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Multi-Criteria decision analysis approach for selecting feasible data analytics platforms for precision farming

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ABSTRACT

Cloud computing has become a crucial part of smart farming systems. It offers various services, from data storage to data analytics and visualization. However, selecting a feasible platform is challenging since many factors and criteria need to be considered by decision-makers based on the organization's requirements to select the most optimal cloud solution. This study aimed to provide a systematic approach to selecting cloud computing-based data analytics platforms for precision farming. There are three important stages within the proposed approach: the preparation stage, the integrated model using Analytic Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) as an evaluation framework, and model evaluation. Three cloud computing platforms were evaluated using the proposed model for a novel smart farming project: Amazon Web Services, Google Cloud Platform, and Microsoft Azure. The results show that Google Cloud Platform (S2) is best optimal platform for the smart farming project called smart-in-ag based on the criteria and requirements defined by stakeholders. To validate the consistency and robustness of our proposed model, the sensitivity analysis method was applied to 13 cases. It was demonstrated that the proposed approach is consistent and robust for helping the experts who choose a cloud computing-based data analytics platform in a smart farming project. To the best of our knowledge, this study is the first application for selection the cloud computing platform for a real smart farming project.

1. Introduction

Smart farming is a management concept that provides the infrastructure to host advanced technology, including cloud computing, big data analytics, data management systems, and the Internet of Things (IoT), to help the agricultural industry observe, measure, analyze, and control field operations (Demestichas and Daskalakis, 2020); (Giray and Catal, 2021); (van Mourik, 2021). Implementing these technologies has increased the farm data in quantity and scope and made farm activities data-driven and data-enabled (Saiz-Rubio and Rovira-Más, 2020); (Wolfert et al., 2017). In smart farming, the data are the essential element generated by several sources, such as IoT devices, sensors, smartphones, or social media, implemented in the field, capturing all activities and operations. Therefore, the term "SMART" in the smart farming context refers to management concepts based on the technologies' wide availability of data. By employing these smart farming technologies and subsequent data, production yields can be increased and optimized with accurate decisions when the appropriate models are in place (Cambra Baseca et al., 2019). On one side, smart farming systems help to improve the final product's quality, on the other side, it allows for better transparency of processes aiming to confirm the 'license to produce' of the agricultural business. For instance, to reduce chemical inputs for agricultural products, the producers can precisely apply them in a specific area by using the generated data and smart farming technologies. As a part of Industry 4.0, smart farming brings many opportunities to increase the quality and quantity of productivity and reduce the environmental load by collecting and processing information and data (Fulton and Port, 2018).

In order to manage, control, and analyze the data used in the system, cloud computing has become one of the crucial parts of smart farming systems (Kaloxylos, 2014); (Junaid, 2021). Cloud computing promises the ability to process any type and size of data with its numerous

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computing technologies. As agriculture has become increasingly data-driven in recent years and likely continues to do so, cloud computing can be used as the infrastructure of a data analytics platform to extract valuable information from the generated data for decision-making. The roles of data analytics models in smart farming systems are to learn and analyze specific patterns and hidden information from the datasets (Nyoman Kutha Krisnawijaya et al., 2022). Moreover, cloud computing is a solution for complex smart farming systems since it can provide flexibility in choosing cloud services that fit customers' needs (Marston et al., 2011). Cloud computing offers various services, from data storage, data analytics, model implementations to data visualization services. The on-demand computational and storage resources for end-user applications are also provided by cloud computing to be accessed at any time (Moysiadis et al., 2021). Besides, the system maintenance costs can be reduced by using a cloud-based platform (Iosup et al., 2011). Therefore, selecting the most suitable cloud computing is key to achieving the organization's goals and purposes (Boutkhoum et al., 2017). However, choosing a feasible platform is challenging since many factors and criteria need to be considered by decision-makers based on the stakeholders' requirements in relation to the infrastructure available to select the best solution. In addition, users often face a wide choice of cloud computing providers but lack the appropriate information or knowledge of cloud computing services which can lead to undesired results (Kumar et al., 2017a).

This study proposes an approach to select the feasible cloud computing as part of a data analytics platform for smart farming in a systematic way. The multi-criteria decision analysis (MCDA) approach is applied for this purpose. This is an important method for handling a complex implementation, like selecting cloud computing for a data analytics platform, with various factors and requirements that need to be considered. Furthermore, the Analytical Hierarchical Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Durak et al., 2021) are integrated to introduce a systematic evaluation framework. In our case, cloud computing is needed as a data analytics platform for the smart farming project. Several studies used MCDA in selecting cloud computing providers and services. For instance, Garg et al. (2013) have tried to rank different cloud computing services by using the AHP method to choose the best one. The combination of two MCDA methods, Fuzzy-AHP and Fuzzy-TOPSIS, is shown by Boutkhoum et al. (2017) to select appropriate cloud computing to manage big data projects. Kumar et al. (2017b) integrated AHP-TOPSIS in order to develop a framework to evaluate and rank cloud computing services. In this research, the AHP has been applied for evaluating criteria weights using pairwise comparison, and TOPSIS ranked the final decision regarding cloud computing based on the weighted criteria.

This study is conducted within the context of the Smart Indonesia Agriculture (smart-in-ag) project. It is an international collaboration between Wageningen University & Research (WUR) in the Netherlands and Institut Pertanian Bogor (IPB) University in Indonesia that involves various researchers' backgrounds. The project aims to improve the quality and quantity of dairy and fish production by implementing smart farming technologies (The Interdisciplinary Research and Education Fund (INREF), 2022). The goal is to develop smart farming systems and increase the acceptance rate of smart farming technologies in Indonesia, specifically for the dairy and fish sectors (The Interdisciplinary Research and Education Fund (INREF). 2022); (Wageningen University Research. 2022). Furthermore, this project supports Indonesian farmers by providing new insights using the data and information from their fields and products using smart farming technologies. This project includes big data analytics, data management and infrastructure, machine learning, IoT, and cloud computing. The project will employ several emerging technologies to collect, store and analyze data from the farm. The farmers will be supported with the information generated by the data analytics platform based on the collected data to improve their daily activities on the farm (Nyoman Kutha Krisnawijaya et al., 2022). The use of these technologies can improve both the process on the farm and the farmers' economy and welfare. All authors of this study are involved in this project to design a system infrastructure, which includes computing modules, communication mechanisms, and data platforms. By means of this study, we objectively decide on a feasible data analytics platform for this project.

To the best of our knowledge, cloud computing selection for data analytics platforms in the smart farming context has not received much attention from researchers. Thus, the contributions of this study are as follows:

(1) To present a systematic approach to handling a complex decision-making process for cloud computing selection for a data analytics platform in a smart farming context.
(2) The validation of the approach using a real-project problem based on the involved stakeholders' backgrounds, needs and subsequent requirements. Furthermore, the practicality of the proposed method will also be assessed.

