

Modernization of Precision Fertilization Based on Artificial Intelligence Technology in Rural Areas

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Abstract

Fertilization in rural areas is still largely carried out based on the habits of farmers, so it is inefficient and has a bad impact on the environment, while existing AI research usually only focuses on technical solutions separately. This research creates an AI reference architecture for precision fertilization approaches in rural agriculture using the design science research method. This method involves a systematic literature review (30 articles from Scopus), model creation with ArchiMate, and focus group discussions with farmers in the Pangalengan area. The result is an architecture that has five drivers, three types of assessments, three objectives, and three requirements. This architecture is realized in the form of three modules, namely a soil nutrient analysis module, a fertilizer recommendation engine that uses AI technology, and a decision support application for farmers. This system is supported by soil sensors and hardware in the form of Arduino or ESP32. Validation by farmers shows that this design is appropriate for their needs and has the potential to increase fertilizer use more efficiently and increase yields, although there are still challenges in terms of ease of use, cost of IoT devices, and internet network availability.

Keywords: *Precision Fertilization, Artificial Intelligence, Rural Agriculture, Enterprise Architecture, ArchiMate.*

A. INTRODUCTION

The agricultural sector has an important role in rural development, but on the other hand, it also faces various major challenges, such as global food security, environmental sustainability, and economic growth (Prasad et al., 2025). Although the agricultural sector makes a significant contribution to the economy, it still faces various serious problems, such as inequality in productivity growth, inefficiency in the use of resources, negative impacts on the environment, and income gaps between rural and urban areas (Fan & Li, 2026). In this context, the management of plant nutrients, especially in the fertilization process, is a crucial aspect in supporting sustainable agriculture, but it still often faces accuracy problems due to the limitations of data-based and technology-based approaches (Koli et al., 2026).

Fertilization practices carried out by farmers are generally based on experience and habits, not based on analysis of soil conditions, land area, and plant types, so that it has the potential to reduce the efficiency of plant nutrient use (Rollon et al., 2021). Fertilizer is a substance that contains chemical elements such as nitrogen, phosphorus, potassium, magnesium and other elements that can increase plant growth and provide nutrients to plants, so that plants can develop tolerance to harmful organisms, such as weeds, insects, and diseases (Hameed & Sawicka, 2017). Meanwhile, excessive

or untargeted use in agriculture not only causes economic waste due to increased costs but can also cause loss of water and nutrients from the soil resulting in environmental damage (Hendricks et al., 2019). These inaccuracies have been proven to reduce the efficiency of nutrient use and have an impact on crop productivity that is not optimal (Cai et al., 2025).

With the existence of *artificial intelligence* (AI) technology, new opportunities have opened up to transform decision-making in the agricultural sector (Swati et al., 2026). This technology is referred to as disruptive technology because it significantly changes the way work is usually done without causing adverse effects (Pavaloaia & Necula, 2023). In this context, AI is used for *precision agriculture*, which optimizes inputs and management practices based on specific land and crop needs (Wu & Zhong, 2025). *Precision agriculture* is a modern agricultural concept that utilizes information and communication technology to improve the quality and productivity of crops more efficiently (Garg et al., 2021). With proper measurements, agricultural productivity growth can occur, as well as reduce production costs, optimize the use of resources, and minimize environmental impacts (Ishak et al., 2009). The application of AI allows automation and accuracy of targets at various stages, ranging from soil conditions, land area, nutrient estimation to fertilizer and crop estimates, with better accuracy and response to environmental conditions in *real time* (Swati et al., 2026). However, the implementation of AI does not only depend on technological aspects, but also requires the involvement of various *stakeholders*, such as farmers, the government to strengthen digital infrastructure, as well as the industrial sector and technology developers as providers of innovative solutions (Huda et al., 2026). Collaboration between *stakeholders* is an important factor in ensuring effective and sustainable adoption of AI technology in the rural agriculture sector (Omotayo et al., 2025).

The use of generative AI has also begun to be applied in the data-driven agriculture sector by integrating machine learning techniques as well as soil and fertilizer data to improve the accuracy of crop recommendations and fertilization in real-world conditions (Reddy et al., 2024). In East Africa, the application of technology, mobile applications, *Variable Rate Applications*, and AI and ML is revolutionizing precision fertilizer application, which provides many benefits to farmers (Fue et al., 2025). AI and ML significantly improve precision fertilization by analyzing data from various sources, such as soil and weather sensors, drones, and satellite imagery (Linaza et al., 2021). However, most of the research is still partial and focuses only on specific technical solutions without considering the interconnectedness between the components of the system as a whole. The implementation of technology in the agricultural sector requires an *enterprise architecture* (EA) approach that provides a structured approach to align information technology infrastructure with business objectives, so that it can support digital transformation, IT development, and modernization processes (Anbananthen et al., 2024).

A number of studies have proposed the application of *artificial intelligence* (AI) in the agricultural sector that covers various aspects in a data-driven manner (Aijaz et al., 2025). However, most focus on developing technical solutions separately without

integrating various system components in a single framework (Khaled et al., 2025). Although AI has great potential in improving agricultural efficiency and productivity, in implementation there are still obstacles related to technology integration, organizational readiness, and coordination between *stakeholders* (Aijaz et al., 2025). This condition shows the need for an architectural approach that is able to integrate business, application, and technology aspects in one system (Anbananthen et al., 2024). Therefore, this study raises a key question, namely: how is the *architectural guide for the adoption of artificial intelligence in optimizing the fertilization process in rural agriculture*?

To answer these problems, the development of architecture in this study is based on the *enterprise architecture (EA)* approach, which is based on the fact that information systems in agriculture are a complex system and involve many *stakeholders*, so this development requires a *blueprint* as a strategic plan for the future (Delima et al., 2016). *Enterprise architecture* is implemented because of its ability to integrate all information technology functions related to its business processes (Marques et al., 2011). This study uses ArchiMate as the EA modeling language, which was developed by *The Open Group* and is designed to visualize and integrate various layers of architecture, namely business, application and technology layers in one unified framework (The Open Group, 2022). Specifically, this research focuses on the use of AI to support decision-making in determining the composition of NPK fertilizers that are appropriate to the conditions at the time. To develop the proposed architecture, this study uses a *design science research* approach that combines *systematic literature review (SLR)* and *focus group discussion (FGD)* as part of the design and validation process. *Systematic Review* is a review that uses an explicit and systematic method to collect and synthesize findings from various studies that address a clearly formulated question (Higgins et al., 2019).

