

Applifix: A Mobile Appliance Repair Booking Application with Vision-Language Classification and Multi-Criteria Technician Ranking in Angeles City

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ABSTRACT

Appliance owners often experience difficulty identifying the appropriate appliance repair service and finding qualified technicians, particularly when technician skills, service categories, and appliance sub-types are not clearly verified. This study proposes Applifix, a mobile appliance repair booking application designed for customers and service professionals in Angeles City, Pampanga. The application integrates vision-language classification to identify appliance categories and sub-types using submitted appliance photos and problem descriptions, while allowing users to manually select from candidate sub-types when classification confidence is below the specified threshold. It also incorporates skills-based technician verification and a multi-criteria technician ranking mechanism using the Analytic Hierarchy Process (AHP), considering skill match, proximity, customer rating, and completion rate. The study will employ a quantitative approach and a descriptive-developmental research design to guide the development and evaluation of the proposed application. The system will facilitate the service process from job request and technician selection to confirmed completion, while maintaining relevant service and work records. The expected outcome is a mobile platform that improves appliance identification, supports the selection of qualified technicians, and provides a more organized and transparent appliance repair booking process for customers and technicians in Angeles City.

Keywords: *Appliance Repair, Mobile Application, Vision-Language Classification, Technician Verification, Analytic Hierarchy Process, Multi-Criteria Ranking*

SECTION I — INTRODUCTION (THE PROBLEM AND ITS SETTING)

1.1 Introduction

Appliance repair plays an important role in extending their useful life of household appliances and reducing unnecessary replacement and waste. The continued increase in electronic waste also highlights the importance of accessible repair services. The Global E-waste Monitor 2024 reported that approximately 62 million tonnes of electronic waste were generated globally in 2022, with the amount projected to reach 82 million tonnes by 2030 (International Telecommunication Union [ITU] & United Nations Institute for Training and Research [UNITAR], 2024). The United Nations Environment Programme (UNEP, 2024) also emphasizes product longevity and resource efficiency as approaches that support sustainable consumption.

At the same time, the increasing use of mobile technology provides an opportunity to make repair services more accessible and organized. In the Philippines, 48.8% of households had internet access at home in 2024, while cellphones were the most widely used device for accessing the internet (Philippine Statistics Authority [PSA], 2025). Digital transactions have also continued to increase, with digital payments accounting for 57.4% of total retail payment volume in the Philippines in 2024 (Bangko Sentral ng Pilipinas [BSP], 2025). These developments provide a suitable environment for mobile platforms that can organize service requests, provider information, transaction records, and customer feedback.

Despite these developments, customers may still experience difficulty identifying the appropriate appliance service and finding a technician with suitable skills. Customers may not always know the exact appliance subtype when submitting a repair request, while information about a technician's practical competency may be limited. There may also be uncertainty regarding estimated service fees, additional material costs, and the technician's previous service record. These concerns indicate a need for a more structured approach to appliance repair service matching and booking.

This study therefore asks: How can a mobile appliance repair booking application assist customers in identifying appliance subtypes, connecting them with service professionals who have verified skills, and recommending suitable technicians based on multiple criteria? To address this question, the researchers propose Applifix: A Mobile Appliance Repair Booking Application with Vision-Language Classification and Multi-Criteria Technician Ranking in Angeles City. The application will use a vision-language model to analyze customer-submitted appliance photographs and problem descriptions and determine the appliance category and subtype. When the classification confidence is below the defined threshold, candidate subtypes will be presented for manual selection.

The proposed application will also record the results of practical skills assessments conducted outside the application. A service professional will only be eligible to offer a specific appliance service after a corresponding passing assessment has been recorded. Eligible professionals will then be ranked using the Analytic Hierarchy Process (AHP) based on skill match, proximity, customer rating, and completion rate. The application will further support the service transaction from request to confirmed completion by presenting estimated fee ranges, recording agreed material costs, documenting service completion, and collecting customer feedback.

The study will be implemented through a controlled pilot deployment in Angeles City. The developed application will be evaluated based on appliance classification performance using accuracy, precision, recall, F1 score, and the Matthews Correlation Coefficient (MCC), while the overall application will be evaluated using selected characteristics of ISO/IEC 25010:2023, particularly functional suitability, performance efficiency, interaction capability, reliability, and security. ISO/IEC 25010:2023 provides a product quality model that can be used for software requirements, measurement, and evaluation.

1.2 Background of the Study

Household appliances support essential daily activities such as food storage, cooking, cleaning, and maintaining comfortable indoor environments. In Angeles City, Pampanga, households rely on these appliances, creating a need for accessible repair and maintenance services. The Philippine Statistics Authority (PSA, 2021) reported that Angeles City had a population of 462,928 based on the 2020 Census of Population and Housing. Repairing malfunctioning appliances can extend their useful life, delay replacement, and reduce discarded electrical and electronic equipment. This is relevant as global e-waste continues to increase, reaching approximately 62 million tonnes in 2022 and projected to reach 82 million tonnes by 2030 (International Telecommunication Union [ITU] & United Nations Institute for Training and

Research [UNITAR], 2024). The United Nations Environment Programme (UNEP, 2024) also emphasizes extending product lifetimes and improving resource efficiency to support more sustainable consumption.

The growth of internet access, mobile devices, and digital payments has created opportunities for technology-based household services. In the Philippines, household internet access increased from 17.7% in 2019 to 48.8% in 2024, while mobile phones remained an important means of accessing the internet (PSA, 2025). Digital payments also accounted for 57.4% of retail payment volume in 2024 (Bangko Sentral ng Pilipinas [BSP], 2025). These developments provide an environment for mobile applications that can connect customers with local service providers and support service requests, communication, and transaction records.

Despite these developments, customers seeking appliance repair services may still experience difficulty identifying the appropriate appliance subtype and determining whether a technician is suitable for a specific repair. Existing platforms such as MyKuya, CoolFind PH, and TapatPH demonstrate the use of digital booking, service categories, and provider verification for household services (MyKuya, n.d.-a; CoolFind PH, n.d.; TapatPH, 2026). However, based on the platforms reviewed for this study, there is limited integration of automated appliance subtype identification, service-specific practical skills verification, and multi-criteria technician ranking within a single appliance repair workflow.

Vision-language models (VLMs) provide a potential approach for assisting customers in identifying appliance categories and subtypes by processing both photographs and problem descriptions (Caffagni et al., 2024; Zhang et al., 2024; Danish et al., 2026). To address uncertain classifications, the system can apply a confidence threshold and present possible subtypes for customer selection. For technician selection, the Analytic Hierarchy Process (AHP) provides a structured method for evaluating and ranking alternatives based on multiple criteria through pairwise comparisons (Saaty, 2023). In this study, the criteria include service-specific practical skills assessment, proximity, customer rating, and completion rate.

Therefore, this study proposes **Applifix: A Mobile Appliance Repair Booking Application with Vision-Language Classification and Multi-Criteria Technician Ranking in Angeles City**. The application will assist customers in identifying appliance subtypes, connect them with technicians who have passed service-specific practical skills assessments, and rank eligible technicians using AHP. It will also support the repair transaction from service request and technician selection to estimated fees, material-cost recording, service completion, and customer feedback.

1.3 Objectives of the Study

General Objective: The general objective of the study is to develop a mobile appliance repair booking application that classifies customer-submitted photographs and problem descriptions into appliance sub-types, matches customers with assessment-verified service professionals through multi-criteria ranking, and manages the service transaction from request to confirmed completion.

Specific Objectives:

1. **To determine** the appliance category and sub-type from a customer's photograph and problem description using a vision-language model constrained to a fixed output schema, with a confidence threshold below which candidate sub-types are presented for manual selection, evaluated on a researcher-labelled test set using accuracy, precision, recall, and F1 score;
2. **To determine** the appliance categories for which a service professional may be booked by recording the outcome and date of an in-person skills assessment conducted outside the application, such that a category is activated only after a recorded passing result;
3. **To recommend** eligible service professionals for an open service request using the Analytic Hierarchy Process (AHP) based on skill match, proximity, rating, and completion rate, with criteria weights determined through pairwise comparisons and a Consistency Ratio of less than 0.10;
4. **To facilitate** the service transaction from request to confirmed completion by broadcasting the request to professionals verified for the identified sub-type, allowing the customer to select a responder, displaying an estimated fee range, recording agreed material costs before work begins, and documenting service completion and customer feedback;
5. **To evaluate** the developed mobile application using ISO/IEC 25010:2023 in terms of functional suitability, performance efficiency, interaction capability, reliability, and security.

1.4 Scope and Limitation of the Study

Scope: The study covers the development of Applifix, a mobile appliance repair booking application for customers and appliance repair technicians in Angeles City, Pampanga. The application includes appliance photo and problem-description submission, VLM-assisted appliance category and subtype identification, manual subtype selection for uncertain classifications, practical skills verification, and AHP-based technician ranking using skill match, proximity, customer rating, and completion rate. VLMs support the processing of visual and textual information for multimodal understanding (Caffagni et al., 2024). AHP provides a structured approach for multi-criteria decision-making using pairwise comparisons (Saaty, 2023). The application also supports service requests, technician selection, estimated fee ranges, recording of agreed material costs, service completion, customer feedback, and a cold-start mechanism for newly verified technicians with limited work history (Liang et al., 2025).

Limitation: The study is limited to appliance repair services within Angeles City, Pampanga. The VLM is limited to the appliance categories and subtypes included in the system and does not perform complete technical diagnosis. Uncertain classifications may require manual customer selection (Caffagni et al., 2024). Practical skills assessments are conducted outside the application, with only the assessment result and date recorded. Technician ranking is limited to the selected AHP criteria. Estimated fees are provided for reference and do not guarantee the final repair cost, as unexpected costs can occur in online transactions (OECD, 2022a, 2022b). The application does not provide repair tools, spare parts, or physical repair services and does not supervise the actual repair process.

1.5 Significance of the Study

The proposed Applifix: A Mobile Appliance Repair Booking Application with Vision-Language Classification and Multi-Criteria Technician Ranking in Angeles City may benefit the following stakeholders:

Customers.

Customers may benefit from a more convenient way to request appliance repair services by submitting appliance photographs and problem descriptions. The application may assist in identifying appliance subtypes, recommending eligible technicians, and providing estimated fee ranges and recorded material costs.

Appliance Repair Professionals.

Appliance repair professionals may benefit from receiving service requests that match their verified skills. The application may also help them build a documented service history through completed jobs and customer ratings, while newly verified professionals may be accommodated through the proposed cold-start mechanism.

Appliance Repair Businesses and Shops.

Local repair businesses and shops may benefit from an additional digital channel for connecting their technicians with customers and organizing service requests according to appliance type and technician eligibility.

Local Community of Angeles City.

Residents may benefit from an accessible mobile platform that connects them with local appliance repair professionals and provides another option for requesting repair services.

Future Researchers and Developers.

Future researchers and developers may use the study as a reference for applications that integrate vision-language classification, practical skills verification, multi-criteria decision-making, and mobile service booking.

1.6 Definition of Terms

Analytic Hierarchy Process (AHP). A multi-criteria decision-making method used to prioritize criteria and rank alternatives through pairwise comparisons (Saaty, 2008). In Applifix, it ranks eligible technicians.

1. **Appliance Subtype.** A specific type of appliance within a broader category. In Applifix, it is identified from the customer's photo and problem description.
2. **Completion Rate.** The proportion of assigned services successfully completed by a technician. It is used in technician ranking.

