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Architectural Design and Implementation of a Psychological Testing Website Integrated with Large Language Models for Personalized Tourism Recommendation in Lagoi, Bintan

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Abstract

This study aims to design and implement a psychological testing website integrated with Large Language Models (LLMs) to map user psychological profiles and generate intelligent, personalized tourism recommendations in the Lagoi tourism area, Bintan, Indonesia. A Design and Development Research (DDR) approach was adopted, structured around the Waterfall model. The system was developed through requirement analysis, architectural design, and prototype implementation using ReactJS, Node.js/Express.js, MongoDB, and integrated with the Google Gemini-2.0-Flash API. Evaluation was conducted via expert validation and user testing. The system demonstrated high capability in analyzing non-linear psychological narratives using LLMs. It extracted travel-relevant personality traits with 90% relevance and 85% consistency (validated by psychologists). These profiles enabled personalized recommendations—such as Trikora Beach for peace-seekers and Treasure Bay for adventure enthusiasts. The average user satisfaction score was 4.15 (±0.72) on a 5-point scale, showing an 18.5% improvement over traditional demographic-based systems. Integrating LLMs with psychological profiling significantly enhances the personalization quality of tourism recommendation systems. This approach provides a scalable and adaptive solution for destination management to understand and serve diverse traveler segments more effectively.

Kata kunci: Large Language Models, Psychological Profiling, Tourism Recommendation Systems, Personalization, Lagoi

1. Introduction

The global tourism industry is undergoing a fundamental shift from mass experiences to deeply personalized and meaningful journeys [24]. This trend is particularly evident in premium destinations such as the Lagoi Tourism Area in Bintan, Riau Islands, Indonesia, which is renowned for its natural beauty, luxury resorts, and diverse recreational facilities [10]. Although tourism continues to be a vital contributor to Indonesia's national economy—reflected in its increasing contribution to GDP and job creation [1]—providing genuinely personalized experiences remains a significant challenge. Conventional tourism recommendation systems, which typically rely on basic demographic data, user-declared explicit preferences, or historical visitation records [12], have shown limited effectiveness in capturing the implicit psychological dimensions that underlie a traveler's motivations, preferences, and behaviors [31]. This limitation highlights an urgent need for innovative approaches capable of interpreting traveler desires at a deeper level. Modern travelers no longer merely seek places to visit; rather, they pursue experiences that resonate with their personal values, interests, and psychological traits. Intrinsic motivations such as the search for adventure, the need for deep relaxation, authentic cultural exploration, or meaningful social interaction are often difficult to infer from explicit data alone. These latent preferences demand more sophisticated inference methods to be effectively identified and utilized in the recommendation process [9].

In response to this critical need, the present study proposes a transformative solution through the design and implementation of a psychological testing website integrated with Large Language Models (LLMs). LLMs possess revolutionary capabilities in understanding, processing, and generating natural language with human-like cognitive nuances [4][34], offering a unique potential to analyze qualitative and narrative responses in psychological assessments. This LLM-based approach is expected to overcome the limitations of traditional recommendation algorithms by deeply exploring users' psychological profiles—including cognitive patterns, core motivations, and personality characteristics that influence travel decisions. Ultimately, such a system enables the generation of

destination and activity recommendations in Lagoi that are not only contextually relevant but also emotionally and personally resonant with each individual traveler.

Although personalization has become a crucial factor in enhancing tourist satisfaction and loyalty, current recommendation systems in the tourism domain largely fail to incorporate travelers' psychological dimensions. Most existing systems are limited to processing explicit preferences or historical behavior data, without the ability to infer latent psychological traits from unstructured or narrative input. This gap persists despite advances in artificial intelligence, particularly in natural language understanding through Large Language Models (LLMs).

To address this gap, the present study investigates how LLMs can be leveraged to analyze psychological narratives and generate personalized destination recommendations that align more closely with individual motivations and personality traits.

The research addresses the following questions:

- RQ1: How can an efficient, scalable, and secure web architecture be designed to integrate LLMs for mapping psychological profiles based on user narratives?
- RQ2: How can a working prototype be implemented and evaluated to provide smart tourism recommendations in the Lagoi region using LLM-extracted psychological traits?
- RQ3: To what extent can the accuracy and consistency of LLMs in analyzing non-linear psychological responses be validated, and what are the implications for improving the relevance and personalization of destination recommendations?

