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Research Article

Designing Effective Smart Farm Information Processing Platforms: An AHP-Guided Methodology

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Abstract: As the global population expands, the demand for increased food production necessitates a corresponding rise in agricultural productivity. Smart farming presents a transformative solution by leveraging advanced technologies such as the Internet of Things (IoT), Cloud Computing, and Artificial Intelligence to optimize resource management and enhance productivity. These technologies enable the collection of vast amounts of data from diverse sources like weather stations, sensors, cameras, and smartphones. This data is crucial for decision support systems that provide actionable insights to improve farm management. However, smart farming faces significant challenges in managing and utilizing the massive volumes of data generated. A primary hurdle is the heterogeneity of agricultural data in terms of format, structure, and semantics, which complicates data integration and hinders effective communication between different systems. The lack of standardized protocols limits the seamless exchange of information among devices, software, and services within the smart farming ecosystem. These obstacles impede data sharing and collaborative service delivery, ultimately hindering the adoption and success of smart farming platforms. To address these challenges, this study employs the Analytic Hierarchy Process (AHP) to systematically evaluate and prioritize the key requirements for designing effective smart farming platforms. This study provides a structured framework for prioritizing essential requirements to enhance smart farming platforms. Addressing these prioritized requirements will facilitate the integration of diverse data sources, improve interoperability, and promote effective data-sharing practices. Ultimately, this will lead to increased productivity and efficiency in modern agricultural systems, meeting the growing global demand for food production.

***Keywords*:** smart farm, information processing, platforms, analytic hierarchy process, requirements

MSC: 68U35, 90B50

1. Introduction

Food production must rise by 70% by 2050 to accommodate the anticipated dramatic global population growth [1]. This surge in population necessitates enhanced agricultural productivity, considering resource limitations and the profitability of farms [2].

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Smart farming, commonly known as the fourth agricultural revolution, utilizes digital technologies to optimize the management of agricultural inputs such as pesticides, fertilizers, and animal feed. This approach helps to lower costs, reduce waste, minimize labor, and promote sustainable environmental practices [3, 4]. In smart farming, key technologies play distinct roles; the Artificial Intelligence (AI) would enable data-driven decision-making by processing large datasets and identifying patterns, while the Cloud Computing (CC) offers scalable, on-demand storage and computational power for handling extensive data, and the Internet of Things (IoT) connects sensors and devices to capture real-time information across the farm environment.

In 2020, the global market of smart farming was valued at USD 13.8 billion, reflecting farmers' increasing demand for solutions that improve livestock production, enhance crop yields, and decrease management costs. This market is projected to grow to USD 22 billion by 2025 [5]. Smart farming generates vast amounts of high-resolution, real-time data from different sensors and systems, covering various farming aspects such as crop growth, livestock health, soil conditions, and environmental aspects [6]. The data which includes spatial imagery, time series, and observations can be refined to eliminate inaccuracies and transformed into specific recommendations aimed at enhancing farm productivity [6, 7].

Technologies such as IoT, AI, and CC are fundamental in generating and analyzing the data necessary for smart farming [8]. However, data integration, as well as utilization of processes and regulations remain as major obstacles [9]. These obstacles include limited digitalization awareness, the need for standardized data analysis methods, privacy and security concerns. The absence of standardized practices and effective management strategies to handle diverse and fragmented data throughout the smart farming ecosystem, as well as the lack of uniform policies and regulations [9–12], are also concerning. Addressing these challenges is essential to reach the full potential of smart farming.

Several platforms have been developed to address some of the challenges of smart farming. For example, an IoT-based platform called SmartFarmNet [2] automates the collection of environmental and agricultural data (soil data, fertilization, and irrigation). It integrates actuators, sensors, and cloud servers to gather and analyze data. The findings given in the study demonstrated that the platform could deliver query replies in near real-time. Also, the research showed that adding more sensors did not significantly affect the system's performance and therefore confirming its scalability. The Smart Farming Oriented BigData Architecture (SFOBA) has been proposed by Mehdi et al. [10]. SFOBA is designed to process large volumes of data in real time, sourced from smart farm systems. A tool developed by Clements et al. [11] integrates diverse data sources for comprehensive disease prediction and livestock production, alongside risk assessment rules. However, these platforms often focus on individual aspects of smart farming and do not offer a holistic solution that considers the diverse and interconnected requirements of smart farming applications.

Our research addresses this gap by employing the Analytic Hierarchy Process (AHP) to systematically evaluate and prioritize the key requirements for designing effective smart farm information processing platforms. The AHP-guided approach focuses on five core categories that involve different requirements. These categories include data management, processing capabilities, security and compliance, user experience and adoption, and Sustainability and Future-Proofing. Each category encompasses related requirements. For example, the data management category encompasses interoperability, reliability, and scalability requirements, while the processing capability category includes real-time data processing, analytics and insights, and integration requirements.

The AHP method aims to enhance collaboration among different stakeholders in the smart farming ecosystem by systematically assessing and prioritizing these requirements. The effort is aimed at creating an effective utilization of diverse data sources, enhance food safety and production, and achieve greater sustainability. The proposed AHP-guided methodology provides a comprehensive framework that enhances the integration of diverse data sources, improves interoperability, and supports robust data-sharing practices, which ultimately boosts the productivity and efficiency of smart farming systems. This research fills an urgent gap by providing a unified approach that considers all the necessary requirements for smart farming applications. This will lead to the development of more integrated, efficient, and sustainable agricultural practices.

2. The workflow of a smart farming platform

The smart farming platform provides a comprehensive and reliable solution for various stakeholders, including farmers, researchers, and technology providers, to collect, share, and utilize diverse data, resources, and insights [13–15]. This enhances the productivity and efficiency of smart farming operations. The platform is organized into distinct stages with defined roles and functions and provides a structured approach to implementing smart farming applications. This framework, illustrated in Figure 1, ensures a thorough understanding and effective execution of the platform's capabilities.

The process begins with data acquisition, where information is gathered from multiple sources such as sensors, satellites, farmers, and external databases. These sources, which include climate and weather data, present diverse types of data in various formats, often leading to compatibility issues and data anomalies [16]. Additionally, the gathered data might include incomplete entries, outliers, and missing values [16, 17]. The primary challenge at this stage is effectively managing this heterogeneity and resolving data issues to ensure the reliability of the data collected. Integrating these disparate sources into a cohesive dataset is crucial for subsequent analysis.