The paper is organized as follows: Section 2 provides the background of the case study used in this research. Section 3 describes the research background and related work. The proposed methodology for achieving the goal is presented in section 4. Section 5 presents the results of the case study. Section 6 discusses the results. Finally, Section 7 concludes the paper.

2. Case Studies: Indonesian smart dairy and fish farming

The population in Indonesia is expected to increase significantly, from 267 million in 2019 to 304 million in 2035 (Badan Perencanaan Pembangunan Nasional, Badan Pusat Statistik, and United Nations Population Fund. "Indonesia population projection, 2022). To anticipate the increasing demand for protein of this growing population, the agricultural productivity in Indonesia needs to be increased. According to Sari et al. (Sari et al., 2021), by expanding the agricultural land or improving the existing land production. Due to land and environmental constraints, simply expanding land for agriculture is not an option. Therefore, it is desired to increase agricultural production to fulfil the protein demands of the Indonesian people (Sari et al., 2021).

WUR and IPB established the smart-in-ag project in 2019 (The Interdisciplinary Research and Education Fund (INREF), 2022) to improve agricultural production by utilizing smart farming technologies, specifically for dairy and fish products. This international collaboration includes veterinarians, practitioners, governments, and industrial partners from the field, and in addition, researchers from the Netherlands and Indonesia. The main purpose of this project is to introduce and expand smart farming systems in Indonesian dairy and fishery production.

Smart-In-Ag aims to identify risk factors and management issues that cause production efficiency losses in the field. In Indonesia, the situation in the field is poorly documented. In addition, smallholder farmers in rural areas have difficulty reaching veterinarians to get advice on animal treatments. Consequently, the farmers must rely on relatively poor diagnostics and often treat their animals with subjective decisions, reducing the products' quality and productivity (Ahmed et al., 2017). In the smart-in-ag project, the data collection is conducted in two regions of Indonesia, resulting in a database containing milk quality and dairy cow health for dairy farming, and for fish farming, pond water quality and fish activity are captured. These generated data will then be processed and analyzed using several data analytics techniques advised by veterinarians and researchers. Thus, data analytics techniques need to be trained on a large data set of cows and fish at various farms. The implementation of advanced data analytics techniques, such as machine learning, and deep learning algorithms, can help farmers by providing valuable knowledge based on on-farm data (Wageningen University Research. "INREF Projects.", 2022); (The Interdisciplinary Research and Education Fund (INREF). "Smart-In-Ag Project Description.", 2022).

Various data types are needed for researchers involved in this project to develop and introduce the data analytics model. Numerous disciplines collaborate to establish the proper analytics model for dairy and fish farming. For instance, on-farm fish data collection is conducted to support the development of 'nutritious pound feeds' to stimulate natural food production in ponds. To achieve this goal, various factors such as feed composition, oxygen dynamics, nutrient ratios in feed, mineral waste, the emissions are needed to be learned. The use of various sensors, such as water quality sensors, helps to acquire on-farm fish data. Regarding dairy farms, a cohort study is conducted to provide accurate data collection to support the scientists in order to improve the health and performance of the participating herds. A proper data infrastructure is needed to acquire, store, analyze, and visualize the on-farm data for all stakeholders involved in this project.

However, for two reasons, it is not easy to define a proper and robust data analytics platform to host all data, models, and applications from an interdisciplinary collaboration project like the smart-in-ag project. First, in this project, various types of data are generated from several devices, as explained before. Moreover, this project needs to host different agricultural domains (i.e., dairy and fish), which require different types of data, analytics models, modules, and applications to establish a smart farming system. The situation is much more complex since all stakeholders have different backgrounds. For instance, the participating scientists include economists, social scientists, environmental scientists, computer scientists, veterinarians, and many others to tackle complex problems. The involvement of non-research stakeholders in this collaboration includes farmers, farm workers, farm management teams, government, investors, communities, and industrial companies.

Another reason is that many expectations and criteria arise when choosing suitable tools for the project due to the collaboration of many stakeholders. In this project, a proper data analytics platform is one of the crucial elements which need to be carefully determined by considering all requirements and needs. The decision to choose the platform should consider not only the technical factors of the system but also user needs and requirements. Therefore, data analytics platform selection is a multi-criteria decision work that must be carefully considered before deciding a final decision.

3. Related work

The selection of a cloud computing provider as part of the data analytics platform for a smart farming system is a crucial problem since the decision has various criteria from different stakeholders. Unfortunately, to the best of our knowledge, little work has been done in the process of selecting the most feasible cloud computing to accommodate smart farming projects. Integrating AHP and TOPSIS as an evaluation tool can be considered an optimal approach because of its flexibility and accuracy.

Garg et al. (2013) proposed a framework called SIMCloud, to measure the ability of cloud computing enterprises to meet the user's requirements in terms of the Quality of Service (QoS). Their work mainly focused on presenting a systematic measurement of all the QoS attributes defined by the Cloud Service Measurement Index Consortium (CSMIC) and ranking the cloud computing services based on these attributes. CSMIC has designed and established Service Measurement Index (SMI) as QoS attributes which can be used as comparison tools by customers among cloud computing services ("Selecting a Cloud Provider.", 2022). The various SMI attributes are Accountability, Agility, Assurance, Financial, Performance, Security and Privacy, and Usability. In this study, the proposed framework applied AHP as a model to evaluate all cloud providers depending on SMI requirements. Yadav and Goraya (2018)) also utilized QoS attributes in their framework, and AHP has been applied to assess the weight of defined criteria. They proposed a novel two-way ranking-based cloud service mapping framework (TRCSM) by evaluating cloud computing providers and service-requesting customers.

Another framework by Abdel-Basset et al. (2018) focused on dealing with conflicting information in the evaluation of cloud services by introducing the Neutrosophic Analytic Hierarchy Process (NAHP) presented in a case study in an e-learning service provider company in Egypt. Meesariganda and Ishizaka (2017) converted the verbal AHP scale into quantitative values for weighting the criteria and alternatives. They applied it in a real case study to select cloud computing providers. Tiwari and Kumar (2020) introduced a cloud service selection approach using the TOPSIS method based on Gaussian distribution. The framework ranked and evaluated the existing cloud services based on the quality of service provided by cloud providers and cloud users' demands and priority. By performing a case study using a real dataset, the effectiveness of the proposed framework was demonstrated.

Lee and Seo (2015) integrated several approaches, such as Balanced Scorecard (BSC), Fuzzy Delphi Method (FDM) and Fuzzy Analytical Hierarchy Process (FAHP) for a cloud selection problem. The BSC concept was used to derive decision-making criteria based on financial, customer, internal business process, and learning and growth perspectives. Furthermore, the FDM was applied to get the decision maker's opinions regarding the list of essential criteria within each BSC perspective. Finally, they used FAHP to select the best cloud computing service based on the weights of decision-making criteria and factors. They stated that their finding would provide a systematic decision-making process to evaluate cloud computing services' performance. Another integrated method was shown by Liu et al. (2016) by combining well-known methods in the decision-making process, such as Statistical Variance (SV), TOPSIS, Simple Additive Weighting (SAW), and the DELPHI-AHP approach. In this study, the authors determined the objective weights of the attributes or criteria and decision-makers. Several important factors from decision-makers, such as managerial skills, were included. This study aimed to improve the quality of decision results to be more accurate and theoretically reasonable.

