5.

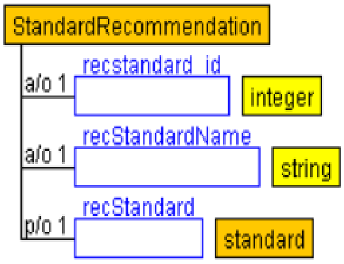

Figure 4. Standard Recommendation class

The *Standard Recommendation* class was introduced as an intermediate semantic construct to make the reasoning process explicit and inspectable, rather than to store recommendations as fixed output. In this design, recommendations were not predefined or permanently stored; instead, they were inferred dynamically through SWRL recommendation rules based on user-specific conditions such as product type, target market, and certification context. The *Standard Recommendation* class served as a semantic anchor that recorded the results of reasoning, allowing inferred recommendations to be queried, examined, and validated using SPARQL. For example, when a user specified an organic product and export market, SWRL recommendation rules inferred applicable certification standards and instantiated corresponding *Standard Recommendation* individuals, which could then be retrieved and explained without hard-coding recommendation logic. This approach improved transparency, traceability, and evaluation of reasoning outcomes.

The transformation between the ontology and the SWRL was a crucial process that enabled structured knowledge from the ontology to be effectively extended to logical inference. The ontology served as a knowledge base, storing knowledge in the form of classes, individuals, and properties, thereby facilitating semantic interoperability. In contrast, SWRL provided inference rules to define "IF–THEN" logic over the ontology data, such as creating rules to infer new properties or classify individuals based on specific conditions.

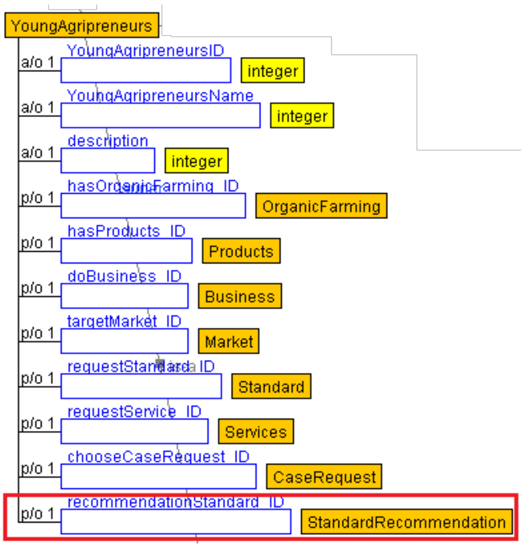

Figure 5. Integration of user conditions with recommendations in the ontology-based system

Accordingly, the transformation layer functioned to convert the visual or structural models of the ontology into SWRL recommendation rules with specific syntax (e.g., OWL-XML). The resulting SWRL recommendation rules were integrated with the ontology and could be applied to infer new knowledge from the existing fact base within the ontology, as illustrated in Figure 6.

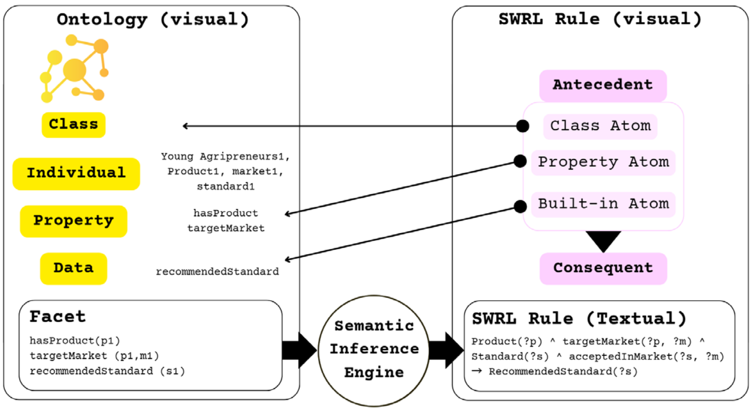

Figure 6. Ontology-to-Semantic Web Rule Language (SWRL) transformation process for knowledge inference

4.3 Rule Structuring and Grouping

Based on the ontology design and analysis of relationships between classes, systematic rule structuring and grouping were performed to develop SWRL-based logical rules that enabled ontology-driven decision support in the context of organic agriculture. The contribution of this study is not a standalone agricultural recommendation system, but an ontology-based DSS in which recommendation output are generated through explicit semantic reasoning over certification, regulatory, and market-access knowledge. The rules were organized according to their use like actionable guidelines for recommendations. The design principles were: (1) identifying the users' needs, and (2) determining the specific purpose for which each SWRL rule would be applied. Subsequently, the rules were grouped into use-case-oriented rule sets. In this study, the rule structure was divided into five principal rule sets, as summarized in Table 3, with the relationships among rule components illustrated in Figure 7.

Table 3 presents a structured overview of the SWRL rule sets at the use-case level, to illustrate how rules are grouped according to decision objectives and ontology components. To maintain readability, the table summarizes rule intent and scope rather than listing full SWRL syntax. The formalized SWRL recommendation rules, including antecedent–consequent expressions and variable bindings, are provided in Appendix B as representative executable examples. This separation allows the main text to focus on rule organization and reasoning logic, while ensuring that formal rule specifications are fully documented for reproducibility.