With the proposed architectural guidelines, this research contributes to the development of knowledge about precision fertilization based on AI technology in rural areas. This overcomes a shortcoming in the existing literature, namely the lack of guidance that connects strategic and technical contexts in the field of smart agricultural systems in rural areas. The architectural guidelines serve as guidelines for efficiently and effectively utilizing AI technology in order to improve the quality of agriculture managed by rural communities (Mukti et al., 2026).

B. METHOD

This research aims to develop artificial intelligence (AI) architecture references in the precision fertilizer-based rural agriculture sector through a review of the latest literature and best implementation practices, especially in supporting a more precise, efficient, and appropriate fertilizer application process in accordance with the needs of agricultural crops. The approach used is *design science research (DSR)* which focuses on designing and developing artifacts to produce information systems that are more effective, efficient, and in accordance with user needs (Giray & Catal, 2021). In

addition, this method is widely used in information systems research, artifact development, architectural design and evaluation (Hevner et al., 2004).

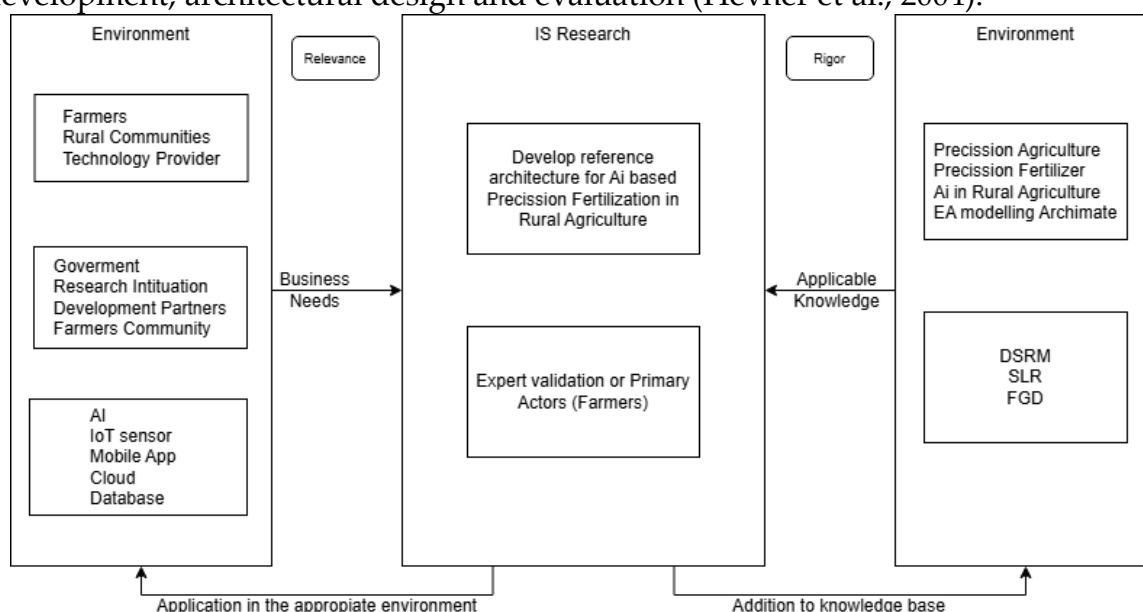


Image 1 Research Methodology

This approach consists of three main components as shown in Figure 1, namely *environment*, *IS Research*, and *knowledge base*, which are interconnected through the *relevance cycle* and the *rigor cycle*. The *relevance cycle* describes the relationship between the needs of the real environment and the research process, while the *rigor cycle* shows the relationship between research and the theoretical foundation and methodology used.

In the *environment* section, several main elements involved in the implementation of *precision fertilizer* in the rural agricultural environment are mapped, in which there are three aspects, namely *people*, *organization*, and *technology*. In the *IS research* section, research is focused on development, this process includes designing an architecture that is able to support more precise and data-based fertilization management. In addition, *expert validation* is carried out by the main actors, namely farmers, this is to ensure that the recommended architecture is in accordance with the needs and conditions of the rural agricultural environment.

Meanwhile, the *knowledge base* section serves as a theoretical and methodological basis for the research. This study uses several related literatures that is in accordance with the discussion, as well as *enterprise architecture modelling* using Archimate. As for the methodological aspect, this study applies the DSR, SLR, and FGD approaches as the main method in the architectural development and evaluation process. Through the integration of these three components, the research hopes to be able to produce a *reference architecture* that is practically relevant and has strong theoretical validity to be applied to rural agricultural environments.

Systematic Literature Review (SLR)

Systematic literature review (SLR) is a research method used to identify, evaluate, and interpret all relevant research on a particular topic in a systematic and structured

manner (Kitchenham & Charters, 2007). The purpose of this method is to produce a literature review that is more objective and transparent than *traditional literature review* because it uses a predetermined study search and selection procedure (Yang et al., 2021). Several main activities are adopted in this method such as *design*, *selection*, and *synthesis* which have previously been studied by Mukti et al. (2026), then readjusted to the needs and focus of research related to the development of Ai architecture on precision fertilization modernization. The SLR approach is also widely used in information systems research because it is able to assist researchers in identifying *research gaps*, *synthesizing evidence*, and building a scientifically strong research foundation (Kitchenham et al., 2010).