In the data preparation stage, the platform addresses these challenges through several preprocessing practices. This includes standardizing data formats, eliminating duplicate entries, handling missing values, and validating the data for accuracy and completeness. This ensures that the data is clean, consistent, and ready for analysis [18]. Data from various sources is then integrated into a centralized infrastructure, making it accessible for further processing. Following preparation, data is stored in a robust and scalable infrastructure designed to handle large volumes of diverse data. Effective data management practices ensure that the data remains consistent, complete, and accurate, facilitating quick retrieval and processing which supports real-time analytics and decision-making [19].

The data processing and analysis stage utilizes mathematical models, statistical methods, and AI techniques to transform raw data into actionable insights [15]. Machine learning, a key component, automates decision-making processes and supports rapid optimization, classification, prediction, and recommendation with minimal human intervention [20]. Advanced analytics include predictive models for forecasting crop yields and anomaly detection algorithms to identify unusual patterns that might indicate pest infestations or disease outbreaks. Model deployment involves implementing developed models to predict new data items, generalizing the model to make accurate predictions based on unseen data [15]. This helps inform future decisions, such as optimal harvest times and irrigation planning. Continuous monitoring and updating of these models ensure they remain accurate and relevant.

The decision-making stage leverages insights from data processing to guide actions. This involves system monitoring, rule management, and metadata management to ensure that recommendations and decisions are based on reliable data [21]. Applications range from disease prediction to pesticide control and water management, which are critical for the efficiency of smart farming.

In the final stage, service delivery and system access, processed data and insights are made accessible to end-users through various services. This includes system monitoring, rule management, and security and privacy measures to ensure data integrity and user confidentiality. APIs play a crucial role in integrating various components and resources, enhancing the system's efficiency and operation.

Ensuring trustworthiness, security, and privacy throughout all stages is paramount. The platform must adhere to relevant policies and regulations to build user confidence [15]. The integration of different components via APIs is essential for creating a cohesive and efficient ecosystem. Trustworthiness not only involves protecting data but also ensuring the transparency and explainability of AI models used, fostering confidence in their recommendations.

The smart farming platform is structured to address challenges at each stage, leveraging advanced technologies to revolutionize agriculture. This structured approach allows stakeholders to make informed decisions, optimize agricultural practices, and enhance overall productivity, contributing to a more resilient and sustainable agricultural sector. In essence, there are many factors and considerations required in order to integrate and synchronize smart farming elements that require decision-making based on prioritized selections.

Figure 1. The structured framework of the smart farming platform

3. Requirements and challenges in smart farming

Table 1. Categories and requirements for smart farming platforms

Category	Requirement	Description	Practical Implications	Source
Data management	Interoperability	Compatibility and seamless communication between different systems and devices.	Ensures smooth data flow between sensors, devices, and platforms.	[21, 23]
	Reliability	Ensuring data consistency, accuracy, and timeliness through robust validation mechanisms.	Prevents data loss and errors, ensuring accurate decision-making.	[24, 25]
	Scalability	Ability to handle increasing data volumes without compromising performance.	Supports expanding data needs as farm operations grow.	[15, 26]
Processing capabilities	Real-time processing	Supporting real-time data processing for immediate insights and actions.	Enables prompt response to changing conditions in the field.	[23, 27]
	Analytics and insights	Advanced tools for predictive analytics, trend analysis, and decision support.	Provides actionable insights for optimizing farm operations.	[28, 29]
	Integration	Integrating various data sources and systems for a holistic view of the ecosystem.	Combines diverse data for comprehensive farm management.	[15, 30]
Security and compliance	Security and privacy	Strong security measures to protect data from unauthorized access and breaches.	Safeguards sensitive farm data against cyber threats.	[31, 32]
	Compliance	Adherence to relevant regulations and standards.	Ensures legal compliance and builds trust with stakeholders.	[33, 34]
	Data governance	Policies and practices for managing data quality, security, and compliance.	Maintains high data standards and regulatory compliance.	[31, 35]
User experience and adoption	Ease of use	User-friendly and intuitive interface to enhance engagement and satisfaction.	Increases adoption rates by simplifying platform usage.	[36, 37]
	Cost-effectiveness	Affordable solutions providing significant value, crucial for small-scale farmers.	Makes advanced farming technologies accessible to all farmers.	[38, 39]
	Support and community	Robust support services and community fostering for shared experiences and best practices.	Enhances user knowledge and platform utility through community support.	[40, 41]
Sustainability and futureproofing	Adaptability	Adaptable to evolving technologies, practices, and environmental conditions.	Ensures long-term relevance and integration of new technologies.	[15, 42]
	Longevity	Designed for longevity with robust infrastructure and regular updates.	Reduces long-term costs and enhances system reliability.	[43, 44]
	Environmental impact	Minimizing environmental impact through optimized energy use and eco-friendly practices.	Promotes sustainable farming and reduces ecological footprint.	[44, 45]

To successfully implement smart farming practices, robust information processing platforms are essential for managing the complex and extensive data generated by modern agriculture [3, 22]. These platforms must be efficient, reliable, and adaptable to address the diverse challenges in agriculture, including varying crop types, soil conditions, climate change, and market dynamics. A clear understanding of these requirements will guide designers and developers in creating smart farming platforms that effectively address the needs of farmers and contribute to sustainable agricultural practices.

In this study, the requirements have been categorized into five main groups: data management, processing capabilities, security and compliance, user experience and adoption, and sustainability and futureproofing. This categorization is designed to provide a structured framework for assessing and prioritizing the various needs of smart farming platforms. Each category encompasses specific requirements, with descriptions and practical implications that underscore their importance in ensuring the platforms' overall effectiveness and sustainability.

The categorization process involves grouping related requirements under broader categories to comprehensively address the unique needs of smart farming systems. For example, the 'data management' category focuses on critical aspects such as interoperability, reliability, and scalability, which are essential for ensuring seamless data flow and managing the increasing data volumes associated with farm operations. Similarly, the 'processing capabilities' category highlights the need for real-time processing, advanced analytics, and integration, all of which are crucial for generating actionable insights and providing a holistic view of the farm ecosystem.

A rational and systematic approach has been created by organizing the requirements in this manner to understand the different aspects that smart farming platforms must address to remain effective and sustainable. This structured categorization also supports the application of the AHP method in this study, facilitating a more detailed and informed comparison and ranking of the various requirements identified. Table 1 details these essential requirements, supported by their practical implications as excerpted from previous related studies.