This study aims to achieve the following objectives:

- To design and validate a web-based system architecture that integrates Large Language Models (LLMs) for effective psychological profiling of users based on narrative input.
- To develop and evaluate a prototype that delivers intelligent, personalized tourism recommendations tailored to user psychology in the Lagoi tourism region.
- To assess the performance and effectiveness of LLMs in processing non-linear psychological test responses, and to analyze their impact on improving relevance, consistency, and user satisfaction in tourism recommendation systems.

This study is expected to contribute significantly in the following dimensions:

Theoretical Contribution: The research expands the interdisciplinary field of tourism psychology and recommender systems by introducing a novel paradigm that leverages the inferential capabilities of Large Language Models (LLMs) to interpret complex and often implicit psychological dimensions of travelers. It bridges the gap between conventional psychometric theories and artificial intelligence applications, paving the way for the development of more accurate and human-centric predictive models for tourism preferences. Moreover, the study offers new insights into how narrative data can be transformed into actionable psychological profiles for personalization purposes.

Practical Contribution: The research delivers a functional prototype and a comprehensive architectural blueprint that can be adopted and customized by tourism stakeholders in the Lagoi area—including destination managers, resort operators, hotels, and travel agencies. By utilizing this system, stakeholders may develop more advanced personalization services, enhance the precision of marketing campaigns, and optimize customer service operations. These improvements are expected to provide a strategic competitive advantage.

Economic and Social Impact: By significantly enhancing traveler satisfaction through tailored experiences, the system has the potential to increase repeat visits and extend the duration of stay, thereby contributing positively to local economic growth in Lagoi via increased revenue and job creation. Additionally, a deeper understanding of tourist psychological profiles may support the development of more inclusive, relevant, and sustainable tourism products, ensuring that tourism benefits not only the economy but also the quality of experience for both visitors and local communities.

2. Research Methodology

This investigation adopts the Design and Development Research (D&D Research) approach, a systematic methodology for designing, developing, and validating technological solutions to practical real-world problems [31]. This approach is well-suited for the development of innovative software system prototypes that require

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iterative refinement, as it emphasizes cycles of design, implementation, and evaluation. The software system development process follows the phases of the Waterfall Model, ensuring a clear project structure, organized management, and systematic documentation at each development stage.

2.1 Research Design

This study is structured as a single case study, focusing primarily on the Lagoi Tourism Area in Bintan. This case study allows for an in-depth analysis of the destination's specific context, including tourist demographic characteristics, types of available attractions, and local market dynamics. It provides valuable insights into how AI-supported, psychology-based recommendation systems can be effectively applied in a real-world tourism environment. The research design is mixed-methods, integrating both quantitative and qualitative components to obtain a holistic understanding and enable data triangulation.

- **Quantitative Methodology**: Used to evaluate system functionality (e.g., response time, system stability, API uptime), LLM performance (e.g., profile analysis consistency), and user satisfaction regarding the relevance of recommendations (via Likert scale measurements and comparisons with baseline data). Numerical data will be analyzed using descriptive and inferential statistics.
- **Qualitative Methodology**: Employed to conduct in-depth analysis of LLM-generated responses to psychological tests (using systematic content analysis of LLM outputs) and to collect narrative feedback from users through semi-structured interviews or open-ended questionnaires. This approach captures user perceptions, experiences, and suggestions that may not be conveyed by quantitative data alone.

2.2 Research Participants

Purposive sampling will be used for initial data collection, prototype testing, and recommendation evaluation. Participants will be adults (aged 18–60) who meet the following inclusion criteria:

- Have a clear interest or intention to engage in tourism activities, with a general preference for natural or relaxation-based destinations that align with the characteristics of Lagoi.
- Willing to voluntarily participate in the online psychological test and provide honest feedback.
- Possess stable internet access and basic skills in using websites and web applications.
- Have sufficient proficiency in the Indonesian language to comprehend complex test items and provide meaningful narrative responses.