3. **Cold-Start Mechanism.** An approach for handling limited historical data for new service providers (De Pessemier et al., 2025). In Applifix, it supports newly verified technicians with limited service history.
4. **Multi-Criteria Technician Ranking.** The process of ranking technicians using multiple criteria. Applifix considers skill match, proximity, rating, and completion rate.
5. **Practical Skills Assessment.** An evaluation of a technician's ability to perform tasks related to a specific service. Passing the assessment makes a technician eligible for the corresponding service.
6. **Proximity.** The distance between the customer's service location and the technician's location.
7. **Service Completion.** The successful fulfillment of a requested appliance repair service.
8. **Service Professional Verification.** The process of confirming that a technician meets the required competency requirements through a practical skills assessment.
9. **Technician Rating.** A customer's evaluation of a technician based on their service experience.
10. **Vision-Language Classification.** The classification of information using visual and textual inputs. In Applifix, it assists in identifying appliance subtypes (Caffagni et al., 2024).
11. **Vision-Language Model (VLM).** An AI model that processes visual and textual information for multimodal tasks (Caffagni et al., 2024). In Applifix, it analyzes appliance photos and descriptions.
12. **Applifix.** The proposed mobile appliance repair booking application for customers and appliance repair technicians in Angeles City.

SECTION II — LITERATURE REVIEW

2.1 Introduction to the Review

This chapter reviews literature and studies related to the development of Applifix: A Mobile Appliance Repair Booking Application with Vision-Language Classification and Multi-Criteria Technician Ranking in Angeles City. The review is organized according to the required Global > National > Local > Focal structure to establish the theoretical, technological, and contextual foundation of the proposed application.

The global literature covers sustainable consumption, mobile and on-demand services, vision-language models, and multi-criteria decision-making. The national literature focuses on Philippine internet and mobile technology use, digital transactions, online services, and consumer protection. The local literature examines existing service platforms and practices related to appliance repair and home services. Finally, the focal literature and studies focus on the specific technologies and methods used in Applifix, including vision-language classification, practical skills verification, and AHP-based technician ranking.

The reviewed literature and studies are synthesized to identify existing approaches, limitations, and the research gap addressed by the proposed system.

2.2 Review of Related Literature and Studies

The development of digital service platforms has changed how customers locate and interact with service providers. Online marketplaces allow users to search for providers, compare available information, request services, and complete transactions without relying entirely on face-to-face arrangements. Luca (2017) explained that online marketplaces can reduce transaction costs by making information about sellers and services more accessible. However, transactions between unfamiliar customers and providers may involve uncertainty regarding service quality. Pavlou and Gefen (2004) found that institutional mechanisms within online marketplaces can strengthen consumer trust by reducing perceived transaction risks. These findings are relevant to service industries such as appliance repair, where customers may have limited technical knowledge for independently assessing a technician's competence.

Online reviews and reputation systems are widely used in digital marketplaces to reduce uncertainty about service providers. Jiao et al. (2021), through a meta-analysis of 107 studies, found that reputation systems can influence seller performance in peer-to-peer online markets. Peña-García et al. (2024) further found that the authenticity and quality of

online reviews are associated with consumer trust and marketplace reputation. These findings highlight the value of reputation information in digital transactions. However, reputation-based information may not fully demonstrate whether a service provider possesses the specific technical skills required for a particular task, indicating the need for additional competency-based qualification mechanisms.

The limitations of reputation-based selection are also evident in the challenges faced by newly registered workers. Liang et al. (2025) examined the cold-start problem in online labor platforms and found that workers without established platform reputations may experience difficulty obtaining opportunities because employers tend to prefer workers with existing histories. Similarly, Parker-Waldern and Leonardi (2026) discussed how platform-based reputation can create barriers for workers whose previous professional experience is not reflected in a new platform's rating history. These findings suggest that digital service platforms may benefit from qualification mechanisms beyond accumulated ratings, particularly for newly registered professionals who possess relevant skills but have limited platform histories.

Artificial intelligence has increasingly been applied to maintenance-related activities. Surucu et al. (2023) reviewed machine-learning applications in condition monitoring and fault detection, demonstrating the use of intelligent systems to interpret equipment-related information. These developments provide a basis for applying computational methods to assist in identifying equipment conditions and supporting technical decision-making.

The development of multimodal artificial intelligence has expanded the ability of systems to process visual and textual information together. Li et al. (2023) introduced BLIP-2, a vision-language framework that connects visual encoders with large language models to support multimodal tasks. Ghosh et al. (2024) reviewed the development and applications of vision-language models in tasks such as image captioning and visual question answering. These developments are relevant to service applications in which customers can provide both photographs and textual descriptions of a problem, providing a technological basis for using vision-language models to assist in appliance subtype identification.

However, vision-language models cannot be assumed to produce accurate classifications in every situation. Karamolegkou et al. (2024) evaluated the reliability of vision-language models as visual assistants and identified challenges such as hallucination and a mismatch between automatic evaluation metrics and human judgment. These findings highlight the need for appropriate evaluation procedures and mechanisms for handling uncertain predictions when VLMs are used in practical applications. Therefore, systems that use VLM-based classification may benefit from labelled test datasets for performance evaluation and manual confirmation when automated predictions do not meet a sufficient confidence level.

After identifying a service requirement, selecting an appropriate provider can be treated as a multi-criteria decision problem. Nydick and Hill (1992) demonstrated the use of the Analytic Hierarchy Process (AHP) for selection problems involving multiple criteria. Repschlaeger et al. (2014) similarly applied AHP to provider selection, demonstrating its usefulness in evaluating several provider characteristics simultaneously. More recently, Neira-Rodado et al. (2024) applied a multi-criteria approach to service-provider selection in an emergency-service context. Collectively, these studies demonstrate that provider selection can involve multiple criteria and can be supported by structured decision-making methods rather than relying on a single measure of performance.

The global literature establishes several concepts relevant to digital appliance-repair service platforms. Online marketplaces can reduce transaction barriers and provide information that supports customer-provider interactions, while reputation systems can help reduce uncertainty about service providers. However, the cold-start problem demonstrates the limitations of relying solely on accumulated platform reputation, highlighting the value of additional qualification mechanisms. Multimodal AI provides a basis for processing visual and textual information, while appropriate evaluation and uncertainty-handling mechanisms are necessary for reliable VLM-based classification. Finally, multi-criteria decision-making methods such as AHP can support structured provider selection when multiple factors must be considered. Together, these concepts provide the theoretical and technological foundation for the proposed service platform.

In the Philippine setting, digital marketplaces provide channels for connecting users with economic opportunities and services. Bayudan-Dacuycuy et al. (2022) examined online marketplace participation in the Philippines and identified factors associated with participation in digital marketplace activities. Their findings provide a national context for the use of digital platforms to facilitate interactions and transactions between users and technicians.

The Philippine digital environment also includes platform-mediated work, in which digital platforms connect workers with employment opportunities. Soriano (2021) examined digital labour in the Philippines and discussed how digital platforms function as intermediaries between workers and sources of employment. Soriano et al. (2021) further examined Filipino digital labor communities and described how digital labor influencers help workers navigate platform opportunities, exchange information, and move across platforms and job types. These findings provide a basis for understanding how digital platforms can facilitate connections between service providers and potential customers in the Philippine context.

However, digital intermediation also involves responsibilities related to information management and platform governance. Pineda and Cayabyab (2023) examined digital labor market intermediaries in the Philippines and discussed

how these platforms facilitate connections between employers and workers while presenting concerns related to cybersecurity, privacy, recruitment, and platform governance. These concerns highlight the need for Philippine digital service platforms to address not only user-provider matching but also the proper management of provider information, transactions, and security.

The national literature demonstrates the relevance of digital platforms as marketplaces and labor intermediaries in the Philippines. However, the reviewed studies primarily examine digital marketplace participation, digital labor, and platform governance at a broader level. While these studies provide a national context for digital intermediation, they do not specifically address the technical requirements of matching customers with appliance-repair technicians based on appliance subtype and verified competency.

The relevance of digital platforms is also evident in Pampanga. Galang et al. (2025) examined the platform economy and ride-hailing services in Pampanga, including Angeles City, Mabalacat City, and San Fernando City, focusing on relationships involving digital platforms, accessibility, convenience, and on-demand services. Although the study focused on transportation rather than appliance repair, its findings provide local context for the use of platform-based services to address location-dependent service needs.

Mobile applications have also been explored in studies associated with Angeles City. Bartolome et al. (2023) proposed the “Pasahero” mobile transit application to provide users with information on bus departure and arrival status. The study aimed to improve commuters’ access to transportation information and reduce waiting and travel times. Although the application focuses on transportation, it provides a local example of how mobile technology can address location-dependent service-access needs in Angeles City.

Local digital marketplaces also demonstrate the use of online platforms to connect consumers with businesses. Agorah Marketplace, a homegrown e-commerce platform launched in Angeles City, initially focused on Kapampangan business owners and local products before expanding its marketplace to a wider range of sellers, buyers, products, and services (Cayabyab, 2021; Manabat, 2021). This provides a local example of how digital platforms can facilitate connections between consumers and locally available businesses.

The reviewed local literature demonstrates the use of mobile applications, location-dependent platforms, and digital marketplaces within Pampanga and Angeles City. However, these examples primarily focus on transportation, general marketplace activities, and other digital services rather than specialized appliance-repair services. Thus, the local literature provides technological and contextual support for developing a location-based digital service platform while leaving an opportunity to explore a specialized appliance-repair service-matching application.

The focal literature brings together the specific concepts relevant to the development of an intelligent appliance-repair booking platform, including multimodal appliance identification, technician competency verification, multi-criteria technician ranking, and digital service transactions.

First, research on vision-language models provides a technological basis for processing appliance information from images and customer descriptions. Li et al. (2023) demonstrated how BLIP-2 connects visual information with language models, while Ghosh et al. (2024) reviewed the broader development and applications of vision-language models. These studies support the use of VLMs in applications that require the combined processing of visual and textual inputs. However, Karamolegkou et al. (2024) emphasized the importance of evaluating VLM outputs because multimodal models may produce unreliable results. Thus, an appliance-repair application can incorporate model evaluation and manual selection mechanisms to address uncertain classifications.

Second, research on reputation systems and the cold-start problem provides a basis for distinguishing technician eligibility from platform reputation. Jiao et al. (2021) demonstrated that reputation systems can influence performance in online markets, while Peña-García et al. (2024) highlighted the importance of review quality and authenticity in establishing trust. Liang et al. (2025) and Parker-Waldern and Leonardi (2026) further showed that workers with limited platform histories may face disadvantages when reputation is heavily relied upon. These findings support the use of documented practical competency as an initial eligibility requirement, while ratings and completed jobs can provide additional information about technician performance after service transactions.

Third, AHP provides a systematic approach for ranking eligible technicians based on multiple criteria. Nydick and Hill (1992), Repschlaeger et al. (2014), and Neira-Rodado et al. (2024) demonstrated the use of multi-criteria approaches for selecting among alternatives. In the context of appliance repair, these principles can be applied to criteria such as skill match, proximity, customer rating, and completion rate. Using multiple criteria allows technician recommendations to consider several aspects of suitability rather than relying solely on a single performance measure.