Figure 7 illustrates the structural relationships among SWRL rule components at the logical level, while Table

3 complements this visualization by summarizing the corresponding rule sets and their use-case scope, to provide a structured overview of how individual rules are organized in the decision support framework.

Table 3. Semantic Web Rule Language (SWRL) rule sets for use-case–driven ontology-based decision system

Rule Set ID	Decision Use Case	Key Ontology Classes Involved	Reasoning Objective	Representative Rule Logic (Conceptual Pattern)
RS1	Product–Market–Standard Matching	Product, Market, Standard	Infer applicable organic certification standards based on product type and target market	IF (Product ∧ TargetMarket) → ApplicableStandard
RS2	Certification Agency Identification	Standard, Agency	Identify suitable certification agencies for a given standard	IF (ApplicableStandard) → CertificationAgency
RS3	Certification Service Selection	Agency, Service, Standard	Recommend certification services aligned with selected standards and agencies	IF (CertificationAgency ∧ Standard) → CertificationService
RS4	Document Requirement Inference	Standard, Document	Infer required supporting documents for certification compliance	IF (ApplicableStandard) → RequiredDocument
RS5	Integrated Recommendation Synthesis	Product, Market, Standard, Service, Document, Standard Recommendation	Generate consolidated and context-aware recommendations across certification and market dimensions	IF (UserConditions) → StandardRecommendation

```
Rule Structuring & Grouping
|
├── Rule set 1: Products, Markets & Standards
│   └── (Product → targetMarket → Market → requiresStandard → Standard)
|
├── Rule set 2: Standard & Agencies
│   └── (Standard → certifiedBy → Agency)
|
├── Rule set 3: Condition Type, Standard & Condition
│   └── (Condition → hasSubstanceType → SubstanceType → appliesToStandard → Standard)
|
├── Rule set 4: Services & Agencies
│   └── (Service → providedBy → Agency)
|
├── Rule set 5: Services & Documents
│   └── (Service → requiresDocument → Document)
```

Figure 7. Structural relationships among components of Semantic Web Rule Language (SWRL) recommendation rules

4.4 Rule Generation for Recommendations

In this study, an ontology-based rule-driven reasoning mechanism was employed to generate decision support recommendations. User inputs such as product type, target market, and certification context were represented as ontology instances and processed through SWRL defined within the ontology. These rules encoded domain knowledge in "IF–THEN" form and were executed using an OWL-compatible reasoning engine to infer recommendation outcomes.

The current implementation focused on the backend reasoning and decision logic rather than on a fully developed end-user interface. User inputs were supplied as structured data instances during the evaluation phase, and recommendation output were retrieved through SPARQL queries over the inferred ontology. This design allowed the reasoning process and inferred results to be examined independently of any implementation of specific user interface.

Accordingly, the contribution of this study lies in the ontology and SWRL-based reasoning framework that supports explainable and context-aware decision support. While a graphical user interface was not implemented in this phase, the proposed architecture was compatible with future integration of web- or form-based interfaces that could capture user inputs and presented recommendations in an interactive decision support environment.

A mechanism design approach with rule-based reasoning was employed to match user data with the ontology knowledge base. SWRL recommendation rules were executed through an OWL-compatible reasoning engine, and SPARQL queries were used to retrieve inferred semantic results. The formal structure of SWRL rules is described earlier in the Introduction; therefore, this section focuses on their practical application in generating recommendations.

Five SWRL-based recommendation rule sets were developed to support organic agriculture certification and market access. Rule Set 1 addressed product–market–standard relationships; Rule Set 2 focused on standards and certification agencies; Rule Set 3 linked condition types, standards, and specific conditions; Rule Set 4 connected services with relevant agencies; and Rule Set 5 related services to required supporting documents. Figure 8 provides an integrated overview of the five rule sets and the overall reasoning flow, illustrating how inferences across *Product*, *Market*, *Standard*, *Agency*, *Service*, and *Document* are combined within the ontology-based DSS. For readability, Figures 9–14 present simplified, illustrative representations of the reasoning logic. These figures are conceptual visualizations rather than screenshots of an end-user interface. The executable SWRL rules were implemented and tested using standard SWRL syntax in the Protégé ontology editor, and the detailed rule specifications and reasoning procedures are reported in the Methodology section.

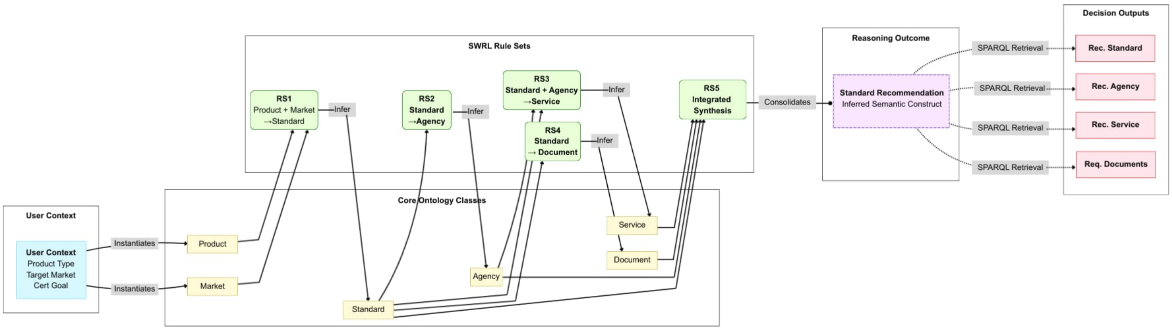

Figure 8. Integrated overview of the five Semantic Web Rule Language (SWRL) rule sets and reasoning flow

Rule Set 1: Product, Market, and Standard (Figures 9 and 10)

Example for Rule Set 1: To provide recommendations on appropriate organic agriculture standards that correspond to the specific products and target markets.