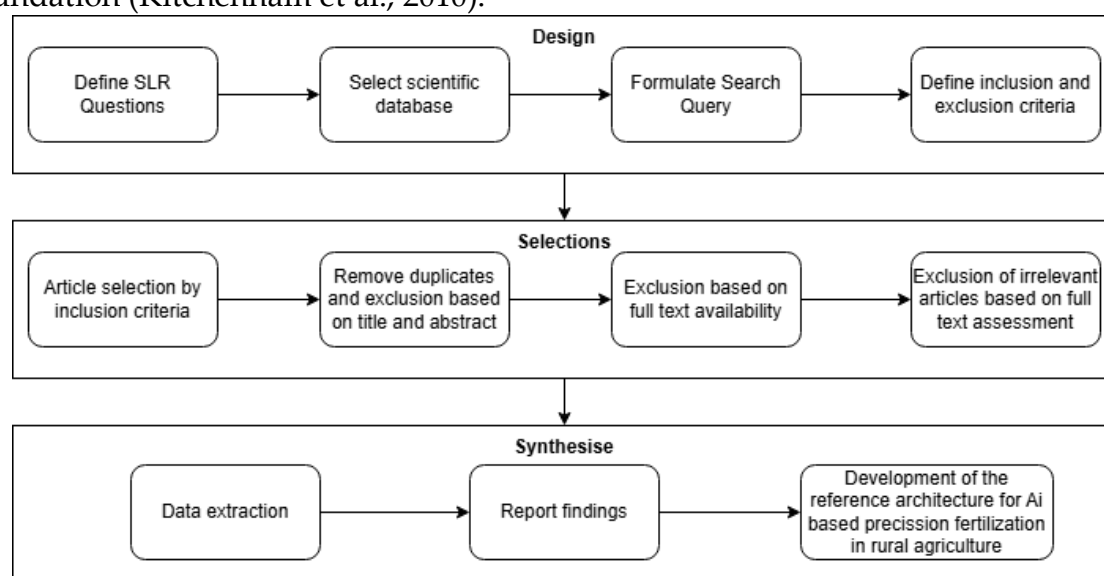


Image 2 Systematic Literature Review Step

In Figure 2 there are several stages in conducting SLR, the first design stage, the research begins by defining *research questions* that are adjusted to the research focus on the development of *reference architecture AI based precision fertilization in rural agriculture*. This stage aims to determine the scope of research and ensure that the literature search process is carried out in a directed manner. The *research questions* in this study are focused on the identification of architectural components, supporting technologies, and AI approaches used in *precision agriculture*, especially in fertilization management and *nutrient management* in rural agricultural environments.

After the *research questions* are determined, the next stage is the selection of the *scientific database* as the main source of research literature. In this study, Scopus is used as the main database because it has a wide scope of scientific publications, is indexed internationally, and is widely used in *systematic literature review* research in the field of information systems and agricultural technology. Furthermore, the article search process is carried out by formulating a *search query* that is tailored to the research topic. The queries used in this study are: ("architecture" OR "design" OR "framework" OR "blueprint") AND ("precision agriculture" OR "digital agriculture" OR "rural agriculture" OR "smart farming") AND ("artificial intelligence" OR "AI" OR "machine learning") AND

("fertilization" OR "fertilizer" OR "nutrient management" OR "crop fertilization prediction").

The query is used to obtain articles relevant to the development of AI architecture on *precision fertilization* in the context of rural agriculture. After the search process is carried out, the next stage is to determine the *inclusion criteria* and *exclusion criteria* to filter articles that are suitable for the research objectives. *Inclusion criteria* in this study include articles published in the form of *journal articles* or *conference proceedings*, indexed by Scopus, discussing *precision fertilizer*, *AI in agriculture*, *nutrient management*, or *enterprise architecture*, and related to the development of systems, frameworks, or *architectures* in the smart agriculture sector. Meanwhile, *exclusion criteria* include duplicate articles, articles that are not directly related to the research topic, articles that do not discuss AI or *precision fertilization*, and articles with incomplete information or not *available full text*.

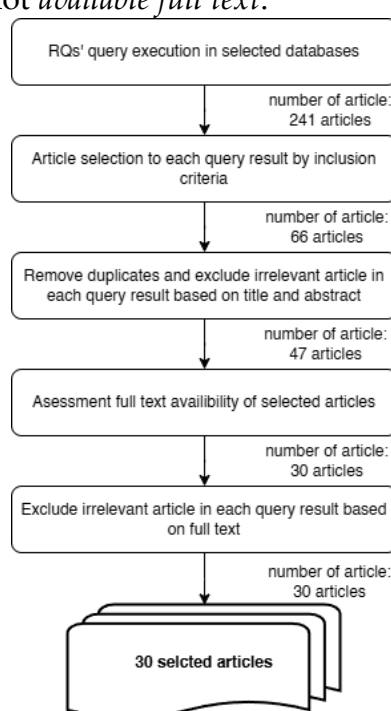


Image 3 Article Selection Process

In the *selection* stage as in Figure 3, the article screening process is carried out in stages to obtain the literature that is most relevant to the research topic. Based on the search results using a query on the Scopus database, as many as 241 initial articles related to this research topic were obtained. Furthermore, an *article selection process* was carried out based on *predetermined inclusion criteria*. In the next stage, *duplicates were removed* and *screening based on titles and abstracts* was carried out to identify the suitability of the articles with the focus of the research, so that the number of articles was reduced to 66 articles. After that, *exclusion based on full text availability* is carried out by evaluating the availability of *full text* and completeness of article information, so that 47 articles can be analyzed further. The last stage of the selection process is the *exclusion of irrelevant articles based on full text assessment*, which is the process of evaluating the content of the article thoroughly to ensure a direct link with the

development of *architecture*, *AI*, *precision fertilization*, and *rural agriculture*. Based on this process, as many as 30 final articles were obtained which were used as the main source in the process of analysis and development of *reference architecture* in this study.

Meanwhile, in the *synthesise* stage, all selected articles are analyzed and synthesized to identify the most relevant components, technologies, methods, and approaches in the development of *AI-based precision fertilization in rural agriculture*. This stage begins with the *data extraction process* to collect important information from each article, such as the purpose of the research, methods used, supporting technologies, architectural components, and implementation results obtained. Furthermore, the results of the analysis are summarized at the *report findings* stage to identify *research gaps*, *research patterns*, and *best practices* in the application of *AI* and *precision fertilization*. Based on the results of the synthesis, the research then develops a *reference architecture for AI based precision fertilization in rural agriculture* that combines business aspects, applications, data, and technology as a guideline for the implementation of smart agricultural systems in rural agricultural environments.

