LAKAD: A PERSONALIZED MOBILE ITINERARY CREATOR WITH FOCUS IN BULACAN TOURISM

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CHAPTER I

THE PROBLEM AND ITS BACKGROUND

Itinerary planning is an important process that can enhance the experience of tourists in their travel such as how well the places interest the user and the flow in which the places are traversed. In the case of the province of Bulacan, this study seeks to propose a mobile personalized itinerary generator as a possible solution to optimizing existing itineraries and providing rich and personalized itineraries of Bulacan tourism, based on the interests of the user. This chapter introduces the background, objectives, significance, and scope of the study.

Background of the Study

In the midst of global advancement in technology and sciences, culture remains a vital part of many people's lives around the world, and so are the habits they have in connection to it. Tourism, being a significant contributor to economic progress, preservation of culture, and local development, relies heavily on how well travel experiences are organized and delivered. One of the most crucial aspects of this process is itinerary planning, a practice which ensures that tourists can maximize their time while visiting multiple points of interest (POIs) efficiently, and enjoy what a place can offer without the unnecessary inconvenience. The ability to create a structured travel plan does not only influence convenience but also impacts tourist satisfaction and chance of returning or recommending the destination to others.

According to United Nations World Tourism Organization (UNWTO) (2023) and Geçikli et al. (2024), the tourism sector has been undergoing a transformation marked by the growing interest in sustainable practices in tourism such as authentic cultural immersion and the exploration of lesser-known destinations. Post-pandemic recovery gave an emphasis on responsible tourism and a shift away from mass tourism towards more personalized and meaningful travel experiences. This trend is evident in the rise of modern tourism markets such as ecotourism, adventure tourism, and cultural heritage tourism, which often focus on underexplored regions. Indigenous tourism in regions such as Fiji, Australia, and Aotearoa New Zealand are gaining popularity as they offer the experiencing of cultural values of guardianship and community wellbeing, leading to authentic cultural exchanges while advancing self-determined and sustainable local development (Scheyvens et al., 2021). While at the same time, the advances in itinerary-planning technologies enables travellers to customize travel routes according to their individual interests, thereby aligning with the global shift toward meaningful and locally-rooted tourism experiences (Halder et al., 2022).

In the Philippines, the Department of Tourism (DOT) has been actively promoting lesser-known destinations and cultural heritage sites to better diversify tourism offerings and distribute its economic benefits across the country. Global trends focusing on sustainable and authentic travel experiences align with DOT's initiatives that include developing new tourism circuits, investing in infrastructure in emerging destinations, and implementing digital marketing campaigns to highlight the unique cultural and natural attractions. In many provinces, recent campaigns have emphasized community-based tourism and the promotion of their local festivals, which aims to provide tourists with deeper cultural immersion while also supporting local economies (Department of Tourism (DOT), 2023). This approach is rooted from the Connectivity, Convenience, and E(quality) strategies of DOT's National Tourism Development Plan (NTDP) to strengthen the value of Filipino identity in every tour, which ensures that Philippine tourism offers authentic experiences with the richness and diversity of Filipino cultures across thousands of islands in the country.

Bulacan, even though a historically active province in the Philippines, still has some of its historical and cultural destinations neglected despite the province's rich heritage, proven by how some culturally relevant sites like Barasoain Church and the Basilica Minore de Immaculada Conception both in Malolos, attract and often have more visitors than others like the Meyto Shrine of Calumpit, which respectively had 78, 30, and 10 visitors, collected among 100 respondents (Canet & Sunpongco, 2025). Thus, promotion of tourism, and by extension, the development of tools that can improve it is a vital aspect to the continued revival of the province's tourism sector. And, as further supported by its Provincial History, Arts, Culture, and Tourism Office (PHACTO), Bulacan's tourist arrival reports show that the municipalities where the aforementioned churches are located had 315,929 and 103,953 visitors respectively for the first three quarters of the year 2025. The Provincial Government of Bulacan launched the Pamana Pass in 2023, an initiative that promotes the tourism engagement of the province (Velasco, 2023). The Pass initiative, although aims to strengthen the relevance and popularity of the destinations, lacks the capability of offering an optimized itinerary plan as the order of visitation is left to be decided by the tourist.

The exploration of new tourism frontiers, especially with the desire for unique, personal journeys, highlights the need for smarter ways to plan trips. Systems that can pull together all sorts of information, offering suggestions perfectly tailored to what each person likes. This is especially important as more and more people want to explore beyond the usual tourist traps and truly experience a destination's uniqueness, which often demands a level of planning that outdated methods just can't deliver (Halder et al., 2022). By using technology to help people understand these special places, they can make their trips more satisfying and ensure these tourism spots grow in a way that benefits everyone. In this regard, itinerary planners and POI recommendation systems are such of the many utilities that can improve this.

Itinerary planning is a process where someone thoughtfully organizes a set of destinations into a detailed schedule in order to maximize their time while taking into account specific constraints that can affect their experience. Nowadays, creating itineraries has become increasingly automated through recommendation systems, which can even generate schedules based on many constraints (Jewpanya et al., 2025; Liu et al., 2024). Some of the modern-day recommendation systems are often a mix of both optimization algorithms and content selection processes. This method resolves not only the scheduling aspect of itinerary recommendation, but also the relevance of the destination suggested to users. However, such itinerary recommendation systems are limited to specific regions, often bound by the capabilities of the model or lack of data that can be used to identify which destinations are to be included (Cui et al., 2025; Papadakis et al., 2024; Yulfihani & Zakariyah, 2024).

The development of itinerary recommendation systems are driven by the need to simplify the complicated problems of manual itinerary planning. However, many existing travel apps struggle with effective itinerary optimization as reports from Skift's, a leading source for travel news and research, Skift Research highlights that many of those applications offer destination suggestions but lack the ability to offer suggestions based on user preferences, which leads to less personalization of travel plans. This report also shows the demand now for a personally curated service, since 30 percent of travelers responded that they are "more likely to use a travel agent now than before the pandemic" (Arora et al., 2022). Although there are many systems that are already developed to cater to this problem, a common weakness they have lies in the overcomplexity of their systems (Postnikova, 2024). Furthermore, general-purpose platforms often fail to provide the necessary level of curation and destination discovery required to highlight local, and unique cultural experiences, and they generally do not align with the Philippines' strategic imperative to build a deeper, distinct Filipino experience (Arora et al., 2022; Department of Tourism (DOT), 2023). These weaknesses expose the need for a simple, localized itinerary recommendation system, particularly in areas with uneven destination popularity like Bulacan.

Planning a travel itinerary manually is a demanding task, as many tourists must differentiate attractions to fit their interest while at the same time meeting limitations in terms of time and location accessibility. Hendrawan et al. (2024) stated that an increase in POIs in combination with limited resources makes it difficult to create itineraries, and while travel agents offer assistance, such services are high cost and inaccessible to many tourists. Porras et al. (2022) also argued that planning itineraries is fundamentally difficult, for it not only involves choosing POIs themselves but also finding an optimal visiting order under numerous constraints, such as personal interests, transportation, and time constraints. These problems demonstrate that classic ways of planning itineraries tend to lead to incomplete or unsatisfactory schedules, which there is value in creating automated systems to plan itineraries more efficiently. From a computational perspective, this problem is closely related to the model of Traveling Salesman Problem (TSP), which is known to have solutions that become exponentially more complex as the number of destinations or POIs increases (Wu & Fu, 2020). And even when functional apps are deployed, itinerary generation has to carefully consider constraints within user satisfaction metrics, which remains a significant task despite advanced recommendation and optimization methods (Papadakis et al., 2024; Yulfihani & Zakariyah, 2024). These limitations point to the need for a practical, user-centered, and localized solution.

To address these identified challenges, a proposed itinerary recommendation system, LAKAD, aims to navigate these problems and offer a tourist utility app for exploring destinations in the province of Bulacan. The system will be developed to feature core utilities that can enhance the travel experience of tourists. Among these features is an itinerary optimization, where the system ensures that travel routes are arranged in the most efficient way possible, minimizing time and cost while still maximizing convenience. The system also aims to provide a personalized itinerary generation for users to tailor travel plans according to their own preferences. Additionally, a tourist spot searching feature will be implemented to allow users to freely and easily browse Bulacan's offered attractions and destinations, which includes heritage sites to natural sceneries. An itinerary navigation feature will help users arrange their trip destinations into a structured schedule according to their desired length of the travel, in addition to features that can guide tourists during their trip like providing directions and other similar functions. Lastly, to help users stay organized, an itinerary management feature will allow users to arrange and keep track of their chosen destinations.

Statement of the Problem

The lack of systems and applications for itinerary generation in Bulacan makes it much harder for tourists to traverse the wonders the province has to offer. As such, the main objective of this study is to develop a mobile personalized itinerary generator for promoting tourist locations in Bulacan as well as providing optimized paths in the itinerary, allowing the tourist to further enjoy their trip. Specifically, this study aims to answer the following questions:

1. How can the proposed system be developed with the following functionalities:
   1.1. Itinerary Optimization,
   1.2. Personalized Itinerary Generation,
   1.3. Tourist Spot Searching,
   1.4. Itinerary Navigation, and
   1.5. Itinerary Management?
2. How acceptable is the proposed system based on the criteria defined in the Technology Acceptance Model?
   2.1. Perceived usefulness,
   2.2. Perceived ease of use,
   2.3. Attitude towards using, and
   2.4. Behavioral intention?
3. How well does the proposed system meet the ISO/IEC 25010:2023 requirements?
   3.1. Functional Suitability,
   3.2. Performance Efficiency,
   3.3. Compatibility,
   3.4. Interaction Capability,
   3.5. Reliability,
   3.6. Security,
   3.7. Maintainability,

3.8. Flexibility, and

3.9. Safety?

Significance of the Study

This study developed an optimized mobile itinerary planner designed to promote tourism in Bulacan as a destination for tourists while providing functional navigation support for locals and commuters. With the integration of personalization and efficiency, the system serves as a tool that highlights the province's attractions, supports its tourism industry, and makes it convenient to organize trips.

Tourists and travelers. The system offers personalized and optimized itineraries based on their interest and time availability. This way, it ensures that their time is maximally optimized as they enjoy major destinations alongside lesser-known examples of Bulacan's cultural, historical, and natural heritage.

Business owners and local establishments. The system offers opportunities for greater exposure, as their products and attractions may be featured in itineraries. This kind of promotion leads to greater customer engagement and supports the growth of local enterprises.

Local tourism sector, government units, and communities. The system provides a modern tool to promote sustainable tourism. Through the distribution of visitors across various attractions and offering organized travel options, it helps in stimulating local economies, sustaining community livelihoods, and improving Bulacan's reputation as a prominent travel destination.

Commuters and local residents. It functions as a navigation tool with optimized routes across Bulacan. Apart from addressing tourism, it gives daily convenience for people who need assistance in moving around the province.

Overall, this study is significant because it supports tourism advancement, sustainable development, and culture enhancement in Bulacan, and presents an example of how optimized and technology-driven solutions may enhance travel and navigation experiences.

Scope and Limitation of the Study

This study focuses on the development of a mobile personalized itinerary generator designed specifically for the province of Bulacan. The system aims to enhance the travel experience of tourists by providing functionalities such as itinerary optimization, personalized itinerary generation, tourist spot searching, itinerary navigation, and itinerary management. By integrating these features, the system seeks to make traveling within Bulacan more convenient, efficient, and engaging for visitors.

The scope of this study is limited to historical, cultural, and heritage tourist destinations within Bulacan. These locations will be requested and validated by the Provincial History, Arts, Culture, and Tourism Office (PHACTO) to ensure accuracy. Tourist destinations outside Bulacan are not included in the recommendations. Route generation and recommendations will be based on weights assigned to each vertex or Point of Interest (POI), which serve as inputs for the optimization process. Data for mapping and location will be sourced from platforms such as Mapbox, OpenStreetMap, and other publicly available datasets.

For route optimization, the system will employ the African Buffalo Optimization (ABO) algorithm, applied within the framework of the Traveling Salesman Problem (TSP). The weighted POIs will allow the system to recommend not only efficient travel paths but also prioritize destinations according to their relative importance or value. This ensures that the itineraries generated are both optimized and meaningful to the user's preferences.

The system will not include additional services such as accommodation booking, ticket reservations, or guided tour arrangements. Personalization of itineraries will be limited to individual users and not group travel. The mobile application will be developed exclusively for the Android operating system due to feasibility and cost considerations, as development for iOS or other platforms falls outside the project's scope. Furthermore, the study will be carried out within a development timeline of approximately seven months, which restricts the number of features and the extent of testing that can be conducted.

Evaluation of the system will be conducted in two ways: validation of tourist destinations by PHACTO and feedback from tourists based on the Technology Acceptance Model (TAM), focusing on perceived usefulness, perceived ease of use, attitude toward using, and behavioral intention. In addition, the system will be assessed against the ISO/IEC 25010:2023 software quality standards, covering functional suitability, performance efficiency, compatibility, interaction capability, reliability, security, maintainability, and flexibility.

CHAPTER II

THEORETICAL FRAMEWORK

This chapter combines significant findings from various literature and studies from tourism, exploration of the traveling salesman problem in itinerary planning, and methods for recommendation for itinerary generation. This comprehensive review will serve as the basis for the development of the LAKAD application by identifying relevant factors optimization algorithms for TSP in itinerary planning and factors to consider when creating personalized recommendation features of the system.

Relevant Theories

Key features of LAKAD rely on established theories of mathematics. This section examines the foundational theories and explains how they are used and related to the concept of itinerary optimization and personalized generation.

Graph Theory

Graph Theory is a branch of mathematics that is still relatively young but is developing quickly. The foundation of graph theory goes back to the 18th century, when Leonhard Euler solved the Königsberg Bridge Problem, which is often thought of as the first problem in the field. Euler's work introduced this approach of representing real-life connections through vertices and edges, which forms the basis of all network studies and relations. In the early 20th century, mathematicians like Kuratowski, Wagner, and Whitney made the field bigger by studying planar graphs and coming up with basic ideas that later became Graph Minor Theory, which connected graph structures to geometry and topology. The proof of the Four Colour Theorem in 1976 made graph theory even more popular and showed how useful it could be for solving complex mathematical and computational problems (Carmesin, 2022).