IF [specify selling product (Kale)]
IF [specify market (European Union market)]
THEN [recommend standard (EU Organic)]

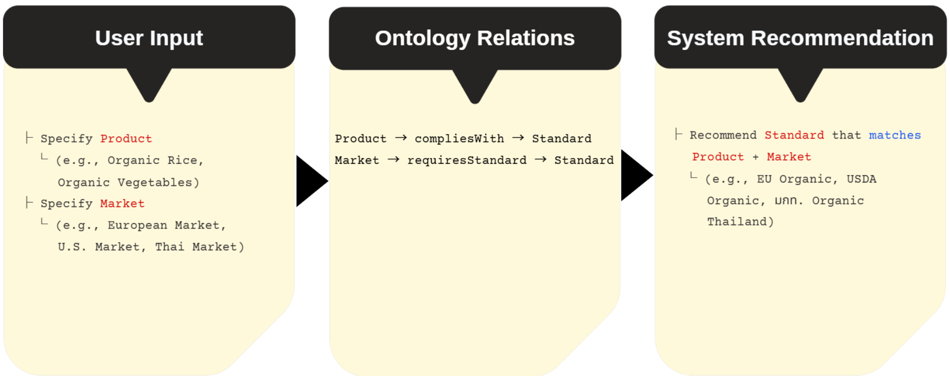

Figure 9. Conceptual workflow of Semantic Web Rule Language (SWRL) Rule Set 1 (product–market–standard inference)

```
swrl

            Product(?p) ^
            hasName(?p, "Kale") ^
            targetMarket(?p, ?m) ^
            Market(?m) ^
            hasName(?m, "European Union market") ^
            Standard(?s) ^
            acceptedInMarket(?s, ?m)
            ? RecommendedStandard(?s) ^
            hasName(?s, "EU Organic”)
```

Figure 10. Simplified illustration of Semantic Web Rule Language (SWRL) Rule Set 1 (product–market–standard inference)

Rule Set 2: Standard and Agency (Figure 11)

Example for Rule Set 2: To provide guidance on the relevant certification authorities corresponding to the organic agriculture standards chosen by the user.

IF [specify standard (EU Organic)]

THEN [recommend agencies (EU Commission, ECOCERT (France), CERES (Germany), Control Union Certifications (Netherlands)]

```
swrl
        Standard(?s) ^
        hasName(?s, "EU Organic ") ^
        CertifyingAgency(?a) ^
        certifiesStandard(?a, ?s)
        ? RecommendedAgency(?a)
        hasName(?s, "EU Commission, ECOCERT
        (France), CERES (Germany), Control Union
        Certifications (Netherlands)")
```

Figure 11. Simplified illustration of Semantic Web Rule Language (SWRL) Rule Set 2 (standard–agency inference)

Rule Set 3: Condition Type, Standard and Condition (Figure 12)

Example for Rule Set 3: To provide recommendations on conditions corresponding to the requirement types and the organic agriculture standards chosen by the user.

IF [specify conditionType (Area Condition)]

IF [specify areaType (Cultivation area)]

IF [specify standard (EU Organic)]

THEN [recommend areaCondition (must undergo a 2-year conversion period)]

```
swrl
        areaCondition(?sc) ^
        hasAreaType(?sc, ?st) ^
        AreaType(?st) ^
        hasName(?st, " Cultivation area") ^
        Standard(?std) ^
        hasName(?std, "EU Organic ") ^
        appliesToStandard(?sc, ?std) ^
        allowedSubstance(?sc, ?sub)
        ? RecommendedSubstance(?sub)
        hasName(?s, must undergo a 2-year
        conversion period)
```

Figure 12. Simplified illustration of Semantic Web Rule Language (SWRL) Rule Set 3 (condition type–standard–condition inference)

Rule Set 4: Service and Agency (Figure 13)

Example for Rule Set 4: To provide guidance on certification authorities, offering services in accordance with the chosen organic agriculture standards.

IF [specify service (Application for import of organic produce/products)]

THEN [recommend agencies (Bureau Veritas Thailand, Ecocert, TÜV NORD Thailand)]

```
swrl
        Service(?s) ^
        hasName(?s, "Application for import of
        organic produce/products") ^
        providesService(?a, ?s) ^
        CertifyingAgency(?a)
        ? RecommendedAgency(?a)
        hasName(?a, Bureau Veritas Thailand,
        Ecocert, TÜV NORD Thailand)
```

Figure 13. Simplified illustration of Semantic Web Rule Language (SWRL) Rule Set 4 (service–agency inference)

Rule Set 5: Services and Documents (Figure 14)

Example for Rule Set 5: To provide guidance on the necessary supporting documents corresponding to the certification services chosen by the user.