The target sample size is 80–150 individuals. This sample size ensures sufficient variation in psychological profiles and tourism preferences to support LLM analysis and provide statistically valid early quantitative findings.

Ethical Considerations: Ethical protocols are a top priority. All participants will be provided with comprehensive informed consent, clearly outlining the research purpose, data collection procedures, types of data collected, how the psychological data will be analyzed by AI and used for tourism recommendations (not clinical diagnosis), data privacy guarantees, and the right to withdraw from the study at any time without consequence. Participant data will be anonymized or pseudonymized upon collection to ensure confidentiality and will be stored securely on encrypted servers.

2.3 Research Materials and Instruments

The materials and instruments used in this study are specifically designed to support psychological data collection, destination characterization, and system development:

Psychological Test Questionnaire (Online Questionnaire):

- **Conceptual Design**: Carefully designed based on personality theories relevant to tourism preferences, specifically the Big Five Personality Traits (Openness to Experience, Conscientiousness, Extraversion, Agreeableness, Neuroticism – [19] and Plog's Tourist Typology (Psychocentric vs. Allocentric – [25]). Questions are formulated to assess these dimensions indirectly through preferences, responses to hypothetical scenarios, and personal travel narratives.
- **Question Formats**: The questionnaire uses a hybrid approach to maximize both qualitative and quantitative input:
    - *Likert Scale Questions*: Measure explicit preferences and general attitudes (e.g., "I prefer well-planned vacations over spontaneous ones," using a 1–5 scale from "Strongly Disagree" to "Strongly Agree").

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  - *Narrative/Open-Ended Questions*: Serve as core input for LLM analysis. These are provocatively designed to elicit emotionally rich, motivational, and reflective personal narratives (e.g., "Describe your most memorable travel experience. What made it special, including interactions with the environment or others? Explain why it was so meaningful to you.").
  - *Text-Based Scenarios (Problem-Solving)*: Participants are presented with hypothetical, unexpected travel situations and asked to describe their responses (e.g., "Imagine you arrive at your dream destination, but the booked accommodation is disappointing. What would be your initial reaction, and what practical steps would you take to resolve the issue?").
- **Validation**: Initial validation involves expert review by at least two psychologists with relevant experience in psychometrics and tourism psychology. A pilot test on a small sample will be conducted to identify ambiguities, unclear instructions, or technical constraints.

Lagoi Destination Dataset:

- **Data Sources**: Comprehensive data on destinations and activities in the Lagoi region is compiled through secondary research from credible and authoritative sources, including official tourism websites (e.g., Bintan Tourism Office), resort websites, leading booking platforms (e.g., Traveloka, Agoda), trusted travel review platforms (e.g., TripAdvisor), and official tourist brochures. When feasible, data is verified through preliminary field observations.
- **Data Structure**: Each destination entry will include both structured and textual attributes relevant for recommendation matching with psychological profiles:
  - *name*: Unique name of the destination or activity.
  - *description*: Rich and detailed textual description of the destination.
  - *activity_categories*: Array of relevant tags (e.g., "water sports," "eco-tourism," "culinary," "cultural," "relaxation," "adventure," "family-friendly," "historical").
  - *psychological_traits*: Tags describing the psychological suitability of the destination (e.g., "high stimulation," "peace-seeker," "extrovert-friendly," "introvert-friendly," "reflective," "family-oriented," "challenging place," "soothing place"). These attributes are curated through content analysis and domain expert validation (e.g., tourism professionals or psychologists).
  - *estimated_cost*: Budget classification (e.g., "Low," "Medium," "High") to support user budget planning.
  - *location*: Specific geographic information or coordinates (optional, for potential map integration).
  - *image_url*: Supporting image URL for UI presentation (with fallback to a placeholder if invalid).
  - *average_rating*: Average user rating from external reviews (optional, if accessible via ethical scraping or API).
  - *short_reviews*: Selected brief quotes or positive sentiments from past visitors (optional).
- **Curation and Maintenance**: The dataset will undergo strict curation to ensure accuracy, relevance, and up-to-date information.

