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Personalized Skincare Recommendation System Based on Ontology and User Preferences

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Abstract

Personalized skincare product selection remains a complex but critically important challenge, as tailoring recommendations to individual skin profiles directly enhances treatment efficacy and fosters consumer trust. Traditional systems, such as content-based and collaborative-filtering, often fail to capture semantic interactions among skin types, concerns, and ingredients. To address these limitations, we propose an innovative ontology-based skincare recommendation system that integrates structured dermatological knowledge with semantic reasoning. Leveraging the Methontology framework, we developed an ontology composed of twelve core classes such as Product, Ingredient, Skin Type, and Skin Concern and more than twenty-five object properties to model interrelated concepts. The knowledge base was populated via web scraping from three prominent platforms (Sociolla, Beautyhaul, Skinsort), yielding over 3,800 products and 28,000 ingredients. We augmented this dataset with dermatological literature to ensure clinical validity. The architecture employs Apache Jena Fuseki and SPARQL for inference, with a React-Node.js web interface. Users input skin type, concerns, and sensitivities, which are translated into RDF triples and processed through semantic rules to generate personalized recommendations. An evaluation based on the Technology Acceptance Model (TAM) assessed Perceived Usefulness and Ease of Use. Ten diverse respondents rated the system with an average score of 4.5 out of 5 (SD = 0.3) and endorsed the relevance of recommendations with a score of 4.8. Our findings demonstrate that semantic technologies can significantly enhance personalization and transparency in skincare solutions. This work lays a robust foundation for future innovations in beauty technology, clinical decision support, and consumer health platforms.

I. INTRODUCTION

Skin, the body's largest organ, plays a vital role in protecting internal systems from environmental stressors. Over the past decade, growing awareness of personal health and appearance has led to a surge in demand for skincare products. These products, ranging from moisturizers to serums containing active ingredients, are not only used to maintain healthy skin, but also to address specific conditions such as dryness, acne, or hyperpigmentation [1], [2]. While the market offers an increasingly wide variety of skincare solutions, users often find it difficult to identify products that suit their individual needs. Skin conditions vary greatly across individuals, and even people with similar profiles may respond differently to the same product. The personalization of skincare, therefore, cannot rely solely on general recommendations or influencer reviews, which frequently lack scientific grounding [3]. Personalized recommendations improve consumer trust and adherence to regimens by addressing individual concerns, leading to greater compliance and measurable improvements in skin health.

To support users in selecting appropriate products, recommendation systems have gained significant traction in recent years. Traditional methods, such as content-based filtering (CB) and collaborative filtering (CF), have been widely adopted in domains like e-commerce and media platforms. These methods use historical data to match users with products based on either item characteristics or user behavior. However, in the skincare context, these approaches exhibit notable limitations. CB techniques primarily focus on basic similarities, often relying on

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matching keywords or analyzing text statistics (such as TF-IDF), but they struggle to account for the deeper, more complex relationships between ingredients, their functions, and the specific skin concerns they address [4], [5]. Furthermore, CF methods are heavily reliant on user history and large datasets, making them prone to common issues like cold-start problems, where new users or products lack sufficient data for recommendations, and data sparsity, which limits the system's ability to make accurate suggestions [6]. Beyond these theoretical constraints, users miss out on clear, actionable guidance for their daily routines—undermining both the ease of use and long-term adherence to skincare regimens.

In contrast, ontology-based recommendation systems provide a more structured, knowledge-driven solution to this problem. Ontologies enable the formal modeling of concepts and relationships in a specific domain, such as skin types, skin concerns, ingredients, and product categories, facilitating a more holistic understanding of how various elements interact within the skincare ecosystem [7], [8], [9]. By integrating domain-specific knowledge into a machine-readable structure, these systems can reason about how different skincare components are connected, going beyond surface-level similarities to provide semantic understanding. This approach not only offers more relevant and explainable recommendations but also enhances the overall accuracy of product suggestions by recognizing the nuanced interactions between skin types, ingredients, and concerns. Practically, consumers benefit from tailored daily-care plans—complete with specific product pairings and usage schedules that seamlessly integrate into their routines, improving both efficacy and user satisfaction. This level of personalization and transparency is crucial, especially in health-related domains like skincare, where the impact of product choices can vary widely across individuals.