A combined approach of Fuzzy AHP and Fuzzy TOPSIS was presented by Kumar et al. (2017b) to propose a selection approach under a fuzzy environment. They utilized these approaches to remove several cloud selection problems, e.g., subjectivity, vagueness, and uncertainty. Boutkhoum et al. (2017) also utilized similar approaches to evaluate, rank, and select the most suitable cloud computing platform for handling big data projects. This study presented the integrated approaches of Fuzzy AHP and Fuzzy TOPSIS.

The literature shows that cloud computing platform selection is a complex problem since multi-criteria on the quality-of-service attributes and stakeholders' needs must be considered. However, none of the existing studies presented cloud computing-based data analytics platform selection for a smart farming context (see Table 1). This study proposes a systematic approach by utilizing the following integrated MCDA approach, AHP and TOPSIS, to cloud computing-based data analytics platform selection in a smart farming project. The outcome of this study provides the requirements on how to host all data, modules, and user interfaces in the applications generated in the smart-in-ag project. Subsequently, it can be decided what cloud computing platform suits best and must be implemented for the two cases described.

4. Proposed approach

In this section, the research workflow used to select the most suitable cloud computing as a data analytics platform for smart farming projects is presented in Fig. 1. It is followed by an explanation of each stage, i.e., the preparation stage, AHP approach, TOPSIS approach, and final stage. The problem hierarchy was constructed in the preparation stage by following the organization's goals, criteria and alternatives. Next, the AHP and TOPSIS approaches were explained to help determine the most optimal option. Finally, the last stage is evaluating the proposed approach and presenting the final decision.

Table 1
Objectives and MCDA approaches.

Approach(es)	Objective(s)	Authors (Year)	Context
AHP	Ranking cloud computing services by using Quality of Service (QoS) attributes. Measuring all the QoS attributes defined by the Cloud Service Measurement Index Consortium (CSMIC) and ranking the cloud computing services based on these attributes.	Garg et al. (2013)	General
Balanced Scorecard (BSC), Fuzzy Delphi Method (FDM) and Fuzzy Analytical Hierarchy Process (FAHP)	Providing a systematic decision-making process to evaluate cloud computing services' performance.	Lee and Seo (2015)	Enterprise
Statistical Variance (SV), TOPSIS, Simple Additive Weighting (SAW), and DELPHI-AHP	Improving the quality of decision results to be more accurate and theoretically reasonable.	Liu et al. (2016)	Enterprise
AHP	Converting the verbal AHP scale into quantitative values for weighting the criteria and alternatives.	Meesariganda and Ishizaka (2017)	Enterprise
Fuzzy AHP and Fuzzy TOPSIS	Removing several cloud selection problems, e.g., subjectivity, vagueness, and uncertainty.	Kumar et al. (2017b)	General
Fuzzy AHP and Fuzzy TOPSIS	Evaluating, ranking, and selecting the most suitable cloud computing platform for handling big data projects.	Boutkhoum et al. (2017)	Big Data project
AHP	Ranking cloud computing providers by using QoS attributes and Service Requesting Customers (SRC). Providing two-way ranking-based cloud service mapping framework (TRCSM).	Yadav and Goraya (2018)	General
Neutrosophic Analytic Hierarchy Process (NAHP)	Ranking cloud services. Dealing with conflicting information in the evaluation of cloud services.	Abdel-Basset et al. (2018)	Enterprise
AHP-TOPSIS	Selecting the most suitable sector to be invested based on specific requirements such as economic, political, and country factors.	Çalık et al. (2019)	Investment
TOPSIS method based on Gaussian distribution	Ranking and evaluating the existing cloud services providers based on the quality of service provided by cloud providers and cloud users' demands and priority	Tiwari and Kumar (2020)	General
AHP - TOPSIS	Ranking and evaluating technopark based on companies' requirements	Durak et al. (2021)	Public place
AHP-TOPSIS	Selecting the most optimal cloud computing-based data analytics platform for a real smart farming project	This study	Smart farming

4.1. Preparation stage

The first stage is the preparation stage which includes four steps. At the beginning of this stage, the first author identified the smart-in-ag project's needs in developing a system infrastructure by consulting and questioning project members in internal meetings. The authors are responsible in the smart-in-ag project for developing the system infrastructure and has long experience in system infrastructure design. After that, the criteria or factors that essentially affect the optimal design are identified through literature studies by the authors. At this step, the potential solutions or alternatives are also identified. All literature, including grey literature such as websites or reports, is used to identify criteria and potential solutions.

The next step is to involve all project members as stakeholders in this study. Then, a questionnaire is distributed to the stakeholders to capture their needs regarding the literature studies' identified criteria. This survey intends to derive the essential criteria from the stakeholders' perspectives. In this stage, a self-reported questionnaire is used as the survey instrument, distributed to the participants through the online form. The stakeholders are asked to determine which items are essential for them. To prevent misunderstandings due to poor understanding of cloud computing, respondents could read instructions on the context or definitions of the terms used in the questions asked. Hence, this survey will bring new insight to the authors on which criteria should be opted for in the AHP process. This final step is an iterative process in which agreement on the criteria from all stakeholders needs to be achieved. In other words, the process repeats till there is consensus regarding criteria and potential solutions. The decision-makers committee is responsible for determining the criteria by considering the inputs from stakeholders since they come from various backgrounds and experiences in smart farming systems.

In the next sub-sections, after involving all project members to define the criteria, a list of these criteria is processed in AHP to weigh each of the criteria. Then, in the TOPSIS, the potential solutions are ranked to get the final decision. Evaluation of the selected approach is needed to demonstrate that the final decision of the approach is robust and consistent. Sensitivity analysis is used as a tool to evaluate the approach.

4.2. Integrated AHP-topsis process

4.2.1. Integrated AHP-TOPSIS approach

The MCDA approaches have been used to help decision-makers to seek the best solution to complex problems over the last decades. Many researchers have put their effort into enhancing the MCDA performance and providing an objective decision-making tool. The proposed integrated approach is designed as effectively as possible to help decision-makers by providing the most feasible solution based on criteria derived from the preparation stage. This study shows that two different methods, AHP and TOPSIS, are integrated to rank the data analytics platform for smart farming systems. The AHP method weighs the defined criteria, and then The TOPSIS ranks the possible solutions. Fig. 1 shows the proposed integrated MCDA approach for selecting data analytics platforms.