4. Methodology

The objective of this study is to evaluate and prioritize the requirements for designing effective smart farm information processing platforms. We proposed the use of AHP structured approach to trigger the best decision for 5 categories studied. It is essential to consider various system requirements to ensure optimal functionality and relevance to the specific needs of the agricultural domain [46] for the smart farming development. The integration of advanced technologies that need to be chosen from many options such as IoT, sensors, and data analytics to enhance productivity, efficiency, and sustainability in agriculture is crucial as it involves monetary investments. To address the complexity of smart farming systems, and difficulty to make a solid decision by stakeholders, this paper applies AHP to rank the requirements and options' importance, as seen in Figure 2. Following this approach, the development decisions can be tailored to meet the unique demands of smart farming environments, effectively.

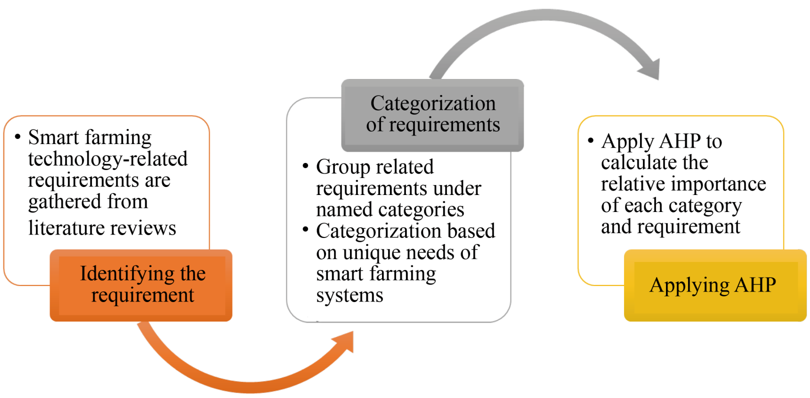

Figure 2. Methodology for identifying and prioritizing smart farms platforms requirements

4.1 *Identifying the requirements*

The first step in the methodology involves identifying the critical requirements for a smart farming system by reviewing relevant literature. The requirements are derived from academic sources such as journal articles, review articles, book, conference paper and white papers from Scopus and WoS databases. To reflect the smart farming trends and challenges, these papers were gathered and screened through the year 2017 until 2024. The screenings have seen 48 most relevant articles selected in this study. This step ensures a strong foundation, as the requirements are based on validated knowledge and real-world applications, which is vital for designing a platform that meets the needs of modern agriculture.

4.2 *Categorization of requirements*

Once the requirements are identified, they are organized into broader categories to facilitate a more structured analysis. Categorization helps in grouping similar requirements under themes, enabling a comprehensive approach to addressing the various aspects of smart farming. We have categorized important aspects from these papers based on the word frequency. It resulted in 5 categories which are: data management, processing capabilities, security compliance, user experience and adoption, and sustainability and future proofing. Each category has three requirements to aid in decision making process, as depicted in Figure 3. This step is crucial for ensuring that the system addresses the needs of different stakeholders, such as farmers, technologists, and policymakers, in a unified manner.

4.3 *Applying AHP*

The final step in the methodology is the application of AHP to rank the identified and categorized requirements based on their relative importance. AHP is chosen due to its structured approach to tackle decision-making problems involving multiple options [47, 48]. It typically organizes the Multi-Criteria Decision-Making (MCDM) problem into three hierarchical tiers: the overall objective, the criteria, and the possible alternatives [49]. After forming this hierarchy, pairwise comparisons are employed to assess the criteria within the same level. AHP is a practical and user-friendly method that can be implemented following the steps illustrated in Figure 3.

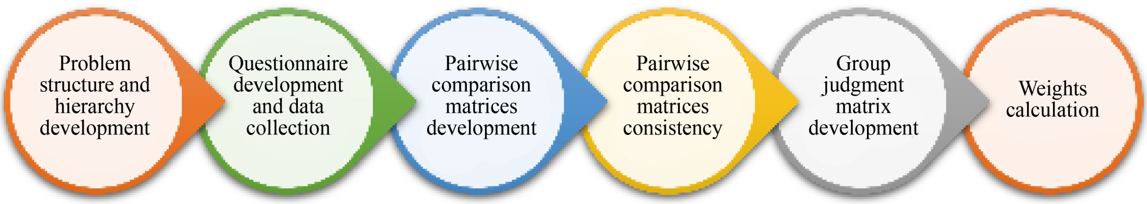

Figure 3. AHP steps

4.3.1 *Problem structure and hierarchy development*

In this step, an appropriate AHP model hierarchy is created. For this research, which aims to evaluate and prioritize the requirements for designing effective smart farm information processing platforms, the AHP hierarchy consists of the objective, categories, and requirements. The study's objective is to evaluate and prioritize the requirements for designing effective smart farm information processing platforms. Therefore, this objective is placed at the top level, followed by categories at the second level, and finally, the requirements at the third level, as illustrated in Figure 4.

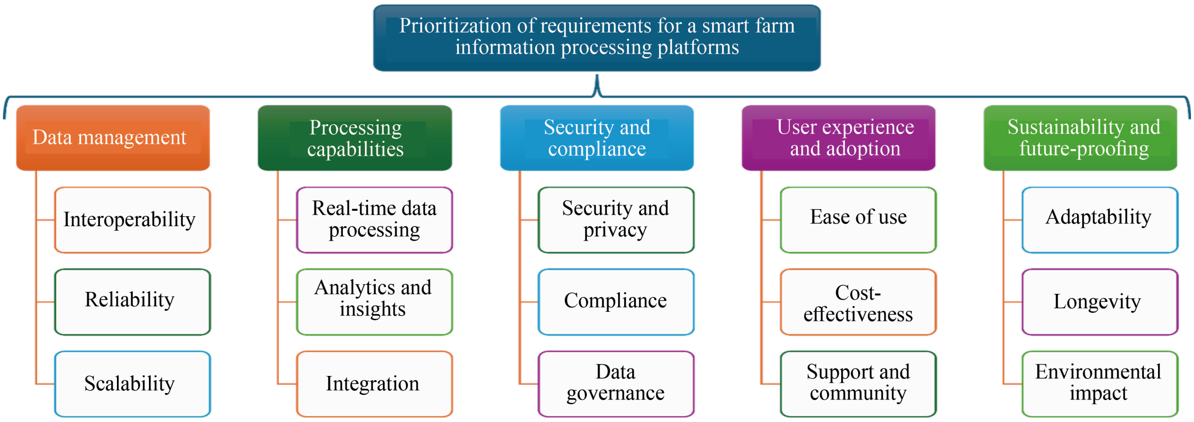

Figure 4. AHP hierarchy for evaluating and prioritizing the requirements for designing effective smart farm information processing platforms

4.3.2 *Questionnafire development and data collection*

In this phase, experts in smart farming, IoT, CC, and AI are asked to conduct pairwise comparisons of the categories and key requirements for designing effective smart farm information processing platforms. Experts assign relative scores to these comparisons using a nine-point scale shown in Table 2. Since AHP is a decision-making method rather than a statistical one, it does not require a statistically significant sample size. Instead, AHP focuses on the quality of decisions, allowing it to work effectively with a small, expert sample.