Despite the potential benefits, existing ontology-based systems in the skincare domain remain relatively narrow in scope. Many of these systems focus primarily on simple relationships, such as linking a product to a specific skin type or matching an ingredient to a known benefit, without considering the more complex, dynamic interactions that may occur between multiple ingredients, skin conditions, and usage patterns [2]. Additionally, reasoning capabilities—arguably the core strength of ontology-based systems—are often underutilized. Many implementations treat ontologies as static taxonomies, rather than leveraging them as dynamic, inferential knowledge bases that can evolve and adapt based on new data and user feedback. This underutilization of reasoning capabilities results in systems that provide limited insight into the personalized skincare needs of users, often overlooking the complex interplay of various factors that influence product effectiveness.

This study aims to address these limitations by proposing a comprehensive ontology-based skincare recommendation system. The system integrates structured domain knowledge, including detailed information about ingredient properties, skin conditions, and product categories, and uses an ontology designed to facilitate semantic reasoning. By formalizing these key aspects of the skincare domain, this system allows for more accurate, relevant, and explainable recommendations. The system accepts user input such as skin type and concerns—and returns personalized product recommendations based on the semantic understanding of the user's needs. The approach goes beyond traditional keyword-based matching by inferring deeper connections between ingredients, concerns, and skin types, providing a more robust and tailored recommendation process.

To assess user acceptance of the proposed system, the Technology Acceptance Model (TAM) is employed, focusing on perceived usefulness and ease of use as key factors. The results from this evaluation provide insight into the system's effectiveness from a user experience perspective, and its potential to improve the skincare product selection process for users with varying needs and preferences. By combining structured domain knowledge with semantic reasoning capabilities, the proposed system aims to improve not only the accuracy and relevance of skincare recommendations but also to build user trust in the recommendations. This study therefore contributes to the growing field of knowledge-based recommendation systems, demonstrating how semantic technologies can be applied effectively in real-world consumer applications, particularly within the rapidly expanding beauty technology and consumer health platforms.

II. Literature Review

As recommendation systems evolve across various domains, new approaches are required to better handle domains that involve complex, multidimensional decisions, such as skincare. Instead of relying solely on historical preferences or text similarity, recent research has explored ways to enhance recommendation accuracy through structured domain knowledge. One promising direction is the use of ontology-based systems, which differ from conventional methods by embedding semantic relationships directly into the recommendation engine.

Ontology-based recommendation systems model knowledge using explicitly defined concepts and relationships among domain entities, enabling richer interpretation and logical reasoning. In the context of skincare, this includes mapping connections between ingredients, skin types, product categories, and specific skin concerns [7], [8]. Unlike content-based filtering (CB) or collaborative filtering (CF), ontology-based systems can understand hierarchical and functional relationships, enabling them to recommend products based on conceptual relevance rather than statistical correlation.

In educational domains, for instance, ontologies have improved learner-content matching by formally representing pedagogical goals and user profiles [10]. A systematic review by [11] confirmed that ontologies have been successfully integrated with AI to enhance personalization and reasoning across diverse domains, including education, computing, and social sciences. In these contexts, ontology reuse and modular construction have further supported system scalability and adaptability [12].

Within the skincare industry, AI-driven systems using deep learning, such as convolutional neural networks (CNNs) [13], have shown promising results in classifying skin types or detecting dermatological conditions from images [14], [15]. However, these systems tend to lack interpretability. The opaque nature of deep learning models limits users' understanding of why specific products are recommended, reducing trust in health-related decisions. Ontology-based systems, by contrast, allow for transparency and explainability, aligning better with the personalized yet sensitive nature of skincare recommendations.

Despite this potential, most ontology-based skincare systems remain limited in scope. Current models often rely on fixed one-to-one mappings, such as linking a product to a skin concern or an ingredient to a function, without capturing the dynamic interactions among multiple ingredients or conditions [16]. Reasoning engines are typically underutilized, reducing the system's ability to provide adaptive or user-aware recommendations. Additionally, few systems incorporate user feedback to improve their knowledge base or adapt to changing user needs over time.

In summary, while ontology-based recommendation systems offer significant advantages in terms of semantic richness and explainability, their application in skincare is still underdeveloped. Future systems must address the complexity of ingredient interactions, model more nuanced user profiles, and leverage reasoning more effectively. This study aims to contribute by building a domain-specific ontology that integrates active ingredients, skin characteristics, and product knowledge into a coherent, inferential framework for personalized recommendations.