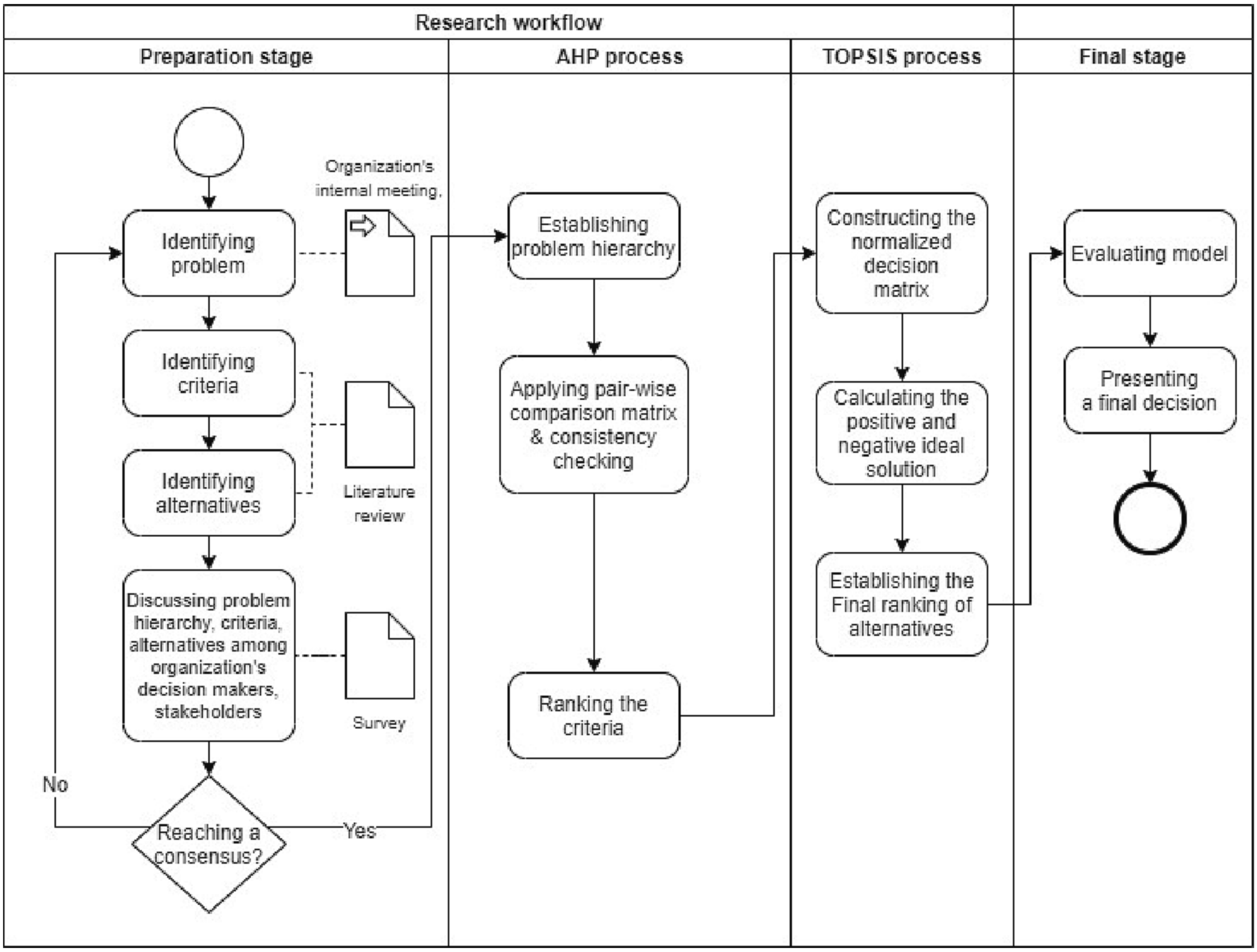

Fig. 1. The workflow of the selected approach for cloud computing selection.

4.2.2. AHP approach

The second stage of the workflow is the AHP process. AHP is one of the well-known MCDM approaches introduced by Saaty (1980). This method requires the decision makers' consideration of quantitative and qualitative data when making the decision. When providing a solution, the AHP approach organizes opinions, perceptions, judgments, and experiences into a multi-level hierarchy to give a clear view of a complex decision problem (Joshi et al., 2011). The approach provides several essential steps, from decomposing the problem to providing the solution (Lee and Seo, 2015); (Sindhu et al., 2017).

First (1), the decision problem is broken down into a hierarchy of manageable comprehended criteria, which can be analyzed independently. (2) Once the hierarchy is established, the internal decision-makers are responsible for evaluating the pairwise comparison matrices needed to calculate the criteria' relative weights. The weight of each criterion is quantified by comparing one to another using the fundamental AHP scale shown in Table 2.

Table 2
Nine-point importance scale.

Importance scale	Scale description
1	Equal importance
3	Weak importance
5	Strong importance
7	Very strong importance
9	Absolute importance

(3) The next step is to normalize the pairwise comparison matrix by following procedures (Saaty, 1980); (Sindhu et al., 2017): a) Sum every matrix column; b) Divide every component of the matrix by its column sum; c) Obtain the average of the rows to get relative weights. (4) Calculate the Eigenvectors and maximum Eigenvalue. (5) After calculating the eigenvalues of the criteria, the consistency rate and consistency index are calculated to verify the consistency of the judgements. The consistency rate is calculated by using the Equation (1):

$$CR = \frac{CI}{RCI} \tag{1}$$

where CR = Consistency Rate, CI = Consistency Index and RCI = Random Consistency Index.

RCI value is shown in Table 3.

The *CI* value can be calculated by using the following equation:

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

where λmax is the Eigenvalue of the pairwise comparison matrix and n is the number of criteria being compared.

The pairwise comparison processes should be repeated once the value of CR is above 0.1. Otherwise, it is acceptable if the value is lower than 0.1.

4.2.3. TOPSIS approach

In the next stage, the TOPSIS method is applied to determine the final

Table 3
Average RCI values.