Table 2. Importance scale for pairwise comparisons

Value	Descriptive term
1	Equally important
3	Moderately important
5	Strongly important
7	Very strongly important
9	Extremely important
2, 4, 6, 8	Intermediate values

A questionnaire was developed based on a pairwise comparison assessment using Table 2. It includes comparisons between categories and between requirements, and it was distributed to 15 experts from various institutions to gather their insights on the key requirements for designing effective smart farm information processing platforms. We received 10 complete questionnaires from the experts. Each expert has at least 7 years of experience in implementing advanced technology solutions. The questionnaire developed for this study is provided in Appendix A.

4.3.3 *Pairwise comparison matrices development*

The pairwise comparison matrices are created by analyzing the experts' responses to the questionnaires. Judgments are expressed as a numerical value. If a category/requirement in a row is deemed x times more important than a category/requirement in a column, the numerical value x is placed in the $[a_{ij}]$ position of the comparison matrix, and its reciprocal $1/x$ is entered in the $[a_{ji}]$ position. When two categories/requirements are considered equally important, a value of 1 is entered in both positions. A category/requirement, compared to itself, always receives a value of 1, resulting in a diagonal of 1s in the matrix. This reciprocal property means that the value assigned to the comparison of one category with another automatically determines the reverse comparison, ensuring that if one category is considered x times more important than another, then conversely, the latter is $1/x$ times as important as the former, thereby preserving consistency in the matrix. Thus, each pairwise comparison matrix, denoted as $A = [a_{ij}]$, is a square matrix of order m with reciprocal property (where the order m represents the total number of categories/requirements being compared), as shown below:

$$A = [a_{ij}] = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1m} \\ a_{21} & 1 & \cdots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & 1 \end{bmatrix} = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1m} \\ \frac{1}{a_{12}} & 1 & \cdots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{a_{1m}} & \frac{1}{a_{2m}} & \cdots & 1 \end{bmatrix}$$

This relationship is often expressed as depicted in Equation (1):

$$a_{ji} = \frac{1}{a_{ij}};\ i,\ j = 1,\ 2,\ \cdots\ m. \tag{1}$$

The purpose of using pairwise comparison matrices in this study is to systematically quantify expert judgments, ensuring consistency in decision-making and enabling the derivation of priority weights for different categories and requirements.

4.3.4 *Consistency of pairwise comparison matrices*

To obtain reliable results, it is imperative to ensure consistency in an expert's evaluations [50]. This consistency can be measured using a Consistency Index (*CI*) that evaluates the consistency of pairwise comparison matrices larger than 2 × 2. The Consistency Ratio (*CR*) serves as the metric, with a *CR* value of 0.10 or less indicating a consistent matrix. If the *CR* exceeds 0.10, the matrix is considered inconsistent, and the expert needs to reassess their judgments. The Consistency Index (*CI*) for a pairwise comparison matrix is calculated using the following equation:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{2}$$

Here, n is the number of elements being compared, and $\lambda_{\max}$ is the maximum eigenvalue of the comparison matrix. The maximum eigenvalue ($\lambda_{\max}$) plays a crucial role in this calculation: it represents the degree to which the judgments in the matrix deviate from perfect consistency. In a perfectly consistent matrix, $\lambda_{\max}$ equals n, making the *CI* zero. Any deviation of $\lambda_{\max}$ from n reflects inconsistencies in the pairwise comparisons, with a larger difference indicating greater inconsistency. Measuring the consistency of pairwise comparison matrices is essential because it ensures that the expert judgments are logically coherent and reliable. This validation is fundamental to the study as it guarantees that the derived priority weights accurately reflect the experts' assessments, enhancing the overall credibility and robustness of the decision-making process.

The *CR* is computed by dividing the *CI* by $RI(n)$, where $RI(n)$ represents the consistency index of a randomly generated pairwise comparison matrix, and its value depends on n, as shown in Table 3. This relationship is expressed as follows:

$$CR = \frac{CI}{RI(n)} \tag{3}$$

Table 3. Random index values for different numbers of elements (n)

Number of elements (n)	$RI(n)$
3	0.58
4	0.90
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.49

4.3.5 *Group judgment matrix development*

To obtain a collective assessment from the individual evaluations of experts, it is necessary to merge their comparison matrices. The geometric mean is used to aggregate the individual judgment matrices, as shown in the following equation:

$$[a_{ij}] = \left(\prod_{i=1}^{m} a_{ij}\right)^{\frac{1}{N}} \; ; \; N: \text{Number of experts} \tag{4}$$

4.3.6 *Weights calculations*

After the comparison matrices are aggregated, a normalized matrix (denoted as N) is constructed for each group judgment matrix to derive the relative weights of the requirements. The process of normalizing the matrix is based on Equation (5).

$$N = [N_{ij}] \; ; \; \{N_{ij}\} = \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}} \tag{5}$$

Once normalized, the requirements weights are determined by calculating the average of each row within the matrix. The average values from these rows correspond to the individual requirement weights, forming a weight vector $W = (w_i)$, where each w_i represents the weight of a requirement from the row of the matrix. Equation (6) shows this process.

$$w_i = \frac{\sum_{j=1}^{m} N_{ij}}{m} \tag{6}$$

In the subsequent stage, the global weights of both the main criteria (categories) and sub-criteria (requirements). The local weights, initially calculated for each category and requirement, are essential for this process. For categories, the local weights directly represent their global weights. However, for the requirement, their global weights are computed by multiplying their local weights by the local weights of their corresponding categories. This relationship is expressed in the equation where the Global Weight of a Requirement (GWR) is the product of its Local Weight (LWR) and the Local Weight of the Category it belongs to (LWC), as represented in Equation (7).

$$GWR = LWR \times LWC \tag{7}$$

5. Results and discussion

In this study, a hierarchical structure with three levels was developed to systematically prioritize the requirements of designing smart farming platforms. At the top level of the hierarchy, the primary objective was to establish a clear prioritization of categories and requirements. The second level consisted of key categories, while the third level was dedicated to specific requirements within each category. To gather data, a questionnaire was distributed to 15 experts from different institutions, who have experience in smart farming technologies. Out of the 15, 10 experts provided complete responses. These experts performed pairwise comparisons of the categories and requirements, and their judgments were used to construct comparison matrices.