These concepts can be integrated into a sequential service-matching process for appliance repair. First, the customer's photograph and problem description can be processed to identify the likely appliance subtype. The identified subtype can then determine which technicians have the required verified competency. Among the eligible technicians, the selected

criteria can be evaluated through AHP to establish a structured ranking. The customer can then select a technician from the available recommendations, after which the transaction can proceed through service confirmation, repair completion, and customer feedback.

The Philippine and local literature provides a contextual basis for applying digital service platforms in Angeles City. Bayudan-Dacuycuy et al. (2022), Soriano (2021), Soriano et al. (2021), and Pineda and Cayabyab (2023) demonstrate the relevance of digital marketplaces and labor intermediation in the Philippine setting. At the local level, Galang et al. (2025), Bartolome et al. (2023), and reports on Agorah provide examples of digital and mobile platforms operating within Pampanga and Angeles City.

Based on the reviewed literature, the identified concepts have primarily been examined as separate components rather than as an integrated, localized appliance-repair platform. The reviewed studies provide support for digital marketplaces, reputation systems, worker qualification, multimodal AI, and multi-criteria provider selection. However, **no single platform was identified within the literature reviewed that combines these functions specifically for appliance repair in Angeles City.** This gap provides a basis for integrating these established concepts into a specialized appliance-repair service platform.

Therefore, Applifix addresses the identified gap by combining vision-language-assisted appliance subtype identification, practical skills-based technician verification, multi-criteria technician ranking, and service transaction management within a single mobile application. The proposed system uses a VLM to assist customers in identifying appliance subtypes, records practical skills-assessment results to determine technician eligibility, and applies AHP to rank eligible technicians based on multiple criteria. It also supports the service process from request and technician selection through service completion and customer feedback. Through these functions, Applifix applies established concepts from global research within the Philippine and local context of Angeles City.

2.3 Conceptual Framework

The conceptual framework presents the relationship between the inputs, processes, and outputs involved in the development of Applifix: A Mobile Appliance Repair Booking Application with Vision-Language Classification and Multi-Criteria Technician Ranking in Angeles City. The framework follows the Input-Process-Output (IPO) model, which organizes the system according to the information required by the application, the processes performed on the collected information, and the resulting outputs.

Figure 1
Input-Process-Output (IPO) Conceptual Framework of Applifix

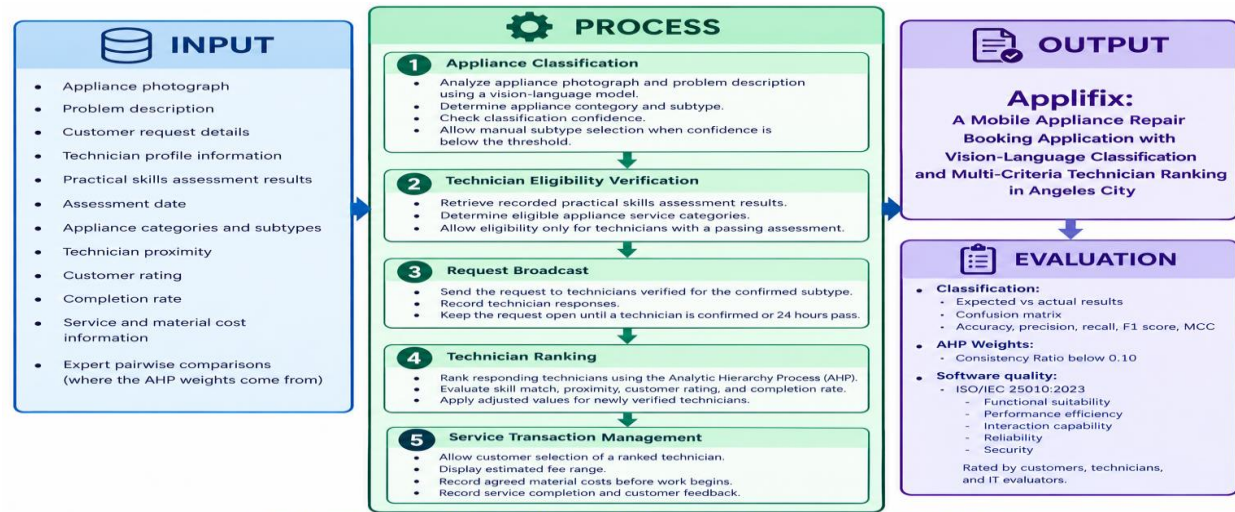


Figure 1. Input-Process-Output (IPO) Conceptual Framework of the Proposed Applifix Application

The conceptual framework illustrates how the information provided by customers and service professionals is transformed into organized appliance repair services. The inputs consist of customer-submitted appliance photographs and problem descriptions, customer request details, technician information, practical skills assessment results, appliance categories, the criteria used for technician ranking, and the experts' pairwise comparisons of these criteria.

The process begins with the classification of the customer's appliance using a vision-language model. The model analyzes the submitted photograph and problem description to determine the appliance category and subtype. When the classification confidence is below the defined threshold, the system provides candidate subtypes for manual selection. The system then verifies technician eligibility based on the recorded results of practical skills assessments conducted outside the application.

After verifying eligibility, the system broadcasts the service request to technicians verified for the confirmed subtype, and interested technicians respond to the request. The system then applies the Analytic Hierarchy Process (AHP) to rank only the responding technicians according to skill match, proximity, customer rating, and completion rate, with adjusted values for newly verified technicians. The customer selects a technician from the ranked list, and the system manages the service transaction by displaying the estimated fee range, recording agreed material costs before work begins, and documenting service completion and customer feedback.

The output of the framework is the developed application, Applifix: A Mobile Appliance Repair Booking Application with Vision-Language Classification and Multi-Criteria Technician Ranking in Angeles City.

The developed application then undergoes evaluation. The classification is evaluated by comparing the expected and actual results of researcher-labelled test photographs, summarized in a confusion matrix (Tables 1 and 2), using accuracy, precision, recall, F1 score, and the Matthews Correlation Coefficient (MCC). The AHP criteria weights are accepted only when the Consistency Ratio is below 0.10. The overall application is evaluated by customers, technicians, and IT evaluators using ISO/IEC 25010:2023 in terms of functional suitability, performance efficiency, interaction capability, reliability, and security.

2.4 Synthesis

The reviewed literature and related studies establish that digital platforms can improve the way customers and service providers connect by providing accessible service information, provider profiles, booking functions, ratings, and other forms of online interaction. Reputation and review systems can help customers evaluate providers based on previous experiences, while digital labor and service platforms can reduce some of the barriers involved in finding and accessing service providers (Luca, 2017; Pavlou & Gefen, 2004; Bayudan-Dacuycuy & Dacuycuy, 2022). However, these approaches commonly rely on ratings, reviews, and previous platform activity, which may not sufficiently demonstrate whether a provider possesses the specific technical skills required for a particular service.

The reviewed studies further emphasize the importance of provider qualification and appropriate matching in service-related platforms. Research on online labor and service marketplaces shows that platform mechanisms can influence how workers and customers are matched, while studies on provider selection demonstrate the need to consider several factors when determining a suitable service provider (Jiao et al., 2021; Peña-García et al., 2024). In appliance repair, technician capability may vary depending on the appliance category and type of problem involved. Therefore, a general provider profile or accumulated rating may not be sufficient to determine whether a technician is appropriate for a particular appliance. This supports the use of service-specific verification in which a technician's practical skills are assessed before being considered eligible for a particular appliance category.

Another concern identified in digital labor and service platforms is the cold-start problem experienced by newly registered providers. Workers with limited ratings, completed jobs, or platform history may have fewer opportunities because recommendation systems often depend on existing user feedback and historical activity (Jiao et al., 2021; Parker-Waldern & Leonardi, 2026). This creates a distinction between having limited platform history and lacking actual skills. A newly verified technician may possess the necessary competency but have insufficient transaction history to compete with established providers. Thus, a mechanism that allows newly verified technicians to remain eligible while maintaining a separate competency requirement is relevant to the proposed system.

The literature also supports the use of multi-criteria decision-making when several factors must be considered in selecting an appropriate provider. The Analytic Hierarchy Process (AHP) provides a structured approach for comparing alternatives based on multiple criteria through pairwise comparisons and weighted priorities (Nydick & Hill, 1992; Repschlaeger et al., 2014). In Applifix, this approach is applied by considering **skill match, proximity, customer rating, and completion rate** when ranking eligible technicians. This allows the recommendation process to consider both technical suitability and service-related factors rather than relying only on customer ratings.

The development of artificial intelligence also provides opportunities to improve how appliance information is processed before technician selection. Vision-Language Models (VLMs) are designed to process and relate visual and textual information, allowing systems to use information from images together with accompanying descriptions. Studies have explored the capabilities and applications of vision-language systems while also identifying challenges involving reliability, evaluation, and classification accuracy (Li et al., 2023; Ghosh et al., 2024; Danish et al., 2026). These findings

are relevant to Applifix because customers can provide both an appliance photograph and a description of the problem, which can assist the system in identifying the likely appliance category and subtype.

However, the reviewed literature indicates that automated classification should not be treated as completely reliable. Vision-language systems may produce uncertain results depending on the quality of the input and the complexity of the classification task (Ghosh et al., 2024; Danish et al., 2026). For this reason, Applifix incorporates a fallback process in which possible appliance subtypes can be presented for manual selection when the system does not reach the required confidence level. The classification component will also be evaluated using accuracy, precision, recall, F1 score, and the Matthews Correlation Coefficient (MCC) to assess how effectively the system identifies the intended appliance subtype

To determine whether each classification is correct, the evaluation compares an expected result with an actual result for every test photograph. The expected result is the correct appliance subtype assigned by the researchers before classification. The actual result is the subtype returned by the vision-language model. A classification is counted as correct only when the actual result matches the expected result. Table 1 shows the format for recording each test case, and Table 2 shows the confusion matrix that summarizes all test cases, from which accuracy, precision, recall, F1 score, and MCC are computed.

Table 1 - Expected and Actual Classification Results

Test ID	Expected Result	Actual Result	Correct
AC-01	Window-type aircon		
AC-31	Split-type aircon		
AC-61	Floor-standing aircon		
RF-01	Single-door refrigerator		
RF-31	Two-door refrigerator		
WM-01	Top-load washing machine		
WM-31	Front-load washing machine		

Note: Actual results will be recorded during testing. The complete list of approximately 210 test cases will be placed in the appendix.

Table 2 - Confusion Matrix of Subtype Classification

Expected (researcher label) / Actual (model output)	WIN	SPL	FLR	1DR	2DR	TOP	FRT
Window-type (WIN)							
Split-type (SPL)							
Floor-standing (FLR)							
Single-door (1DR)							
Two-door (2DR)							
Top-load (TOP)							
Front-load (FRT)							

Note: Rows are expected results and columns are actual results. Cells on the diagonal are correct classifications. Values will be filled after testing.

Studies concerning digital platforms in the Philippine setting further demonstrate the growing use of online systems for connecting users with services and opportunities. Philippine digital labor and service platforms provide examples of how technology can support service access and interactions between users and providers (Bayudan-Dacuycuy & Dacuycuy,

2022; Soriano, 2021; Pineda & Cayabyab, 2023). Existing platforms such as **TapatPH**, **CoolFind PH**, **MyKuya**, and **Teko PH** also demonstrate functions related to service requests, provider information, booking, and customer interaction. However, these platforms do not specifically combine appliance subtype identification, service-specific practical technician verification, multi-criteria technician ranking, and appliance repair transaction management within a single system.