Number of Criteria	1	2	3	4	5	6	7	8	9	10
RCI value	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

rank of the alternatives. TOPSIS is known as one of the attractive methods introduced by Hwang and Yoon (1981). The main idea of this approach is that the best alternative should be at the least geometric distance from the positive ideal solution while being the farthest geometric distance from the negative ideal solution (Hanine et al., 2016); (Çalık et al., 2019). The positive ideal solution means the most feasible solution with the most significant benefits and lowest cost among the alternatives. Meanwhile, the negative ideal solutions provide the worst solution with the highest cost and are less beneficial. The basic steps of the TOPSIS approach can be seen below (Çalık et al., 2019).

a. Create a decision matrix $D = [X_{ij}]$. The structure is shown as follows:

$$\begin{array}{cc} & C_1 C_2 \cdots C_n \\ D = \begin{array}{c} S_1 \\ S_2 \\ \vdots \\ S_m \end{array} & \begin{bmatrix} X_{11}X_{12}\cdots X_{1n} \\ X_{21}X_{22}\cdots X_{2n} \\ \cdots\cdots\cdots \\ X_{m1}X_{m2}\cdots X_{mn} \end{bmatrix} \end{array} \tag{3}$$

where X_{ij} is the judgment of performance rating alternative S_i regarding each criterion C_j.

b. Construct the normalized decision matrix $R = [r_{ij}]$ by using the following equation.

$$r_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{m} X_{ij}^2}}, i = 1, 2, \cdots, m; j = 1, 2, \cdots, n \tag{4}$$

where x_{ij} is the judgement of performance.

c. Calculate the weighted normalized decision matrix W_{ij} by multiplying the normalized decision matrix with its associated weights as follows:

$$W_{ij} = w_j \times r_{ij}; i = 1, 2, \cdots, m; j = 1, 2, \cdots, n \tag{5}$$

d. Identify the positive ideal solution (A^+) and negative ideal solutions (A^-) as follows:

$$A^+ = \{W_1^+, \cdots, W_n^+\} = \{(MaxW_{ij}|j \in J), (MinW_{ij}|j \in J')\} \tag{6}$$

$$A^- = \{W_1^-, \cdots, W_n^-\} = \{(MinW_{ij}|j \in J), (MaxW_{ij}|j \in J')\} \tag{7}$$

where J represents the Beneficial criteria, and J' defines the non-Beneficial criteria.

e. Determine the final ranking of the alternatives by calculating the Euclidean distance of all alternatives to the positive (D^+) and negative (D^-) Ideal solutions are as follows:

$$D^+ = \sqrt{\sum_{j=1}^{n} (W_{ij} - W_j^+)^2}, i = 1, 2, \cdots, m. \tag{8}$$

$$D^- = \sqrt{\sum_{j=1}^{n} (W_{ij} - W_j^-)^2}, i = 1, 2, \cdots, m. \tag{9}$$

Then calculate the relative closeness coefficient of each alternative to the ideal solution using the following equation:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}, i = 1, 2, .., m \tag{10}$$

$0 \leq C_i \leq 1$

The optimal alternative is the one that has the most significant index value.

4.3. *Final stage*

In this stage, the performance of the AHP and TOPSIS approach is analyzed using sensitivity analysis. Sensitivity analysis is a method to review the performance of a mathematical decision-making approach by changing its input. This method helps to check the consistency of the decision-making approach results with respect to various risks and inputs (Hanine et al., 2016); (Kumar, 2021). The consistent results obtained from sensitivity analysis reflect the robustness of the approach. The proposed approach in this research is reviewed using some scenarios in sensitivity analysis to ensure the approach has consistent results.

5. The application of the proposed approach in the smart farming project

5.1. *Problem, criteria, and alternatives identification*

As explained before, the smart-in-ag project is an international collaboration to introduce the smart farming system to Indonesian dairy and fish farming. In this study, the targeted stakeholders are project members involved in this collaboration. While decision-makers in this study are responsible for developing system infrastructures that other members will use to store, manage, analyze, and control their data.

In this research, an internal meeting among decision-makers has been done in order to define the main problem. The main problem that has been identified is how to determine the most appropriate cloud computing as part of data analytics platforms in the smart-in-ag project. After defining the problem, the literature review was conducted to derive information regarding the criteria and the potential alternatives for selecting data analytics platforms. Several items, such as data issues, technological perspectives, stakeholders' needs, and the project's purposes, were considered and discussed in the internal meeting.

From the literature, it was found that several criteria to evaluate and select the cloud computing providers can be chosen according to the quality of the cloud computing services. The CSMIC introduced the Service Measurement Index (SMI) framework, which consists of various QoS attributes to measure the quality of cloud computing services. All attributes in the SMI hierarchy have been characterized based on International Standard Organization (Garg et al., 2013); (Siegel and Perdue, 2012). The SMI framework defines several attributes, such as Accountability, Agility, Assurance, Financial, Performance, Security and Privacy, and Usability. Each attribute has sub-items that define the measurement of the cloud computing services ("Selecting a Cloud Provider." http://spark.adobe.com/page/PN39b/ (accessed March 14, 2022). It is also found that financial criterion is the key factor in determining cloud computing for a data analytics platform. After that, to identify other criteria, our previous Systematic Literature Review (SLR) (N. Nyoman Kutha Krisnawijaya, B. Tekinerdogan, C. Catal, and R. v. d. Tol, 2022) research article's results were used to identify the features of data analytics platforms in smart farming systems.

Furthermore, project managers, researchers, system developers, and other project members involved in the project were asked to weigh the criteria for their importance through a survey. The survey participants are asked to rate between 1 and 5 according to the importance of certain criteria. The criteria with the high scores are then selected to be included as inputs for data analytics platform selection.

Based on the literature review and project members' input, three main criteria and 12 sub-criteria that are the most essential and pertinent to selecting a data analytics platform were concluded as inputs to the AHP-TOPSIS method. The main criteria are Feature, Quality of services, and Financial, which are divided into several sub-criteria. The feature consists of data storage, data collection platform, data analytics, real-time processing, and data visualization. Quality of services is characterized by interoperability, security management, data integrity, and scalability. Financial is broken down into billing price, free trial, and financial flexibility. All criteria and a brief definition are shown in Table 4.

Several well-known public cloud computing providers were found during our previous SLR work. This research selected these cloud computing providers as potential alternatives for our problem: Amazon Web Services (AWS), Google Cloud Platform (GCP), and Microsoft Azure. Another reason for choosing these providers is based on the Gartner Magic Quadrant ("Magic Quadrant for Cloud AI Developer Services.", 2022); ("Cloud Infrastructure and Platform Services Reviews and Ratings.", 2022), which presented the top list of cloud providers led by these three providers. In the next stage, the AHP procedure is applied to weigh the selected criteria, and then the alternatives are ranked using the TOPSIS approach. These steps are explained in the following subsections.

5.1.1. Weighting criteria application in AHP

The first step of the AHP approach is to develop a hierarchy model of data analytics platform selection according to the main criteria, sub-criteria, and alternatives. The three main criteria are included in the first level, and the sub-criteria in the second level can be seen in Fig. 2.

After constructing the hierarchy model, decision-makers need to determine the weight of criteria using pairwise comparison matrices for all elements in each hierarchy level and quantify the preferences using the scale shown in Table 1. The initial pairwise comparison matrix for the main criteria is shown in Table 5. The pairwise comparison matrices for the second level, from Feature to Financial sub-criteria, can be seen in Table 6, Table 7, and Table 8, respectively.

The final step of the AHP approach is to normalise the weight of criteria and calculate the consistency ratio (CR) of each pairwise comparison matrix using Equation (1). The result of these steps is that the CR of each matrix is less than 0.1, as shown in Table 9.