To ensure the reliability of the expert judgments, the *CR* was calculated for each comparison matrix using Equations (2) and (3). Subsequently, group judgment matrices were developed using Equation (4), representing the collective opinions of the experts. Each matrix was checked for consistency, and the results showed that all matrices met the acceptable consistency threshold. This confirmed the validity of the obtained weights. Then, these matrices were normalized using Equation (5).

The final weights and rankings of the categories and requirements calculated using Equations (6) and (7) are presented in Table 4. Additionally, Tables 5, 6, 7, 8, and 9 provide detailed group judgment matrices and consistency tests for the categories and their corresponding requirements within the hierarchical structure. These results provide a robust framework for prioritizing the key requirements necessary for designing smart farming platforms.

Table 4. Weights and ranks of smart farming requirements

Category	Category weight	Requirement	Local weight %	Global weight %	Rank
Data management	41%	Interoperability	52.4%	21.484%	1
		Reliability	28.7%	11.767%	3
		Scalability	19%	7.79%	6
Processing capabilities	29.9%	Real-time processing	52.9%	15.8171%	2
		Analytics and insights	30.2%	9.0298%	5
		Integration	16.9%	5.0531%	8
Security and compliance	14.1%	Security and privacy	64.1%	9.0381%	4
		Compliance	24.2%	3.4122%	9
		Data governance	11.7%	1.6497%	12
User experience and adoption	10.2%	Ease of use	59.7%	6.0894%	7
		Cost-effectiveness	26.8%	2.7336%	11
		Support and community	13.5%	1.377%	13
Sustainability and futureproofing	4.9%	Adaptability	62.6%	3.0674%	10
		Longevity	25%	1.225%	14
		Environmental impact	12.4%	0.6076%	15

5.1 *Prioritization of categories*

The analysis revealed that data management is the most critical category (weight = 41%). This finding reflects the fundamental role that data plays in smart farming systems, where managing, sharing, and storing data effectively is crucial.

The importance of this category can be explained by the increasingly data-driven nature of agriculture, where multiple devices, such as IoT sensors, drones, and machinery, continuously generate huge amounts of data. In such a context, robust data management that supports interoperability, reliability, and scalability is indispensable. Without effective data management, the potential benefits of smart farming, such as optimizing resource use, improving crop yields, and reducing environmental impacts, cannot be fully realized.

The second highest priority is assigned to the processing capabilities category (weight = 29.9%), which emphasizes the need for real-time data processing and insightful analytics. In the context of smart farming, real-time processing is critical for immediate decision-making, whether it be adjusting irrigation schedules, applying fertilizers, or monitoring livestock. Smart farm platforms must be able to process data quickly and efficiently, allowing farmers to respond to real-world events on time. Moreover, the integration of Analytics and Insights plays a fundamental role in making sense of large datasets, enabling predictive modeling and trend analysis. Without strong processing capabilities, farms risk losing the timeliness and accuracy of data, which are essential for optimizing operations.

Security and compliance category (weight = 14.1%) ranked third, underlining the growing concern over the protection of sensitive agricultural data. As smart farming systems become more interconnected and reliant on cloud-based services, they are increasingly vulnerable to cyber-attacks. Data breaches could lead to the loss of valuable proprietary information or sensitive environmental and operational data, which may affect competitive advantages or even regulatory compliance. The high ranking of this category underscores that smart farming platforms need for strict data governance frameworks, robust cybersecurity measures, and adherence to legal and regulatory standards to ensure the integrity and confidentiality of the data being handled.

The user experience and adoption category (weight = 10.2%) emerged as the fourth-highest category, indicating the importance of designing platforms that are user-friendly and cost-effective. Smart farming platforms will only be successful if they are accessible to farmers with varying levels of technological proficiency. Many farmers, especially in rural areas, may lack advanced technical skills or resources to adapt to complex systems. Hence, ensuring ease of use and offering community support to help farmers adopt and adapt to new technologies is essential. Additionally, cost-effectiveness is a key consideration for adoption, as farmers need to justify their investment in smart farming technologies by ensuring a good return on investment.

The sustainability and futureproofing category (weight = 4.9%) ranked lowest among the categories but remains essential for ensuring the long-term viability of smart farming platforms. As environmental concerns continue to grow, platforms that are adaptable, resource-efficient, and capable of minimizing their environmental impact will be critical for future-proofing agriculture. The relatively lower weight suggests that, while important, these factors may be perceived as secondary compared to the immediate challenges of managing and processing data and ensuring security.

Table 5 provides the consistency test and group judgment matrix for the category matrices. The consistency was confirmed with a result of $CR = 0.0354$, which is lower than the acceptable threshold of 0.10. This indicates that the weights obtained from these matrices are reliable.

Table 5. Categories group judgment matrix and consistency test

Category	Data management	Processing capabilities	Security and compliance	User experience and adoption	Sustainability and futureproofing	Priority vector	Consistency vector
Data management	1	1.876028	3.579789	3.519482	5.757238	0.4136	2.1329
Processing capabilities	0.533041	1	2.980364	3.519482	5.075295	0.2862	1.4758
Security and compliance	0.279346	0.335529	1	1.888175	3.684268	0.1613	0.8447
User experience and adoption	0.284133	0.284133	0.529612	1	3.015676	0.1126	0.589
Sustainability and futureproofing	0.173694	0.197033	0.271424	0.331601	1	0.0563	0.2953
Consistency test	λ_{max}			5.1585			
	n			5			
	CI			0.0396			
	CR			0.0354			

5.2 *Requirement-level prioritization*

The requirement-level prioritization provides deeper insights into the specific needs that must be addressed when designing smart farming platforms.