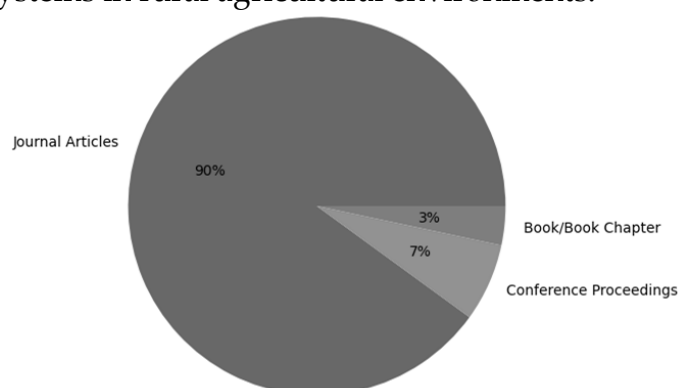


Image 4 Distribution of References by Publication Type

Based on the analysis of 30 references used in this study, Figure 4 shows that the majority of literature sources come from scientific journal articles as many as 27 publications (90%). Meanwhile, 2 references (6.67%) come from international conference proceedings and 1 reference (3.33%) comes from books or *book chapters*. These results show that the foundation of the research is dominated by journal publications that have gone through a *peer review* process, thus providing a high level of credibility and scientific validity in supporting the development of *AI architecture for precision fertilization* in rural agricultural environments.

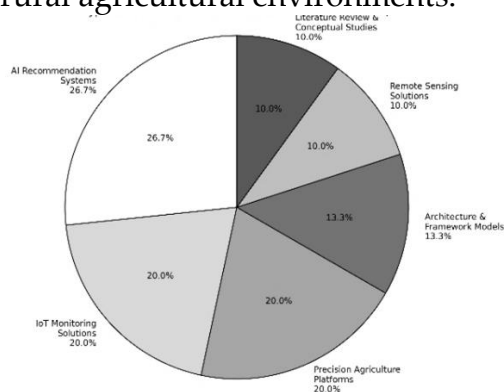


Image 5 Types of Artefacts Discussed in the Selected Articles

The diagram in Figure 5 provides an overview of the types of artifacts that are most discussed in the 30 selected articles used as the basis for development in this study. Based on the results of the analysis, most of the research focused on *AI recommendation systems* (26.7%), which include the development of fertilizer recommendation systems, crop recommendations, and machine learning-based decision support systems to assist farmers in determining the right actions based on land conditions and plant nutrient needs. Furthermore, *IoT monitoring solutions and precision agriculture platforms* each have a proportion of 20%, which shows that previous research has developed many sensor-based monitoring solutions as well as digital platforms that support integrated and data-based agricultural management.

In addition, 13.3% of the research discussed *architecture and framework models*, which included the development of frameworks, conceptual models, and architectural approaches to support digital transformation in the agricultural sector. Although the number is smaller than the research oriented to system implementation, this research group has an important role because it is the foundation for designing integration between business, application, data, and technology aspects. Meanwhile, *remote sensing solutions* (10%) focus on the use of satellite imagery, drones, and multispectral sensors to support monitoring land and plant conditions, while *literature review and conceptual studies* (10%) contribute in the form of knowledge synthesis, identification of research trends, and mapping of developing technologies in the fields of *precision agriculture* and *artificial intelligence*.

These results show that most of the previous research is still oriented towards the development of technical solutions, such as AI-based recommendation systems, precision agriculture platforms, and IoT-based monitoring systems. On the other hand, research that specifically addresses aspects of architecture and system integration is still relatively limited. These findings show that there is a *research gap*, that is, there are not many studies that propose a *reference architecture* that is able to integrate various components of technology, data, applications, and business processes in one comprehensive framework. Therefore, this study contributes by proposing an *AI based precision fertilization reference architecture* that not only pays attention to the implementation aspect of technology, but also models the relationship between business needs, application functions, digital services, technology infrastructure, and *stakeholders* in the rural agricultural environment. Thus, the resulting architecture is expected to be a guideline for the development and implementation of *precision fertilization systems* that are integrated, sustainable, and in accordance with the real needs of farmers.

Focus Group Discussion (FGD)

In the framework of designing architectural reference for the implementation of *artificial intelligence* (AI) in the rural agriculture sector, empirical validation of the conceptual draft is essential to ensure that the proposed solution not only works technically, but can also be used in operations. For this purpose, this study adopts the Focus Group Discussion (FGD) method as a participatory qualitative evaluation

instrument. *Focus Group Discussion (FGD)* is a qualitative research method that is conducted through targeted group discussions to gain an in-depth understanding of participants' perceptions, experiences, and views on a particular topic through interaction between group members (Afiyanti, 2008). In this study, FGD is used as a validation method for the design of an AI-based precision *agriculture* enterprise system architecture that will be designed at the next stage, so that later it can be known that the design is suitable for the needs and real conditions in the field.

The use of FGD in the validation process was chosen because this method is able to generate *collective insights*, strengthen the validation process to clarify user needs, and support system design evaluation through interactive communication between participants (Nyumba et al., 2018). The discussion was carried out in groups by involving the main actors directly related to agricultural activities in the Pangalengan area, especially farmers as the main users of the system. During the FGD process, the participants provided input related to the needs of soil monitoring, fertilizer recommendations, agricultural data management, to the need for IoT technology integration for further development and AI in supporting agricultural decision-making in *real time*.

The results of the discussion showed that the participants generally agreed with the proposed enterprise architecture design because it was considered to be able to help improve the efficiency of fertilizer use, agricultural productivity, resource management, and support more integrated agricultural digitalization. In addition, farmers also said that the use of AI and IoT-based systems is considered relevant to modern agricultural challenges such as inefficient fertilization, limited land monitoring, and low technology utilization in the agricultural sector.

C. RESULTS AND DISCUSSION

This section presents the results of the *Systematic Literature Review (SLR)* process that has been carried out on 30 selected articles. The results of the analysis are divided into two main parts, namely *demographical analysis* and *identification of key architectural components* used as the basis for the development of *reference architecture*. *Demographical analysis* is carried out to identify the distribution of publications based on year, type of publication, journal or *conference source*, as well as research trends related to *precision fertilizer*, *artificial intelligence*, *nutrient management*, and *smart farming*. This analysis shows that AI-related research in *precision fertilizer* has increased significantly in recent years as IoT technology, machine learning, and data-driven agriculture develop.

Furthermore, the main results of the SLR are focused on the identification of the architectural components that are most often used in the previous research according to the list of articles in Appendix A. Based on the results of the literature synthesis in accordance with Table 1, several main architectural aspects are obtained consisting of *drivers*, *assessments*, *goals*, *requirements*, *business functions*, *business processes*, *application components*, *application services*, *technology components*, *devices*, and *software systems*.