2.4 Web Development Frameworks

- **Frontend**: ReactJS will be used for the frontend user interface, leveraging Context API for efficient and lightweight state management. ReactJS is chosen for its efficiency in building dynamic, interactive single-page applications (SPAs) that are responsive across devices (desktop, tablet, mobile). Its strong community ecosystem, optimal rendering performance, and support for modular components are key advantages.
- **Backend**: Node.js with the Express.js framework will serve as the backend API. Node.js is selected for its efficient non-blocking I/O capabilities, allowing it to handle multiple requests concurrently with low latency. This is ideal for applications that frequently interact with external APIs (e.g., LLM API) and databases. Express.js provides a minimalist yet powerful framework for building lightweight and organized RESTful APIs.

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- **Database Management System (DBMS)**: MongoDB will be used as the NoSQL database solution. It is chosen for its flexible document schema, well-suited for storing varied and semi-structured data such as narrative psychological test responses and LLM-analyzed profiles. MongoDB's horizontal scalability also supports future growth in data volume and user base.

2.5 LLM API Integration

Primary Model: The integration will utilize the Google Gemini API (specifically version Gemini-2.0-Flash) as the core engine for psychological analysis. Gemini is selected for its advanced capabilities in understanding complex natural language, semantic inference, and support for structured output in JSON format. Its ability to generate responses conforming to predefined schemas is essential for producing standardized psychological profiles that can be seamlessly integrated into the recommendation system.

API Utilization: Interaction with the LLM involves sending prompts containing user test responses along with the desired JSON schema for output. Prompt design will be optimized to guide the LLM in producing structured and relevant inferences. To ensure stable and efficient performance, the system will implement API rate limiting management, robust error-handling mechanisms, and optimized API calls.

2.6 System Development Procedure (Waterfall Model)

The web system development procedure will be conducted sequentially based on the phases of the Waterfall Model [32] [27]. Although the Waterfall Model is often seen as less flexible than Agile methodologies, it is chosen for this research context due to its clarity, comprehensive documentation support, and strict quality control—beneficial for academic prototype development where requirements are relatively well-defined.

Phase 1: Requirement Engineering and Analysis

This phase focuses on thorough understanding and detailed documentation of the system's functional and non-functional requirements as well as user expectations, involving direct engagement with potential users and domain stakeholders.

- **Functional Requirements**:
  - User Account Management (registration, secure login/logout, profile updates).
  - Psychological Test Module (step-by-step question delivery, acceptance of narrative and multiple-choice responses, real-time input validation).
  - LLM Integration Module (sending text to the LLM API, receiving and parsing structured psychological profile output, asynchronous response handling).
  - Destination Recommendation Module (profile matching algorithm, personalized recommendation display, filtering and sorting features).
  - User Dashboard (displays analyzed psychological profile, test history, recommendation history, feedback submission options).
- **Non-Functional Requirements**:
  - *Performance*: Target page response time < 2 seconds; API latency < 5 seconds for most operations including LLM calls; system capable of handling at least 100 concurrent users without significant degradation.
  - *Security*: Strong password hashing (e.g., bcrypt), session management using JSON Web Tokens (JWT), protection against common threats (e.g., NoSQL Injection, XSS), and strict privacy and integrity controls over users' psychological data.
  - *Usability*: An intuitive and visually appealing user interface, clear navigation, streamlined user interaction flows, and responsive design across devices (desktop, tablet, smartphone).
  - *Maintainability*: Clean, modular, well-documented code that can be easily modified and extended in the future.
- **Psychological Questionnaire Analysis**: Finalizing the design of the questionnaire, including question formats and scenarios, with a focus on optimizing qualitative inputs for LLM analysis.

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- **Lagoi Destination Dataset Structuring**: Classifying and curating the destination dataset, including validating psychological_traits attributes for each destination through expert review.
- **Development Environment Setup**: Configuring the development server, database tools, software dependencies (Node.js, ReactJS, MongoDB driver), and version control system (Git) to support collaborative development.

Deliverable: A comprehensive Software Requirement Specification (SRS) document containing Use Case diagrams, User Stories, and detailed requirement descriptions.

Phase 2: System Design

This phase translates the collected requirements into architectural blueprints and detailed design specifications for all system components, including data structures and inter-module interactions.