Within the data management category, the highest priority was assigned to interoperability (local weight = 52.4%). This highlights the essential role of ensuring that different components within the farming ecosystem can seamlessly communicate with each other. Interoperability enables the integration of diverse technologies, which is critical in multi-faceted farming operations. For instance, IoT devices might collect data on soil moisture, while weather stations provide climate forecasts. Without interoperability, these systems could not interact efficiently, potentially leading to incomplete decision-making. Reliability (local weight = 28.7%) and scalability (local weight = 19%) are also important within this category. Reliability ensures that data systems consistently perform under various conditions, which is crucial for maintaining the integrity of farming operations. Scalability, on the other hand, becomes increasingly important as farms grow or introduce more data-generating devices. A scalable platform can handle growing datasets without sacrificing performance, making it indispensable for large-scale farming operations or those planning for future expansion. Table 6 shows the consistency test and group judgment matrix for the data management category. The consistency was verified with a result of ($CR = 0.0113 < 0.10$).

Table 6. Data management group judgment matrix and consistency test

Requirement	Interoperability	Reliability	Scalability	Priority vector	Consistency vector
Interoperability	1	2.047673	2.459509	0.5226	1.5785
Reliability	0.488359	1	1.691726	0.287	0.8643
Scalability	0.406585	0.591112	1	0.1904	0.5725
Consistency test	λ_{max}		3.0131		
	n		3		
	CI		0.0065		
	CR		0.0113		

Real-time processing (local weight = 52.9%) was identified as the top priority in the processing capabilities category. Smart farming environments require instant feedback for irrigation control, pest management, or harvesting decisions. Real-time data analysis allows farmers to act immediately on insights, which improves efficiency and reduces risks. For example, a sudden drop in temperature could trigger immediate protective actions for frost-sensitive crops, or the detection of pests could prompt early intervention before damage spreads. Also, analytics and insights (local weight = 30.2%) play a critical role, as the ability to derive actionable insights from data is crucial for optimizing farming practices. Without advanced analytics, the wealth of data generated by smart farming systems may go underutilized. Lastly, integration (local weight = 16.9%) ranked lower but remains necessary for connecting different systems within the farm, ensuring that data flows seamlessly between devices and is accessible for processing and analysis. The group judgment matrix for the processing capabilities category was checked for consistency, and the results were satisfactory ($CR = 0.0182 < 0.10$). Table 7 displays the consistency test and group judgment matrix.

Table 7. Real-time processing group judgment matrix and consistency test

Requirement	Real-time processing	Analytics and insights	Integration	Priority vector	Consistency vector
Real-time processing	1	2.023696	2.712972	0.5277	1.6003
Analytics and insights	0.494145	1	2.071933	0.3029	0.9147
Integration	0.368599	0.482641	1	0.1695	0.5101
Consistency test	λ_{max}	3.0211			
	n	3			
	CI	0.0106			
	CR	0.0182			

For the security and compliance category, security and privacy (local weight = 64.1%) was assigned the top priority, reflecting the critical need to protect sensitive agricultural data within smart farm platforms. These platforms, often relying on IoT devices and cloud-based infrastructure, are particularly vulnerable to cyber threats. Compliance (local weight = 24.2%) and data governance (local weight = 11.7%) were also deemed essential, ensuring adherence to industry standards and maintaining control over data access and usage. As smart farm platforms become more complex, ensuring robust security measures and compliance with evolving regulations will be crucial to protecting the privacy of farmers and the integrity of agricultural operations. The group judgment matrix for the security and compliance category was checked for consistency, and the results were deemed acceptable ($CR = 0.0498 < 0.10$). Table 8 presents the detailed consistency test and group judgment matrix.

Table 8. Security and compliance group judgment matrix and consistency test

Requirement	Security and privacy	Compliance	Data governance	Priority vector	Consistency vector
Security and privacy	1	3.365865	4.31736	0.6356	1.9756
Compliance	0.2971	1	2.625298	0.2452	0.747
Data governance	0.231623	0.380909	1	0.1192	0.3598
Consistency test	λ_{max}	3.0577			
	n	3			
	CI	0.0289			
	CR	0.0498			

Within user experience and adoption, ease of use (local weight = 59.7%) was identified as the top priority, which suggests that smart farming platforms must be accessible and intuitive for farmers. Due to the diversity in technological proficiency among farmers, ensuring that platforms are easy to operate is essential for widespread adoption. Complex platforms that require advanced technical knowledge may hinder farmers from integrating them into their operations, thus limiting the reach and impact of smart farming innovations. Cost-effectiveness (local weight = 26.8%) was also important, as the cost of implementing and maintaining smart farming platforms can be a major barrier to adoption. Providing solutions that offer a favorable return on investment can help ease this concern. Finally, support and community (local weight = 13.5%) reflects the need for continuous assistance and a collaborative network to help farmers fix issues and learn how to maximize the platform's benefits. The group judgment matrix for the user experience and adoption category was checked for consistency, and the result was acceptable ($CR = 0.0275 < 0.10$). Table 9 presents the detailed consistency test and group judgment matrix.

Table 9. User experience and adoption group judgment matrix and consistency test

Requirement	Ease of use	Cost-effectiveness	Support and community	Priority vector	Consistency vector
Ease of use	1	2.656402	3.703937	0.594	1.8151
Cost-effectiveness	0.376449	1	2.380026	0.27	0.8174
Support and community	0.269983	0.420163	1	0.1361	0.4099
Consistency test	λ_{max}		3.032		
	n		3		
	CI		0.016		
	CR		0.0275		

Lastly, adaptability (local weight = 62.6%) emerged as the most significant requirement in the sustainability and futureproofing category. Since the agricultural sector faces constant change, whether due to climate shifts, technological advancements, or evolving market demands, smart farming platforms must be flexible enough to adapt to new conditions. Platforms that are adaptable ensure long-term relevance and resilience. Longevity (local weight = 25%) and environmental impact (local weight = 12.4%) also play a role, as designing systems built to last and minimize environmental footprints is becoming increasingly important in sustainable agriculture. The group judgment matrix for the sustainability and futureproofing category was checked for consistency, and the result was acceptable ($CR = 0.0333 < 0.10$). Table 10 shows the consistency test and group judgment matrix.