Table 1 SLR Result

Architectural Aspect	Definition	Component	Reference
Driver	Main motivations behind adopting Ai based precision fertilization systems in rural agriculture	Food security	P1, P2, P7, P10, P11, P20, P30
		Sustainability	P2, P3, P5, P7, P9, P18, P19, P29
		Productivity	P2, P6, P11, P20, P24, P27
		Agriculture resource	P4, P15, P17, P23, P30
		Nutrient efficiency	P10, P16, P29
Assessment	Challenges and issues identified form current agricultural fertilization practices	Inefficient nutrient management	P1, P2, P3, P7, P10, P11, P15
		Limited technology adoption and integration	P1, P4, P5, P6, P8, P11, P19, P20, P27
		Environmental and resource sustainability challenges	P2, P3, P7, P9, P15, P20, P29, P30
Goal	Intended outcomes to address agriculture fertilization challenges	Improve agricultural productivity and efficiency	P2, P6, P7, P10, P11, P20, P23, P24, P26, P29
		Enhance sustainable nutrient management	P2, P3, P7, P10, P15, P18, P19, P25, P29
		Enable intelligent and automated decision making	P9, P12, P15, P17, P20, P24, P27
Requirement	System capabilities required to achieve precision fertilization goals	Ai based fertilizer recommendation system	P1, P6, P10, P15, P23
		Precision nutrient analysis	P10, P15, P25, P29
		Scalable digital agriculture platform	P4, P18, P20
Business function	Core agricultural activities supported by the architecture	Fertilizer management	P6, P12
		Crop recommendation	P8, P13, P15, P24, P25
		Soil Monitoring	P3, P15, P25
		Resource optimization	P2, P4, P23, P30
Application component	Software applications supporting Ai based precision fertilization	Ai fertilizer recommendation engine	P1, P6, P10, P15, P21, P23
		Soil nutrient analysis module	P10, P15, P25, P29
		Farmer decision support application	P6, P15, P24, P26
Application service	Exposed digital services provided by the application	Fertilizer recommendation server	P1, P6, P10, P15, P21, P23
		Nutrient analysis service	P10, P15, P25, P29
		Decision support service	P6, P15, P24, P26, P28
		Reporting and visualization service	P4, P15, P20, P24
Technology component	Infrastructure supporting and	Application server	P6, P15, P21, P24
		Cloud infrastructure	P5, P12, P17, P20, P24

Architectural Aspect	Definition	Component	Reference
	precision fertilization services	Data storage infrastructure	P4, P6, P15, P25
Device	Physical devices collecting and processing agricultural data	Soil sensor	P1, P10, P12, P15, P25
		Mobile device	P6, P8, P13, P24
		Arduino/ ESP32 Device	P13, P23, P25
System software	Software platforms supporting execution and analytics	Ai framework	P2, P5, P10, P27, P30
		Database management system	P4, P6, P15, P25
		Analytics engine	P3, P4, P18, P20, P30

The results of the analysis show that the motivation aspect of architecture is initiated by five *main drivers*, namely *food security*, *sustainability*, *productivity*, *agriculture resource*, and *nutrient efficiency*. The five *drivers* show that the application of artificial intelligence in precision fertilization is not only aimed at increasing agricultural productivity, but also to support food security, nutrient use efficiency, environmental sustainability, and optimization of agricultural resources. These findings show that the need for digital transformation in the agricultural sector no longer focuses solely on increasing crop yields, but also on creating a more efficient and sustainable agricultural system.

Based on the literature review, there are three main groups of problems (*assessment*) that are the basis for architectural development. The first problem is *inefficient nutrient management* which includes inefficient use of fertilizers, soil nutrient imbalances, and excessive fertilizer application. The second problem is *limited technology adoption and integration* which shows low adoption of digital technology, lack of integration between agricultural systems, and limited data interoperability. The third problem is *environmental and resource sustainability challenges* related to the impact of climate change, high dependence on manual labor, and the need for more sustainable management of agricultural resources. The three *assessments* show that modern agricultural problems do not only come from the cultivation aspect, but also from the limitations of technology use and resource management.

To answer these various challenges, this study identifies three main goals, namely *improve agricultural productivity and efficiency*, *enhance sustainable nutrient management*, and *enable intelligent and automated decision making*. The first goal focuses on increasing the productivity of agricultural products and the efficiency of fertilizer use. The second goal focuses on sustainable plant nutrition management to reduce the environmental impact due to excessive fertilizer use. Meanwhile, the third goal aims to support faster, more accurate, and automated decision-making through the use of AI technology and *digital agriculture*.

The results of the analysis further show that the three goals are translated into three main requirements *of the system*, namely *the Ai based fertilizer recommendation system*, *precision nutrient analysis*, and *scalable digital agriculture platform*. These needs are the main foundation in designing an architecture that is able to automatically

produce fertilizer dosage recommendations based on soil conditions and plant needs, conduct precise nutrient analysis, and provide a digital platform that can be used sustainably in rural agricultural environments. At the *business layer*, this study identifies four main business functions that support the precision fertilization process, namely *fertilizer management*, *crop recommendation*, *soil monitoring*, and *resource optimization*. These functions describe the core activities carried out in fertilization management, ranging from monitoring soil conditions, analyzing plant needs, providing fertilizer recommendations, to optimizing the use of agricultural resources. These four business functions are the basis for determining the application and service needs that must be available in the proposed architecture.

Based on these business needs, this research produces three main *application components* that are more specific to the research objectives. The first component is the *AI fertilizer recommendation engine* which functions as the core of the system to produce recommendations for fertilizer types and doses using *artificial intelligence* and *machine learning techniques*. The second component is the *soil nutrient analysis module* which is tasked with analyzing soil nutrient content as the basis for the recommendation process. The third component is the *farmer decision support application* which provides an interface for farmers to access analysis results, fertilizer recommendations, and other supporting information. These three components represent key applications that directly support the implementation of *AI-based* precision fertilization.

Furthermore, the *application component* provides several *application services* that can be used by users and other systems. These services include *fertilizer recommendation service*, *nutrient analysis service*, *decision support service*, and *reporting and visualization service*. These four services allow the system to provide automatic fertilizer recommendations, conduct soil nutrient analysis, support farmer decision-making, and present information in the form of easy-to-understand reports and visualizations. From a technology perspective, this architecture is supported by three main *technology components*, namely *application server*, *cloud infrastructure*, and *data storage infrastructure*. *Application servers* are used to run application logic and AI models, *cloud infrastructure* supports centralized data storage and processing, while *data storage infrastructure* functions to store soil data, crop data, fertilization data, and agricultural historical data needed in the analytical process. The infrastructure is supported by physical devices in the form of *soil sensors*, *mobile devices*, and *Arduino/ESP32 devices* that function as a medium for collecting and exchanging data from the agricultural environment to digital systems.