- **System Architecture Design**:
  - *Three-Tier Architecture*: The system is structured into three independent but interconnected layers: the Presentation Layer (Frontend), Business Logic Layer (Backend API), and Data Layer (Database). This separation enhances scalability, maintainability, and security.
- **Functional Module Design**:
  - Each functional module (Authentication, Psychological Testing, LLM Integration, Recommendation) will be elaborated with internal workflows, including data flow diagrams and API interaction maps.
  - The recommendation algorithm design will emphasize how psychological profiles inferred from the LLM are compared against the psychological_traits attributes of destinations to generate personalized recommendations.
- **UI/UX Design**: Wireframes (low-fidelity page layouts), mockups (detailed static visuals), and interactive prototypes (user interaction simulations) will be developed for key pages, including the homepage, registration/login screen, multi-step psychological test interface, user dashboard, and recommendation results page. The design process emphasizes visual consistency, accessibility (in accordance with basic WCAG guidelines), and user flows that are intuitive and minimize cognitive load.
- **Database Design**: A NoSQL schema will be implemented using MongoDB. Each collection is structured to support specific application functionalities:
  - **users**:
    - *Function*: Stores user credentials and core profile data for authentication and account management.
    - *Fields*:
      - _id (ObjectId): Unique user ID (Primary Key)
      - username (String): Unique username (indexed, unique constraint)
      - password (String): Hashed password (encrypted, unreadable)
      - email (String): Optional email address (indexed)
      - created_at (Timestamp): Account creation time (indexed)
      - last_login (Timestamp): Most recent login time
  - **test_responses**:
    - *Function*: Stores raw user responses from psychological tests; essential for audits, reanalysis, or future LLM fine-tuning.
    - *Fields*:
      - _id (ObjectId): Unique test response ID (Primary Key)
      - user_id (ObjectId): Reference to users collection (Foreign Key, indexed)
      - answers (Array): Array of {question_id, question_text, response_type, response_value} objects

DOI: https://doi.org/10.31004/riggs.v4i2.1129

        - timestamp (Timestamp): Test submission time (indexed)
    - **user_profiles**:
        - *Function*: Stores psychological profiles analyzed and extracted by the LLM; foundational for recommendation generation.
        - *Fields*:
            - _id (ObjectId): Unique profile ID (Primary Key)
            - user_id (ObjectId): Reference to users collection (Foreign Key, indexed, unique)
            - tipe_wisatawan (String): General tourist classification (e.g., "Allocentric – Social Explorer")
            - dimensi_big_five (Object): Big Five scores/descriptions (e.g., { "openness": "High", "conscientiousness": "Moderate", ... })
            - motivasi_utama (Array): Primary travel motivations (e.g., ["cultural exploration", "relaxation", "physical adventure"])
            - preferensi_lingkungan (Array): Environmental preferences (e.g., ["open nature", "authentic destinations", "lively places"])
            - analisis_narasi_kunci (String): Key narrative insights and psychological inferences from LLM
            - confidence_score_llm (Number): Confidence score from LLM (optional)
            - last_updated_at (Timestamp): Last time the profile was updated/analyzed (indexed)
    - **destinations**:
        - *Function*: Stores structured data on all curated destinations and activities within the Lagoi region; populated manually or via batch import.
        - *Fields*: Defined previously with name, description, activity_categories, psychological_traits, estimated_cost, location, image_url, average_rating, and short_reviews
    - **recommendation_logs**:
        - *Function*: Records each recommendation session including profile used, destinations recommended, and user feedback. Essential for system performance analytics and future algorithm refinement.
        - *Fields*:
            - _id (ObjectId): Unique log ID (Primary Key)
            - user_id (ObjectId): Reference to users collection (Foreign Key, indexed)
            - profile_snapshot (Object): Snapshot of user's psychological profile at the time of recommendation
            - recommended_destinations (Array): List of destination IDs recommended
            - timestamp (Timestamp): Time recommendation was issued (indexed)
            - user_feedback_relevance (Number): User feedback on relevance (optional, scale 1–5)
            - feedback_comment (String): User's free-text feedback (optional)

Deliverable: A comprehensive System Design Document (SDD), including architectural diagrams, detailed database schemas with indexing strategy, and finalized UI/UX designs (approved wireframes and mockups).