Table 10. Sustainability and futureproofing group judgment matrix and consistency test

Requirement	Adaptability	Longevity	Environmental impact	Priority vector	Consistency vector
Adaptability	1	3.051405	4.155652	0.6228	1.9125
Longevity	0.327718	1	2.44949	0.2518	0.7632
Environmental impact	0.240636	0.408248	1	0.1255	0.3781
Consistency test	λ_{max}		3.0386		
	n		3		
	CI		0.0193		
	CR		0.0333		

5.3 *Top ten ranked requirements*

The global weights calculated in this study offer a clear and comprehensive understanding of how each requirement contributes to the overall success of smart farming platforms. These weights reflect the aggregated significance of each requirement, considering both the category and the specific needs within each category. Through global weights, we can prioritize the most critical aspects of smart farming platforms and provide insights into their relative importance across the hierarchy of requirements. The top ten ranked requirements shed light on the essential components that should be prioritized when designing and developing smart farming platforms.

At the top of the list is interoperability (global weight = 21.48%), which makes it the most critical requirement overall. This emphasizes the necessity for smart farming platforms to facilitate seamless communication and integration among various devices, systems, and software used within farming operations. The importance of interoperability lies in the fact that different technologies, including IoT sensors, drones, and data analytics tools can work together harmoniously. A failure to establish robust interoperability would result in fragmented data, inefficiencies, and the potential for misinformed decision-making. Therefore, it is recommended that developers prioritize using open standards, APIs, and protocols that foster interoperability across diverse agricultural systems.

Real-time processing ranked second (global weight = 15.82%), is another important requirement of smart farming platforms. In the fast-paced environment of modern agriculture, where conditions can change rapidly, the ability to process data in real-time is essential. Whether adjusting irrigation schedules based on soil moisture levels or deploying pest control measures in response to real-time sensor data, timely decisions can significantly enhance productivity and reduce waste. Therefore, smart farming platforms should be equipped with advanced real-time processing capabilities, ensuring farmers can access up-to-date insights that allow them to react swiftly to changing conditions.

Reliability (global weight = 11.77%) emerged as the third most critical requirement. Reliability is essential to the consistent performance of smart farming platforms, ensuring that data collection, processing, and system functionalities remain dependable under various conditions. Agricultural environments are often subject to unpredictable factors such as extreme weather, making it vital that smart farming platforms are resilient and can operate without interruptions. Developers are encouraged to implement reliability-focused features, such as failover systems, redundancy in data storage, and robust testing protocols to ensure platforms can withstand operational challenges.

Security and privacy (global weight = 9.04%) ranked fourth, highlighting the growing need for safeguarding sensitive farming data. As the adoption of cloud-based systems and IoT devices in agriculture increases, so do the risks of cyber threats and unauthorized data access. Protecting proprietary farming information, operational data, and other sensitive materials is crucial for maintaining trust in these platforms. Developers should implement strong encryption, user authentication, and regular security audits to mitigate risks and ensure compliance with data protection regulations.

Analytics and Insights (global weight = 9.03%) also ranks among the top priorities, displaying the vital role of data-driven decision-making in modern farming. Advanced analytics capabilities allow farmers to extract actionable insights from vast amounts of data generated by sensors and other devices. This enables farmers to optimize resource use, predict trends, and make informed strategic decisions. Smart farming platforms should therefore integrate artificial intelligence and machine learning tools to provide predictive analytics that support proactive decision-making.

Scalability (global weight = 7.79%) ranked sixth, emphasizing the need for platforms that can grow alongside expanding farming operations. As farms increase in size or introduce new technologies, the data load on smart farming systems will inevitably rise. A scalable platform ensures that the system can accommodate this growth without compromising on performance or efficiency. Developers should focus on creating architectures that allow for easy scaling, whether it be through cloud computing, modular system designs, or other flexible solutions that can handle increasing demands.

Ease of use (global weight = 6.09%) ranked seventh, highlighting that user experience remains a key factor. Smart farming platforms should be accessible to a wide range of users, many of whom may not have extensive technical knowledge. Platforms that are intuitive and user-friendly will see higher adoption rates, as they lower the barrier for farmers to integrate digital technologies into their operations. Developers should focus on designing clear, simple interfaces and providing sufficient training or support materials to ensure that farmers can quickly and easily understand how to use the platform.

Integration (global weight = 5.05%) ranked eighth, reinforcing the importance of ensuring smooth data flow between various systems and devices. Smart farming platforms must be able to integrate data from multiple sources, including weather stations, soil sensors, and market forecasts, to provide comprehensive and actionable insights. Developers can ensure a more effective and holistic decision-making process by enhancing platform integration capabilities to consolidate all relevant data.

At the ninth priority, compliance (global weight = 3.41%) has emerged. This demonstrates the importance of adhering to legal and regulatory frameworks in the design and operation of smart farming platforms. As agriculture becomes more regulated in terms of environmental impact and data management, ensuring compliance with national and international regulations is critical. Developers should collaborate with policymakers and legal experts to ensure that platforms meet the necessary standards for environmental sustainability, data privacy, and other relevant areas.

Finally, adaptability (global weight = 3.07%) ranked tenth, which reflects the need for smart farming platforms to be flexible and future-proof. As technology continues to evolve and environmental conditions shift, adaptable platforms will be better positioned to meet future challenges. Developers should focus on creating flexible architectures that can accommodate new technologies, regulatory changes, and evolving user needs without requiring extensive overhauls.

5.4 *Comparison with alternative decision-making methods*

A comparison with other decision analysis methods has been included to emphasize this study's originality and scientific contribution. Alternative MCDM approaches such as Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS), Fuzzy AHP, and the Analytic Network Process (ANP) offer different advantages. However, AHP was chosen for this study due to its straightforward hierarchical structure, ease of implementation, and robustness in incorporating expert judgments. Unlike TOPSIS, which relies on the distance to an ideal solution, or FANP and ANP, which require complex interdependencies and substantial data, AHP efficiently handles qualitative assessments and is particularly well-suited for scenarios with limited sample sizes. This comparative advantage makes AHP an effective tool for prioritizing requirements in smart farming platforms.

5.5 *Practical efficiency testing*

In addition to theoretical advantages, the efficiency of the proposed AHP-guided methodology can be practically evaluated through case studies and pilot implementations. For instance, a smart farming platform can be developed or simulated using the prioritized requirements obtained via AHP. Its performance can then be benchmarked against specific metrics such as data integration efficiency, real-time processing speed, system reliability, and user adoption rates. Comparative experiments might also be conducted, where decision-making outcomes using AHP are compared with those from other MCDM methods. Metrics such as decision accuracy, computational time, and stakeholder satisfaction can be employed to validate the practical benefits of the AHP approach. Such empirical assessments demonstrate the methodology's efficiency in real-world scenarios and provide feedback for continuous improvement.