Overall, the reviewed literature provides established foundations for digital service platforms, reputation systems, technician qualification, cold-start considerations, multi-criteria decision-making, and Vision-Language Models. Nevertheless, the reviewed studies address these concepts mainly as separate functions or in different application contexts. The identified gap is the lack of a localized appliance repair platform that integrates these functions into one mobile application. **Applifix addresses this gap by combining VLM-assisted appliance subtype identification, practical skills-based technician verification, AHP-based technician ranking, consideration for newly verified technicians, and service transaction management for customers and technicians in Angeles City.** Through this integration, the proposed system applies established technological and decision-making approaches to a specific appliance repair context that is not sufficiently addressed by the reviewed studies.

SECTION III — METHODOLOGY

3.1 Research Design

This study will use a Descriptive-Developmental Research Design with a Quantitative Approach to develop and evaluate Applifix: A Mobile Appliance Repair Booking Application with Vision-Language Classification and Multi-Criteria Technician Ranking in Angeles City. The descriptive component will identify user needs and system requirements, while the developmental component will guide the design, development, testing, and refinement of the application. This approach is consistent with design-science research, which focuses on developing and evaluating technological artifacts to address real-world problems (Hevner et al., 2004).

The application will integrate Vision-Language Model (VLM) classification for appliance subtype identification, practical skills-based technician verification, and Analytic Hierarchy Process (AHP) for ranking eligible technicians. The system will be evaluated using appropriate performance measures and selected ISO/IEC 25010:2023 quality characteristics. Quantitative results will be analyzed to determine whether the application meets its intended requirements and provides a functional solution for appliance-repair booking in Angeles City.

3.2 System Development Methodology

The study will use the Agile methodology, following Scrum-based sprints (Schwaber & Sutherland, 2020). Agile supports iterative development through short cycles, allowing each part of the application to be developed, tested, and reviewed before proceeding to the next cycle. This approach is suitable for the study because the system objectives can be developed and evaluated incrementally, while activities involving external participants, such as technician skills assessment and expert pairwise comparison surveys, can be conducted alongside development.

Development will be organized into six two-week sprints, with each sprint having a defined goal. Each sprint will begin with planning based on the product backlog and end with a review of the completed features and a brief retrospective.

Table 3 - Sprint Plan

Sprint	Goal
1	Project setup, database, account registration, customer and technician profiles
2	Photo and problem description submission, vision-language classification with a fixed output schema, confidence threshold, and manual sub-type selection
3	Recording of assessment outcomes and dates, category activation after a passing result, technician profile display
4	Service address and schedule, estimated fee range, request broadcast to verified technicians, responder list

5	AHP-based ranking of responding technicians, adjusted values for newly verified technicians, booking confirmation
6	Material cost recording, service completion, customer feedback, integration, and system testing

Three activities will be conducted in parallel with the sprints. First, the researchers will collect and label appliance photographs for the test set, which will be used to evaluate the classification after Sprint 2. Second, the expert panel will complete the pairwise comparison survey, with the resulting criteria weights prepared before Sprint 5. Third, technicians will be recruited and assessed to ensure that verified technicians are available for the pilot deployment. After Sprint 6, the completed application will be deployed in a controlled pilot and evaluated as described in Section 3.6.

Participants and Sampling

The study will use purposive sampling to select participants who meet predefined criteria relevant to their respective roles in the study.

Table 4 - Participants of the Study

Participant	Number	Criteria	Role
Technicians	5 to 10	Repairs at least one of the covered appliance categories in Angeles City; willing to undergo the skills assessment	Take the skills assessment, use the application during the pilot, evaluate the application
Assessor	1 to 2	Holds an NC II in the relevant field and has at least two years of industry experience	Conducts the practical skills assessment
Expert panel	5 to 7	At least [NUMBER] years of experience in appliance repair service	Completes the AHP pairwise comparison survey
Customers	20	Resides in Angeles City; owns an appliance in a covered category; gives informed consent	Uses the application during the pilot, evaluates the application
IT evaluators	3	IT professionals or faculty with software development experience	Evaluates the application using ISO/IEC 25010:2023

Data Collection Instruments

1. **Labelled Test Set.** Approximately 30 photographs will be collected for each appliance subtype, taken by the researchers in actual homes. Each photograph will be labelled with its correct subtype by the researchers before classification. This label serves as the expected result. Duplicate images will be removed before evaluation.
2. **Skills Assessment Checklist.** One practical task will be prepared for each appliance category, using a checklist to record whether a technician is assessed as competent or not yet competent. The checklist will be modelled on the structure of TESDA competency assessments.
3. **AHP Pairwise Comparison Questionnaire.** Experts will compare the four technician-ranking criteria in pairs using Saaty's 1–9 scale to determine the relative importance of each criterion.

4. **Technician Interview Guide.** The interview will collect the fees charged by technicians for different appliance subtypes. The gathered information will be used to establish the estimated fee ranges in the application.
5. **ISO/IEC 25010:2023 Evaluation Questionnaire.** A five-point Likert-scale questionnaire will be used to evaluate the application based on the five selected quality characteristics identified in Objective 5.

3.3 Requirement Specification and Analysis

This section presents the functional and non-functional requirements of the proposed Applifix: A Mobile Appliance Repair Booking Application with Vision-Language Classification and Multi-Criteria Technician Ranking in Angeles City. It also describes the system processes and data relationships through Data Flow Diagrams (DFDs), an Entity Relationship Diagram (ERD), and process flowcharts. These models provide a structured representation of how the system receives, processes, stores, and produces information.

3.3.1 Functional Requirements

The functional requirements describe the operations that the Applifix system must perform for customers, service professionals, and administrators.

Customer Requirements

The system shall allow customers to:

- Create an account and log in to the application.
- Submit an appliance photograph and problem description for service requests.
- Identify the appliance category and subtype using a vision-language model, with manual subtype selection when confidence is below the defined threshold.
- View recommended eligible service professionals and their relevant information.
- Select a responding service professional and view the estimated service fee.
- Review and record agreed material costs before the service is completed.
- Confirm service completion and record the completed transaction.
- Provide a rating and feedback after a completed service.

Service Professional Requirements

- The system shall allow service professionals to:
- Create an account and maintain their professional profile.
- Record practical skills assessment results and assessment dates, with appliance service categories activated only after a corresponding passing assessment.
- Receive and view applicable service requests based on their verified appliance service categories.
- View relevant information about appliance repair requests and respond to applicable requests.
- Record the completion of accepted appliance repair services.
- Maintain records of completed services and customer ratings.

Technician Ranking Requirements

The system shall:

- Identify and retrieve eligible service professionals based on the requested appliance service.

- Evaluate eligible service professionals using skill match, proximity, customer rating, and completion rate.
- Apply AHP using pairwise comparisons to determine the relative weights of the ranking criteria and verify that the Consistency Ratio (CR) is below 0.10.
- Generate and present a ranked list of suitable service professionals.

Administrator Requirements

The system shall allow the administrator to:

1. Manage customer and service professional accounts.
2. Record and manage practical skills assessment results and activate or restrict service categories based on assessment outcomes.
3. Manage appliance categories and subtypes.
4. Monitor service transactions, customer ratings, and service history.

3.3.2 Non-Functional Requirements

The non-functional requirements describe the quality characteristics that the proposed application should satisfy. These requirements are aligned with the selected characteristics of ISO/IEC 25010:2023 identified in the approved proposal.

Functional Suitability

The system should provide the required functions for appliance classification, technician eligibility verification, technician ranking, service booking, service completion, and feedback.

Performance Efficiency

The system should process requests and display classification and technician-ranking results within a reasonable response time under the conditions of the controlled pilot deployment.

Interaction Capability

The application should provide an interface that enables customers, service professionals, and administrators to complete their respective tasks appropriately.

Reliability

The system should consistently perform its required functions and maintain service, booking, assessment, and feedback records without unintended loss or corruption.

Security

The system should protect user accounts and stored information through appropriate authentication and access controls, ensuring that users can access only functions and information appropriate to their roles.

3.3.3 Data Flow Diagram

Level 0 – Context Diagram

The Level 0 Context Diagram represents Applifix as a single system interacting with three external entities: **Customer, Service Professional/Technician, and Administrator.**

- **Customer:** Provides account information, appliance photographs, problem descriptions, and service requests. Receives appliance classification results, technician recommendations, booking information, and service records.
- **Service Professional/Technician:** Provides profile information, skills assessment information, service responses, and service completion details. Receives applicable repair requests and service-related information.

- **Administrator:** Provides account, appliance category, and skills assessment information. Receives system and transaction records.

Figure 2. Level 0 Context Diagram of Applifix

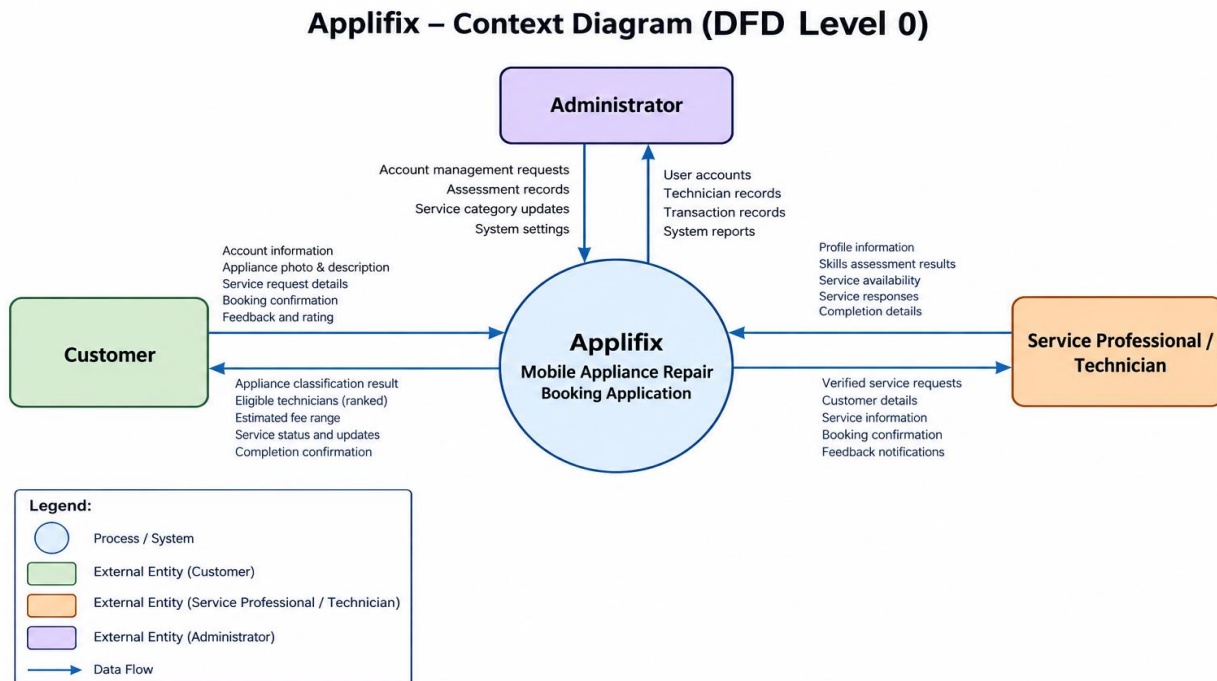


Figure 3.3.1 DFD Level 0 (Context Diagram) of Applifix

Level 1 – Data Flow Diagram

The Level 1 DFD decomposes the Applifix system into five major processes:

1.0 Manage User Accounts

Manages customer, service professional, and administrator account information.