A graph is a set of vertices and edges, where each edge connects exactly two vertices. Topologically, a graph can be thought of as a one-dimensional simplicial complex (Carmesin, 2022). A graph $G = (V, E)$ is composed of a set of vertices V and a set of edges E. There are two types of graphs, directed graphs, which have edges that can only go in one direction, and undirected graphs, where edges allow movement in both directions. Additionally, they can be weighted, it means that each edge has a number that represents different factors like cost, time, and distance.

In this study, the concept of graph theory will be applied to represent the points of interest (POI) as nodes and the distance between every connected vertex as the edges. This graphical representation of cities and their distances is one of the common applications of graph theory and allows access to powerful algorithms and methods for optimization.

Traveling Salesman Problem (TSP)

This is a specific problem under the field of graph theory. According to Pop et al. (2024), the Traveling Salesman Problem (TSP) has been in the history of combinatorial optimization since 1930, and was properly provided a mathematical formulation by Merrill M. Flood. TSP became very popular since it is a widely investigated optimization problem, often serving as a benchmark for modern optimization algorithms.

The problem states that, given a set of cities, the salesman's goal is to find the shortest possible route that visits each city exactly once. The TSP has many variants such as the asymmetric TSP in which the distance from point A to point B is different from point B to point A. Most real life applications of TSP are asymmetric which means ATSP is important to consider due to the presence of one way roads. It can easily be seen how the idea of TSP can be applied to itineraries. Each location of itineraries will be nodes and the distances between them are the edges. The goal of the system for the itinerary is to find the route which covers the least distance (Pop et al., 2024).

Orienteering Problem

The Orienteering Problem (OP) is a routing problem that aims to maximize the total rewards collected along a route within a given travel budget (Yu et al., 2022). Similar to this, Morandi et al. (2024) explains OP as the task of planning a route for one vehicle that has to follow a travel budget. The problem is depicted as a graph where the roads have distances and the locations have points or reward values. The goal in this problem is to create a path that starts and ends at the depot, stays within the travel limit, and collects as many rewards as possible from the places visited. Similarly, it originated from a sport of the same name, where participants visit check-points with pre-determined scores, in an attempt to maximize their total score within a specific time (Lim et al., 2019). Pěnička et al. (2019) described OP as a type of problem in operations research, introduced to it in 1984 by Tsiligirides. They then explained that OP is a problem that combines the combinatorial optimization problem Knapsack Problem (KP) with Traveling Salesman Problem (TSP). These two work separately as TSP, given a set of customers, seeks to find the sequence in which to visit selected customers, constrained within a budget, while also minimizing the tour path. The subset of selected customers is selected by the KP, where it maximizes the collected profit based on the selection of customers to be visited within the budget constraints. This will be used in the recommendation feature of the system where the user provides input for the time or distance constraint to generate an itinerary for the user.

Technology Acceptance Model

The Technology Acceptance Model (TAM) is one of the well-known theories in explaining and predicting users' acceptance of information systems. Fred D. Davis developed this theory in 1989 to understand the psychological factors affecting individual's acceptance and usage of technology. According to Marikyan and Papagiannidis (2025), the model is based on the Theory of Reasoned Action (TRA), which highlights how an individual's attitude and subjective norms influence their behavioral intention. By concentrating on the variables that influence users' attitudes toward using a particular system, TAM modifies this framework to fit the technological environment.

The model provides a theoretical framework for assessing how likely it is that technology will be adopted in different situations. It has been one of the most widely applied models due to its simplicity and strong explanatory capacity to pinpoint the primary psychological factors influencing users' adoption of new technologies. Through this framework, researchers and developers can analyze how users perceive a system and identify where modification can be made to enhance acceptance and satisfaction (Marikyan & Papagiannidis, 2025). TAM postulates that the acceptance of technology is primarily determined by an individual's behavioral intention (BI), which is shaped by two cognitive responses: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (Marikyan, 2025). According to Aburbeian et al. (2022), these two constructs are considered the most critical variables influencing the use or rejection of new technology.

Software Product Assessment Framework (ISO/IEC 25010:2023)

ISO/IEC 25010:2023 is part of the Systems and Software Quality Requirements and Evaluation (SQuaRE) series, and it identifies the models to be used for describing and evaluating the quality of software and system products. It provides common terminology and concepts that enable developers, consumers, and evaluators to specify quality requirements and to determine whether a product meets the requirements. The standard emphasizes that both functional and non-functional aspects of performance should be reflected in the defined characteristics and sub-characteristics used in the evaluation of the quality of the product ("ISO/IEC 25010", 2024; "Systems and software engineering — Systems and software Quality Requirements and Evaluation (SQuaRE) — Product quality model", 2023).

The model states that the product quality model consists of nine primary characteristics: functional suitability, performance efficiency, compatibility, interaction capability, reliability, security, maintainability, flexibility, and safety. Each characteristic is made up of sub-characteristics which describe quantifiable components of quality, like operability, scalability, coexistence, correctness, and completeness. To keep up with changing technological contexts, the 2023 revision includes revised terminology, replacing interaction capability for usability and flexibility for portability. This system ensures that from a theoretical basis, software products are evaluated consistently to meet user expectations for performance, reliability, and safety throughout their life cycle.

Review of Related Literatures and Studies

This section presents studies relevant to the development of the proposed itinerary planner. It covers works on Bulacan tourism, optimization techniques for the Traveling Salesman Problem (TSP), and related approaches in itinerary planning. By reviewing these studies, the foundation for the system is established and the choice of African Buffalo Optimization (ABO) as the core algorithm is justified.

Tourism in Bulacan

The study of Canet and Panaligan (2024) found that tourism development in Bulacan is highly influenced by accessibility, infrastructure, promotion, and the preservation of cultural and natural heritage. While Bulacan shows great potential as a tourist destination because of its rich history and heritage, the issues such as weak promotion, limited facilities, and transportation continue to limit its growth. A study by Canet and Sunpongco (2025), investigates why some historical and cultural destinations in Bulacan remain neglected despite the province's rich heritage. Using a mixed method design, they combine surveys and interviews to capture both statistical data from tourists and tourism officers. The survey results showed that most visitors were young ranging from 19 to 29. Most of the respondents are women and most of the tourists came from within Bulacan itself. The findings of the study showed that popular landmarks like Barasoain Church and the Basilica Minore de Immaculada Conception, both in Malolos City, attract the most visitors. On the other hand, attractions in other municipalities such as Meyto Shrine in Calumpit and Francisco Balagtas Museum in Balagtas, showed lower visitations. This imbalance reflects the uneven promotion of Bulacan's cultural sites.

This uneven promotion aligns with the findings of Canet and Panaligan (2024) that one of the issues is the weak promotion. Fortunately, Canet and Sunpongco examined the promotional strategies used by tourism offices and found that online promotions, social media campaigns, and partnership with bloggers and vloggers were the most effective methods of engaging younger audiences. While traditional approaches such as brochures, festivals and community-driven activities still play a role, digital strategies are better suited for Gen Z and millennial demographic. They emphasized the importance of collaboration among local government units, schools, communities, and tourism stakeholders to ensure consistent promotion and sustainable tourism development.

The local government of Bulacan has also recognized the importance of tourism in the province. In 2023, the Provincial Government of Bulacan launched the Bulacan Heritage Pass a tourism initiative that focuses on local culture, heritage conservation, and community engagement. The Pass consists of twenty historical and cultural landmarks in the province. The landmarks include Barasoain Church, Casa Real de Malolos, the Malolos Cathedral, and the historic train stations in Guiguinto and Meycauayan, offering a structured route and incentives for completion (Velasco, 2023). While the Heritage Pass strengthens heritage preservation and promotional efforts, it does not provide optimized travel sequencing for visitors, leaving tourists to plan routes on their own. This gap underscores the need for systems that not only identify attractions but also generate efficient itineraries tailored to tourists' time and travel constraints.

Digital strategies also play a critical role in Bulacan's tourism promotion, Santos et al. (2023), studied how social media content is disseminated to the users. They surveyed a total of 100 respondents (50 working staff + 50 tourists) in San Rafael, Bulacan and found that 57 percent agreed that social media helped them determine their next choice of destination and 61 percent agreed that social media is a good strategy to make more tourist locations known to people. In line with this, Dela Cruz et al. (2022) also surveyed 100 tourists that visited Dona Remedios Trinidad, Bulacan to determine the effectiveness of using social media in promoting a tourist destination and asked questions ranging from how social media influences traveler's decisions to the problems faced by tourists when using social media as a guide for tourism. They found that most travelers agreed that social media does influence the choice of destination of travelers. While problems reported by tourists is the spread of false or misleading information, different expectations, and inaccurate photos / videos to different tourist destinations. Clearly, the importance and role of social media in making tourist locations well-known is irreplaceable but is also prone to misleading information, highlighting the need for verified and curated information of tourist attractions in Bulacan.

Existing Optimization Techniques for TSP

Traveling Salesman Problem (TSP) has many ways to solve it using different algorithms, one of those is the exact method. According to Violina (2021), exact methods such as Brute Force and Branch and Bound algorithms are used to solve the TSP. The brute-force method involves trying each possibility one at a time until all of them have been explored, comparing the outcomes, and selecting the smallest one. When applying brute force to the TSP, the outcome is be optimal but less effective. This is because every possible combination must be tested before obtaining the best results. Applying this technique results in O(n!), where n is the number of cities that need to be traversed. Even with just 20 cities, a solution like this is not feasible.

In contrast, the Branch and Bound (BB) algorithm is a technique for methodically searching the solution space. In this case, a status space tree is used to arrange the solution space. This algorithm uses a broad search scheme, often known as Breadth First Search (BFS), to build a status space tree. However, the expanded node is determined by the node with the lowest "cost" value among the other live nodes rather than the sequence of generation. Although exact algorithms like Brute Force and Branch and Bound provide optimal solutions, they are restricted by exponentially growing time complexity as the number of vertices increases.

Heuristic approaches, particularly nature-inspired metaheuristic algorithms Sabery et al. (2023), offer computationally efficient solutions for real-world optimization problems. Generally, metaheuristic algorithms begin with an initial solution and follow a set of heuristic principles to explore the search space and iteratively improve it. These guidelines help the algorithm avoid local optima and locate globally optimal or nearly optimal solutions by directing the search process toward promising areas of the search space.

In line with this, Barb-Ciorbea (2023) compared an exact method, Mixed Integer Linear Programming (MILP), with a heuristic approach, Ant Colony Optimization (ACO), for solving the Traveling Salesman Problem with time window constraints. In the experiment, the MILP formulation with 100 cities generated more than 1000 variables, while the heuristic approach was limited to 15 ants. Results showed that MILP required more than 500 seconds to obtain the solution, whereas ACO was able to produce results in about 100 seconds. The exact approach is advantageous because it guarantees the best solution; however, its runtime becomes very high as the number of cities increases.

For larger instances, the heuristic approach produced solutions much more quickly, although without the guarantee of global optimality. Despite this, both algorithms were able to achieve the best result in the tested scenario. Moreover, the heuristic demonstrated an additional advantage by aiming to minimize waiting duration at nodes when waiting could not be avoided. These findings emphasize that while exact methods provide precision, heuristic methods like ACO are better suited for larger and more time-sensitive problems (Barb-Ciorbea, 2023). This demonstrates that while exact methods are strictly optimal with respect to accuracy, their exponentially growing time complexity renders them impractical to apply to large-scale or time-constrained situations.

The goal of most heuristic algorithms is to find an optimal path to an instance of the traveling salesman problem. For instance, the study of Wu and Fu (2020) applied the Agglomerative Greedy Brain Storm Optimization (AG-BSO) in solving instances of the traveling salesman problem. This algorithm is a variant of what is called the Brain Storm Optimization framework (BSO), a method that addresses the computational challenges posed by TSP using the concepts modeled after human brainstorming. They compared AG-BSO with traditional metaheuristic strategies like Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), and even Ant Colony Optimization (ACO). The results found AG-BSO achieved greater solution accuracy and better robustness producing less standard deviation, which for most instances is less than 1 percent, compared to traditional algorithms.

The increased robustness was also found in the study of Hossain and Yılmaz Acar (2024) where they compared new optimization algorithms against old optimization algorithms for solving the Traveling Salesman Problem and concluded that the new algorithms demonstrated greater effectiveness than the old algorithms in medium-scale instances. The new algorithms used in the study which are the Artificial Bee Colony (ABC), Grey Wolf Optimization (GWO), and the Salp Swarm Algorithm (SSA) performed with a lot less standard deviation compared to the classic algorithms such as the Genetic Algorithm (GA), Ant Colony Optimization (ACO), and Simulated Annealing (SA). This means that on average, the three newer algorithms produced more consistent results than the classic three. However, they also stated that although newer algorithms produced better outputs, traditional algorithms such as GA and ACO remained to demonstrate strengths for specific instances. The findings of Odili et al. (2021) also aligns with it as they studied some complex hybrid models' performance such as Cooperative Genetic Ant System (CGAS), Max-Min Ant System (MMAS), and Model-Induced Max-Min Ant Colony Optimization (MIMM-ACO) were found to have an error of 2.56 percent only with MIMM-ACO having 0 percent error and accurately solving all instances given in the study.

However, this great performance output from these algorithms comes at the cost of greater computation time. The AG-BSO algorithm from the study of Wu and Fu (2020) took a whole 9.05 seconds to solve a small vertex TSP instance. This performance to computation time discrepancy also aligns in the comparative study of Hossain and Yılmaz Acar (2024) where ABC took an average of 4 seconds, 3 seconds for SSA, and 7 seconds for GWO when solving small vertex TSP instances. While an average of 15.5 seconds for MIMM-ACO, 32.83 seconds for MMAS and 52.02 seconds for CGAS was observed by Odili et al. (2021) for solving the given instances in their comparative study. While newer and complex algorithms outperform traditional ones in accuracy and robustness, their higher computation times may pose challenges for resource-constrained environments such as mobile devices.