IF [specify service (Application for import of organic produce/products)]

THEN [recommend document (Application form for Certification, Identification card, Product and source information, Activity records, Organic product certificate from the country of origin, Residue analysis results, Internal Control System)]

```
swrl

            Service(?s) ^
            hasName(?s, "Application for import of
            organic produce/products") ^
            providesService(?a, ?s) ^
            CertifyingAgency(?a)
            ? RecommendedAgency(?a)
            hasName(?a, Application form for
            certification, Identification card,
            Product and source information, Activity
            records, Organic product certificate
            from the country of origin, Residue
            analysis results, Internal Control
            System)
```

Figure 14. Simplified illustration of Semantic Web Rule Language (SWRL) Rule Set 4 (service–agency inference)

4.5 Evaluation of SWRL-Based Recommendation Rule Performance

This section reports the evaluation results of the SWRL recommendation rules, which were written in SWRL and developed to facilitate ontology-based decision support and recommendation generation. As summarized in Table 4, the evaluation results indicated that the recommendation rules provided highly accurate guidance, achieving a precision of 100%, while the recall of complete information averaged 93.03%. The overall performance, measured by the F-measure, was 96.39%, demonstrating that the system can provide effective decision support under the evaluated scenarios and has potential for practical application. However, there remains potential for further development to improve recall and enhance coverage, as summarized in Table 4. It should be noted that in the evaluation, no false positive results (FP = 0) were observed across the tested scenarios; all deviations from perfect performance were due to relevant items not being retrieved (false negatives), which affected recall but not precision.

Table 4. Retrieval performance of Semantic Web Rule Language (SWRL) recommendation rule sets

Item	Result Counts				Precision (%)	Recall (%)
	Test Terms	Correctly Retrieved Terms (True Positives, TP)	Incorrectly Retrieved Terms (False Positives, FP)	Relevant Terms Not Retrieved (False Negatives, FN)		
Retrieval of target products and markets	6	5	0	1	100.00	83.33
Retrieval of standards and certification bodies	11	9	0	2	100.00	81.82
Retrieval of requirement types, standards, and specific conditions	26	26	0	0	100.00	100.00
Retrieval of certification services and the corresponding service providers	17	17	0	0	100.00	100.00
Retrieval of services and the supporting documents required for certification	6	6	0	0	100.00	100.00
		Average			100.00	93.03
		F-measure			96.39	

It is important to note that the reported precision reflects the absence of false positives within a bounded and case-based evaluation of rule execution. Because the system relies on explicit ontology and SWRL rule reasoning rather than model training, the conventional notion of "overfitting" in machine learning does not apply in the same way. Instead, performance variation primarily arises from rule coverage and knowledge completeness (i.e., missed relevant items affecting recall). Accordingly, the 100% precision outcome should be interpreted as logical correctness under the tested scenarios rather than as statistical generalization to all possible contexts.

Although Table 4 reports a precision value of 100% for several rule sets, this result should be interpreted within the scope of the case-based evaluation design. The evaluation scenarios were constructed to test logical correctness of SWRL rule inference against well-defined certification requirements, rather than to assess performance under large-scale or noisy real-world conditions. In these scenarios, the reasoning process produced no false positive recommendations, suggesting that all retrieved recommendations were logically valid given the specified user conditions and ontology constraints. However, this does not imply universal or population-level precision; rather, it reflects the deterministic nature of rule-based reasoning under controlled test cases. Recall values below 100% indicate that some relevant recommendations are not inferred, thus highlighting opportunities for expanding rule coverage and ontology refinement in future work.

5. Discussion

The findings of this study demonstrated that ontology-driven and rule-based reasoning could effectively support organic agripreneurs in navigating complex decision environments. By developing five structured sets of SWRL-based recommendation rules, this study demonstrated how ontology-driven semantic reasoning could be operationalized to support logically consistent and context-sensitive decision support in organic agriculture. While the rule sets represented a central technical contribution, the study also contributed an author-developed organic agriculture ontology that formally modelled certification standards, agencies, services, and documentation workflows, i.e., elements that were often fragmented or weakly represented in existing agricultural ontologies.

Building on prior ontology-based decision support research in agriculture, this study demonstrated how SWRL-based "IF–THEN" recommendation rules could extend the inferential capabilities of an ontology-driven DSS beyond static knowledge representation. Rather than redefining the foundational role of ontologies, the contribution of this work lies in the five structured SWRL recommendation rule sets, which operationalize conditional domain knowledge related to organic certification standards, agencies, services, and documentation. These rule sets enable context-sensitive reasoning that has been difficult to achieve in ontology-only agricultural systems, particularly in regulatory and compliance-oriented decision contexts. By integrating ontology modelling with SWRL-based rule execution, the proposed approach advanced prior agricultural DSS by providing explainable and rule-driven recommendations grounded in formal domain knowledge.