5.1.2. Ranking alternatives using TOPSIS analysis

In this step, the normalized weights that were previously calculated using the AHP approach are used as inputs. Firstly, the decision-makers need to evaluate the data analytics platform alternatives according to each sub-criterion which is shown in Table 10. In this process, the points presented in Table 1 were used to weigh each alternative based on decision-makers opinions and preferences.

After this step, the aggregate rating matrix must be normalized by applying Equations (4) and (5). The positive and negative ideal solutions of the alternatives must be calculated using Equations (6) and (7). The results of these calculations are presented in Table 11.

Finally, the ranking of alternatives is calculated and determined using Equations (8) and (9). The best alternative is the one with the shortest distance to the positive ideal solution and with the longest distance to the negative ideal solution. Furthermore, Equation (10) is used to calculate each alternative's relative closeness coefficient (Ci) to the ideal solution. The best alternative is the one with the most significant index value. The result of these processes is shown in Table 12.

5.1.3. Sensitivity analysis

A sensitivity analysis was conducted to ensure the robustness of the

Table 4
A brief definition of all criteria.

Criteria	Brief description	Sub-criteria	Brief description
Feature (C1)	The feature is essential in selecting a platform for data analytics purposes. The ability of a platform to accommodate all users' needs to manage and analyze their data with a wide range of analytics tools significantly affects users' decisions in choosing the platform (N. Nyoman Kutha Krisnawijaya, B. Tekinerdogan, C. Catal, and R. v. d. Tol, 2022).	Data storage (C11)	The feature is related to storing, managing, and controlling the data needed by the customers.
		Data collection platform (C12)	The feature is provided by cloud computing to accommodate and manage customer data collection activities. For instance, cloud computing could connect, manage, and control various IoT assets from the end-users across edge and cloud systems.
		Data Analytics (C13)	The feature is for analytics purposes offered by cloud computing. For instance, machine learning or deep learning solutions. Big data analytics tools have recently been vital for data analytics purposes in smart farming systems.
		Real-time processing (C14)	Recently, stakeholders' requirements to get and process real-time field data have been increasing. Consequently, the features related to real-time processing are essential in selecting cloud computing for smart farming systems.
		Data visualization (C15)	The feature is related to building web or mobile-based applications for showing informative reports and dashboards that are easy to read and share.
Quality of service (C2)	A set of values for measuring and selecting the performance of cloud computing services.	Interoperability (C21)	The ability of cloud computing services to work alongside other services, both from the same or other

(continued on next page)

Table 4 (*continued*)

Criteria	Brief description	Sub-criteria	Brief description
	Quality of service is an essential factor that needs to be considered to choose feasible cloud computing (Garg et al., 2013); ("Selecting a Cloud Provider." http://spark.adobe.com/page/PN39b/ (accessed March 14, 2022); (Kumar et al., 2017b).		cloud computing providers.
		Security management (C22)	The ability of cloud computing to accommodate customers' needs regarding the security of data, applications, and security infrastructure. This criterion is part of Security and Privacy attributes in SMI QoS attributes.
		Data integrity (C23)	The ability of cloud computing to ensure keeping the form of the data that is created, stored and used by customers so that the data keep valid and accurate for further purposes.
		Scalability (C24)	The ability of cloud computing to meet client requirements by quickly increasing or decreasing the amount of service available.
Financial (C3)	Financial is an important criterion that affects people's decision in selecting cloud computing ("Selecting a Cloud Provider." http://spark.adobe.com/page/PN39b/ (accessed March 14, 2022)	Billing price (C31)	The cost that needs to pay by customers.
		Free trial (C32)	The amount of money given by cloud computing providers that potential customers can use to experience cloud computing services for free.
		Financial flexibility (C33)	The customers can arrange their own payment based on their needs.

result generated from the two phases of the AHP-TOPSIS approach proposed in this paper. In this analysis, the weights obtained from the AHP method are exchanged between two criteria while others remain in the same position (Gumus, 2009); (Hanine et al., 2016). For instance, in the first case, the weight of criterion C11 is exchanged with C12 while other criteria are constant. In the next case, the weight of criterion C11 is exchanged with C13, C14, ……., and C33 and about thirteen experiments are used to analyze our approach's performance (Zaidan et al., Feb 2015).

Table 13 shows the detail of the experiment processes in sensitivity analysis, and Fig. 3 presents the results graphically. It was found that Google Cloud Platform (S2) remains the best choice with the highest score. The sensitivity analysis results show that there is no change in alternatives' ranking with different inputs according to the weights of criteria. It demonstrates that our approach is relatively consistent and robust to various criteria weights.

6. Discussion

The smart-in-ag project is a project intended to establish a smart farming system for Indonesian agriculture in two specific cases. Several stakeholders from various backgrounds are involved in this consortium. A challenge when working in a diverse group is dealing with different expectations, knowledge gaps and different opinions from a large group of members. For instance, defining a feasible data analytics platform is difficult since so many views from the project members need to be considered and conflicts must be resolved. Group dynamics make achieving consensus more difficult since reaching the final decision implies a greater complexity and is a time-consuming process. Furthermore, it might lead to unsuccessful results if a consensus is not reached. Therefore, a systematic approach is clearly needed to provide an equal voice for all project members and accommodate their opinions.

MCDA is a method to help the decision-makers accommodate all criteria that arise from discussion among stakeholders. In the data analytics platform selection, the MCDA method was used to help the decision-makers committee to choose the best solution based on the stakeholders' requirements. To ensure that all project members have equal opportunity to express their opinions, a survey asking about their views on criteria was distributed. In addition, their background and experiences in smart farming were also asked to determine their knowledge in this field. Since the project members come from various backgrounds, some are unfamiliar with cloud computing technologies. Therefore, terms were clearly defined, and the context was provided to mitigate potential risks, as such, the participants easily understood the matter. Furthermore, AHP and TOPSIS, which are part of the MCDA approach were used to provide an objective analysis. The AHP was utilized to define the main problem and break it down into criteria and sub-criteria that affect the issue's decision. The described steps of the AHP approach were followed, from defining criteria to making comparative judgements. In this study, three main criteria were defined: Feature, Quality of Service, and Financial, each criterion having sub-criteria. In total, thirteen sub-criteria were used to select the data analytics platform. These criteria were obtained from our previous SLR research (N. Nyoman Kutha Krisnawijaya, B. Tekinerdogan, C. Catal, and R. v. d. Tol, 2022), the Service Measurement Index (SMI) framework and other existing literature.