While some algorithms found focus on the accuracy of finding the most optimized route, there are still approaches that not only prioritizes optimal routing but also the speed at which it can be obtained. This is demonstrated in the study of Hossain and Yılmaz Acar (2024) where they compared new optimization algorithms against old optimization algorithms for solving the Traveling Salesman Problem. The new algorithms Artificial Bee Colony (ABC), Grey Wolf Optimization (GWO), and Salp Swarm Algorithm (SSA) are compared to traditional metaheuristic algorithms like Genetic Algorithm (GA), Ant Colony Optimization (ACO), and Simulated Annealing (SA). The new algorithms show promising results in quickly finding a quality optimized route for medium-scale instances of 200 - 500 vertices, as compared and confirmed by a t-test against GA, SA, and ACO. On the other hand, a different comparative study of Wadi and Umar (2025) highlighted the capability of ACO and Particle Swarm Optimization (PSO) to provide a fast execution speed with minimal solution quality reduction, albeit PSO being parameter-sensitive. They also examined another swarm-based approach in the form of Elephant Herding Optimization (EHO), which consistently outperformed both ACO and PSO by achieving lower optimal costs while maintaining short execution times. Their study demonstrated the practicality of the swarm-based approaches in large-scale instances, over exact methods.

There are also algorithms that focus on faster execution time at the cost of less solution quality to the route planning. These fast algorithms, however, are most suitable for hardware-related limitations such as processing power in mobile devices. The study of Odili et al. (2021), comparing five metaheuristic algorithms and one heuristic algorithm to solve the TSP using 15 instances from TSPLIB, shows that the metaheuristic algorithm, African Buffalo Optimization (ABO), a swarm-inspired algorithm from the ability of buffalo herds to organize, had an accuracy of 98.6 percent and is the fastest to complete all instances with only a total computation cost of 20.58s, 3 times faster than the above-mentioned MIMM-ACO. Thus, their study concluded that ABO is the better algorithm of all six compared in terms of efficiency. PSO has also been shown to perform well in terms of runtime as Wadi and Umar (2025) found that it provided faster solutions compared to ACO across a variety of problem sizes, although PSO was observed to be sensitive to parameter configurations. Simulated Annealing, being a traditional approach, also proved its value in great runtimes as Hossain and Yılmaz Acar (2024) noted its performance in small-scale datasets with 14 - 52 vertices. Overall, PSO excels in rapid convergence across varying problem sizes, SA remains an effective option for small-scale applications, and ABO provides the best balance of accuracy and speed.

However, it is important to note that many of these algorithms have been tested under different experimental settings and datasets. Some studies evaluate multiple algorithms on the same benchmark, such as ABO against other metaheuristics in the study of Odili et al. (2021), or ABC, GWO, SSA, GA, ACO, and SA in the study of Hossain and Yılmaz Acar (2024), or ACO, PSO, and EHO in Wadi and Umar (2025). Although, ACO is mentioned twice, it is important to note that they are tested under different experimental conditions, which makes direct comparison across studies difficult. As a result, the performance of an algorithm such as ACO may vary between studies depending on the dataset and evaluation criteria.

Despite these differences, the literature consistently highlights African Buffalo Optimization (ABO) as a balanced approach in terms of accuracy and computational speed. This study does not claim that ABO is universally superior, rather it is identified as the most suitable choice for the proposed system due to its efficiency in resource-constrained environments like mobile devices. Supporting this, Odili et al. (2020) demonstrated that ABO achieved better or near-optimal solutions across multiple TSP benchmarks, with lower margins of error compared to other swarm-based methods. Similarly, Algani and Methkal (2023) reported that ABO outperformed both the Lin-Kernighan algorithm and Honey Bee Mating Optimization, attaining up to 99.5 percent accuracy while requiring significantly less computation time for asymmetric TSP. These findings highlight ABO's practicality for mobile applications, where both speed and efficiency are critical.

Tourism Recommender Systems

Tourism is an important aspect of society, as it enables people to explore different places, cultures, and experiences while also contributing to economic and social development. Organizing trips, whether to a destination or multiple destinations, usually requires a lot of time and effort. Kedkaew et al. (2024) note that while acquiring travel information for planning a trip is important, the experience is not without challenges, for acquiring and evaluating travel plans is a lot of work. In response to this challenge, Alrasheed et al. (2020) describe tourism recommender systems as tools integrated in travel and tourism applications that enhance service quality by filtering vast amounts of information on the web and customizing it to travelers' particular needs. Such systems help people find destinations matching their needs and constraints, for example, financial need or traveling dates, while also considering contextual factors like weather and safety. In essence, tourism recommender systems are decision-support tools that simplify the destination planning and improve travel experience.

With the ever-increasing data available online through social media, personalized recommender systems have been able to provide better recommendations and have become more relevant in our lives, making it easier to discover new things in life (Li et al., 2024).

One popular recommendation method is through Collaborative Filtering (CF). This method is used to predict a user's preferences or opinions by using the collective information of other users of the system. It basically analyzes the similarity between user's preferences and provides a recommendation that way (Li et al., 2024; Widayanti et al., 2023). However, this method is severely set back by the "cold start" problem where it requires a large enough data of users and their interaction to generate recommendations. Thus, this method is not applicable for the proposed system as no user to user interaction is planned, and the system is a standalone mobile application where the algorithms run on the device locally.

Another popular recommendation method is the Content-based Filtering (CBF). It uses a feature list of item and compare it with items preferred by a specific user previously. The items that match in similarity are recommended to the user. CBF works by storing user profile based on item features which are most commonly preferred by the user. These features are used to map the similarity of one item with other by similarity equation. Then, it compares each item's features with the user profile and recommend it based on the degree of similarity. Unlike CF, it does not require any feedback from the user (Raghuwanshi & Pateriya, 2019). However, just like CF, it is also prone to the "cold start" problem especially for new users. Additionally, CBF doesn't have much control over route-level constraints like travel time, distance and budget.

Due to the shortcomings of CF and CBF and since the proposed system is standalone mobile application with no external server, An algorithmic approach is the desired approach for TRS. One algorithmic approach is based on Orienteering Problem (OP). According to Lim et al. (2019) Tour recommendation has its roots in the OP and similar variants where a key feature is that they do not incorporate any personalization for individual users.

A study by Yochum et al. (2020) proposed an Adaptive Genetic Algorithm with dynamic crossover and mutation probabilities (AGAM) to handle personalized multi-objective itinerary planning. Their approach integrates mandatory POIs, popularity ratings, visit duration, travel time, and costs into a weighted fitness function. By using data from platforms like TripAdvisor, GoogleMaps, and Flickr, AGAM adapts during evolution to avoid stagnation and produce diverse solutions. They tested the model with a dataset for six cities namely Budapest, Edinburgh, Toronto, Glasgow, Perth, and Osaka. AGAM was compared against two baseline heuristics, MaxN a greedy approach that prioritizes the maximum number of POIs, and MaxP also a greedy approach that prioritizes POIs with the highest rating. The results show that while MaxN and MaxP performed better at including mandatory POIs, AGAM generated richer itineraries with higher-rated POIs. AGAM shows more effective use of time budgets, and improved user enjoyment, but at the expense of higher cost and fewer mandatory POIs. This study shows that algorithmic approach can provide personalized itinerary for tourists.

Another study by Tenemaza et al. (2020), proposes a mobile recommender system that addresses the Tourist Trip Design Problem (TTDP), modeled as a Time-Dependent Orienteering Problem with Time Windows (TDOPTW). The aim was to build a system that not only recommends tourists itineraries but also optimizes them in real time while considering Tourist's personal interest, POI constraints (opening hours, time of visit, travel time), and Contextual factors such as lunch times and location. Their approach combines k-means clustering to organize POIs based on user interests and available days with Genetic Algorithm enhanced with parameterized fitness function to include any element of the context to create an optimized recommendation. To test the power of their recommender system, they create a mobile application that uses their algorithm. Evaluation with 131 tourists demonstrated that accuracy and diversity of recommendations strongly influenced user satisfactions. Retrieval metrics such as precision and recall confirmed the system's ability to balance tourist preferences with contextual constraints.

Together, these studies show a similar research direction in tourism itinerary optimization with metaheuristics. The AGAM framework by Yochum et al. (2020) highlights adaptability through genetic algorithms and diverse real world data sources to produce personalized itineraries. On the other hand, the TD-OPTW approach of Tenemaza et al. (2020) focuses on contextual constraints, ensuring that the generated itineraries are not only optimized but also feasible in practice. While AGAM prioritizes richer and higher rated itineraries even at the cost of efficiency, Tenemaza et al. (2020) balances user interest with practical constraints. These results indicate that algorithmic approach can provide personalization as opposed to Lim et al. (2019). All in all, these studies show the effectiveness of metaheuristic methods in tourist applications, demonstrating that algorithmic strategies can significantly improve the quality, adaptability, and satisfaction of itinerary recommendations.

Review of Related Systems

This section presents different related systems that feature such as: itinerary optimization, where in a group of locations is selected and the order of visitation becomes an output; and personalized itinerary recommendation, where based on the user's preferences and other factors, an itinerary is generated.

Trippit: An Optimal Itinerary Generator

Trippit by Nguyen and Shoubber (2019) addresses a fundamental problem in itinerary planning which is the optimization of the itinerary itself which is a fundamental limitation of Google Maps. Although Google Maps supports multiple stops, it leaves the sequencing to the user and often resulting in inefficient trip planning. Manual planning takes time and significant effort to optimize in terms of total distance traveled and how long each location to visit for. The study also stressed the fact that most travelers would often switch between Google Maps and Yelp for planning itinerary. The system eliminates the difficulty in travel planning which makes vacation trips more time efficient and enjoyable to travelers.

The system was developed using the Waterfall method where each design phase is completed first before beginning the next. An android application was developed using React Native library and called network APIs such as the Google Places API and Foursquare Places API to calculate the optimized itinerary provided by the user. Users can input point of interests (POI) in which the application then retrieves the information from the respective APIs and calculates and outputs the optimized tour based on a greedy algorithm. Their system also calculates the best time to visit each input.

Trippit underwent several testing phases: primary testing, where they compared the results of the system to a known small list of itineraries; unit and integration testing, where they tested the logic and the correctness of the user interface; and alpha testing, with 10 users and was validated using a user satisfaction survey, in which most of the alpha users were satisfied with the resulting itinerary. However, through the selection of the algorithm and device came its limitation, which is that the application can only process up to 12 points of interest (POI). Its evaluation is also a concern as it didn't use any standard evaluation methods like ISO/IEC 25010:2023 standard or the Technology Acceptance Model (TAM). Although a small prototype, Trippit can be considered a good enough system as it was able to produce good itineraries with a simple smartphone application without the use of advanced tools like Google OR.

Optimization of Tourism Destination Recommendations in Batang Regency Using Content-based Filtering

Yulfihani and Zakariyah (2024) created a tourism recommendation system for Batang Regency in Indonesia. They applied Content-Based Filtering (CBF) for their recommendation system, using tourist preferences as their data source. Tourists interact with the system by adding destinations to a wishlist. The system then uses the wishlist to learn the tourist's preferences. The recommender factors category similarity where it compares the categories of wishlist items like nature, culture, culinary, and leisure; and location similarity by calculating the distance between destinations using the Haversine formula, which finds the shortest distance between two points on Earth using latitude and longitude. The total similarity then calculated with 70 percent category similarity and 30 percent location similarity. The system ranks all available attractions by their total similarity score and the top 10 destinations are recommended to the tourist. The system was tested in different scenarios such as single item in wishlist, multiple items from same category with same/different locations, and multiple items from mixed categories. They use precision, recall, and F1 score as a metric for the system.

The system was designed with a three-tier architecture that includes Backend, Web Admin Panel, and Mobile Application. The backend was built using Laravel (PHP framework) and MySQL, it acts as the hub for all operations including user authentication, processing recommendations using the CBF algorithm, and managing communication between the mobile app, admin panel, and database. The Web admin panel is for administrators and also developed using Laravel, it enables admins to manage tourist destinations, categories (nature, culture, culinary, etc.). Any changes made in the admin panel updates the backend database which instantly reflects to the mobile apps. The Mobile application was developed using Android Studio and Kotlin, it connects the backend using RESTful APIs via Retrofit. The app provides tourists with Login/registration, wishlist management, personalized recommendation based on wishlist and CBF algorithm, viewing details of attractions, and Filtering by categories and proximity.

The system provides highly accurate and relevant recommendations for tourists, especially in simple preference scenarios. The Content-based filtering approach worked well for aligning recommendations with tourists interests, and achieving a very high F1 score of 0.965. However, performance dropped slightly in complex scenarios like when the wishlist items mixed with different categories and locations. The Authors recommend future improvements such as expanding the dataset, using hybrid models (CBF + collaborative filtering), and adding user feedback mechanisms to further refine recommendations.

However, their study is solely focused on the recommendation aspect of the system, and not on the itinerary optimization. While the system can recommend destinations based on user preferences, it does not optimize the sequence of visits or consider travel constraints like time and distance. Additionally, they didn't include an evaluation for the system like ISO/IEC 25010:2023 standard or the Technology Acceptance Model (TAM), only the evaluation for the Content-based filtering was provided.

Visit Planner: A Personalized Mobile Trip Design Application based on a Hybrid Recommendation Model

Visit Planner (ViP) a mobile application prototype developed by Papadakis et al. (2024). It offers personalized recommendations for an itinerary based on user preference which are either explicitly collected by the application or assessed through the user's behavior within it. ViP utilizes an Expectation Maximization method to offer the user an itinerary that tailors to their satisfactory needs while taking into consideration time and spatial constraints that concern both the user and the destination. The application currently focuses on the city of Agios Nikolaos in Crete. The system requires a user to create a secured profile in a registration process, wherein demographic information and essential data for the algorithm is collected. After this registration process, the user is also asked to specify their preferences in three different ways of their choice, one is by rating categories of POI, another choice is by stating if they like or dislike the category, and another one is by selecting their most preferred category. These categories are carefully specified by analyzing responses collected from 150 visiting tourists, in addition to local and expert knowledge in Agios Nikolaos.

The architecture of the system consists of main components like the front-end User Interface, back-end database, the middleware for processing the information, the recommendation components, and the itinerary creation components. The front-end of the application is an android app available in Google Play. The back-end is composed of MariaDB databases for the purpose of storing necessary information of users and POIs for smooth operations and functionalities. The middleware, built upon the basis of Spring Boot Framework aims to process the controlling flow between the system components and perform the functionalities. It works by receiving queries from the front-end, and then sending those to the recommendation algorithms. The recommendation and itinerary creation components comprises four several recommendation algorithms to tender the needs of the user, where each user is assigned a different algorithm for their cases in performance evaluation wise. ViP integrates multiple, novel recommender algorithms which can adapt to different user profiles.