Placing these results in the context of existing literature, this study contributes an ontology-based DSS that operationalizes domain knowledge through the integration of ontology modelling and SWRL-based reasoning. While ontologies provide a formal structure for organizing agricultural knowledge, their inferential capability is often limited when used alone. The incorporation of SWRL recommendation rules enabled conditional reasoning that supported explainable and context-sensitive recommendations within organic agriculture certification contexts. In contrast to prior semantic applications in agriculture, which have largely focused on production-related problems such as disease prediction or irrigation management, this study extends semantic decision support to certification, market, and documentation processes that remain underrepresented in the literature.

The findings also confirm the theoretical assumptions outlined in the introduction and literature review, particularly the identified gap between data availability and actionable decision making in organic agriculture. The results indicate that integrating ontology structures with rule-based reasoning can transform domain knowledge into logically consistent recommendations, addressing limitations associated with purely statistical approaches and ontology-only frameworks. The observed performance outcomes suggest that the framework effectively supports structured reasoning within the defined decision scope rather than serving as a predictive model for open-ended environments.

Importantly, the empirical results demonstrate the practical value of the proposed framework in supporting organic agripreneurs. The high precision and recall achieved across rule sets indicate that domain knowledge can be operationalized into consistent and interpretable recommendations, especially in certification- and market-related decision contexts where information is often fragmented. These findings should therefore be interpreted as evidence of logical validity and feasibility under controlled reasoning conditions, rather than as claims of universal applicability or performance beyond the evaluated scope.

The evaluation results, showing perfect precision under controlled case-based scenarios and an average recall of 93.03%, indicated that the rule formulations were logically sound and effective within the defined reasoning scope. However, rather than claiming novelty in the general use of semantic reasoning, this study contributes by applying semantic reasoning specifically to certification- and market-oriented decision contexts for young agripreneurs, an area that has received limited attention in prior work. The reported precision values reflected logical validity under controlled reasoning scenarios and should not be interpreted as predictive performance in open-ended environments, where incomplete or noisy inputs may affect inference outcomes. These findings confirmed that semantic reasoning approaches could address the fragmented and inconsistent flow of information often encountered by young agripreneurs.

The system was not evaluated through direct interactive use by young agripreneurs in this study; rather, participant-derived requirements informed the ontology modelling and SWRL rule formulation, while system performance was assessed through researcher-led and case-based reasoning scenarios grounded in real-world organic certification contexts. This design-oriented evaluation was undertaken to validate the logical correctness, internal consistency, and inferential soundness of the proposed ontology-driven rule framework. Consequently, the practical relevance of the findings was demonstrated through the feasibility of generating context-sensitive and logically valid recommendations under controlled conditions, rather than through user-centered performance metrics. While agripreneurs contributed at the design stage by articulating domain-specific information needs, direct usability testing and participatory evaluation remain important directions for future work to assess real-world adoption, user experience, and decision impact.

The study also acknowledged several limitations. Although the recommendation rule sets demonstrated high logical correctness, the recall results indicated that some relevant cases were not retrieved, suggesting the need to refine rule coverage further and expand the ontology to accommodate additional variables, such as regional regulatory differences and emerging certification schemes. In addition, the evaluation relied on case-based testing informed by a sample of 50 agripreneurs, which, while appropriate for system validation, may not fully represent the diversity of organic agriculture practices across different geographic contexts. Future research will therefore extend the evaluation to independent datasets and cross-context validation to further assess the robustness and generalizability of the proposed framework.

Regarding generalizability, the proposed framework distinguishes between context-specific instantiation and transferable semantic structure. Certain ontology components—such as specific certification standards, regulatory agencies, and documentation requirements—are inherently tied to the Thai organic agriculture context and reflect country-specific regulatory frameworks. However, the upper-level ontology classes and relationships (e.g., *Product*, *Market*, *Standard*, *Service*, *Agency*, and *Document*) represent domain-generic decision constructs, and the SWRL rule templates encode abstract condition–action logic (such as linking product–market combinations to applicable standards or mapping services to required documentation) that is not jurisdiction-specific in form. Consequently, while the current implementation is grounded in the Thai regulatory environment, the underlying ontology–rule architecture can be systematically adapted to other national or regional contexts by substituting locally relevant entities and constraints. The framework should therefore be understood as a portable semantic design blueprint rather than a universally validated operational system.

Despite these limitations, the implications are significant for both theory and practice. Theoretically, the study advanced the field by demonstrating how semantic technologies could move beyond conceptual integration toward practical and scalable decision support. This directly addressed the gaps identified in the introduction, where previous research often emphasized feasibility rather than durability or transferability (Kamilaris et al., 2016; Seydoux et al., 2017). Practically, the system provided agripreneurs with a transparent, explainable, and actionable tool for decision making, thereby reducing the cognitive burden associated with certification procedures and market navigation. By linking products, standards, agencies, and documents in a unified framework, the system offered a pathway to reduce transaction costs and improve competitiveness in both domestic and international markets. Given that the requirement analysis employed a purposive sampling strategy, the identified user needs should be interpreted as illustrative rather than statistically representative, with the primary purpose of anchoring the system design in authentic real-world practice. In addition, because the evaluation was conducted through a researcher-led and case-based validation process rather than direct user execution, future research might incorporate interactive user testing to complement and extend the current evaluation approach.