Phase 3: Implementation

In this phase, the approved designs are translated into functional, modular, and standards-compliant code.

- **Frontend Development (ReactJS)**:
    - Development of modular React components (e.g., AuthForm, PsychTest, RecommendationCard, Dashboard)
    - Client-side input validation for responsive user experience

DOI: https://doi.org/10.31004/riggs.v4i2.1129

  - Integration with backend APIs using fetch/Axios
  - Responsive styling using modular CSS or Tailwind CSS for consistent cross-device experience
- **Backend API Development (Node.js/Express.js)**:
  - RESTful endpoint development for core operations (e.g., /api/register, /api/login, /api/test/submit, /api/recommendations, /api/profile)
  - Implementation of business logic for data validation, user authentication (JWT), database operations, and LLM orchestration
  - Conceptual backend code illustrations (e.g., analyzeWithLLM function and /api/test/submit endpoint) to demonstrate core workflow
- **LLM Integration**:
  - Backend module (e.g., llmService.js) for Google Gemini API interaction
  - Includes prompt construction, HTTP POST request handling, structured JSON response parsing, and external API error handling
- **Database Development**:
  - MongoDB initialization using native driver or Mongoose ODM
  - Creation of collections (users, test_responses, user_profiles, destinations, recommendation_logs)
  - Index implementation for query performance
  - Initial data population for destinations from curated dataset

Deliverable: Fully functional prototype source code, well-structured and maintained in a version control repository (e.g., Git), ready for internal testing and user acceptance testing (UAT).

Phase 4: Testing

Testing ensures all modules perform correctly and meet requirements:

- **Unit Testing**: Verifies individual functions/modules (e.g., password hashing, LLM analysis, input validation) using Jest/Mocha.
- **Integration Testing**: Tests interactions between components (e.g., frontend-backend, backend-LLM/database).
- **System Testing**: Full end-to-end flow (user registration → test → recommendations → dashboard).
- **Performance Testing**: Measures response time, concurrency (100+ users), and server resource usage.
- **Security Testing**: Identifies vulnerabilities (NoSQL injection, XSS) and checks access control.
- **User Acceptance Testing (UAT)**: Participants test usability and recommendation relevance. Feedback gathered via questionnaires and interviews.

Deliverable: Test report summarizing cases, results, bug logs, and UAT feedback.

Phase 5: Deployment and Maintenance

Though academic in scope, this phase simulates real-world readiness:

- **Prototype Deployment**: Web system hosted on cloud/staging server for broader testing.
- **Monitoring and Maintenance**: Conceptual planning for uptime monitoring, bug fixing, feature updates, and security/performance log analysis.

Deliverable: Deployed prototype, initial monitoring report, and maintenance plan.

2.7 Data Analysis

Mixed-method analysis evaluates system performance and user impact:

- **LLM Output Evaluation**:

DOI: https://doi.org/10.31004/riggs.v4i2.1129

  - *Consistency*: Measured with metrics like Cohen's Kappa.
  - *Expert Review*: Psychologists assess LLM output validity and relevance to Big Five & Plog types.
  - *Pattern Discovery*: NLP topic modeling (e.g., LDA/NMF) to identify recurring traits and motivations.
- **Descriptive Statistics**:
  - Summarizes participant demographics and Likert-scale feedback.
  - Visualized via bar charts, pie charts, or histograms.
- **Recommendation Relevance**:
  - *User Satisfaction*: Mean and SD of relevance scores.
  - *Comparison*: Statistical tests (e.g., t-test/ANOVA) to compare LLM vs baseline recommendation systems.
  - *Qualitative Feedback*: Thematic analysis (Braun & Clarke) of open-ended user responses to highlight system strengths and improvement areas.

3. Research Findings

This chapter presents key findings from the design, development, and evaluation of the "Lagoi PersonaTrip" website prototype. It includes verification of the system architecture, implementation details, psychological analysis via LLM, and evaluation of recommendation quality.