The algorithms include model-based collaborative filtering that uses synthetic coordinate based system for recommendations (SCoR), hierarchical content-based similarity measures, a hybrid content-based recommendation using Weighted Extended Jaccard approach combined with the second one, and Bayesian recommender algorithm. Any of these algorithms is applied to generate personalized POI suggestions. And once candidate POIs are retrieved, an expectation-maximization-based itinerary creation component sequences them into a feasible route by maximizing user satisfaction function constrained under temporal and spatial factors.

I-AIR: Intention-aware travel itinerary recommendation via multi-signal fusion and spatiotemporal constraints

Cui et al. (2025) developed I-AIR (Intention-Aware Itinerary Recommendation), a system based on deep learning that aimed to generate personalized and practical traveling itineraries. The two primary components of the system are an Itinerary Construction Policy, which organizes selected Points of Interest (POIs) into a logical and sequential trip, and an Intention-Aware POI Scoring Model, which assesses the relevance of possible POIs based on user preference and contextual cues. To model user preferences, I-AIR applied a Transformer-based sequential encoder that identified time patterns from check-in history, an explicit feedback encoder that synthesized long-term preferences from ratings and likes, and a Graph Convolutional Network (GCN) that represented POI relationships through co-visitation patterns. These components were integrated via a multi-signal fusion layer to generate customized POI relevance scores. In optimizing the route, the system applied a greedy algorithm that picked the top-scoring viable POI at each step while removing possibilities that violate prohibitions such as travel time, wait time, business hours, and total time budget. The model was trained using a combination of next-POI prediction and explicit feedback reconstruction on datasets including user trajectories, ratings, dwell times, and POI attributes.

During evaluation, the system was tested on eight real-word datasets, including four each of theme parks and city tourism. These datasets included detailed information such as user check-in records, wait times at attractions, and tourists' reviews, and provided implicit and explicit feedback signals. The evaluation measures applied were precision, recall, and F1-scores, and comparative baseline systems included were Greedy-Popular (GPop), Greedy-Near (GNear), PersQ, EffiTourRec, DCC-PersIRE, BERT-Trip, and DLIR. Results showed that I-AIR outperformed the other systems significantly across all datasets, with higher precision in both theme park and city tourism scenarios.

Synthesis of the Review

The reviewed theories and literature establish the foundations and identify the gaps that this study aims to address. Graph Theory, the Traveling Salesman Problem (TSP), and the Orienteering Problem provide the mathematical framework for route optimization, while models such as the Technology Acceptance Model (TAM) and ISO 25010 serve as evaluative guides for usability and system quality. Prior research highlights the limitations of exact algorithms in solving large-scale routing problems, particularly in mobile environments with limited computational resources. This has led to the rise of heuristic and metaheuristic approaches. Among these, African Buffalo Optimization (ABO) emerges as a promising solution due to its demonstrated balance between accuracy and efficiency, outperforming or matching other metaheuristics such as Genetic Algorithms, Ant Colony Optimization, and Particle Swarm Optimization, while requiring fewer resources. These characteristics make ABO well-suited for itinerary planning on mobile devices.

In the context of tourism, studies reveal that Bulacan's cultural and historical richness remains underutilized due to weak promotion and uneven visitation across sites Canet and Sunpongco (2025). While initiatives such as the Bulacan Heritage Pass Velasco (2023) showcase heritage landmarks and encourage structured visits, they do not provide optimized sequencing of destinations. Likewise, existing tourism applications and mapping systems offer navigation but lack integrated route optimization. Social media, although influential in promoting destinations, presents risks of misinformation and lacks curated, reliable guidance for tourists.

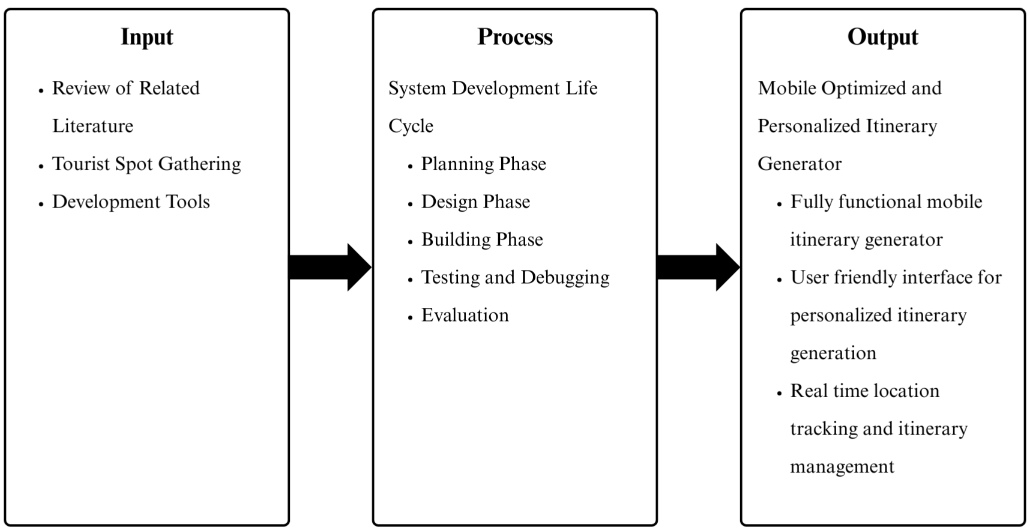
Taken together, these findings underscore the need for a system that not only promotes Bulacan's tourist sites but also generates optimized itineraries tailored to visitor preferences, time, and travel constraints. This study addresses that gap by developing a mobile-based itinerary recommender system powered by AGAM which features further optimization by ABO. By bridging theoretical optimization methods with the practical needs of local tourism, the system contributes both to computational research and to Bulacan's cultural tourism development.

Conceptual Framework

This section explains the key inputs, processes, and outcomes in development of the study using an Input-Process-Output (IPO) model.

Figure 1

Input-Process-Output (IPO) Model



Input

The input contains the review of the methods used by related studies and systems, which will be used as foundation in the study. These methods consist of different algorithms used for solving the traveling salesman problem and selecting which algorithm is the most applicable in the mobile platform as well as which recommendation model is a fit for itinerary recommendation. The second input is the gathering of tourist spot locations or point of interests (POI). These POIs are locations in Bulacan which can be considered as tourist attractions. These will be gathered from and verified by the Provincial History, Arts, Culture, and Tourism Office (PHACTO) to assess the correctness of the POIs included in the system. Development tools refer to the hardware and software tools that will be used to actually develop the application. These include operating systems such as Windows or Ubuntu, integrated development environments (IDE) such as Visual Studio or Android Studio, and design pieces of software like Figma or Adobe Illustrator.

Process

The AGILE methodology will be used in the software development of LAKAD, specifically the Kanban method. Kanban method is a visual process management system that can manage knowledge and work by considering the Just In Time (JIT) delivery approach Alaidaros et al. (2021). The first phase of the development will be planning and analyzing the different requirements of the system such as flow charts, entity relationship diagrams, and use cases. Afterwards, mockup user interface will be made to fully outline the look and feel of the application. Building phase will be the actual development of the core features of the application and testing and debugging will refer to the testing of the correctness of the core features' implementation. The power of AGILE methodology will be used to iteratively cycle between building phase and testing to evaluation by users and professionals to quickly enhance features and get immediate feedback. The system will go through rigorous evaluation by professionals through ISO 25010 and through TAM by its intended users.

Output

The expected output of this study is a fully functional mobile itinerary recommendation and optimization system in the scope of Bulacan. LAKAD application will be able to optimize the route to be taken for the user's itinerary as well as recommend personalized itineraries that may interest the user.

Definition of Terms

This section provides the operational definitions of terms used in the study.

African Buffalo Optimization (ABO). An optimization algorithm inspired by the social behavior and communication patterns of African buffalo herds.

Algorithms. A repeated sequence of finite steps used to solve specific problems or perform calculations.

Android. A mobile operating system designed primarily for smartphones and tablets, developed by Google.

Android Studio. An Integrated Development Environment (IDE) used for developing and debugging Android applications, primarily using the Kotlin programming language.

Bulacan. A province in the Republic of the Philippines, situated in the Central Luzon Region, north of the national capital. It is known for its historical heritage and diverse industries.

Genetic Algorithm (GA). A metaheuristic optimization algorithm inspired by the principles of natural selection and evolution, often used to solve routing problems like the TSP.

Itinerary. A detailed plan or route for a journey, including a list of places to visit and a schedule of events.

Itinerary Management. A feature that allows users to organize, edit, and monitor their selected destinations and travel schedules.

Itinerary Navigation. A feature that provides users with directions and guidance throughout their travel route.

Itinerary Optimization. The process of planning the most efficient route or order of destinations for travel, determined through the use of optimization algorithms.

ISO/IEC 25010:2023. An international software quality standard that defines key characteristics such as functionality, reliability, performance efficiency, security, maintainability, and compatibility.

Kotlin. A modern programming language officially supported by Google for Android development, known for its conciseness and safety features.

Mobile Application (App). A software program designed to operate on mobile devices such as smartphones or tablets.

Mobile Phone. A portable electronic device used for communication, capable of making and receiving calls, and equipped with various additional features.

Optimization Algorithm. A computational method designed to find the best or most efficient solution to a given problem.

Orienteering Problem (OP). A combinatorial optimization problem that involves selecting a subset of locations to visit within a given time or distance constraint, maximizing the total score or reward collected.

Personalized Itinerary Recommendation. A feature that suggests travel routes and destinations tailored to the individual preferences and constraints of the user.

Provincial History, Arts, Culture, and Tourism Office (PHACTO). The government office responsible for promoting and preserving the history, arts, culture, and tourism of Bulacan province.

Point of Interest (POI). A destination or tourist spot specifically preferred by a tourist, such as historical sites, natural attractions, or cultural landmarks.

Recommendation System. A system or algorithm that suggests destinations to users based on preferences, collected data, or other relevant parameters.

Technology Acceptance Model (TAM). A theoretical framework used to understand and predict user acceptance and adoption of new technologies.

Tourism. The activity of traveling to and visiting places of interest for leisure, culture, or recreation.

Tourist. A person traveling from place to place for pleasure or interest.

Tourist Spot. A place or attraction that can be visited by a tourist, often holding significant cultural or historical meaning.

Tourist Spot Searching. A feature that enables users to browse, locate, and explore tourist destinations within the province.

traveling Salesman Problem (TSP). A combinatorial optimization problem that seeks the shortest possible route to visit all given destinations and return to the starting point.

CHAPTER III

RESEARCH METHODOLOGY

In this chapter, the researchers will discuss the research design, model adoption, process of developing the system, system evaluation, population and sample, data collection, data processing, and ethical considerations.

Research Design

This study will employ a quantitative applied research design which uses quantitative methods to provide a structured framework for the development and evaluation of the proposed mobile personalized itinerary generator for tourists and alike.

Applied Research

The applied research aspect of the study will focus on developing and implementing a system for generating personalized itineraries and optimizing existing itineraries for the interests of the user. The primary objective of this study is to create a mobile application that optimizes itineraries using the ABO algorithm and generates personalized itineraries with travel budget using AGAM algorithm. Through an applied research approach, the features to be implemented in the system will be important for the needs of its intended users which are the tourists and their itinerary needs.

Quantitative Research

The quantitative research aspect of this study will seek to measure and analyze the quality, standards, and acceptability of the system using quantitative methods by collecting user and professional feedback. The researchers will assess the quality and standards using the ISO/IEC 25010 standard by seeking professionals to assess the system. While the acceptability of the system for tourists will be analyzed using the TAM. The survey will gauge the user's satisfaction with the system using a 10-point rating scale, providing insights to the system's ease of use and usefulness. Incorporating quantitative approach for the study ensures an empirical and evidence-based support for the quality and acceptability of the proposed system.

Model Adoption

The models adopted for the system are the traveling salesman problem for the optimization of the itineraries and orienteering problem for the generation of personalized itineraries with allocation of travel distance budget.

African Buffalo Optimization

The African Buffalo Optimization (ABO) algorithm is a meta-heuristic method inspired by the cooperative behavior of African buffaloes in their search for food. It models how buffalo herds communicate, explore, and exploit their environment to find optimal grazing areas. In optimization problems such as the Traveling Salesman Problem (TSP), ABO can be used to determine the shortest possible route that visits all cities exactly once while minimizing travel cost or distance.

According to Odili et al. (2022), the algorithm begins by initializing a population of buffaloes, where each buffalo is randomly placed within the solution space. Next, the fitness value of each buffalo is calculated based on the total travel cost of its route. The buffaloes then update their positions using the ABO update rules, which are derived from the buffaloes' communication signals. These signals guide the herd collectively toward better solutions by balancing exploration (searching new areas) and exploitation (refining known good areas). During this process, buffaloes construct new tours by adding unvisited cities based on their attractiveness and the herd's accumulated experience. This cycle continues until the stopping criteria, such as a maximum number of iterations or convergence, are met. Finally, the best solution found by the herd is output as the optimized route.

Formally, the algorithm can be expressed using two main update equations. The first is for buffalo's memory or exploitation behavior:

$$m'_k = m_k + lp1(bg - w_k) + lp2(bp_k - w_k) \tag{1}$$

Where m_k represents the buffalo's previous movement (exploitation term), bg is the global best fitness representing the herd's best solution, and bp_k is the individual buffalo's best-known position. The parameters $lp1$ and $lp2$ are learning coefficients that control the influence of herd communication and personal experience, respectively. This equation enables each buffalo to adjust its movement based on both the global herd direction and its own previous success, allowing it to return to a more rewarding position if it strays into less optimal regions.

The second equation controls the buffalo's exploration within the search space:

$$w'_k = \frac{(w_k + m_k)}{\lambda} \tag{2}$$

Where w_k represents the buffalo's exploratory move, m_k represents the exploitation or memory component, and $\lambda \in (0, 1]$ is the exploration driver that regulates how strongly the buffalo explores new areas. After updating both memory and position, the algorithm checks if the global best bg has improved. If so, it proceeds to the next iteration; otherwise, it continues refining current solutions. The process repeats until the stopping condition is met (e.g., maximum iteration count or convergence). Once completed, the herd's best-known position bg is returned as the optimal solution, representing the most efficient tour or path discovered by the algorithm.