At the supporting software layer, the architecture utilizes the *AI framework*, *database management system*, and *analytics engine*. The *AI framework* is used to build and run artificial intelligence models that generate fertilizer recommendations, the *database management system* is used to manage data storage in a structured manner, while the *analytics engine* supports the process of data analysis and the presentation of information needed for decision-making. Overall, the results of this literature synthesis show that the proposed *reference architecture* can include the linkages between motivational aspects, business needs, applications, and technologies needed

to support the implementation of *Ai based precision fertilization* in rural agricultural environments in an integrated and sustainable manner.

Motivation View

Motivation view is one of the *viewpoints* used to model aspects of organizational motivation, which is the basis for enterprise architecture development (ArchiMetric, 2023). This diagram is used to explain the main reasons why a change, system development, or digital transformation needs to be carried out in a certain organization or business environment (Hosiailuoma, 2022). In addition, this diagram is important in supporting communication between stakeholders because it is able to visualize the relationship between business motivation, system needs, and the direction of architecture development in a more structured and easy-to-understand manner (ArchiMetric, 2023).

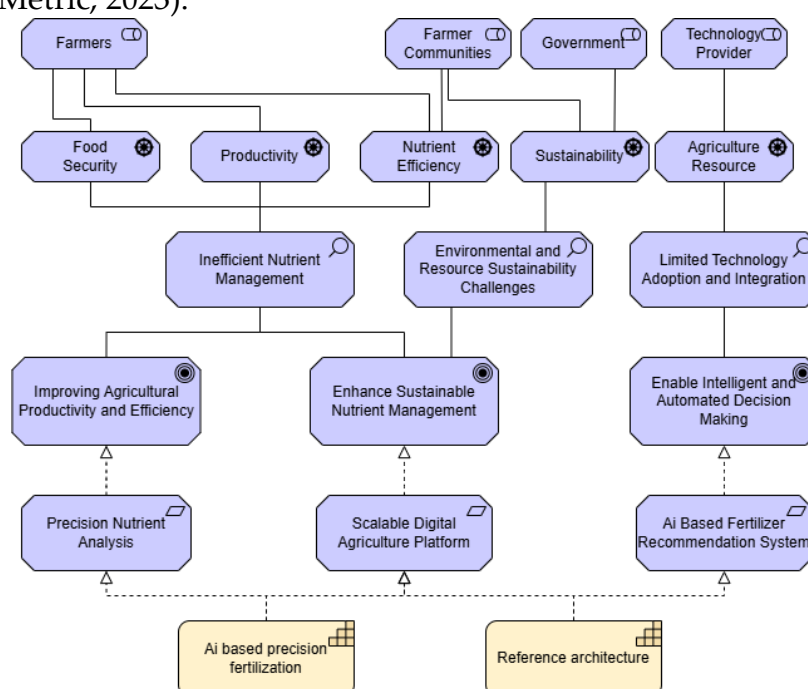


Image 6 Motivation View

In accordance with Figure 6, it shows a *motivation view* that describes the relationship between *stakeholders*, *assessments*, *goals*, *drivers*, and *requirements* in the development of this research. The *stakeholder* section identifies four main actors involved, *farmers*, *farmer communities*, *government*, and *technology providers*. These stakeholders have different but interrelated interests in the implementation of artificial intelligence-based precision agriculture. Farmers and farming communities focus on improving production yields and fertilizer use efficiency, governments have an interest in food security and the sustainability of the agricultural sector, while technology providers play a role in providing digital solutions that support agricultural transformation.

Based on the needs of these *stakeholders*, five main *drivers* were identified that motivated the development of architecture, namely *food security*, *productivity*, *nutrient efficiency*, *sustainability*, and *agriculture resource*. These *drivers* showed that the

implementation of an AI-based fertilizer recommendation system is not only aimed at increasing agricultural productivity, but also to support food security, improve the efficiency of nutrient use, maintain environmental sustainability, and optimize the use of agricultural resources. These five *drivers* are the main factors that drive the need for digital transformation in the fertilization management process in rural agricultural environments.

The literature analysis then produced three main *assessments* that describe the problems in the existing conditions. *The first assessment is inefficient nutrient management*, which reflects various problems related to improper fertilizer use, soil nutrient imbalance, and low fertilization efficiency. *The second assessment is environmental and resource sustainability challenges*, which are related to the environmental impact due to excessive use of fertilizers and the need for more sustainable management of agricultural resources. *The third assessment is limited technology adoption and integration*, which shows that the use of digital technology is still low and the limitations of data and system integration in agricultural activities. To overcome these various problems, three main *goals* are set that the proposed architecture wants to achieve. The first is *improving agricultural productivity and efficiency*, which focuses on increasing the productivity of agricultural products and the efficiency of fertilizer use. Second, *enhancing sustainable nutrient management*, which aims to create more sustainable and environmentally friendly plant nutrition management. Third, *enable intelligent and automated decision making*, which is oriented towards the use of digital technology and artificial intelligence to support automated and data-driven decision-making processes.

To realize these goals, this study identified three main *requirements*. *The first requirement is the Ai based fertilizer recommendation system*, which functions to produce recommendations for the type and dosage of fertilizer based on soil conditions and plant needs. *The second requirement is precision nutrient analysis*, which supports the process of accurately analyzing soil nutrient content as the basis for making recommendations. *The third requirement is a scalable digital agriculture platform*, which provides a digital platform that is able to integrate agricultural data, services, and business processes in a sustainable manner and is easy to develop in the future. All of these requirements are then realized in an architectural solution represented by *the AI Based Precision Fertilization Reference Architecture* element at the very bottom of the diagram. This architecture is the main artifact of the research that integrates soil nutrient analysis capabilities, AI-based fertilizer recommendations, and digital farming platforms into one structured architectural framework. Thus, this *motivational view* shows clear *traceability* from *stakeholder* needs to the resulting architectural solutions, thus ensuring that the proposed architectural design is able to answer real problems and user needs in the implementation of artificial intelligence-based precision agriculture.