2.0 Classify Appliance Request

Receives the appliance photograph and problem description, processes them through the vision-language classification component, and records the identified appliance category, subtype, and classification confidence.

3.0 Verify and Rank Technicians

Checks technician eligibility based on recorded skills assessment results and applies AHP using skill match, proximity, rating, and completion rate to generate technician rankings.

4.0 Manage Service Booking

Manages service requests, technician responses, customer selection, estimated fees, and agreed material costs.

5.0 Manage Service Completion and Feedback

Records service completion, customer ratings, feedback, and technician service history.

Figure 3. Level 1 Data Flow Diagram of Applifix

Applifix – Data Flow Diagram (Level 1)

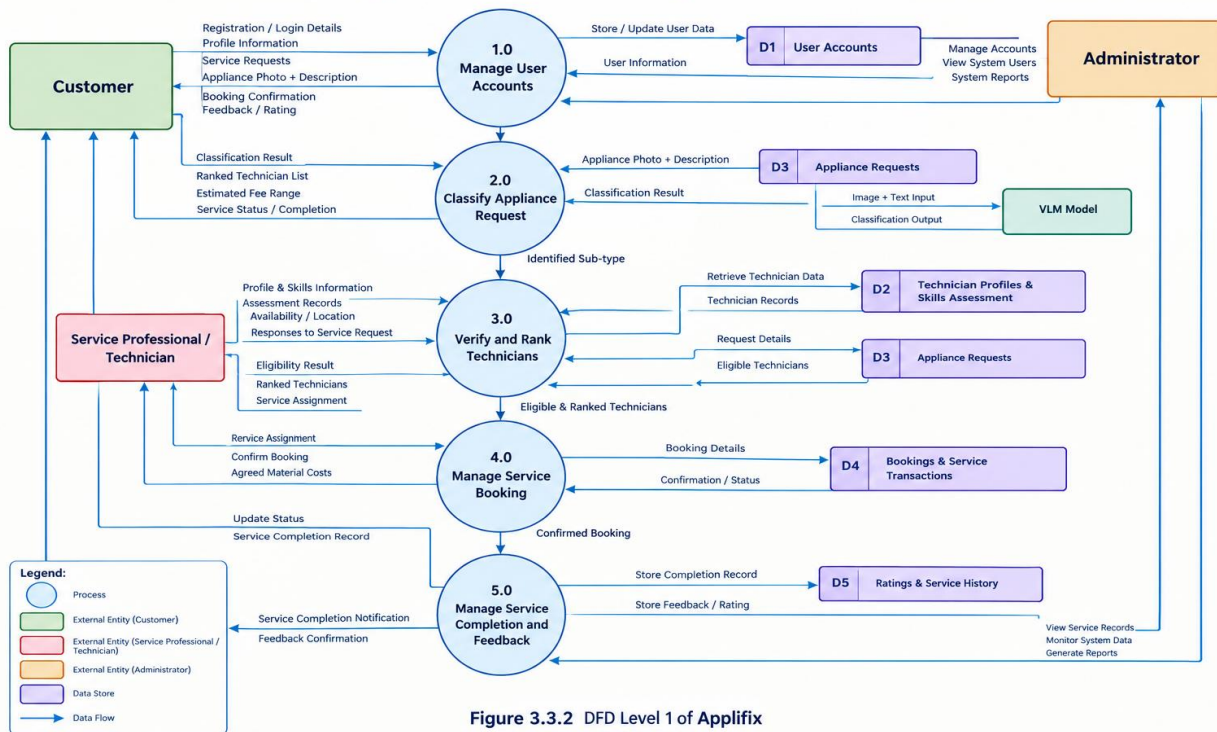


Figure 3.3.2 DFD Level 1 of Applifix

Main Data Stores

The Level 1 DFD uses the following main data stores:

- **D1 – User Accounts:** Stores customer, service professional, and administrator account information.
- **D2 – Technician Profiles and Skills Assessment:** Stores technician profiles, assessment results, assessment dates, and verified service categories.
- **D3 – Appliance Requests:** Stores appliance photographs, problem descriptions, classification results, and service request details.
- **D4 – Bookings and Service Transactions:** Stores booking information, technician responses, customer selections, estimated fees, material costs, and service completion records.
- **D5 – Ratings and Service History:** Stores customer ratings, feedback, and completed service history.

3.3.4 Entity Relationship Diagram

The Entity Relationship Diagram (ERD) presents the major entities, attributes, and relationships used to organize the information stored by Applifix.

Major Entities

User – Stores account information for application users.

- user_id
- name
- email
- phone

- password_hash
- address
- user_type
- created_at

Technician – Stores the professional profile of a service technician.

- technician_id
- user_id
- full_name
- bio
- location
- profile_photo
- verification_status
- created_at

Skills Assessment – Stores the results of practical skills assessments conducted outside the application.

- assessment_id
- technician_id
- appliance_category
- assessment_date
- result
- status
- remarks

Appliance Request – Stores customer repair requests and appliance classification results.

- request_id
- customer_id
- appliance_photo
- problem_description
- identified_category
- identified_subtype
- classification_confidence
- request_status
- created_at

Technician Ranking – Stores the ranking results generated for eligible technicians.

- ranking_id
- request_id
- technician_id
- skill_match
- proximity
- rating
- completion_rate
- ahp_score
- rank_position

Booking – Stores information about the confirmed repair service.

- booking_id
- request_id
- technician_id
- customer_id
- estimated_fee_min
- estimated_fee_max
- agreed_material_costs
- booking_status
- completion_status
- created_at

Feedback – Stores customer ratings and feedback after a completed service.

- feedback_id
- booking_id
- customer_id
- technician_id
- rating
- comment
- created_at

Entity Relationships

The primary relationships are:

- One **User** may have one **Technician** profile.
- One **Technician** may have many **Skills Assessment** records.

- One **User** may submit many **Appliance Requests**.
- One **Appliance Request** may have many **Technician Ranking** records.
- One **Technician** may appear in many **Technician Ranking** records.
- One **Appliance Request** may have zero or one confirmed **Booking**.
- One **Technician** may have many **Bookings**.
- One **Booking** may produce one **Feedback** record after a completed service.

Figure 4. Entity Relationship Diagram of Applifix

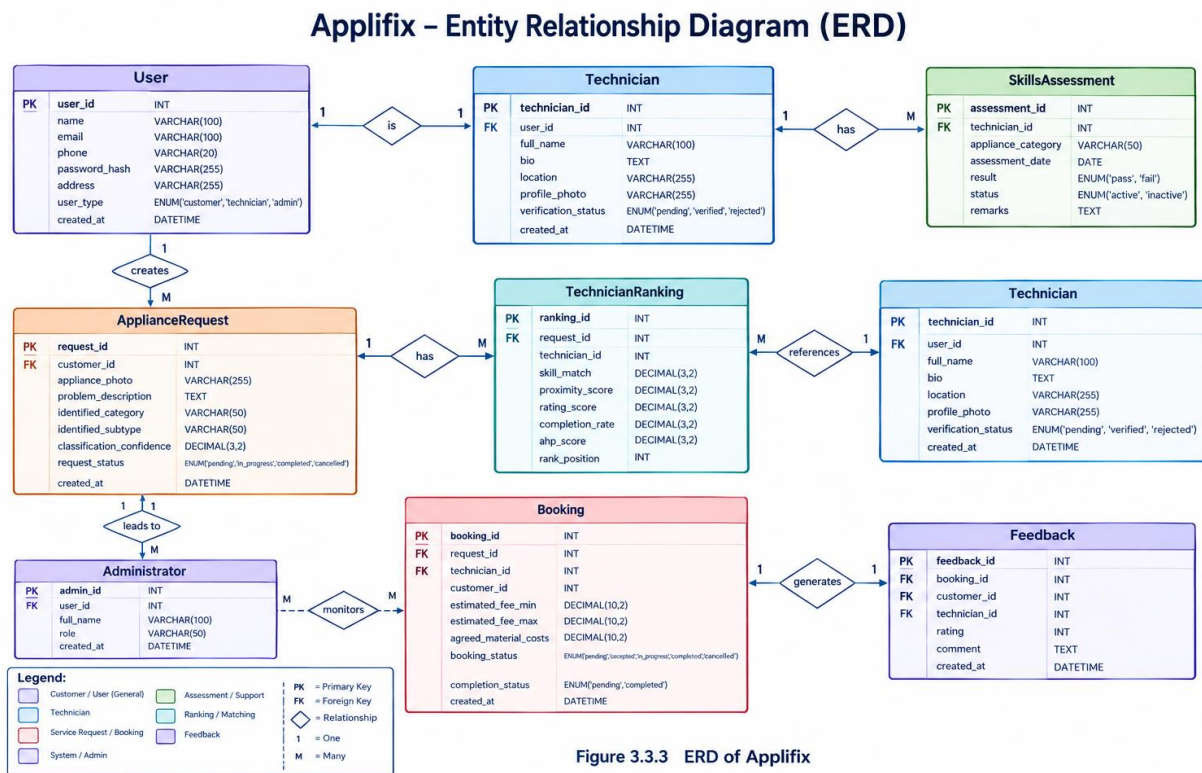


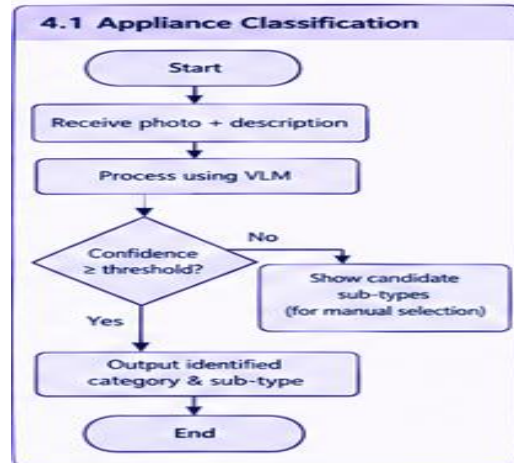
Figure 3.3.3 ERD of Applifix

3.3.5 Process Flowcharts

Appliance Classification Flowchart

The process begins when the customer submits an appliance photograph and problem description. The system processes the inputs through the vision-language classification component and receives the predicted appliance category, subtype, and confidence value. If the confidence meets the defined threshold, the predicted subtype is accepted. Otherwise, the system presents candidate subtypes for the customer to select manually.

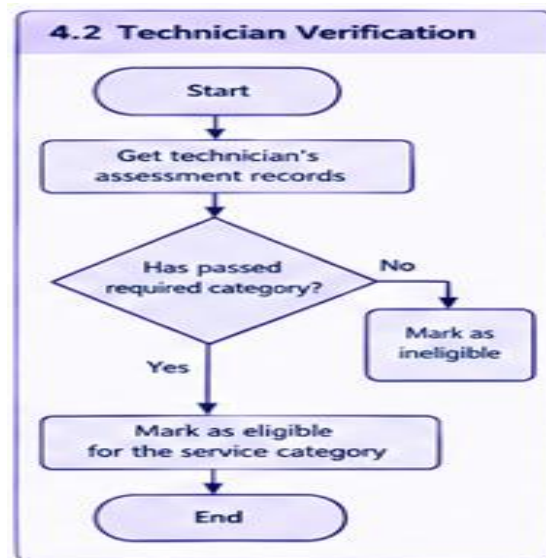
Figure 5. Appliance Classification Process Flowchart



Technician Eligibility Verification Flowchart

The process begins by retrieving the technician's recorded practical skills assessment. The system checks the assessment result for the requested appliance category. If the technician has a passing assessment, the corresponding service category is activated and the technician becomes eligible for related service requests. If the assessment is not passed, the technician is not eligible for that service category.