In conclusion, this study reinforced the value of combining ontological modelling with SWRL-based reasoning to create DSS that were both logically sound and practically applicable. The strong evaluation outcomes highlighted the potential for scaling such systems to support a broader range of stakeholders in organic agriculture. Ultimately, the findings provided a clear takeaway: semantic rule-based systems could transform fragmented knowledge landscapes into integrated decision environments, to enable organic agripreneurs to make informed, efficient, and sustainable choices that strengthen their competitiveness in a growing global market.

6. Conclusions

In summary, this study demonstrated that ontology-based modelling combined with SWRL could provide effective, explainable, and context-specific recommendations for organic agripreneurs, with evaluation results confirming high precision and strong recall. By addressing a critical gap in existing research, namely the lack of decision support tools that integrated certification requirements, market opportunities, and documentation into a unified framework, the study advanced both theory and practice in agricultural decision support. Despite remaining limitations such as the need to extend rule coverage and to validate the system across more diverse international contexts, these challenges also created clear opportunities for future research to refine and scale the proposed framework. Overall, the findings highlighted the capacity of semantic rule-based systems to transform fragmented domain knowledge into actionable decision support, thus enabling agripreneurs to navigate certification processes more effectively, enhance competitiveness, and contribute to the sustainability of the global organic agriculture sector. Further empirical validation across national and regional settings would help assess the adaptability of the framework and its cross-context applicability.

Author Contributions

Conceptualization, S.C., M.K., and W.C.; methodology, S.C. and M.K.; software, S.C.; validation, S.C. and M.K.; formal analysis, S.C. and M.K.; investigation, S.C. and M.K.; resources, M.K. and W.C.; data curation, S.C.; writing—original draft preparation, S.C. and W.C.; writing—review and editing, M.K. and W.C.; visualization, S.C.; supervision, W.C.; project administration, W.C.; funding acquisition, S.C. All authors have read and agreed to the published version of the manuscript.

Funding

This research was supported by the Graduate School of KhonKaen University, Thailand (Grant No.: 631S217-C).

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Acknowledgements

The authors would like to acknowledge the organic agripreneurs who participated in the requirement analysis and provided valuable domain insights that informed the ontology modelling and rule development. The authors also thank the institutional representatives who shared information regarding certification standards and documentation processes, which supported the accuracy of the knowledge structure.

Conflicts of Interest

The authors declare no conflicts of interest.

References

Afzal, H. & Kasi, M. K. (2019). Ontology-based knowledge modelling for rice crop production. In *Proceedings of the 2019 7th International Conference on Future Internet of Things and Cloud (FiCloud), Istanbul, Turkey* (pp. 343–350). https://doi.org/10.1109/ficloud.2019.00057.

Afzal, H., Kasi, M. K., Kasi, B., Naeem, B., & Sami, S. K. (2021). An ontology-driven decision support system for rice crop production. *J. Appl. Emerg. Sci.*, *11*(1), 85–94. https://doi.org/10.36785/BUITEMS.JAES.410.

Alharbi, A. F., Aslam, M. A., Asiry, K. A., Aljohani, N. R., & Glikman, Y. (2024). An ontology-based agriculture decision-support system with an evidence-based explanation model. *Smart Agric. Technol.*, *9*, 100659. https://doi.org/10.1016/j.atech.2024.100659.

Berners-Lee, T., Hendler, J., & Lassila, O. (2001). The Semantic Web: A new form of Web content that is meaningful to computers will unleash a revolution of new possibilities. *Sci. Am.*, *284*(5), 34–43. https://doi.org/10.1038/scientificamerican0501-34.

Bi, J., Wu, R., Yuan, H., Wang, Z., Zhang, J., & Zhou, M. (2025). Ontology-based semantic reasoning for multisource heterogeneous industrial devices using OPC UA. *IEEE Internet Things J.*, *12*(13), 25020–25032. https://doi.org/10.1109/jiot.2025.3556934.

Buhl, E. S., Maae, E., Matthiessen, L. W., Nielsen, M. H., Maraldo, M., Møller, M., Elleberg, S., Al-Rawi, S. A. J., Offersen, B. V., & Korreman, S. S. (2024). Data harvesting vs data farming: A study of the importance of variation vs sample size in deep learning-based auto-segmentation for breast cancer patients. In *XXth International Conference on the use of Computers in Radiation therapy, 8–11 July 2024, Lyon, France*. https://doi.org/10.48550/arXiv.2404.03369.

Buitendag, A. A. K. & Hattingh, F. G. (2024). A smart agricultural knowledge management framework to support emergent farmers in developmental settings. *Interdiscip. J. Inf. Knowl. Manag.*, *19*, 016. https://doi.org/10.28945/5315.

Chansanam, W. & Tuamsuk, K. (2016). Development of Imaginary Beings Ontology. In A. Morishima, A. Rauber, & C. Liew (Eds.), *Digital Libraries: Knowledge, Information, and Data in an Open Access Society* (pp. 231–242). Springer. https://doi.org/10.1007/978-3-319-49304-6_28.