Requirement Realization View

The requirement realization view is used to illustrate how the main needs of the system can be realized into business components, applications, application services, and technologies in the *AI based precision fertilization architecture*. This diagram shows the relationship between the layers of the enterprise architecture ranging from the business, application, to technology layers to ensure that all *system requirements* can be implemented in an integrated manner. In addition, this diagram also helps in visualizing how business needs are translated into application capabilities and technological infrastructure that support the *precision fertilizer process in rural agriculture environments*.

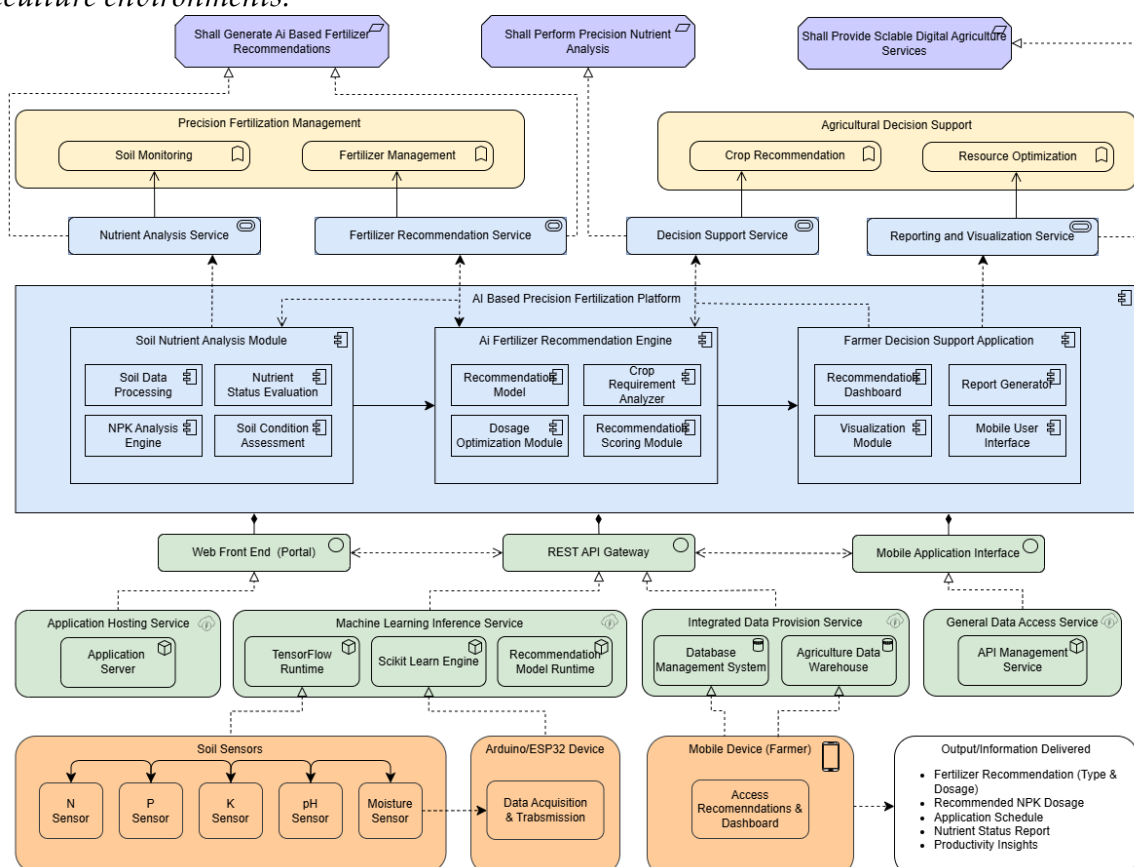


Image 7 Requirement Realization View

Based on Figure 7, it shows how the requirements that have been identified in the *motivation view phase* are realized through business functions, application services, application components, technology services, and devices that support the implementation of artificial intelligence-based fertilizer recommendation systems. At the very top, there are three main needs that are the basis for system development, namely *AI based fertilizer recommendations*, *precision nutrient analysis*, and *scalable digital agriculture services*. These three needs are realized by two groups of business functions, namely *precision fertilization management* and *agricultural decision support*. The function of *precision fertilization management* includes *soil monitoring* and *fertilizer management* activities that focus on collecting information on soil conditions and managing fertilization recommendations. Meanwhile, the *agricultural decision support* function

consists of *crop recommendations* and *resource optimization* that support agricultural decision-making based on available data.

To support these business functions, the system provides four application services, namely *nutrient analysis service*, *fertilizer recommendation service*, *decision support service*, and *reporting & visualization service*. These services act as functional interfaces that can be accessed by users and other applications. *The nutrient analysis service* is in charge of analyzing soil nutrient content, *the fertilizer recommendation service* produces fertilizer recommendations that are in accordance with the soil conditions, *the decision support service* helps the decision-making process, while *the reporting & visualization service* presents the results of analysis and recommendations in the form of easy-to-understand reports and visualizations. At the *application components level*, the platform consists of three main components that are the core of this research. The first component is *the soil nutrient analysis module* which is responsible for processing soil data, analyzing NPK elements, evaluating nutrient status, and assessing soil conditions. The second component is *the Ai fertilizer recommendation engine* which utilizes an artificial intelligence model to produce fertilizer dosage recommendations based on the results of soil analysis and plant needs. This module includes a *recommendation model*, *dosage optimization module*, *crop requirement analyzer*, and *recommendation scoring module*. The third component is the *farmer decision support application* which provides a recommendation dashboard, information visualization, report generator, and user interface that can be accessed by farmers. These three components form the main flow of the system, starting from analyzing soil conditions, making fertilizer recommendations, to submitting recommendations to users.

The integration layer provides a communication mechanism between components through the Web Front End, REST API Gateway, and *mobile application interface*. This layer allows for the exchange of data between applications, field devices, and end users in an integrated manner. The use of REST APIs also supports interoperability and continuous service development. At the technology layer, the system is supported by several main services, namely *application hosting service*, *machine learning inference service*, *integrated data provision service*, and *general data access service*. *Application hosting service* provides an environment to run applications, while *machine learning inference service* runs artificial intelligence models using frameworks such as TensorFlow and Scikit Learn. *The integrated data provision service* functions to manage the database and agricultural data warehouse, while *the general data access service* provides data access and API services for other components in the system. At the device layer (Edge/Farm Devices), the system utilizes *soil sensors*, *Arduino/ESP32 devices*, and *mobile devices (farmer)*. Soil sensors are used to measure parameters such as Nitrogen (N), Phosphorus (P), Potassium (K), pH, and soil moisture. The data obtained is collected and sent via an Arduino or ESP32 device to a central platform for further processing. The results of the analysis and recommendations are then submitted to farmers through mobile devices in the form of easy-to-understand dashboards and reports.