Figure 6. Technician Eligibility Verification Flowchart



AHP Technician Ranking Flowchart

The process begins by identifying technicians who are eligible for the requested appliance service. The system evaluates eligible technicians based on skill match, proximity, customer rating, and completion rate. AHP uses pairwise comparison weights to calculate the weighted scores for each technician. The consistency of the pairwise comparisons is then checked to ensure that the Consistency Ratio (CR) is below 0.10. Once the condition is satisfied, the system generates the ranked list of eligible technicians.

Figure 7. AHP Technician Ranking Process Flowchart



Booking and Service Completion Flowchart

The process begins when a customer submits a repair request. The system presents eligible and ranked technicians, and the customer selects a responding technician. The system records the estimated service fee and agreed material costs. After the repair is completed, the service completion is recorded, and the customer can provide a rating and feedback.

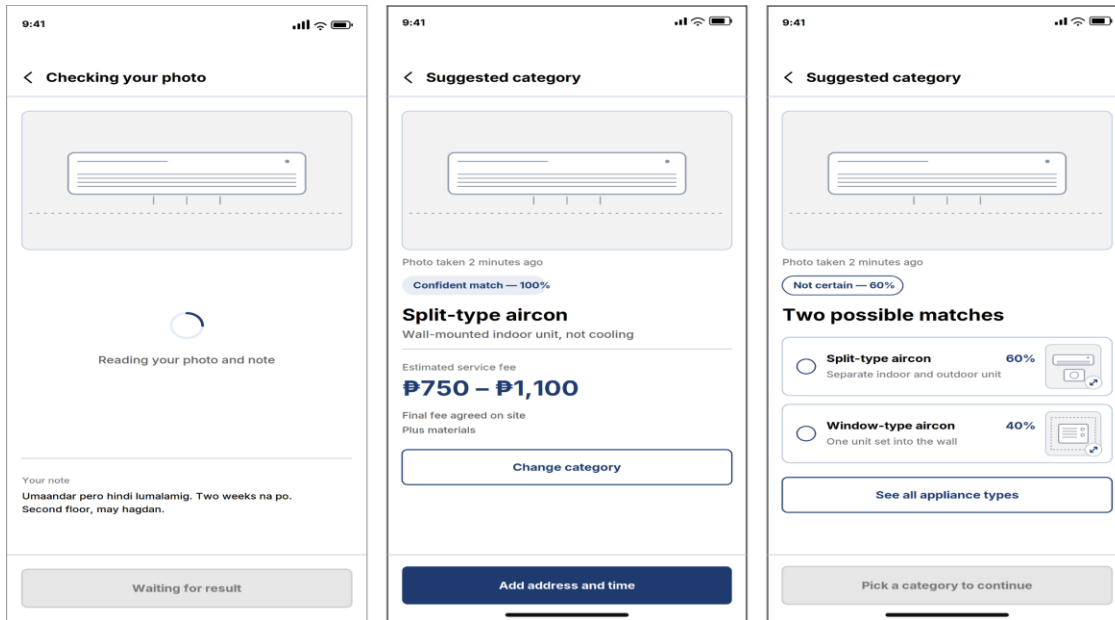
Figure 8. Booking and Service Completion Process Flowchart



3.4 System Design Specification

This section presents the logical and physical specifications of Applifix. The logical specification describes the application modules, their functions and processing logic, and the user interface wireframes. The physical specification describes the technologies, hardware, and system architecture required to develop and operate the application.

Figure 9. Appliance Classification Result: Loading, High Confidence, and Below Threshold



Note: Names, fees, confidence values, and scores shown in the wireframes are illustrative.

Figure 9 shows the three states of the classification result. While the vision-language model processes the submitted photograph and problem description, the customer sees a loading screen displaying the submitted note. When at least four of five model responses agree, the application displays the identified subtype, confidence value, and estimated fee range, with an option to change the category. If the agreement does not meet the threshold, the application displays candidate subtypes with example images, and the customer must select one before proceeding.

Figure 10. Service Address and Waiting for Responses

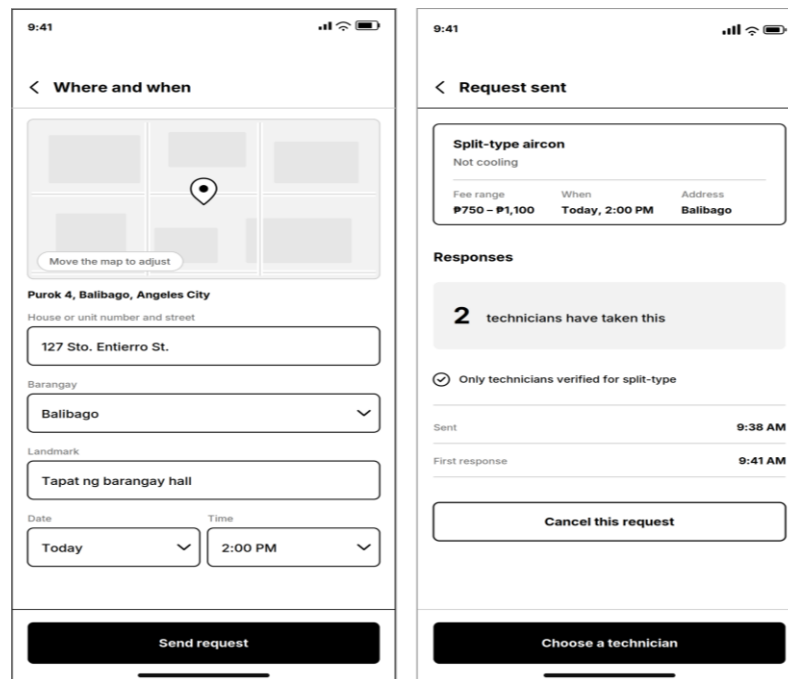


Figure 10 shows how the customer sets the service address by moving the map pin, selecting the barangay, and adding a landmark before choosing a schedule. After submitting the request, the customer can view the number of technicians who have responded. The application also indicates that only technicians assessed for the requested appliance subtype can receive the service request.

Figure 11. Technician's Incoming Request

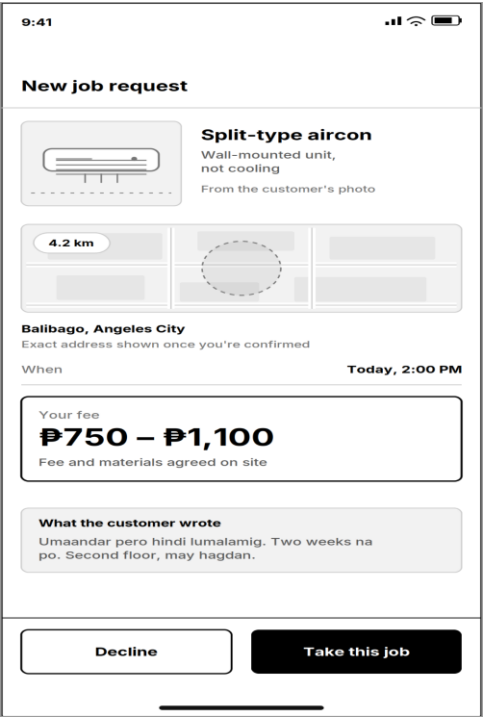


Figure 11 shows the service request received by a verified technician. It displays the appliance subtype identified from the customer's photograph, general location and distance, schedule, estimated fee range, and customer note. The customer's exact address is revealed only after the customer confirms the technician.

Figure 12. Ranked List of Responding Technicians

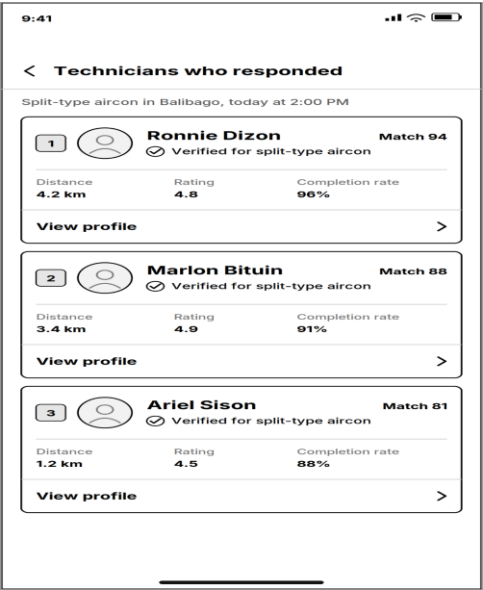


Figure 12 shows the responding technicians ranked according to their AHP scores. Each technician card displays the verification status for the requested subtype, distance, customer rating, completion rate, and overall AHP match score. The AHP score combines the four ranking criteria to determine the technician's position in the ranked list.

Figure 13. Technician Profile

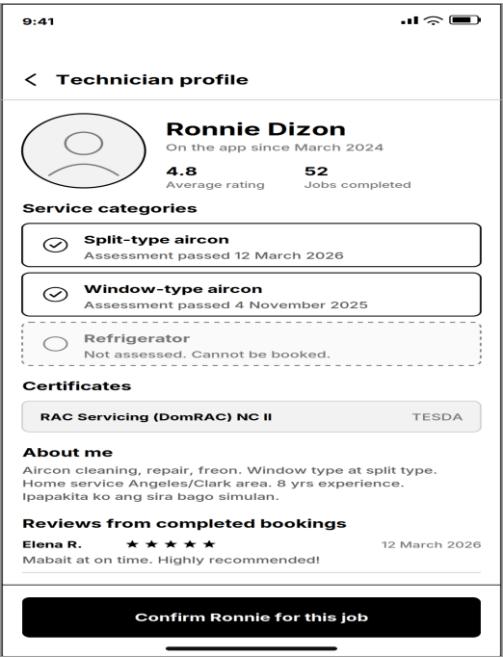


Figure 13 shows the technician profile, which lists each appliance category and its corresponding assessment date. Categories without a passing assessment remain visible but are marked as not bookable. The profile also displays supporting certificates and customer reviews from completed bookings.

Figure 14. Booking Status

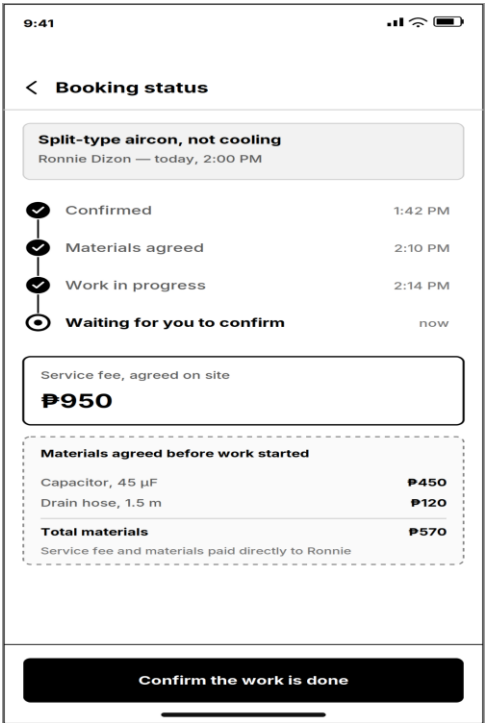


Figure 14 shows the booking status after the technician has inspected the appliance. The agreed service fee and itemized material costs are displayed, with the material costs agreed upon before the repair begins. After the work is completed, the customer confirms the completion of the service.