Then, in the pairwise comparison, the proposed AHP approach resulted in CR values below 0.1 which means that our approach is relatively consistent and can be continued to the TOPSIS model. The next step is for the decision-making committee to discuss with respect to data analytics alternatives according by using sub-criterion and also give the scale of preference regarding the alternatives. For this case, the committee used the references from ("Cloud Providers Comparison.", 2022) and ("Public Cloud Services Comparison.", 2022) to provide the rate of each option. The result of our proposed model is Google Cloud Platform (S2) which is the most optimal one for the smart-in-ag project based on the criteria and requirements defined by stakeholders. To validate the consistency and robustness of our approach, sensitivity analysis method was applied to 13 different cases, resulting in the remaining S2 as the most optimal option for all scenarios. We can state that our approach can be used to select data analytics platforms for smart farming systems. The proposed approach was established to help decision-makers in the smart farming context solve complex problems, such as choosing a feasible data analytics platform. The integrated AHP-

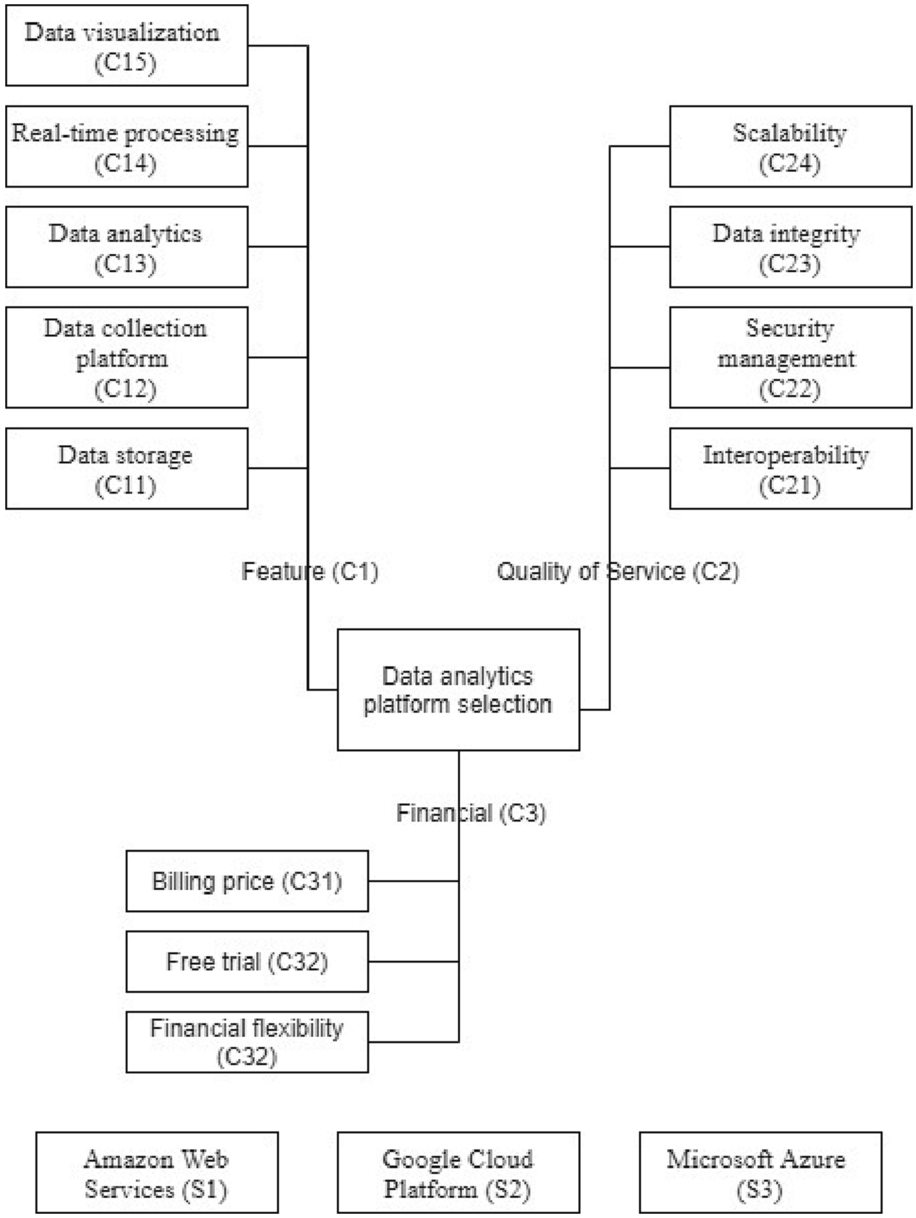

Fig. 2. The evaluation criteria hierarchy.

Table 5
The comparison matrix for the main criteria.

Criteria	Criteria	Feature	Quality	Financial
C1	Feature	1.00	1.00	5.00
C2	Quality of services	1.00	1.00	3.00
C3	Financial	0.20	0.33	1.00

TOPSIS approach systematically helps recognize significant criteria and solutions for our decision-making process in the data analytics platform selection.

Although we have carefully chosen and defined the criteria that affect the decision on selecting a data analytics platform, we realize that so many other criteria can significantly influence the decision but are not covered by this study due to the scope of this smart farming project. Moreover, the comparative judgements were made based on decision-makers' preferences, experiences, or references. Even though the decision-makers committee in this study has many years of experiences

Table 6
The comparison matrix of sub-criteria with respect to Feature (C1).

Criteria	Criteria	Data storage	Data collection platform	Data Analytics	Real-time processing	Data Visualization
C11	Data storage	1.00	0.33	0.33	3.00	3.00
C12	Data collection platform	3.00	1.00	3.00	5.00	3.00
C13	Data Analytics	3.00	0.33	1.00	3.00	3.00
C14	Real-time processing	0.33	0.20	0.33	1.00	1.00
C15	Data Visualization	0.33	0.33	0.33	1.00	1.00

Table 7
The comparison matrix of sub-criteria concerning Quality (C2).

Criteria	Criteria	Interoperability	Security management	Data integrity	Scalability
C21	Interoperability	1.00	0.33	0.20	1.00
C22	Security management	3.00	1.00	0.33	3.00
C23	Data integrity	5.00	3.00	1.00	5.00
C24	Scalability	1.00	0.33	0.20	1.00

Table 8
The comparison matrix of sub-criteria with respect to Financial (C3).

Criteria	Criteria	Billing process	Free Trial	Financial flexibility
C31	Billing price	1.00	0.33	0.20
C32	Free Trial	3.00	1.00	0.33
C33	Financial flexibility	5.00	3.00	1.00

Table 9
The normalized sub-criteria weightings.

Criteria	Level One	CR	Sub-Criteria	Level Two	CR
Feature	0.48	0.03085	Data storage	0.17	0.085331
			Data collection platform	0.42	
			Data Analytics	0.25	
			Real-time processing	0.07	
			Data visualization	0.09	
Quality of services	0.41		Interoperability	0.10	0.026048
			Security management	0.25	
			Data integrity	0.55	
			Scalability	0.10	
Financial	0.11		Billing price	0.11	0.047725
			Free Trial	0.26	
			Financial flexibility	0.63	

Table 10
Input values of the TOPSIS approach.