Table 2 Application Components of Ai based Fertilizer Precision

Application Component	Description	Supported Domain
Soil Nutrient Analysis Module	The module is tasked with processing and analyzing soil condition data, including NPK content, pH, moisture, and other fertility parameters to produce accurate information on soil nutrient status.	Nutrient Efficiency, Sustainability
Ai Fertilizer Recommendation Engine	An artificial intelligence-based module that generates recommendations for fertilizer types, dosages, and application schedules based on soil conditions, plant needs, and available agricultural data to improve fertilization effectiveness.	Productivity, Food Security, Nutrient Efficiency
Farmer Decision Support Application	An application that provides dashboards, visualizations, reports, and fertilization recommendation results to help farmers make faster, more precise, and data-driven decisions.	Productivity, Agriculture Resource, Food Security

Table 2 describes the main application components that make up the architecture of an artificial intelligence-based precision fertilization system. Each component has a different role, from analyzing soil conditions and nutrient content to produce Ai-based fertilization recommendations, to presenting the results of analysis and recommendations to farmers through a decision support interface. Thus, this table shows how the functional needs of the system are realized through application components that are integrated with each other to support the fertilization process. In addition, *the supported domain* shows the relationship of each application component to the main domain referred to in Figure 6. The domain presents the strategic objectives to be achieved through the implementation of the system, so that each application component is designed to contribute to one or more domains according to its functions and capabilities.

Primary Actors Validation

The primary actors validation stage is carried out to evaluate the suitability of the Ai based precision fertilization architecture with the needs and real conditions in the rural agriculture environment. The validation process involves farmers as the main actors, because farmers are the main users of the system that will interact directly with precision agriculture technology. This validation aims to ensure that the proposed architectural design is able to support agricultural activities effectively, is easy to use, and is in accordance with the problems faced by farmers in the fertilization process and management of agricultural land.

In this study, the validation process was carried out with farmers in the Pangalengan area, Bandung Regency, which is one of the agricultural areas with high levels of horticultural cultivation and intensive agricultural activities. Validation

activities were carried out through discussions, interviews, and evaluations of the architectural model that had been designed. Some of the aspects that were validated included the need for Ai-based fertilizer recommendations, real-time monitoring of soil conditions, ease of use of *mobile applications*, integration of agricultural sensors, and the ability of the system to help make more accurate and efficient fertilization decisions.

The validation results show that most farmers consider that the use of AI and IoT technology in *precision fertilization systems* can help improve the efficiency of fertilizer use, reduce waste, and support increased productivity of agricultural products. In addition, farmers also consider that the feature of monitoring soil conditions and data-based fertilizer recommendations is one of the main needs in supporting modern agricultural activities in rural environments. However, some farmers said that the aspects of ease of use of applications, the affordability of IoT devices, and the availability of internet networks in agricultural areas are still challenges in the implementation of the system as a whole.

Based on the results of the validation, the proposed architecture is considered to be in accordance with the main needs of farmers in Pangalengan, especially in supporting the data-based fertilization process, and precision agriculture management. The input from the farmers is then used as a basis for improving several architectural components, especially in the aspects of *user interface*, integration of field equipment, and simplification of the flow of use of the system to make it easier for users to adopt in *rural agriculture environments*.

D. CONCLUSION

This research has succeeded in developing a reference architecture for the modernization of precision fertilization based on artificial intelligence (AI) in rural agricultural environments using the enterprise architecture (EA) approach and ArchiMate modeling. The development of the architecture is carried out through a design science research (DSR) approach that integrates systematic literature review (SLR) and focus group discussion (FGD), so that the resulting architecture has a strong theoretical basis and is relevant to the needs of users in the field. Based on the results of the analysis of 30 selected articles, this study succeeded in identifying the main architectural aspects which include drivers, assessment, goals, requirements, business functions, application components, application services, technology components, devices, and software systems that support the implementation of Ai based precision fertilization in rural agricultural environments.

The results show that the development of precision fertilization systems is driven by five main drivers, namely food security, productivity, nutrient efficiency, sustainability, and agriculture resource. Meanwhile, the main problems found in existing conditions can be grouped into three main assessments, namely inefficient nutrient management, limited technology adoption and integration, and environmental and resource sustainability challenges. Based on these problems, this study identifies three main goals to be achieved, namely increasing agricultural

productivity and efficiency, supporting sustainable nutrition management, and enabling smart and automated decision-making through the use of AI technology.

To realize these goals, this study proposes three main system needs, namely AI based fertilizer recommendation system, precision nutrient analysis, and scalable digital agriculture platform. These needs are then realized through three main application components that are at the core of the proposed architecture, namely the soil nutrient analysis module, ai fertilizer recommendation engine, and farmer decision support application. These three components are supported by various application services, technology infrastructure, sensor devices, and analytics platforms that are integrated with each other to produce more accurate fertilizer recommendations based on soil conditions and plant needs. Thus, the resulting architecture is able to connect the data collection process, soil nutrient analysis, AI model processing, and the delivery of recommendations to farmers in one integrated framework.

Based on the results of primary actors validation conducted with farmers in the Pangalengan area, Bandung Regency, it was found that most farmers assessed that the use of AI and IoT technology in precision fertilization systems could help improve the efficiency of fertilizer use, reduce waste, support real-time land monitoring, and increase agricultural productivity. However, several implementation challenges are still found, especially related to the ease of use of applications, the affordability of IoT devices, and the limitations of internet network infrastructure in rural agricultural environments.

Overall, this research contributes in the form of an enterprise architecture that can be used as a guideline in the development of an Ai based precision fertilization system in rural agriculture environments. The resulting architecture not only supports the integration of AI technology, and data analytics in the precision fertilization process, but also supports a more efficient, sustainable, and data-based digital transformation of agriculture. For further research, development can be focused on the implementation of system prototypes, evaluation of the performance of AI models in real conditions, and the development of interoperability between digital agriculture platforms so that system implementation can be carried out more widely and scalably in various rural agricultural environments.

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