3.4.1 Logical Specification

The application has two user types: customers and technicians. Skills assessment results are recorded directly in the database by the researchers after each assessment. The application is organized into six modules.

Account and Profile Module. Customers and technicians can register and sign in. Technician profiles display verified appliance categories, assessment dates, ratings, and completed jobs. Unassessed categories remain visible but are marked as not bookable.

Appliance Classification Module. The customer submits an appliance photograph and problem description, which are processed by a vision-language model using a fixed output schema. The same request is processed five times, and confidence is based on the proportion of responses that identify the same subtype. When at least four of five responses agree, the identified subtype is shown. Otherwise, the candidate subtypes are presented for manual selection. The customer confirms the subtype before continuing, while appliances outside the defined subtypes are handled at the category level.

Assessment Record Module. The database stores each technician's assessment result and date for each appliance category. A category becomes bookable only after a passing result is recorded, and technicians cannot modify these records through the application.

Service Request Module. The customer sets the service address using a map pin, barangay, and landmark, then selects a preferred schedule. The application displays the estimated fee range and sends the request to technicians verified for the confirmed subtype. Responding technicians are added to the responder list. The request remains open until a technician is confirmed or 24 hours have passed. Technicians may withdraw their response and respond to up to three open requests. If no technician responds, the customer is notified and may resubmit the request.

Responding technicians are ranked using the Analytic Hierarchy Process (AHP) based on four criteria: **skill match**, measured by completed jobs for the same subtype with a passed assessment as the starting value; **proximity**, based on distance from the service address; **rating**, based on the average customer rating; and **completion rate**, based on the proportion of confirmed bookings that were completed.

The criteria weights are computed from the expert panel's pairwise comparisons and accepted when the Consistency Ratio is below 0.10. For each request, the criteria values are normalized, multiplied by their weights, and summed to produce each technician's score. Responding technicians are then ranked from highest to lowest score.

To address the limited history of newly verified technicians, rating and completion values are adjusted using the formula **Adjusted value = $(v / (v + m)) \times R + (m / (v + m)) \times C$** , where v is the number of rated or completed jobs, R is the technician's value, C is the overall average, and $m = 5$ (Liang et al., 2025). The adjusted values are used only for ranking, while technicians without reviews are displayed as **"Newly verified"** with their assessment date.

Service Transaction Module. The customer selects a ranked technician to confirm the booking. After inspecting the appliance, the technician records the required materials and costs, which the customer approves before work begins. After the service is completed, the customer confirms completion and may provide a rating and feedback. Only completed bookings are eligible for customer ratings.

Each booking moves through five states:

Table 5 - Booking States

State	Meaning
Open	The request has been broadcast and is waiting for responders
Confirmed	The customer has selected a technician
In Progress	Material costs have been agreed and work has started

Completed	The customer has confirmed that the work is done
Expired	No technician was confirmed within 24 hours

User Interface Wireframes. Figures 9 to 14 present the wireframes of the main application screens, including the classification process and results, service address and technician responses, incoming technician requests, ranked technicians, technician profiles, and booking status.

3.4.2 Physical Specification

Table 6 - Technology Stack

Component	Technology	Purpose
Mobile application	Flutter (Dart), Android	Customer and technician interfaces
Authentication	Firebase Authentication	Account registration and sign-in
Database	Cloud Firestore	Profiles, assessment records, requests, bookings, ratings
File storage	Cloud Storage for Firebase	Appliance photographs
Server functions	Cloud Functions for Firebase	Classification requests, request broadcast, ranking computation
Notifications	Firebase Cloud Messaging	Request alerts to technicians
Classification	Gemini API	Vision-language model; the exact model version is recorded at the time of evaluation
Maps	MapLibre with OpenFreeMap tiles	Map display and pin placement
Reverse geocoding	Nominatim	Converts the pin location into an address

Hardware Requirements. The application will run on Android smartphones with Android 10 or higher, a rear camera, GPS, and an active internet connection. Testing will include devices from manufacturers such as Xiaomi, Realme, OPPO, and vivo to check compatibility and notification delivery across different devices.

System Architecture. The application will use Firebase for authentication, data storage, file storage, and notifications. Vision-language model requests and technician ranking calculations will be processed through Cloud Functions to protect the API key and prevent modification from the user's device. Map services will use OpenFreeMap and Nominatim, while database security rules will restrict access based on user roles and limit assessment record updates to authorized researchers.

3.5 Implementation

The developed application will be implemented through a controlled pilot deployment in Angeles City. Appliance repair professionals will be recruited through direct outreach, local repair shops, and social media, followed by a practical skills assessment. Only technicians who pass the assessment will be activated for their corresponding services. After sufficient verified technicians are available, customers will be recruited through Facebook, QR-code materials, posters, participating technicians, and permitted community channels. Selected customers will use the application for appliance classification, technician selection, service booking, and feedback. The researchers will monitor the pilot and evaluate the application based on the defined technical and usability criteria.

3.6 Testing and Evaluation

The application will be tested at four levels. Unit testing will check each module on its own, such as the classification request, the eligibility check, and the ranking computation. Integration testing will check that the modules work together, from classification through request broadcast, ranking, and booking. System testing will check the complete application against the objectives using the test cases in Table 7. User acceptance testing will take place during the controlled pilot, where customers and technicians use the application for actual service requests.

Table 7 - Sample Functional Test Cases

Objective	Test Case	Expected Result
1	Submit a photo where at least four of five responses agree	Identified sub-type and estimated fee range are shown
1	Submit a photo where fewer than four of five responses agree	Candidate sub-types are shown, and the customer cannot continue without selecting one
2	Broadcast a request for a sub-type the technician has not passed	The technician does not receive the request
2	Record a passing assessment result for the technician	The category becomes bookable and the technician receives matching requests
3	Three verified technicians respond to one request	Responders are listed in order of their AHP score
3	A newly verified technician with no ratings responds	The technician is ranked using adjusted values and shown as "Newly verified"
4	No technician is confirmed within 24 hours	The request changes to Expired
4	Technician records material costs	Work cannot be marked as started until the customer agrees
4	Customer confirms completion	Booking changes to Completed and the customer can leave a rating

The evaluation will cover three areas: classification accuracy, consistency of the AHP weights, and application quality based on ISO/IEC 25010:2023.

Evaluation of the Classification

The classification will be evaluated using approximately 210 researcher-labelled photographs, with 30 photographs for each of the seven subtype classes. Each photograph and its description will be processed by the application, and the actual result will be compared with the expected result recorded by the researchers. The actual result is the subtype returned by the majority of the five model responses. Where no subtype has a majority, the photograph is counted as misclassified. Results will be recorded in the format shown in Table 1 and summarized in a confusion matrix following Table 2. Accuracy, precision, recall, F1 score, and the Matthews Correlation Coefficient (MCC) will be computed using the following formulas:

$$\text{Accuracy} = \text{Correct classifications} / \text{Total photographs}$$

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

$$\text{F1 Score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

$$\text{MCC} = (\text{TP} \times \text{TN} - \text{FP} \times \text{FN}) / \sqrt{[(\text{TP} + \text{FP})(\text{TP} + \text{FN})(\text{TN} + \text{FP})(\text{TN} + \text{FN})]}$$

TP represents correctly classified photographs, FP represents photographs incorrectly assigned to a class, FN represents photographs of a class assigned to another class, and TN represents photographs of other classes that were correctly not assigned to that class. Each value is computed per class, treating that class as positive and all other classes as negative. Overall precision, recall, F1 score, and MCC will be reported as macro averages, giving equal weight to each class (Opitz, 2024). MCC ranges from -1 to +1, where +1 indicates perfect classification and 0 indicates performance no better than random guessing. It is included because it remains reliable if the final number of photographs per class is uneven (Chicco & Jurman, 2023; Tamura et al., 2026). Where the denominator of the MCC formula is zero for a class, the value for that class is set to 0. The study will also report the percentage of photographs below the 80% confidence threshold that require manual subtype selection. Appliances outside the seven subtype classes will be evaluated only at the category level and excluded from these metrics.

Evaluation of the AHP Weights. Each expert's pairwise comparison matrix will be checked using the Consistency Ratio (CR):

$$\text{CI} = (\lambda_{\text{max}} - n) / (n - 1)$$

$$\text{CR} = \text{CI} / \text{RI}$$

where λ_{max} is the largest eigenvalue, n is the number of criteria (four), and RI is the random index. Experts with a CR of 0.10 or higher will review their comparisons once. Accepted judgments will be combined using the geometric mean, and the resulting matrix must have a CR below 0.10 before the criteria weights are used in the application.

Evaluation of Software Quality

The application will be evaluated using ISO/IEC 25010:2023 (International Organization for Standardization, 2023) based on the five characteristics identified in Objective 5. Questionnaire items will be based on the relevant sub-characteristics, and each respondent group will evaluate only the characteristics applicable to their use of the application, as shown in Table 8.

Table 8 - Evaluation Characteristics and Respondents

Characteristic	Sub-characteristics	Respondents
Functional suitability	Functional completeness, functional correctness, functional appropriateness	Customers, technicians, IT evaluators
Performance efficiency	Time behavior, resource utilization, capacity	IT evaluators
Interaction capability	Appropriateness recognizability, learnability, operability, user error protection, user engagement, inclusivity, user assistance, self-descriptiveness	Customers, technicians, IT evaluators

Reliability	Faultlessness, fault tolerance, availability, recoverability	Customers, technicians, IT evaluators
Security	Confidentiality, integrity, non-repudiation, accountability, authenticity, resistance	IT evaluators

In addition to the questionnaire, classification time behavior will be measured directly. For each test-set photograph, the time from submission to the displayed result will be recorded, and the mean, median, and longest times will be compared with the 10-second target.

Questionnaire responses will use a five-point Likert scale and be summarized using the weighted mean:

$$\bar{x} = \Sigma(f \times x) / n$$

where f is the frequency of each rating, x is the rating value, and n is the total number of respondents. The resulting means will be interpreted using the scale in Table 9, with equal intervals of 0.80 calculated as (5 – 1) / 5.

Table 9 - Likert Scale Interpretation

Rating	Mean Range	Interpretation
5	4.21 to 5.00	Strongly Agree
4	3.41 to 4.20	Agree
3	2.61 to 3.40	Neutral
2	1.81 to 2.60	Disagree
1	1.00 to 1.80	Strongly Disagree

REFERENCES

AlRossais, N. (2025). Novel models for the warm-up phase of recommendation systems. *Computers*, 14(8), 302. <https://www.mdpi.com/2073-431X/14/8/302>

Bangko Sentral ng Pilipinas. (2025). *2024 report on e-payments measurement*.