Adaptive Genetic Algorithm with Dynamic Mutation and Crossover Probabilities (AGAM)

The study also chose to adopt a modified variant of the genetic algorithm developed by Yochum et al. (2020) called Adaptive Genetic Algorithm with Dynamic Mutation and Crossover Probabilities or AGAM for the optimization of recommended itineraries defined in terms of TSP. AGAM addresses itinerary planning as a Multi-Objective Optimization Problem, an optimization technique rooting from orienteering problems. As discussed in their work, Yochum et al. (2020) developed AGAM to generate optimal and personalized travel itineraries by balancing several objectives such as point of interest (POI) rating, and distance of POIs between the next one. Rooting from GA, AGAM simulates the process of natural evolution and utilizes genetic operators such as selection, crossover, and mutation to iteratively improve the quality of itineraries which, unlike traditional GA that use fixed mutation rates, also employs dynamic adjustments in parameters during the evolutionary process in a way that can maintain population diversity and therefore generate efficient and adaptive solutions.

AGAM works by taking specific factors that can affect the results of a solution. In this paper, the goal is to generate an optimal solution of a recommended itinerary, which lets the model take into account factors similar to the ones proposed by Yochum et al. (2020). These factors include mandatory POIs, all POIs, POI distance, and POI rating. The factor referring to mandatory POIs also means that the sequence of each itinerary requires a starting and ending destination. In addition to these factors, AGAM also requires a certain probability that determines the chances of mutation and crossover to happen.

To better understand the factors taken into account in this study, it is defined as follows; The popularity of a POI q_i is given by the visit count of the POI's governing municipality. The rating of a POI q_i is given by taking the average rating of all visitors for q_i.

$$R(q_i) = \frac{1}{x}\sum_{j=1}^{x} r_{q_i}(u_j) \tag{3}$$

AGAM considers the population set $P = p_1, \ldots, p_n$ where each individual $p_i = q_1, q_2, q_3, \ldots, q_n$ is a sequence where each q_i is a POI. This means that AGAM treats each POI sequence p_i as an individual gene, hence P as a sequence of itineraries. Yochum et al. (2020) noted that measuring different factors involves variables with inconsistent units and scales, and that each gene sequence may vary in length depending on the number of POIs selected. They addressed this by applying a normalization method that converts all variable values into a uniform range between 0 and 1, so that the algorithm can fairly compare and combine the factors within a fitness function. This fitness function normalizes the evaluation of the quality of each p_i by integrating the input factors defined earlier. In this way, every itinerary p_i in P obtains different weights given by the function:

$$f(p_i) = w_1 Ti(p_i) + w_2 Tn(p_i) + w_3 Tr(p_i) + w_4 Tp(p_i) \tag{4}$$

Where, $f(p_i)$ is the fitness function score of each itinerary p_i. w_j is an adjustable weight of each factor which depends on the user's preference. $Ti(p_i)$ is the sum of all interest values of each POI in the itinerary p_i. Each POI contains an interest value which quantifies how interested the user is in that specific POI category. $Tn(p_i)$ is the total number of POIs included in the itinerary relative to the maximum number of POIs that can be visited within the user's $MAXT$. It is obtained by dividing the number of POIs in the itinerary p_i by the maximum possible number of POIs. $Tr(p_i)$ is the total rating of p_i given by taking the sum of all q_i rating $R(q_i)$ in p_i and dividing it by the best possible rating of all POIs in consideration combined $MAXR$ = Number of POIs $*$ Maximum Rating.

$$\frac{\sum_{j=1}^{n} R(q_j) \in p_i}{MAXR}, \text{ such that } n = \text{last POI} \tag{5}$$

$Tp(p_i)$ is the total popularity of p_i given by the sum of all q_i popularity $P(q_i)$ in p_i and dividing it by the total popularity count of the all POI $MAXP$.

$$\frac{\sum_{n}^{i=1} P(q_i) \in p_i}{MAXP}, \text{ such that } n = \text{last POI} \tag{6}$$

Moreover, AGAM's most important part is the dynamic crossover and mutation probabilities that it uses. This property of AGAM serves as a guide and is helpful in finding the best solution since it prevents the system from repeatedly computing in a local optima, a region of solutions that can be optimal but lacks diversity, a kind of deadlock where the system ignores every other possible optimal solution outside the current locality. Yochum et al. defined this probabilities as:

$$PC = \begin{cases} pc_1 - \dfrac{(pc_1 - pc_2)(f' - f_{avg})}{f_{max} - f_{avg}}, & f' \geq f_{avg} \\ pc_1, & f' < f_{avg} \end{cases} \tag{7}$$

In this case, PC is the probability of crossover. pc_1 and pc_2 are the input bounds that will limit the crossover. These values are often defined where $pc_1 \geq pc_2$, f' then corresponds to the larger valued fitness score of two selected parents, f_{max} is the largest valued fitness score among the set of populations P, and f_{avg} refers to the average fitness score of the population P. The next one is for the probability of mutation.

$$PM = \begin{cases} pm_1 - \dfrac{(pm_1 - pm_2)(f' - f_{avg})}{f_{max} - f_{avg}}, & f \geq f_{avg} \\ pm_1, & f < f_{avg} \end{cases} \tag{8}$$

where, pm_1 and pm_2 are also predefined bounds to limit mutations, and prevent oversaturation, and f is the fitness score of a parent that has to mutate. Furthermore, the parameters pc_1, pc_2, pm_1, and pm_2 are all predefined input bounds selected through parameter tuning, which controls the range of possible crossover and mutation probabilities during the evolution process.

Process of Developing the System

The development of the system will follow a structured approach that is divided into distinct phases to ensure a systematic and efficient creation of the mobile application. These phases include analysis, planning, design, development, testing, and review, each contributing to the overall quality and functionality of the final product.

Analysis

The analysis phase of the development involves outlining the system's scope, objectives, and requirements. This is done by reviewing the existing literature in itinerary recommendation and local tourism in the province of Bulacan. This phase establishes the key features of the proposed system, LAKAD, that will integrate five major features designed to provide optimized, personalized, and efficient itinerary planning for tourists exploring Bulacan. Each feature combines techniques, verified local data, and user-centric design principles.

1. **Personalized Itinerary Generation** The main feature of the proposed application will be a personalized itinerary generator focusing on the diverse cultural, historical and heritage tourist destinations located across the province of Bulacan. The system will be developed to adapt to user-specific factors that can affect the personalization aspect of an itinerary. This feature aims to cater the personal preferences that a user has while still promoting the exploration of the rich tourism culture of the region.
2. **Itinerary Optimization** The optimization feature of the system will work in arrangement with the personalized itinerary generator by employing the ABO algorithm. The optimization will further help the maximization of travel distance and constraints to visit every possible destination within the generated itinerary.
3. **Tourist Spot Searching** A tourist spot search feature will allow users to explore Bulacan's tourist attractions specifically through an interface where they can search through a catalog of tourist destinations that will be verified by the Provincial History, Arts, Culture, and Tourism Office (PHACTO) of Bulacan. Furthermore, the system will display important and relevant information such as location and short description about the tourist spot.
4. **Itinerary Management** An Itinerary Management feature of the system will allow users to manage and organize itineraries. The users may add, edit, or remove destinations from their itinerary. It will also allow the tracking of visited and unvisited

locations so that users are informed of the status of their progress in the itinerary. Users will also be able to save and reload itineraries for future use.

5. **Itinerary Navigation** This feature will assist the user during travel by providing real-time navigation support. Users will be able to track their current location and visualize routes similar to Google Maps. It will displace direction, travel duration, and distances between tourist spots and support live GPS tracking to help users follow their itinerary accurately.

To ensure consistent implementation of the mobile application, the following system requirements for mobile devices will be recommended as shown in Table 1

Table 1

Recommended System Requirements for Mobile Devices

Category	Specification
Operating System	Android 9.0 (Pie) or higher.
Processor (CPU)	Octa-core 1.8 GHz or equivalent.
Memory (RAM)	Minimum 3 GB
Storage	At least 200 MB free space
Display	720 x 1280p or higher.
Internet Connectivity	Required for fetching map data and API requests.
GPS	For location tracking and navigation.

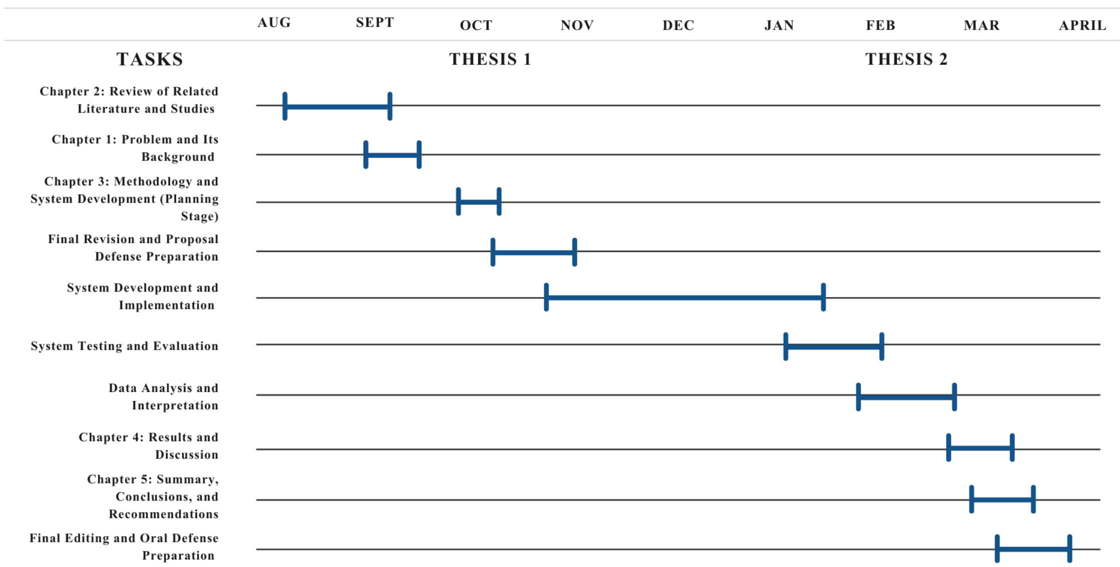
These requirements ensure that the application runs efficiently on most modern mid-range Android smartphones. Devices with higher specifications are expected to experience smoother performance, especially when generating optimized itineraries or handling large datasets of tourist locations.

Planning

The Gantt chart provides a visual timeline of the schedule of the research activity that will be conducted in the process of developing LAKAD. It outlines the sequence of tasks relating to Thesis I and Thesis II, including the flow of each phase of the research from documentation and planning until system development, evaluation, and final defense.

Figure 2

Gantt Chart



The **Thesis I** output focuses on the research documentation and planning for development of LAKAD. This process begins with the Review of Related Studies (Chapter 2), in which local and foreign studies are gathered, evaluated, and organized to develop the theoretical and conceptual framework. By gathering information in Chapter 2, determining the best algorithm for the system, and the appropriate approach to execute the idea, the researchers were able to establish a solid foundation that would be the basis of the succeeding phases. After completing Chapter 1: Problem and its Background and Chapter 2, the researchers finalize the concepts, models, and methods that will be utilized in Chapter 3: Methodology preparation. Chapter 3 defines the research design, the selected development model, and the desired process on creating the system, as well as the foundation on system evaluation and data gathering that will be conducted on Thesis II.

For **Thesis II**, the researcher will proceed to the implementation and completion phase. The group will develop and implement the proposed system based on the design created in Thesis I.

System Development and Implementation. This phase will focus on building and integrating the components of the system based on the planned design. In the development process, the construction of the front-end, database integration, and feature implementation following the chosen development model. Testing and debugging processes will be carried out on a regular basis to ensure proper functionality and performance.

System Testing and Evaluation. This phase is aimed at testing the reliability, usability, and general quality of the system. Various testing procedures will be conducted to ensure that every function works as planned and meets user needs. Feedback will be collected from users and a system analyst to identify areas that need improvement.

Data Analysis and Interpretation. This stage will include data processing and data analysis that are conducted from the system evaluation. Responses collected will be organized, encoded, and statistically analyzed to determine user perceptions as well as the general performance of the system.