Chatterjee, S. & Kar, A. K. (2018). Effects of successful adoption of information technology enabled services in proposed smart cities of India: From user experience perspective. *J. Sci. Technol. Policy Manag.*, *9*(2), 189–209. https://doi.org/10.1108/JSTPM-03-2017-0008.

Cleverdon, C. (1967). The Cranfield tests on index language devices. *Aslib Proc.*, *19*(6), 173–194. https://doi.org/10.1108/eb050097.

Dhivya, N. & Karthikeyan, C. (2021). A case study of an organic Agripreneur adopting integrated farming system model at Kullagoundenpudur village of Erode district in Tamil Nadu, India. *J. Appl. Nat. Sci.*, *13*(SI), 162–166. https://doi.org/10.31018/jans.v13isi.2822.

Di Noia, T., Mirizzi, R., Ostuni, V. C., Romito, D., & Zanker, M. (2012). Linked open data to support content-based recommender systems. In *Proceedings of the 8th International Conference on Semantic Systems, Graz, Austria* (pp. 1–8). https://doi.org/10.1145/2362499.2362501.

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *Am. J. Theor. Appl. Stat.*, *5*(1), 1–4. https://doi.org/10.11648/j.ajtas.20160501.11.

Fernández, M., Cantador, I., López, V., Vallet, D., Castells, P., & Motta, E. (2011). Semantically enhanced Information Retrieval: An ontology-based approach. *J. Web Semant.*, *9*(4), 434–452. https://doi.org/10.1016/j.websem.2010.11.003.

Gruber, T. R. (1993). A translation approach to portable ontology specifications. *Knowl. Acquis.*, *5*(2), 199–220. https://doi.org/10.1006/knac.1993.1008.

Horrocks, I., Patel-Schneider, P. F., Boley, H., Tabet, S., Grosof, B., & Dean, M. (2004). *SWRL: A Semantic Web Rule Language Combining OWL and RuleML*. https://www.w3.org/Submission/SWRL/

Hwang, H. Y., An, N. H., Lee, S. M., Kang, D. I., Jeong, J. A., & Lee, C. R. (2022). Soil labile organic carbon fractions and carbon management index in response to different fertilization under organic maize farming system. Korean *J. Soil Sci. Fertil.*, *55*(4), 522–532. https://doi.org/10.7745/kjssf.2022.55.4.522.

IFOAM. (2020). *The World of Organic Agriculture 2020: Statistics and Emerging Trends*. Bonn, Germany: IFOAM–Organics International. https://www.fibl.org/en/shop-en/5011-organic-world-2020

IFOAM. (2024). *The IFOAM NORMS for Organic Production and Processing*. Bonn, Germany: IFOAM–Organics International. https://www.ifoam.bio/our-work/how/standards-certification/organic-guarantee-system/ifoam-norms

Janssen, S. & van Ittersum, M. K. (2007). Assessing farm innovations and responses to policies: A review of bio-economic farm models. *Agric. Syst.*, *94*(3), 622–636. https://doi.org/10.1016/j.agsy.2007.03.001.

Jing, X., Min, H., Gong, Y., Biondich, P., Robinson, D., Law, T., Nohr, C., Faxvaag, A., Rennert, L., Hubig, N., & Gimbel, R. (2023). Ontologies applied in clinical Decision Support System rules: Systematic review. *JMIR Med. Inform.*, *11*, e43053. https://doi.org/10.2196/43053.

Kalyani, Y., Vorster, L., Whetton, R., & Collier, R. (2024). Application scenarios of digital twins for smart crop farming through cloud–fog–edge infrastructure. *Future Internet*, *16*(3), 100. https://doi.org/10.3390/fi16030100.

Kamilaris, A., Gao, F., Prenafeta-Boldu, F. X., & Ali, M. I. (2016). Agri-IoT: A semantic framework for Internet of Things-enabled smart farming applications. In *2016 IEEE 3rd World Forum on Internet of Things (WF-IoT), Reston, VA, USA* (pp. 442–447). https://doi.org/10.1109/wf-iot.2016.7845467.

Kamilaris, A., Kartakoullis, A., & Prenafeta-Boldú, F. X. (2017). A review on the practice of big data analysis in agriculture. *Comput. Electron. Agric.*, *143*, 23–37. https://doi.org/10.1016/j.compag.2017.09.037.

Kim, Y. H., Lee, S. M., Jung, J. A., Kang, D. I., An, N. H., Lee, C. R., & Hwang, H. Y. (2025). Effect of organic and conventional farming practices on the greenhouse gas emissions and stable organic carbon in rice-onion rotation cropping system. *Korean J. Soil. Sci. Fert.*, *58*(1), 125–132. https://doi.org/10.7745/kjssf.2025.58.1.125.

Lin, S., Gao, J., Zhang, S., He, X., Sheng, Y., & Chen, J. (2020). A continuous learning method for recognizing named entities by integrating domain contextual relevance measurement and Web farming mode of Web intelligence. *World Wide Web*, *23*(3), 1769–1790. https://doi.org/10.1007/s11280-019-00758-x.

Miller, T., Durlik, I., Łobodzińska, A., Dorobczyński, L., & Jasionowski, R. (2024). AI in context: Harnessing domain knowledge for smarter machine learning. *Appl. Sci.*, *14*(24), 11612. https://doi.org/10.3390/app142411612.