Bartolome, D. A., Gubac, M. L., Rivera, C. J., & Mababa, J. (2023). "Pasahero": A mobile transit application that tracks the departure and arrival status of buses. In *Proceedings of the 13th Annual International Conference on Industrial Engineering and Operations Management*. IEOM Society International. <https://doi.org/10.46254/AN13.20230599>

Bayudan-Dacuycuy, C., & Dacuycuy, L. B. (2022). Harnessing the potential of online marketplaces in the Philippines: Insights from the National Information and Communications Technology Household Survey. *Asia & the Pacific Policy Studies*, 9(3), 288–316. <https://doi.org/10.1002/app5.365>

Caffagni, D., Cocchi, F., Barsellotti, L., Moratelli, N., Sarto, S., Baraldi, L., Cornia, M., & Cucchiara, R. (2024). The revolution of multimodal large language models: A survey. *Findings of the Association for Computational Linguistics: ACL 2024*, 13590–13618. <https://doi.org/10.18653/v1/2024.findings-acl.807>

Cayabyab, C. A. (2021, July 4). Agorah Marketplace: The new go-to for online shopping. *SunStar Pampanga*.

Chicco, D., & Jurman, G. (2023). The Matthews correlation coefficient (MCC) should replace the ROC AUC as the standard metric for assessing binary classification. *BioData Mining*, 16, Article 4. <https://doi.org/10.1186/s13040-023-00322-4>

Cremades, L. V., & Ponsich, A. (2025). Simple and objective determination of criteria weights for evaluating alternatives when using the Analytic Hierarchy Process. *International Journal of the Analytic Hierarchy Process*, 16(3). <https://ijahp.org/index.php/IJAHP/article/view/1177>

Danish, S., Sadeghi-Niaraki, A., Khan, S. U., Dang, L. M., Tightiz, L., & Moon, H. (2026). A comprehensive survey of vision-language models: Pretrained models, fine-tuning, prompt engineering, adapters, and benchmark datasets. *Information Fusion*, 126, 103623. <https://doi.org/10.1016/j.inffus.2025.103623>

De Pessemier, T., Willems, B., & Martens, L. (2025). Active learning algorithm for alleviating the user cold start problem of recommender systems. *Scientific Reports*, 15, 24493. <https://doi.org/10.1038/s41598-025-09708-2>

Dong, J., Zhang, Y., Zhu, H., Ong, Y.-S., & Koniusz, P. (2026). Hierarchically robust zero-shot vision-language models. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 37642–37652. https://openaccess.thecvf.com/content/CVPR2026/html/Dong_Hierarchically_Robust_Zero-shot_Vision-language_Models_CVPR_2026_paper.html

Galang, N. A. A., Villeno, A. M. M., Camaro, P. J., & Cabauatan, R. R. (2025). Impact of digital platform economy and ride-hailing services on urban mobility in Pampanga. *Journal of Technology and Systems*, 7(1), 28–57. <https://doi.org/10.47941/jts.2506>

Ghosh, A., Acharya, A., Saha, S., Jain, V., & Chadha, A. (2024). Exploring the frontier of vision-language models: A survey of current methodologies and future directions. *arXiv*. <https://arxiv.org/abs/2404.07214>

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly*, 28(1), 75–105. <https://doi.org/10.2307/25148625>

International Organization for Standardization. (2023). *ISO/IEC 25010:2023: Systems and software engineering—Systems and software quality requirements and evaluation (SQuaRE)—Product quality model*. ISO.

International Telecommunication Union, & United Nations Institute for Training and Research. (2024). *The global e-waste monitor 2024*.

Jiao, R., Przepiorka, W., & Buskens, V. (2021). Reputation effects in peer-to-peer online markets: A meta-analysis. *Social Science Research*, 95, 102522. <https://doi.org/10.1016/j.ssresearch.2020.102522>

Jiao, R., Przepiorka, W., & Buskens, V. (2022). Moderators of reputation effects in peer-to-peer online markets: A meta-analytic model selection approach. *Journal of Computational Social Science*, 5, 1041–1067. <https://doi.org/10.1007/s42001-022-00160-0>

Karamolegkou, A., Rust, P., Cui, R., Cao, Y., Søgaard, A., & Hershcovich, D. (2024). Vision-language models under cultural and inclusive considerations. In N. Soni, L. Flek, A. Sharma, D. Yang, S. Hooker, & H. A. Schwartz (Eds.), *Proceedings of the 1st Human-Centered Large Language Modeling Workshop* (pp. 53–66). Association for Computational Linguistics. <https://doi.org/10.18653/v1/2024.hucllm-1.5>

Kokkodis, M. (2021). Dynamic, multidimensional, and skillset-specific reputation systems for online work. *Information Systems Research*, 32(3), 688–712. <https://doi.org/10.1287/isre.2020.0972>

Li, J., Li, D., Savarese, S., & Hoi, S. (2023). BLIP-2: Bootstrapping language-image pre-training with frozen image encoders and large language models. *Proceedings of the 40th International Conference on Machine Learning*, 202, 19730–19742. <https://proceedings.mlr.press/v202/li23q.html>

Liang, C., Hong, Y., & Gu, B. (2025). Monitoring and the cold start problem in digital platforms: Theory and evidence from online labor markets. *Information Systems Research*, 36(1), 600–620. <https://doi.org/10.1287/isre.2021.0146>

Luca, M. (2017). Designing online marketplaces: Trust and reputation mechanisms. *Innovation Policy and the Economy*, 17, 77–93. <https://doi.org/10.1086/688845>

- Lukac, M., & Grow, A. (2021). Reputation systems and recruitment in online labor markets: Insights from an agent-based model. *Journal of Computational Social Science*, 4, 207–229. <https://doi.org/10.1007/s42001-020-00072-x>
- Manabat, J. (2021, July 6). Homegrown e-commerce Agorah officially launches. *Punto! Central Luzon*.
- MyKuya. (n.d.). *MyKuya*.
- Neira-Rodado, D., Jimenez-Delgado, G., Hernandez-Palma, H., & Donado-Acosta, A. M. (2024). A strategic hybrid model to determine the critical criteria for the selection of the most appropriate city ambulance service provider. *Procedia Computer Science*, 231, 648–653. <https://doi.org/10.1016/j.procs.2023.12.169>
- Nydick, R. L., & Hill, R. P. (1992). Using the Analytic Hierarchy Process to structure the supplier selection procedure. *International Journal of Purchasing and Materials Management*, 28(2), 31–36. <https://doi.org/10.1111/j.1745-493X.1992.tb00561.x>
- OECD. (2022). *Measuring financial consumer detriment in e-commerce* (OECD Digital Economy Papers No. 326). OECD Publishing. <https://doi.org/10.1787/4055c40e-en>
- Opitz, J. (2024). A closer look at classification evaluation metrics and a critical reflection of common evaluation practice. *Transactions of the Association for Computational Linguistics*, 12, 820–836. https://doi.org/10.1162/tacl_a_00675
- Parker-Waldern, S. H., & Leonardi, P. M. (2026). Cold starts and burning desires: Reputation system misalignment and late-career transitions to platform work. *Administrative Science Quarterly*. Advance online publication. <https://doi.org/10.1177/00018392261464889>
- Pavlou, P. A., & Gefen, D. (2004). Building effective online marketplaces with institution-based trust. *Information Systems Research*, 15(1), 37–59. <https://doi.org/10.1287/isre.1040.0015>
- Peña-García, N., Losada-Otálora, M., Pérez Auza, D., & Cruz, M. P. (2024). Reviews, trust, and customer experience in online marketplaces: The case of Mercado Libre Colombia. *Frontiers in Communication*, 9, 1460321. <https://doi.org/10.3389/fcomm.2024.1460321>
- Philippine Statistics Authority. (2021). *Highlights of the Region III (Central Luzon) population: 2020 Census of Population and Housing*.
- Philippine Statistics Authority. (2025). *Percentage of households with internet connection increased to 48.8 percent in 2024*.
- Pineda, C. N. P., & Cayabyab, L. A. S. (2023). *Facilitating employment opportunities in the digital space: A study on the activities and services of digital labor market intermediaries in the Philippines*. Department of Labor and Employment, Institute for Labor Studies. <http://serp-p.pids.gov.ph/publication/public/view?slug=facilitating-employment-opportunities-in-the-digital-space-a-study-on-the-activities-and-services>
- Repschlaeger, J., Proehl, T., & Zarnekow, R. (2014). Cloud service management decision support: An application of AHP for provider selection of a cloud-based IT service management system. *Intelligent Decision Technologies*, 8(2), 95–110. <https://doi.org/10.3233/IDT-130181>
- Saaty, T. L. (2008). Decision making with the analytic hierarchy process. *International Journal of Services Sciences*, 1(1), 83–98. <https://doi.org/10.1504/IJSSCI.2008.017590>
- Saaty, T. L. (2023). On using pairwise comparison in the analytic hierarchy process: Validity is goal while consistency is means. *Information Sciences*, 648, 119630. <https://doi.org/10.1016/j.ins.2023.119630>
- Saaty, T. L. (2023). *The analytic hierarchy process*. McGraw-Hill.
- Saputra, F. A., & Budilaksono, S. (2025). Sistem pengambilan keputusan untuk pemilihan teknisi terbaik pada PT Ganchang Net menggunakan AHP dan ELECTRE. *Jurnal Ilmiah Teknik Informatika (TEKINFO)*, 26(1). <https://journals.upi-yai.ac.id/index.php/TEKINFO/article/view/468>
- Schwaber, K., & Sutherland, J. (2020). *The Scrum guide: The definitive guide to Scrum: The rules of the game*. <https://scrumguides.org/scrum-guide.html>

Soriano, C. R. R. (2021). Digital labour in the Philippines: Emerging forms of brokerage. *Media International Australia*, 179(1), 57–73. <https://doi.org/10.1177/1329878X21993114>

Soriano, C. R., Cabalquinto, E. C. B., & Panaligan, J. H. (2021). Performing “digital labor bayanihan”: Strategies of influence and survival in the platform economy. *Sociologias*, 23(57), 84–111. <https://doi.org/10.1590/15174522-113027>

Surucu, O., Gadsden, S. A., & Yawney, J. (2023). Condition monitoring using machine learning: A review of theory, applications, and recent advances. *Expert Systems with Applications*, 221, 119738. <https://doi.org/10.1016/j.eswa.2023.119738>

Tamura, J., Itaya, Y., Hayashi, K., & Yamamoto, K. (2026). Statistical inference of the Matthews correlation coefficient for multiclass classification. *Journal of Applied Statistics*. Advance online publication. <https://doi.org/10.1080/02664763.2026.2666305>

TapatPH. (2026). *TapatPH: Verified home service professionals*.

United Nations Environment Programme. (2024). *A policymakers' guide to life cycle assessment*.

Verma, P., Van, M.-H., & Wu, X. (2026). Vision language models for scientific image analysis: An evaluation highlighting opportunities and challenges. *npj Computational Materials*, 12, 218. <https://www.nature.com/articles/s41524-026-02069-y>

Xiong, M., Hu, Z., Lu, X., Li, Y., Fu, J., He, J., & Hooi, B. (2024). Can LLMs express their uncertainty? An empirical evaluation of confidence elicitation in LLMs. In *The Twelfth International Conference on Learning Representations*. <https://openreview.net/forum?id=gjeQKFxFpZ>

Zhang, J., Huang, J., Jin, S., & Lu, S. (2024). Vision-language models for vision tasks: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 46(8), 5625–5644. <https://doi.org/10.1109/TPAMI.2024.3369691>

Zou, L., Chen, Q., Deng, Z., & Li, G. (2026). Enhancing user cold-start recommendation with graph structures and semantic dependencies. *Knowledge-Based Systems*, 336, 115280. <https://www.sciencedirect.com/science/article/abs/pii/S0950705126000249>