Design

Figure 3

System Architecture

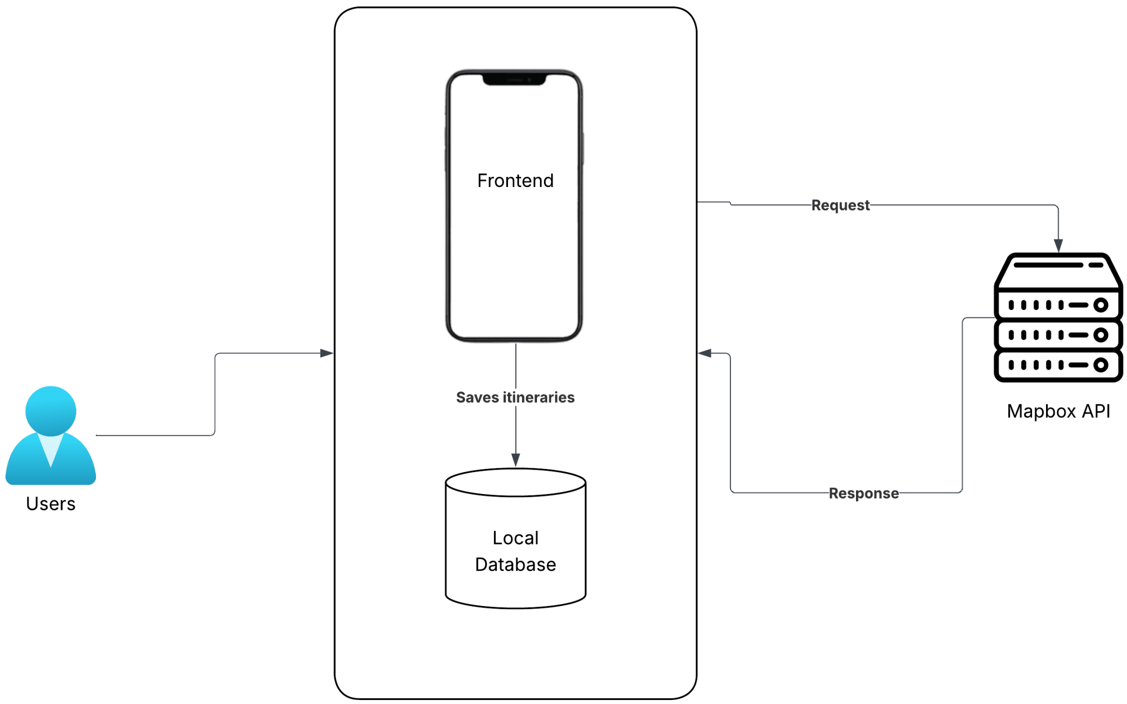
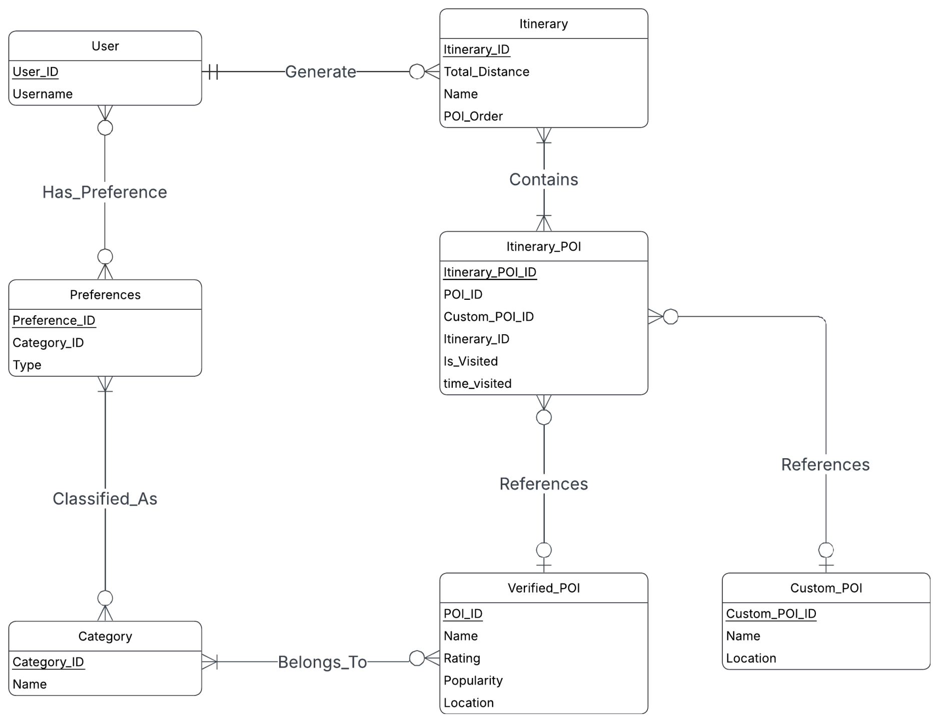


Figure 3 illustrates the system architecture of LAKAD: A Personalized Mobile Itinerary Creator and how the different components of the application interact to provide personalized and optimized travel itineraries for users. At the core of the system is the mobile frontend, which serves as the main interface where users can search for tourist destinations, generate itineraries, and manage their travel plans. When a user interacts with the application, the frontend communicates with the Mapbox API to send requests for map data, location coordinates, and optimized routes. The API processes these requests and returns the corresponding responses, which are then displayed on the user interface in the form of maps and travel routes. In addition, the application stores user-generated itineraries and relevant information in a local database, allowing users to access and manage their itineraries even without an internet connection. Overall, the architecture demonstrates a client-based design where most operations occur locally on the mobile device, ensuring efficiency, data accessibility, and a seamless user experience while minimizing reliance on external servers. Figure 4 shows the entity relationship diagram (ERD) of the proposed system which illustrates the relationships between different entities within the mobile itinerary generator application.

Figure 4

Entity Relationship Diagram



Development

This development phase pertains to the actual coding and implementation of the system's features inside an android application. The researchers' will utilize the AGILE methodology, particularly the kanban method for the software development life cycle. This will include weekly meetings and development checks by the researchers to ensure the system is properly developed to its intended uses.

The application will be written in Kotlin programming language which allows fast android development. The system will also utilize the Jetpack Compose framework for implementing graphical user interfaces and Android Studio IDE for developing the application as shown in table 2.

Table 2

List of Tools for Development

Name	Description
Android Studio	A robust IDE for developing and debugging android applications.
Kotlin	A powerful programming language for developing android applications as replacement for java.
Jetpack Compose	A library for developing reactive graphical user interfaces in android.
Git	A software for versioning and managing software projects.
GitHub	Host for git repositories that allows online collaboration.

Testing

For the testing phase, LAKAD will undergo rigorous evaluation to ensure the overall functionality and quality. The process will include system integration and user acceptance testing. System testing will focus on validating each module of the system by using test cases that will evaluate the logic of the system which will identify and resolve potential issues affecting itinerary generation and recommendation features. Integration testing will be conducted to ensure that all components of the system, such as itinerary generation and optimization, management, and user interface, operates cohesively to provide a seamless user experience.

Review

The review phase will focus on evaluating the overall functionality and usability of the system after development is completed. The researchers will gather views and opinions of users, including a system analyst to determine whether the system runs efficiently and serves its desired purposes. Guided by their observation, necessary adjustments and enhancements will be designed to refine the system.

System Evaluation

This section outlines the methods and criteria used to evaluate LAKAD, the proposed mobile itinerary generator system. It details the instruments and standards for assessment, describes the target population and sampling approach, and explains the procedures for data collection and analysis. The goal is to ensure that the system meets user needs and quality benchmarks through structured evaluation using both user and expert feedback.

Evaluation Instrument

The proposed system will be evaluated using the Technology Acceptance Model (TAM), as it provides a theoretical framework for understanding the process by which users accept and adopt new technologies. TAM is widely applied in system development studies for calculating the level of user acceptance based on their perceptions and intentions for using a system. To evaluate the effectiveness and acceptance of the proposed system, the following key constructs will be evaluated:

1. **Perceived Usefulness**. This construct measures how much users would believe that system usage would improve their task performance. It looks at whether system functionalities like itinerary recommendation, generation, and optimal route provide concrete value and efficiency to the user.
2. **Perceived Ease of Use**. This measures the degree of which users find the system easy to learn and operate. It singles out features including interface design, feature clarity, and the convenience of performing tasks.

3. **Behavioral Intention to Use**. This criterion measures the tendency and likelihood of the user to continue using the system in the future. It measures the intentions of the people to recommend or repeatedly use the system as their preferred tool.
4. **Attitude Toward Use**. This assesses the sentiment, satisfaction, and positive impression towards using the system. It measures how much the user enjoys interaction with the system and whether they find it useful and interesting.

The proposed system will also be evaluated by IT professionals using the ISO / IEC 25010 questionnaire which evaluates the system's quality and user satisfaction. The following criteria will be used in the questionnaire and are based on the ISO / IEC 25010 standards:

1. **Functional Suitability**. This will focus on how well the proposed system meets the user's needs. The questions will focus on the system's main features such as itinerary optimization, personalized itinerary generation, and itinerary management.
2. **Performance Efficiency**. This will assess the system's ability to provide fast and efficient processing and its capability to handle large amounts of tasks. The questions will assess the system's response time when it comes to itinerary optimization and generation as well as managing the itineraries of the user.
3. **Compatibility**. This will evaluate the system's compatibility with other external systems that the users might use. The questionnaire will verify how well the proposed system integrates and works alongside other mapping applications and systems.
4. **Interaction Capability**. This will focus on the system's usability, accessibility, and user satisfaction. Through this, the system will be assessed on how easy the system is to navigate, how intuitive and simple the user interface is for itinerary planning, and how effectively it guides the users.
5. **Reliability**. This will assess the system's dependability and consistency in performing its intended functions. The criterion will assess how well the system can operate without failure, maintain stability, and recover from unexpected errors or interruptions.

6. **Security**. This criterion will ensure that all collected data remains confidential, secure, and protected. Access to the data will only be available to the researchers and authorized users. No information will be shared with third parties without proper consent.
7. **Maintainability**. This will assess the ability of the system to be updated, debugged, and improved. This criterion will focus on the ability of the system to adapt to changes and its efficiency during system updates. It will ensure that new features or fixes can be integrated without disrupting existing functionalities of the system.
8. **Flexibility**. This will evaluate the system's ability to adapt to changing user needs, technological changes, and requirement changes. The criterion will assess how easily the system can support new itinerary features, and integrate additional modules or tools.
9. **Safety**. This will focus on ensuring that the system does not cause any harm to its users. The criterion will assess how well the system protects users from potential risks, errors, or negative consequences that may arise from using the system.

Population and Sample

The respondents for this study will consist of two distinct groups: end-users (tourists) for the Technology Acceptance Model (TAM) evaluation and IT professionals for assessing the proposed applications' quality with ISO/IEC 25210:2023.

A total of 20 IT professionals with experience in software engineering, quality assurance, or user experience, preferable with mobile application experience, will be selected through purposive sampling.

For the end-users, the sample size will be estimated using Cochran's formula (9), due to the large and unknown tourist population.

$$n_0 = \frac{Z^2 p(1-p)}{e^2} \tag{9}$$

To achieve a sample of at least 100, the margin of error e is set at most 0.098, assuming $p = 0.5$ and a Z-score of 1.96 for a 95 percent confidence level. Tourists aged 18 above will be purposively selected from major tourist hotspots in Bulacan, such as Barasoain Church, Philippine Arena, and other prominent resorts and historical landmarks to represent the top 5-10 most visited destination in the province.

Table 3

Summary of Population and Sample

Respondent Group	Population	Sample Size
End-users (Tourists)	Tourists visiting Bulacan attractions	100
IT Professionals	Software engineers, QA, UX professionals	20

Data Collection

The data collection for this study will involve two primary instruments: a Technology Acceptance Model (TAM) questionnaire for end-users and an ISO/IEC 25010:2023 evaluation for IT professionals.

The TAM will utilize a 5-point Likert scale (1=Strongly Disagree, 5=Strongly Agree) to assess user responses across constructs such as Perceived Usefulness, Perceived Ease of Use, Intent to Use, and Actual Use, with 3–5 items in each construct. The use of 5-point scale is justified by its balance between simplicity and reliability in measuring users' perceptions, it also reduces cognitive load on the side of end-users.

For IT professionals, the ISO/IEC 25010:2023 evaluation will use a 10-point Likert scale (1=Strongly Disagree, 10=Strongly Agree) to achieve greater precision and granularity in professional assessments. This broader scale will allow technical evaluators to make finer distinctions for the following software attributes: Functional Suitability, Performance Efficiency, Compatibility, Interaction Capability, Reliability, Security, Maintainability, and

Flexibility, with 3–5 items per construct. Each of these attributes will be measured with 3-5 distinct survey items.

The data collection process will start with an orientation and the acquisition of informed consent. Subsequently, participants will be given a brief explanation of the application before being allowed to explore it independently. Following this, end-users will complete the TAM, while IT professionals will complete the ISO/IEC 25010:2023 and provide qualitative feedback. All responses will be transferred to a CSV file for analysis, with no personal data collected beyond optional contact information for follow-ups. Furthermore, all data will be stored on an encrypted drive, with access strictly limited to the researchers.

Data Processing and Analysis

The collected data will go through preprocessing and analysis to ensure accuracy in interpretation. Descriptive statistical methods will be used to summarize and interpret the collected data. The mean (Equation 10) and standard deviation (Equation 11) will be computed to provide an overview of respondents' perceptions and evaluations. These measures will help to determine how well the system meets the user expectations and software quality standards. The results will be presented in tables and figures, with verbal interpretation according to the defined scales for TAM and ISO/IEC 25010:2023.

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{10}$$

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{11}$$

where x_i is the score given by respondent i, and n is the total number of valid responses.

Table 4

Verbal Interpretation Scale for ISO/IEC 25010.2023 (10-point Likert Scale)

Range	Descriptive Rating	Verbal Interpretation
8.50 – 10.00	Highly Acceptable	The system fully meets or exceeds requirements; very useful and effective.
6.50 – 8.49	Acceptable	The system meets requirements and is generally useful, with minor issues.
4.50 – 6.49	Moderately Acceptable	The system is somewhat adequate but still needs refinements to be fully useful.
2.50 – 4.49	Slightly Acceptable	The system shows minimal adequacy but requires major improvements.
1.00 – 2.49	Not Acceptable	The system fails to meet requirements; not useful or practical.

Table 5

Verbal interpretation Scale for TAM (5-point Likert Scale)

Range	Descriptive Rating	Verbal Interpretation
4.50 – 5.00	Highly Acceptable	The user strongly perceives the system as useful, easy to use, and intends to use it.
3.50 – 4.49	Acceptable	The user generally perceives the system as useful and easy to use, with a positive intention to use it.
2.50 – 3.49	Fairly Acceptable	The user has mixed feelings about the system's usefulness and ease of use, with uncertain intention to use it.
1.50 – 2.49	Slightly Acceptable	The user generally perceives the system as not useful or difficult to use, with a negative intention to use it.
1.00 – 1.49	Not Acceptable	The user strongly perceives the system as not useful, very difficult to use, and has no intention to use it.

The analysis will help to identify both the strengths and areas for improvement within LAKAD mobile application. By integrating end-user acceptance data with expert quality evaluations, the study ensures a comprehensive understanding of the application's usability, efficiency, and overall software quality.

Ethical Consideration

Ethical considerations will play a crucial role in the conduct of this study, especially since it will involve the participation of real people, and government institutions and offices. The ethical guidelines will strictly be followed in compliance with the Data Privacy Act of 2012 (Republic Act No. 10173), to uphold the integrity of the research and to ensure the privacy and security of all collected data. Obtaining informed consent, implementing data encryption, and enforcing strict access controls will be observed to safeguard the rights, and confidentiality of all individuals and institutions involved in the evaluation and development of the system.

Informed Consent

Participants of the study will be required to give an informed consent before responding to any personally identifying data or opinions that will be collected for the study, usability testing, and system evaluation. Consent materials will inform respondents about the study purpose, what data will be collected, how the data will be used, risks and benefits, and contact details for further questions regarding the study. The project will follow recognized Philippine guidance on ethical review and informed consent processes such as the Data Privacy Act of 2012 (Republic Act No. 10173). Participants will also be given the freedom to withdraw their responses at will, at which point the collected data from them will be discarded and deleted. In addition to individual respondents, the study will also involve data collection from government offices, particularly from Bulacan Provincial History, Arts, Culture, and Tourism Office (PHACTO) and other related agencies that maintain official records on local attractions, and tourism statistics. As per the request of the PHACTO, a letter required to be sent will formally address the Provincial Governor and the Head of the Provincial Tourism Department to request permission to access relevant datasets or documents. These data will include, but will not be limited to, lists of Points of Interest (POIs), and visitor statistics of tourism establishments. The request letters will clearly outline the purpose of the data use, the scope of the requested information, and the intended outcomes of the study. Only publicly shareable or officially permitted data will be considered and will be used in compliance with all terms set by the concerned government offices. The use of such data will be limited strictly to academic and system development purposes.