Mouakher, A., Bertaux, A., Labbani, O., Hugol-Gential, C., & Nicolle, C. (2020). Ontology for smart viticulture: Integrating inference rules based on sensor data. In *Service-Oriented Computing – ICSOC 2019 Workshops* (pp. 168–177). Springer. https://doi.org/10.1007/978-3-030-45989-5_14.

Nisa, M. U., Azam, M., Rafiq, T., Sattar, M., Zahra, A., & Zafar, S. (2024). Ontology-based smart irrigation system:

Enhancing agricultural water management. *Asian Bull. Big Data Manag.*, *4*(1). https://doi.org/10.62019/abbdm.v4i1.131.
Norman, D. A. (2013). *The Design of Everyday Things*. Basic Books.
Noy, N. F. & McGuinness, D. L. (2001). *Ontology development 101: A guide to creating your first ontology* (pp. 1–5). Stanford, CA, USA: Stanford Knowledge Systems Laboratory. http://www-ksl.stanford.edu/people/dlm/papers/ontology-tutorial-noy-mcguinness.pdf
O'Connor, M. J. & Das, A. K. (2011). A method for representing and querying temporal information in OWL. In A. Fred, J. Filipe, & H. Gamboa (Eds.), *Biomedical Engineering Systems and Technologies* (pp. 97–110). Springer. https://doi.org/10.1007/978-3-642-18472-7_8.
Ponciano, C., Schaffert, M., & Ponciano, J. J. (2024). ODKAR: "Ontology-based dynamic knowledge acquisition and automated reasoning using NLP, OWL, and SWRL". In *Proceedings of the 20th International Conference on Web Information Systems and Technologies (WEBIST 2024), Porto, Portugal* (pp. 457–465). https://doi.org/10.5220/0013071500003825.
Power, D. J. (2002). *Decision Support Systems: Concepts and Resources for Managers*. Bloomsbury Academic.
Power, D. J. (2007). *A Brief History of Decision Support Systems*. http://dssresources.com/history/dsshistory.html
Reda, R., Carbonaro, A., de Boer, V., Siebes, R., van der Weerdt, R., Nouwt, B., & Daniele, L. (2022). Supporting smart home scenarios using OWL and SWRL rules. *Sensors*, *22*(11), 4131. https://doi.org/10.3390/s22114131.
Ricci, F., Rokach, L., & Shapira, B. (2022). *Recommender Systems Handbook*. Springer. https://doi.org/10.1007/978-1-0716-2197-4.
Ristoski, P. & Paulheim, H. (2016). Semantic Web in data mining and knowledge discovery: A comprehensive survey. *J. Web Semant.*, *36*, 1–22. https://doi.org/10.1016/j.websem.2016.01.001.
Russell, S. & Norvig, P. (2020). *Artificial Intelligence: A Modern Approach (4th ed.)*. Pearson Education Limited.
Sarwar, S., García-Castro, R., Qayyum, Z., Safyan, M., Munir, F., & Iqbal, M. (2018). Ontology based e-learning systems: A step towards adaptive content recommendation. *Int. J. Inf. Educ. Technol.*, *8*(10), 700–705. https://doi.org/10.18178/ijiet.2018.8.10.1125.
Seydoux, N., Drira, K., Hernandez, N., & Monteil, T. (2017). Capturing the contributions of the semantic web to the IoT: A unifying vision. *arXiv Preprint*, arXiv:1709.03576. https://doi.org/10.48550/arXiv.1709.03576.
Shim, J. P., Warkentin, M., Courtney, J. F., Power, D. J., Sharda, R., & Carlsson, C. (2002). Past, present, and future of decision support technology. *Decis. Support Syst.*, *33*(2), 111–126. https://doi.org/10.1016/s0167-9236(01)00139-7.
Tomic, D., Drenjanac, D., Wöber, W., Hörmann, S., & Auer, W. (2015). Enabling semantic web for precision agriculture: A showcase of the project agriOpenLink. In A. Filipowska, R. Verborgh, & A. Polleres (Eds.), *CEUR Workshop Proceedings* (Vol. 1481, pp.26–29).
Tomic, S. D. K., Drenjanac, D., Lazendic, G., Hörmann, S., Handler, F., Wöber, W., Schulmeister, K., Otte, M., & Auer, W. (2014). AgriOpenLink: Semantic services for adaptive processes in livestock farming. In *Proceedings of the International Conference of Agricultural Engineering, 06–10 July 2014, Zurich* (p. C0274).
van Harmelen, F., Lifschitz, V., & Porter, B. (2008). *Handbook of Knowledge Representation (1st ed.)*. Elsevier.
van Rijsbergen, C. J. (1979). *Information Retrieval (2nd ed.)*. Butterworths.
Willer, H., Trávníček, J., Meier, C., & Schlatter, B. (2023). *The World of Organic Agriculture: Statistics and Emerging Trends 2023*. FiBL, IFOAM-Organics International. https://www.fibl.org/de/shop/1254-organic-world-2023
Wilson, T. D. (1999). Models in information behaviour research. *J. Doc.*, *55*(3), 249–270. https://doi.org/10.1108/eum0000000007145.