3.1 System Architecture Validation

The web system was designed using a three-tier architecture which proved robust and scalable:

- **Presentation Layer (Frontend)**:
  - Developed with **ReactJS**, featuring responsive Single Page Application (SPA) design.
  - Key components include dynamic form handling, progress indicators for psychological testing, and responsive layout adapting to desktop and mobile.
  - Performance testing indicated an average page load time of <2 seconds under standard network conditions.
- **Business Logic Layer (Backend)**:
  - Built using **Node.js** and **Express.js**, serving as the central API hub.
  - Key API endpoints such as /api/register, /api/login, /api/test/submit, and /api/recommendations were validated for functionality and security.
  - Backend latency remained low (avg <100ms), excluding LLM API calls.
- **Data Layer (Database)**:
  - **MongoDB** was chosen for its document-based, schema-flexible structure, well-suited for varied and semi-structured user input data.
  - Collections were structured for users, psychological test responses, inferred user profiles, destinations, and recommendation logs.
  - Data integrity checks confirmed consistent storage and retrieval under load.
- **AI Integration Layer (LLM Module)**:
  - Utilized **Google Gemini 2.0-Flash API** for psychological profiling.
  - User narratives were sent as prompts, and structured JSON profiles were returned.
  - Average LLM response time was 3-7 seconds, suitable for asynchronous analysis.

3.2 Website Prototype Implementation

- **User Interface (UI/UX)**:

DOI: https://doi.org/10.31004/riggs.v4i2.1129

  - Home page featured high-resolution images of Lagoi, motivational taglines, and call-to-action buttons.
  - Registration/Login included inline validation and user feedback.
  - Psychological test UI combined Likert questions and rich narrative fields, with visual progress indicators and tooltips.
- **Security and Authentication**:
  - Passwords were hashed with **bcrypt**.
  - Sessions secured using **JWT** for stateless authentication.
- **Psychological Testing Module**:
  - Designed to assess both explicit and implicit preferences.
  - Included open-ended narrative prompts (e.g., coping with travel disruptions, meaningful travel experiences).
  - Input validated both client- and server-side for completeness.
- **LLM-Based Psychological Profiling**:
  - Prompts were tailored to guide the LLM into extracting Big Five personality traits, traveler types (Allocentric vs Psychocentric), and travel motivations.
  - Output format was JSON and included confidence scores.
  - Profiles stored in the user_profiles collection and used directly for matching.
- **Destination Recommendation Engine**:
  - Used profile-matching against curated destinations dataset.
  - Filtering logic prioritized psychological compatibility and relevance.
  - Results presented as visual cards with descriptions and rationale ("recommended because you prefer calm, nature-based experiences").

4. Evaluation of LLM Analysis and Recommendation Relevance

LLM Performance Evaluation

- **Internal Consistency**:
  - Repeat test scenarios yielded profile similarity of **85%**, indicating stable inferencing.
- **Expert Validation**:
  - Two licensed psychologists reviewed 20 random LLM outputs.
  - Profile relevance scored **90% agreement** with narrative input.
  - Inter-rater reliability (Cohen's Kappa): **$\kappa = 0.82$** ("very good" agreement).

Recommendation Satisfaction

- **Quantitative Feedback (n=80)**:
  - Likert scale (1-5) mean relevance score: **4.15 (SD = 0.72)**.
  - **35%** rated 5 (Very Relevant), **43%** rated 4, **15%** rated 3, only **7%** rated 1 or 2.
  - Indicates 78% positive reception.

Comparison to Baseline System

- **Baseline**: Demographic-based recommendation system (age, gender, popular locations).
  - Average score: **3.50 (SD = 0.85)**.
- **LLM-Based**: **4.15 (SD = 0.72)**.

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- **Statistical Test**: Paired t-test: $t(79)=5.21$, $p<0.001$, **Cohen's d = 0.58** (moderate to large effect size).

Qualitative Feedback Themes

- **"Surprisingly Accurate"**: Many users felt the system understood unspoken preferences.
- **"Better Than Usual"**: Compared favorably with traditional travel platforms.
- **Improvement Areas**:
  - Add transportation and travel duration data.
  - Build itinerary planner.
  - Enable sharing of profiles/ recommendations.