Confidentiality and Privacy

All personal or sensitive information collected during the study will remain confidential. Any identifiable data from participants or government records such as names or addresses will be anonymized before analysis or publication by not digitizing said fields and replacing them with code or identifiers instead. Access to raw data will be restricted to authorized research team members only, and all information will be securely stored in digital repositories.

Data Protection

All collected data will be processed and stored in compliance with the Data Privacy Act of 2012 (Republic Act No. 10173) and its Implementing Rules and Regulations (IRR). The principles of transparency and legitimate purpose in handling personal and institutional data will be followed. Appropriate technical and organizational security measures, such as encrypted file storage and secure data transmission will be implemented to protect information from unauthorized access or loss. The collected physical data will be safely compiled in one clearbook folder which will be stored inside a vault for the duration of the study and will be disposed of one month after the final defense and digitally collected data will be encrypted in a spreadsheet file only accessible by the researchers, and will be deleted one month after the final defense.

Ethical Data Collection

The data collection process will be guided by integrity and accountability. Only information relevant to the objectives of the system will be gathered. The collection of data will not include sensitive personal information unless necessary and, if in any case is, will be collected under the permission of the respondent. In compliance with Philippine regulations, the consenting respondents that will be considered for the survey will strictly be 18 years old and above. For survey and usability testing activities, participation will be entirely voluntary, and responses will be treated as confidential. For institutional data, such as those obtained from PHACTO or other local government offices, the researchers will follow the formal request procedures and uphold any data-sharing agreements or confidentiality clauses that will be imposed by the office.

Transparency and Integrity

The researchers will maintain transparency throughout the conduct of the study. All research methods, procedures, data sources, and analytical processes will be accurately documented and reported. The team will strictly avoid misrepresentation of data, selective reporting of results, or exaggeration of the system's capabilities. Acknowledgment will be given to all sources of information, including government offices and online databases. Conflicts of interest, if any, will be disclosed openly. All representations made to data providers, research participants, and readers will be honest and verifiable. The study will uphold the principles of academic integrity, guided by the ethical standards outlined by the Data Privacy Act of 2012 (Republic Act No. 10173), Republic Act No. 8293 (Intellectual Property Code of the Philippines), and institutional research ethics guidelines of Bulacan State University (BulSU).