Criteria	Weight	S1	S2	S3
C11	0.17	5	8	3
C12	0.42	7	5	6
C13	0.25	7	7	6
C14	0.07	7	8	7
C15	0.09	8	7	6
C21	0.10	6	8	6
C22	0.25	8	8	8
C23	0.55	7	8	7
C24	0.10	6	7	6
C31	0.11	7	5	7
C32	0.26	5	8	7
C33	0.63	7	8	7

in the system infrastructure design, there is a possibility that their opinions might be biased or were affected from their previous experiences.

To the best of our knowledge, the articles in the literature describing data analytics platform selection for the smart farming system are very limited. Therefore, this study is conducted to demonstrate the selection of the most feasible cloud computing platform for the data analytics in the smart farming project. This investigation provides a systematic approach for finding and ranking criteria influencing data analytics selection and potential cloud computing platform. The proposed approach has been applied systematically in this research. Thus, it can be easier for

Table 11
The weighted normalized decision matrix.

Criteria	S1	S2	S3	A+	A-
C11	0.09	0.14	0.05	0.14	0.05
C12	0.28	0.20	0.24	0.28	0.20
C13	0.15	0.15	0.13	0.15	0.13
C14	0.04	0.05	0.04	0.05	0.04
C15	0.06	0.05	0.04	0.06	0.04
C21	0.05	0.07	0.05	0.07	0.05
C22	0.15	0.15	0.15	0.15	0.15
C23	0.31	0.35	0.31	0.35	0.31
C24	0.05	0.06	0.05	0.06	0.05
C31	0.07	0.05	0.07	0.05	0.07
C32	0.11	0.18	0.16	0.18	0.11
C33	0.35	0.40	0.35	0.40	0.35

Table 12
Final ranking of the alternatives.

Alternatives	D+	D-	Ci	Rank
S1	0.110554979	0.091002	0.45149393	2
S2	0.080520704	0.132202	0.62147631	1
S3	0.123695853	0.059795	0.32587476	3

decision-makers in other smart farming projects to follow the required steps in the proposed approach in selecting a data analytics platform. As the proposed approach has three stages and consider several criteria, the application of this approach may take relatively longer time in the first trial compared to the application of a trivial decision-making technique. However, the learning curve of the model is not steep, and the next applications do not cause extra overhead.

7. Conclusion

This study applied an integrated MCDA approach to selecting the most feasible data analytics platform for a smart farming system. We focused on utilizing the MCDA approach to help domain experts in smart farming choose a data analytics platform. The AHP and TOPSIS techniques were integrated to select the optimal data analytics platform in a systematic way. Furthermore, the stakeholders were informed on definitions and context before they defined the criteria for a data analytics platform. Then, a sensitivity analysis is conducted to ensure the robustness of the proposed platform. Therefore, after passing those processes, it is demonstrated that the proposed approach is consistent and robust for helping the experts choose cloud computing as a data analytics platform in the agricultural domain. However, further research is required in order to evaluate the proposed model for different criteria and other domains. In addition, the judgment processes of data analytics platform selection are based on the experts' personal knowledge, opinions, experiences. Even though, the present experts have a long experiences of system infrastructure design, the involvement of other experts may bring different perspectives.

CRediT authorship contribution statement

Ngakan Nyoman Kutha Krisnawijaya: Conceptualization, Methodology, Writing – review & editing. **Bedir Tekinerdogan:**

Table 13
Sensitivity analysis.

Cases	C11	C12	C13	C14	C15	C21	C22	C23	C24	C31	C32	C33	Ranking
1 (main)	0.17	0.42	0.25	0.07	0.09	0.10	0.25	0.55	0.10	0.11	0.26	0.63	S2-S1-S3
2	0.42	0.17	0.25	0.07	0.09	0.10	0.25	0.55	0.10	0.11	0.26	0.63	S2-S1-S3
3	0.25	0.42	0.17	0.07	0.09	0.10	0.25	0.55	0.10	0.11	0.26	0.63	S2-S1-S3
4	0.07	0.42	0.25	0.17	0.09	0.10	0.25	0.55	0.10	0.11	0.26	0.63	S2-S1-S3
5	0.09	0.42	0.25	0.07	0.17	0.10	0.25	0.55	0.10	0.11	0.26	0.63	S2-S1-S3
6	0.10	0.42	0.25	0.07	0.09	0.17	0.25	0.55	0.10	0.11	0.26	0.63	S2-S1-S3
7	0.25	0.42	0.25	0.07	0.09	0.10	0.17	0.55	0.10	0.11	0.26	0.63	S2-S1-S3
8	0.55	0.42	0.25	0.07	0.09	0.10	0.25	0.17	0.10	0.11	0.26	0.63	S2-S1-S3
9	0.10	0.42	0.25	0.07	0.09	0.10	0.25	0.55	0.17	0.11	0.26	0.63	S2-S1-S3
10	0.11	0.42	0.25	0.07	0.09	0.10	0.25	0.55	0.10	0.17	0.26	0.63	S2-S1-S3
11	0.26	0.42	0.25	0.07	0.09	0.10	0.25	0.55	0.10	0.11	0.17	0.63	S2-S1-S3
12	0.63	0.42	0.25	0.07	0.09	0.10	0.25	0.55	0.10	0.11	0.26	0.17	S2-S1-S3
Equal	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	S2-S1-S3

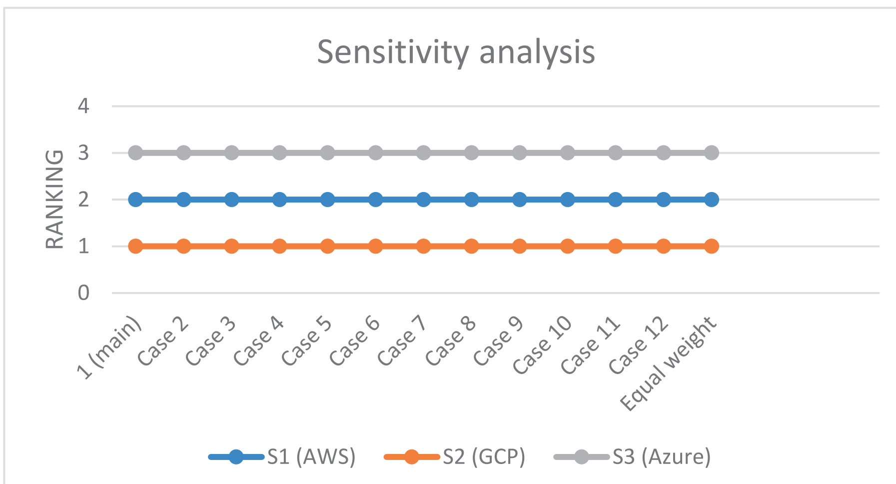

Fig. 3. The results of sensitivity analysis.

Conceptualization, Methodology, Writing – review & editing, Supervision. **Cagatay Catal:** Conceptualization, Methodology, Writing – review & editing, Supervision. **Rik van der Tol:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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