The "Lagoi PersonaTrip" platform demonstrates a robust integration of LLM-based personality profiling and destination matching, significantly improving the relevance and personalization of tourism recommendations. The system performed well across architectural, functional, and user satisfaction metrics.

5. Discussion

This section discusses the feasibility, effectiveness, and impact of integrating Large Language Models (LLMs) for psychological profiling in tourism recommender systems. It interprets findings, compares with previous research, explores theoretical and practical implications, and outlines limitations and future research directions.

5.1 Key Findings

- **Psychological Profiling via LLM**: Gemini-2.0-Flash achieved strong internal consistency (85%) and high expert-rated accuracy (90%, $\kappa = 0.82$), validating its effectiveness in inferring user personality traits from narrative input.
- **Enhanced Personalization**: The LLM-enabled system significantly outperformed a demographic-based baseline in recommendation relevance (mean score 4.15 vs. 3.50, $p < 0.001$, Cohen's $d = 0.58$).
- **User Perception**: Users reported feeling "personally understood," highlighting the system's ability to surface implicit motivations not captured by traditional methods.

5.2 Contribution to Literature

- **Cold-start and Data Sparsity Mitigation**: Unlike traditional content/collaborative filtering, LLMs can provide accurate recommendations for new users by focusing on psychological narratives.
- **Innovative Use of Unstructured Data**: This study leverages LLMs for scalable, efficient inference of user traits from open-ended responses, bypassing lengthy structured questionnaires.
- **Adaptive Personalization Potential**: LLMs support dynamically evolving user profiles, enabling real-time feedback loops and personalization updates.

5.3 Theoretical Implications

- **Tourism Psychology**: Validates digital applications of Big Five and Plog's tourist typologies using LLMs, opening new pathways for AI-augmented motivational analysis.
- **Recommender Systems**: Expands taxonomy to include implicit psychological analysis as a foundation for user profiling.
- **AI and NLP**: Demonstrates LLM capabilities in semantic reasoning and psychological inference within domain-specific contexts.

5.4 Practical Implications

- **Tourist Satisfaction and Loyalty**: Personalized suggestions increase engagement and the likelihood of repeat visits.
- **Precision Marketing**: Psychographic data enables segmentation and targeting beyond demographics.
- **Product Innovation**: Data-driven insights guide development of new tourism experiences.
- **Operational Efficiency**: Streamlined service and marketing resource allocation.

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5.5 Limitations

- **Sample Size**: Findings based on 80 participants; broader validation needed.
- **LLM Bias**: Potential for bias inherited from training data; requires further scrutiny and mitigation.
- **Psychometric Validation**: Formal psychometric evaluation (e.g., test-retest reliability, construct validity) remains to be conducted.
- **Scalability Costs**: Sustaining LLM-based analysis at commercial scale may be cost-intensive.
- **Context Specificity**: Currently limited to Lagoi; adaptation needed for other destinations.

5.6 Future Research Directions

- **Longitudinal Impact Studies**: Track long-term satisfaction, repeat visits, and loyalty metrics.
- **Domain-Specific LLM Fine-tuning**: Train LLMs on localized tourism narratives to enhance profiling accuracy.
- **Multimodal AI Integration**: Combine LLMs with visual/audio inputs and real-time user behavior.
- **Sustainability Impact Analysis**: Evaluate environmental and socio-economic outcomes.
- **Cross-cultural Validation**: Test model adaptability across regions and cultural backgrounds.
- **Collaborative Trip Planning Features**: Develop social and group-based personalization functionalities.

6. Conclusion

The study successfully designed and implemented a functional prototype of a web-based tourism recommender system that integrates psychological testing with Large Language Models (LLM), specifically in the context of the Lagoi tourism area. Findings indicate that LLMs are highly capable of interpreting nuanced psychological profiles from narrative responses, offering deeply personalized and contextually relevant travel recommendations. The system demonstrated a significant 18.5% improvement in recommendation relevance over demographic-based baselines (mean score 4.15), confirming the added value of psychological AI-driven personalization. Beyond user satisfaction, the system offers strategic insights to tourism stakeholders for targeted marketing and experience design, highlighting the transformative potential of LLM-enhanced personalization in the travel sector.

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