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APPENDICES

APPENDIX A

SYSTEM FLOW CHART

Figure A.1

Home Page

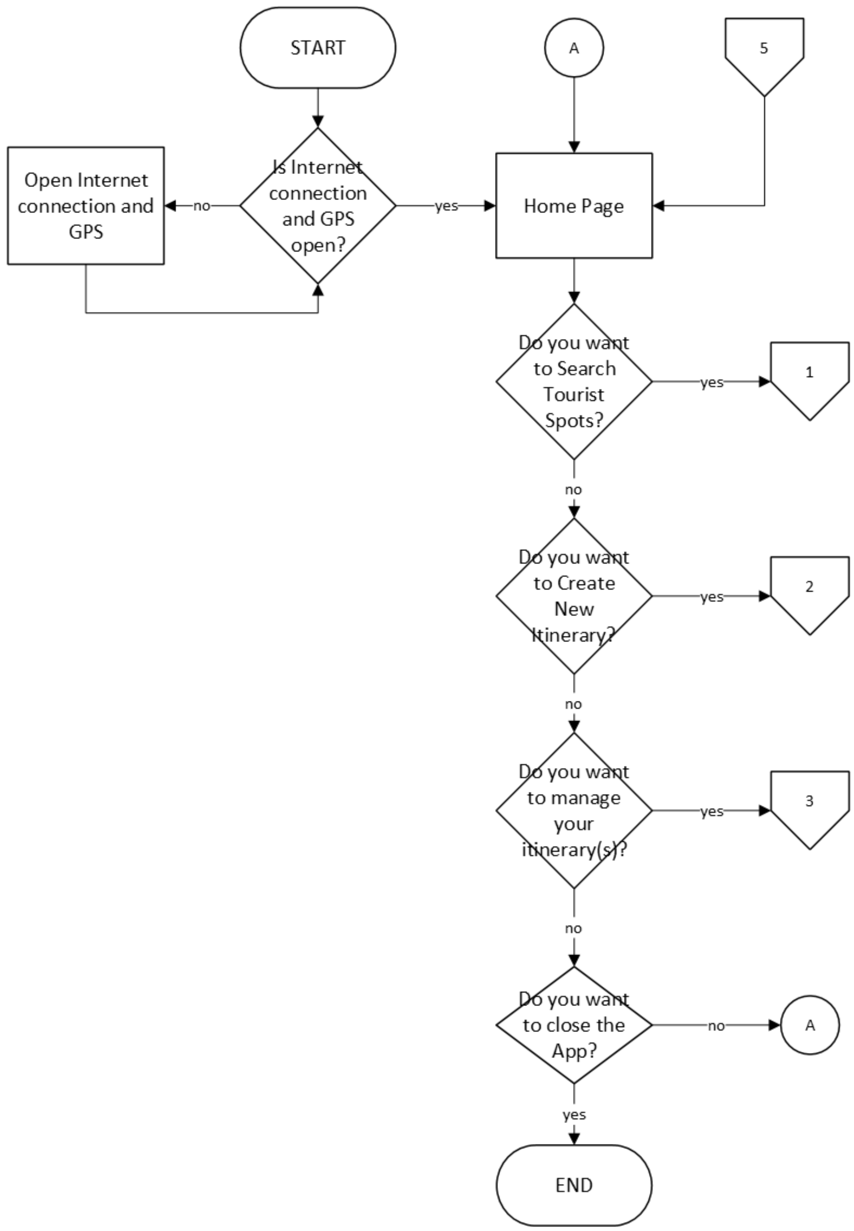

Figure A.2

Personalized Itinerary Generation

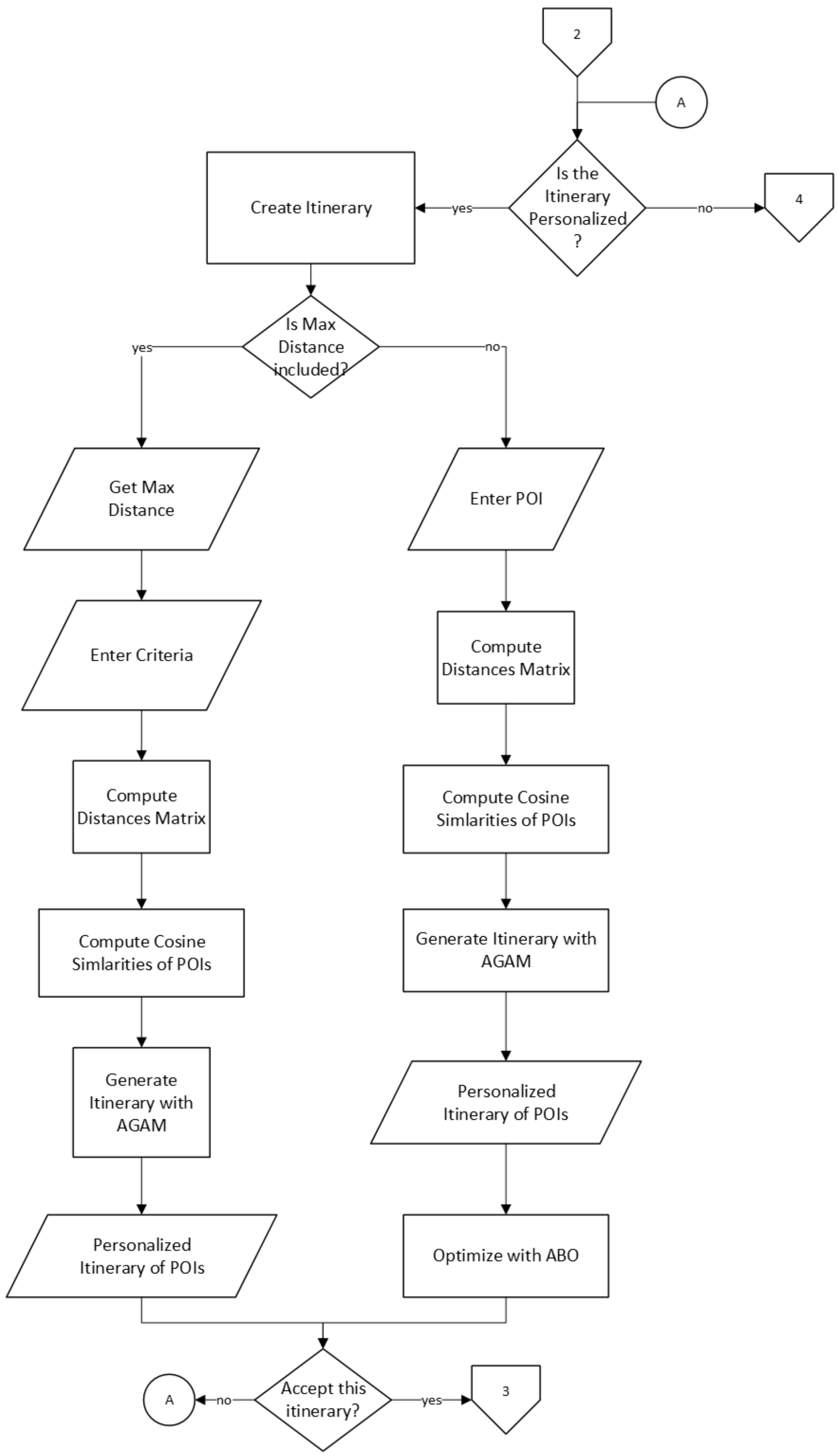

Figure A.3

Itinerary Optimization

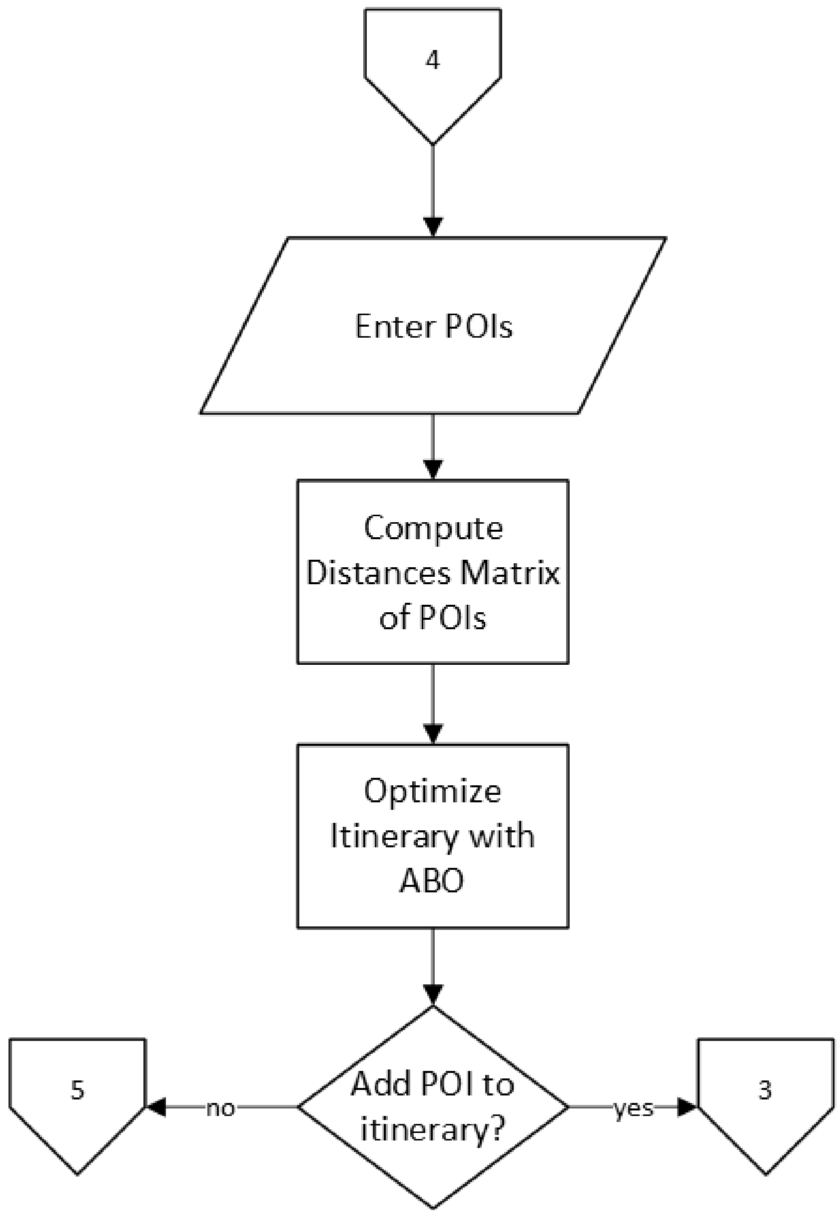

Figure A.4

Tourist Spot Searching

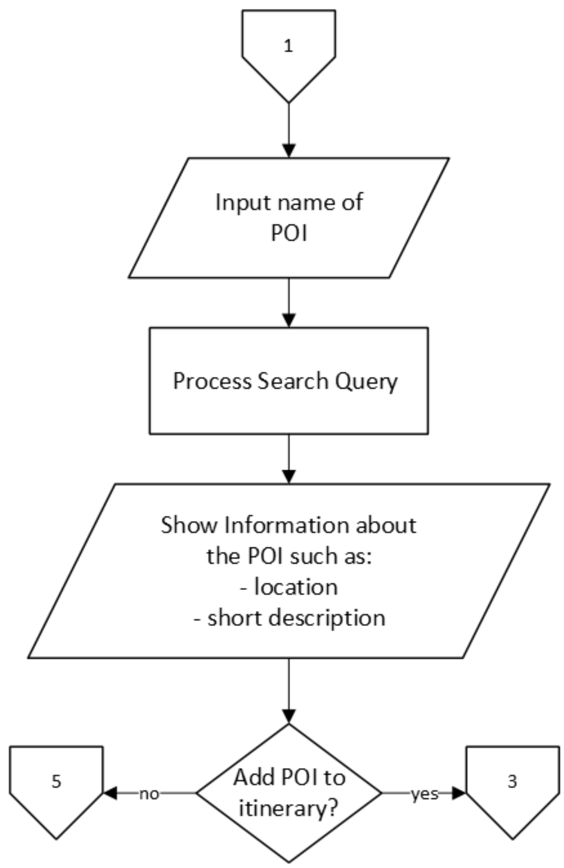

Figure A.5

Itinerary Management

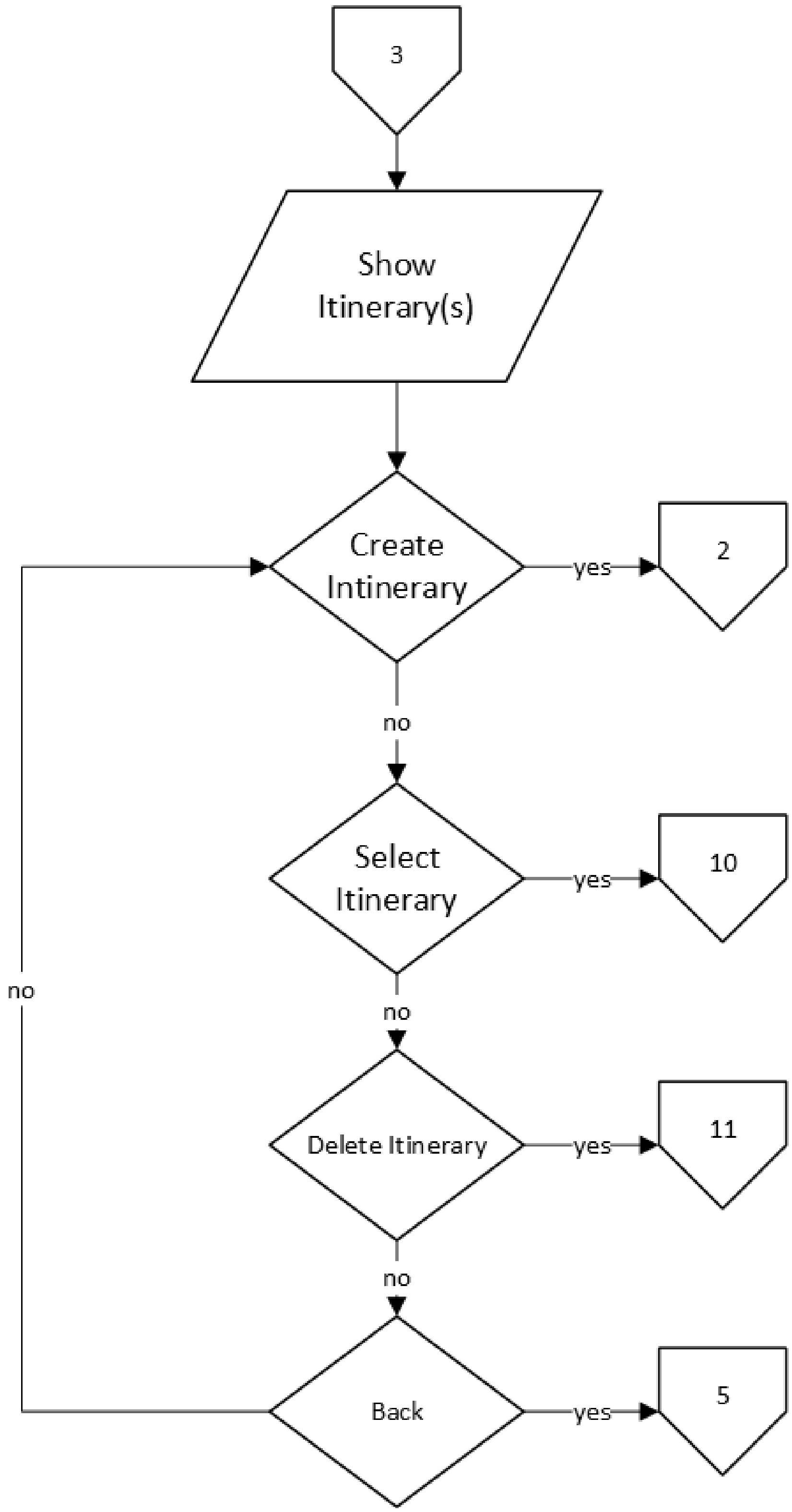

Figure A.6

Selecting Itinerary

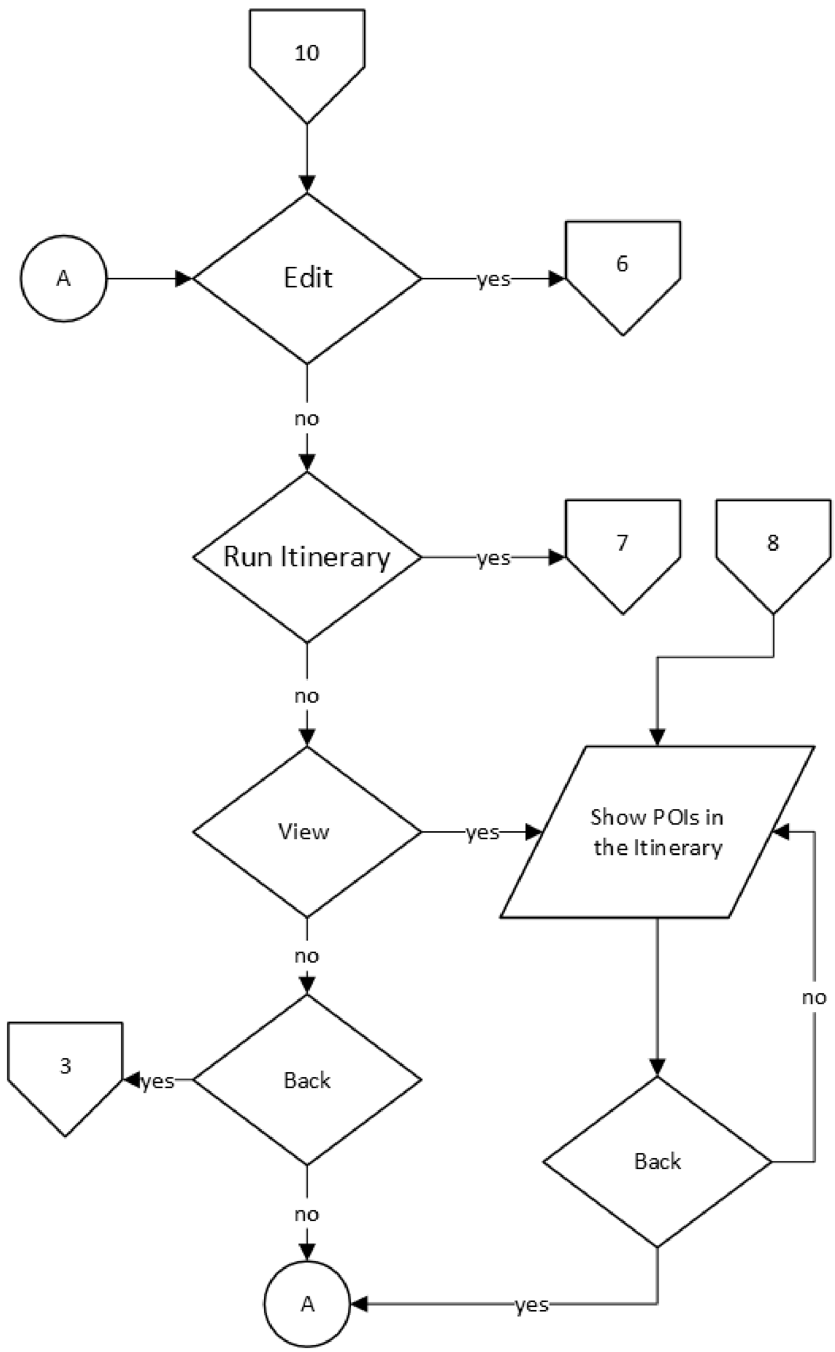

Figure A.7

Deleting Itinerary

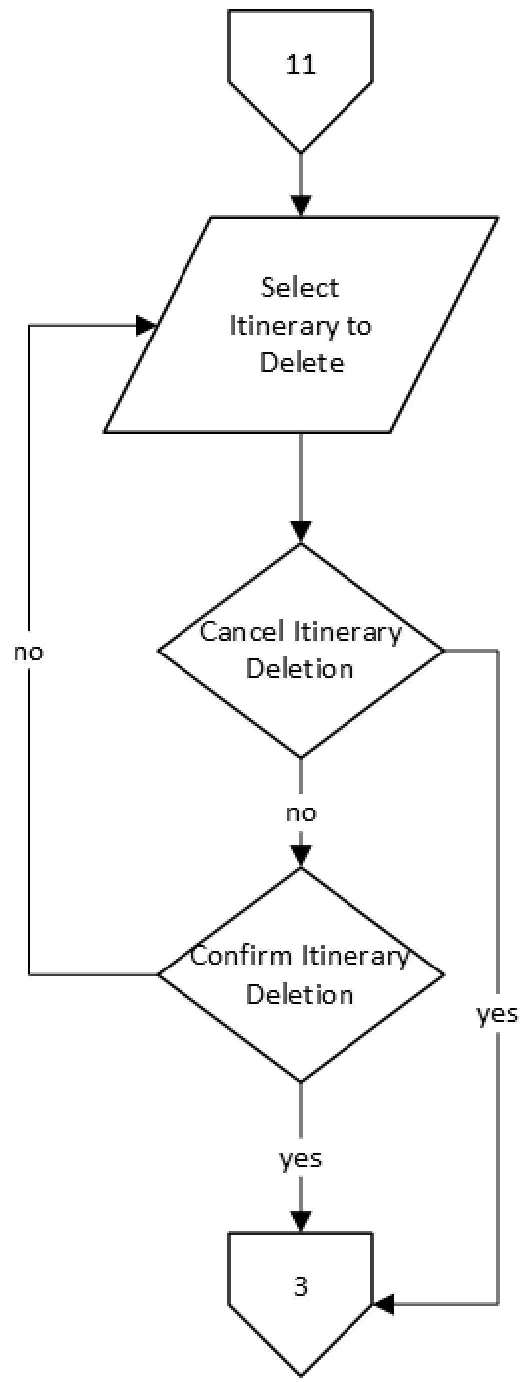

Figure A.8

Editing Itinerary

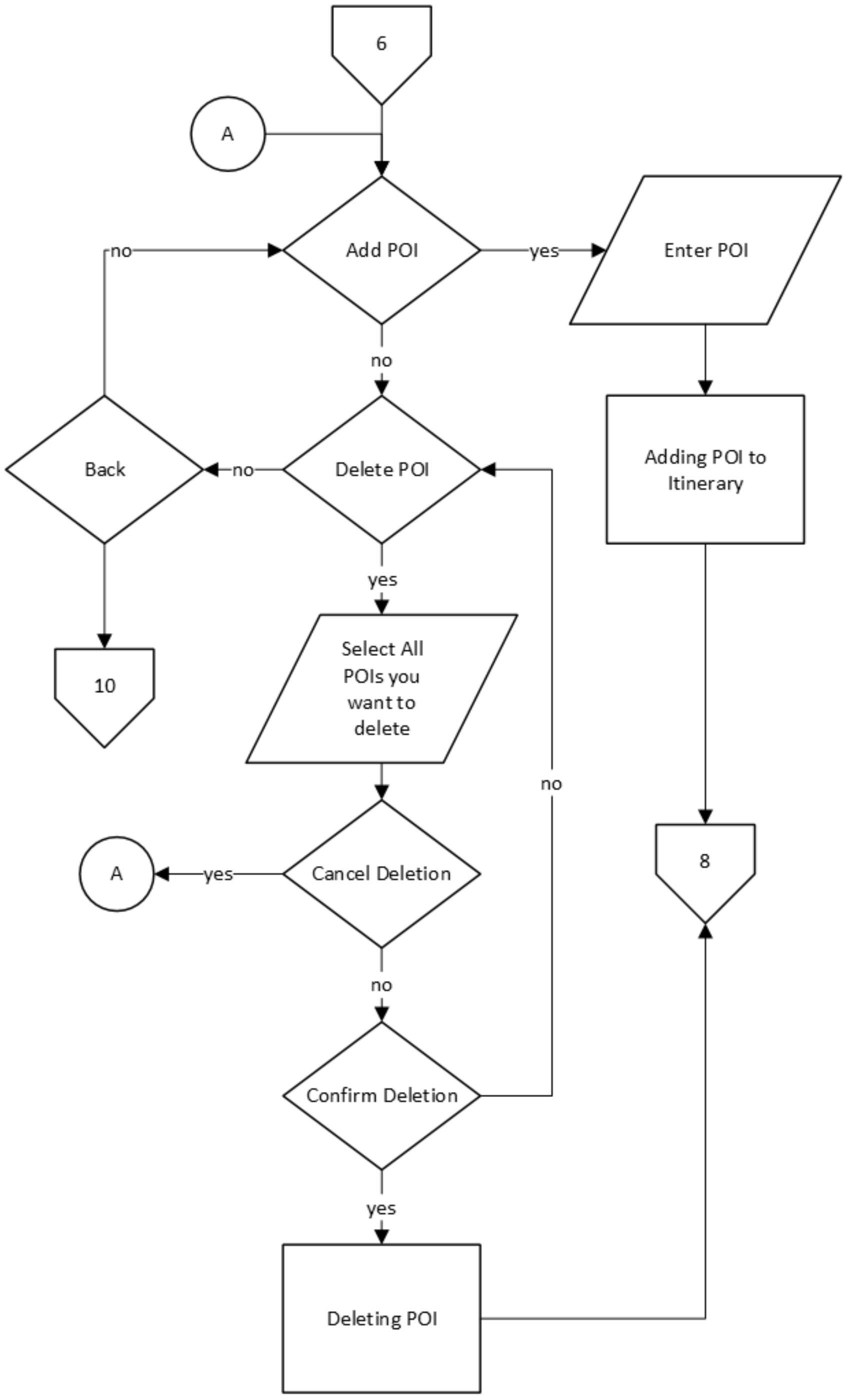

Figure A.9

Itinerary Navigation