5.6 *Comparison with related studies*

Several studies have addressed aspects of smart farming platforms, yet most have focused on individual challenges rather than providing a comprehensive prioritization framework. For example, the SmartFarmNet platform [2] primarily emphasizes real-time data acquisition and scalability, while the Smart Farming Oriented Big Data Architecture (SFOBA) [10] concentrates on processing large data volumes in real time. Other works, such as that by Clements et al. [11], integrate diverse data sources for disease prediction and livestock production, but these studies do not systematically prioritize requirements across multiple dimensions. In contrast, our AHP-guided methodology holistically evaluates and prioritizes technical and non-technical requirements, including data management, processing capabilities, security, user experience, and sustainability. This comprehensive approach not only enhances the decision-making process but also offers insights into the relative importance and interrelationships among these requirements. Future research could further validate our findings by comparing the outcomes of our methodology with those derived from alternative decision analysis methods or through empirical field studies.

6. Conclusions

In conclusion, this study has emphasized the critical role of advanced technologies such as IoT, Cloud Computing, and Artificial Intelligence in revolutionizing agricultural productivity through smart farming. The developed three-level hierarchy effectively prioritizes smart farming platform requirements by structuring the overall goal at the top, key categories in the intermediate level, and specific requirements at the lowest level.

Expert insights were gathered through questionnaires distributed to 15 professionals specializing in smart farming technologies, with 10 providing complete responses which shows positive acceptance to the study's initiatives. The AHP analysis revealed that data management is the most critical category, holding a weight of 41%, emphasizing the necessity of effective data management, sharing, and storage. While these technologies offer immense potential to optimize resource management and enhance productivity, the challenges of managing and integrating heterogeneous data remain a significant obstacle to their full adoption. As shown in the study, for data management category, Interoperability emerged as the top requirement with a global weight of 21.48%, underscoring the need for seamless communication between various devices and systems. Processing capabilities ranked second with a weight of 29.9%, highlighting the importance of Real-Time Processing (15.82%) for immediate decision-making, such as adjusting irrigation schedules or applying pest control measures based on real-time data.

Other significant categories included Security and Compliance (14.1%), stressing the importance of robust cybersecurity measures to protect sensitive agricultural data, and user experience and adoption (10.2%), emphasizing the design of user-friendly and cost-effective platforms to encourage widespread adoption among farmers with varying technical skills. Sustainability and futureproofing (4.9%) was identified as the least impactful category, yet it still underscores the importance of smart farming platforms adapting to environmental changes and technological advancements for long-term viability.

The prioritization of these requirements is expected to have a substantial economic impact. By focusing on key areas such as data management and real-time processing, smart farming platforms can significantly reduce operational costs, optimize resource allocation, and improve yield predictions. Enhanced interoperability and streamlined data integration can lower the expenses associated with data inconsistencies and system redundancies, while robust security measures build stakeholder confidence, promoting wider adoption. In essence, the framework not only enhances technological integration but also drives economic efficiency by enabling cost-effective decision-making and improved return on investment in agricultural technologies.

By employing the Analytic Hierarchy Process (AHP), this study has successfully identified and prioritized the key requirements for developing effective smart farming platforms. Addressing these priorities will help overcome data-related challenges by improving interoperability, fostering standardized communication protocols, and enhancing data-sharing practices across systems. The proposed framework offers a pathway toward more efficient and integrated smart farming solutions, ultimately contributing to meeting the increasing global demand for food production. This work lays a foundation for future research and development efforts aimed at optimizing agricultural systems through enhanced data management and technological integration.

7. Limitations

While the AHP-guided methodology offers a structured approach and effectively incorporates expert judgments, it is not without limitations. One major concern is the potential subjectivity inherent in expert evaluations. Since pairwise comparisons rely on individual opinions, biases or differences in interpretation can affect the resulting weights. Another limitation is that AHP assumes independence among criteria, which might not fully capture the complex interdependencies in smart farming systems. Future studies could mitigate these issues by integrating complementary techniques (e.g., fuzzy logic or other multi-criteria decision-making methods) and by validating the outcomes through larger-scale field studies or real-world pilot implementations.

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Conflict of interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

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Appendix A

AHP questionnaire developed for this study.

Table 11. Pairwise comparison questionnaire for categories

Criteria (Categories)	The left side is more important ←								Equal	The right side is more important →								Criteria (Categories)
	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	
Data management	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Processing capabilities
	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Security and compliance
	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	User experience and adoption
	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Sustainability and futureproofing
Processing capabilities	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Security and compliance
	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	User experience and adoption
	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Sustainability and futureproofing
Security and compliance	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	User experience and adoption
	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Sustainability and futureproofing
User experience and adoption	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Sustainability and futureproofing

Table 12. Pairwise comparison questionnaire for data management category

Sub-criteria (Requirements)	The left side is more important ←								Equal	The right side is more important →								Sub-criteria (Requirements)
	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	
Interoperability	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Reliability
	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Scalability
Reliability	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Scalability

Table 13. Pairwise comparison questionnaire for processing capabilities category

Sub-criteria (Requirements)	The left side is more important ←								Equal	The right side is more important →								Sub-criteria (Requirements)
	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	
Real-time processing	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Analytics and insights
	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Integration
Analytics and insights	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Integration

Table 14. Pairwise comparison questionnaire for security and compliance category

Sub-criteria (Requirements)	The left side is more important ←								Equal	The right side is more important →								Sub-criteria (Requirements)
	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	
Security and privacy	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Compliance
	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Data governance
Compliance	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Data governance

Table 15. Pairwise comparison questionnaire for user experience and adoption category

Sub-criteria (Requirements)	The left side is more important ←								Equal	The right side is more important →								Sub-criteria (Requirements)
	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	
Ease of use	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Cost-effectiveness
	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Support and community
Cost-effectiveness	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Support and community

Table 16. Pairwise cmparison questionnaire for sustainability and futureproofing category

Sub-criteria (Requirements)	The left side is more important ←								Equal	The right side is more important →								Sub-criteria (Requirements)
	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	
Adaptability	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Longevity
	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Environmental impact
Longevity	⑨	⑧	⑦	⑥	⑤	④	③	②	①	②	③	④	⑤	⑥	⑦	⑧	⑨	Environmental impact