III. METHODS

This study employs a structured approach to develop a personalized skincare recommendation system, leveraging an ontology-based framework [17]. The primary objective is to enhance the relevance, accuracy, and explainability of skincare recommendations by formally and semantically modeling domain-specific knowledge [18]. To guide the development process, the Software Development Life Cycle (SDLC) was adopted, utilizing a modified waterfall methodology. Figure 1 illustrates the stages of this methodology. The methodology consists of four main stages: requirement analysis, system design, implementation, and evaluation [19]. Each phase is described in detail below.

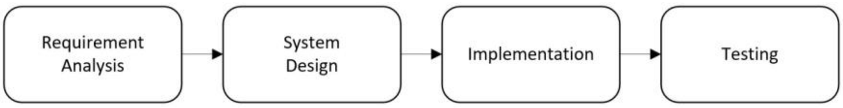


Fig. 1 Waterfall method

A. Requirement Analysis

The first phase of the study involved identifying both functional and non-functional requirements through a comprehensive literature review of existing skincare recommendation systems, ontologies, and relevant domain-specific factors. This phase was supplemented by a user survey, which aimed to capture key factors influencing skincare product selection, such as ingredient compatibility, skin type requirements, and specific skin concerns. The survey results highlighted these elements as central to the user's decision-making process. To ensure domain relevance, we mapped survey-identified factors to real-world practices by consulting dermatologists and industry guidelines, which informed the eventual selection of 12 core classes (e.g., Product, Ingredient, Skin Type, Skin Concern, Formulation, ApplicationFrequency) that directly reflect typical clinician and consumer decision points. The findings from this phase ensured that the system's design would address critical user needs while maintaining a robust scientific basis and maintaining accuracy in product recommendations based on ingredient profiles [20].

B. System Design

During the system design phase, the ontology was developed using the Methontology framework, a widely recognized methodology for structured ontology development [21]. This framework guided the identification of core classes and properties within the skincare domain. The 12 main classes were chosen by (1) aligning with dermatological taxonomy (e.g., mapping 'Skin Type' to Fitzpatrick categories), (2) reflecting consumer-facing concepts (e.g., 'Skin Concern' covering acne, dryness, sensitivity), and (3) validating against product labeling standards (e.g., 'Formulation' to capture lotion, serum, cream distinctions). Furthermore, object properties (e.g., treatsConcern, suitableForSkinType) and data properties (e.g., BPOMNumber, IngredientName) were defined to capture the intricate semantic relationships inherent in the domain. These relationships were represented within the ontology to facilitate semantic reasoning.

The ontology was modeled using Protégé, an open-source ontology editor frequently employed for OWL-based ontology creation. In parallel with the ontology design, wireframes and data flow diagrams were developed to define the structure and user interface of the web application. These design tools ensured that the interface was intuitive, and that the interaction between the user's input and the reasoning system was seamless and user-friendly.

C. Implementation

The implementation phase involved two major components: (1) constructing the ontology-based knowledge base, and (2) integrating the ontology with the web-based application.

To populate the ontology, web scraping techniques were employed to extract data from prominent Indonesian skincare platforms, including Sociolla, Beautyhaul, and Skinsort. The scraped data included product names, descriptions, active ingredients, usage instructions, and skin compatibility information. Raw data underwent a multi-step preprocessing pipeline: duplicates were removed, ingredient names were standardized via a controlled vocabulary, missing values were imputed using domain heuristics, and outliers (e.g., extreme ingredient counts) were flagged for manual review. Challenges such as inconsistent HTML structures and rate-limiting by target sites were mitigated by implementing adaptive parsing rules and respectful delays, ensuring data integrity and compliance with platform usage policies. Additionally, relevant dermatological and cosmetic literature was reviewed to further enhance the depth and accuracy of the knowledge base.

The web-based recommendation system was developed using the React framework for the frontend and Node.js for the backend, ensuring a responsive and scalable application. PostgreSQL, a highly robust and flexible relational database, was utilized to manage the data efficiently. The backend communicates with the ontology via SPARQL queries, enabling the system to infer relevant product recommendations based on user inputs. For instance, when a user indicates their skin type and concerns (e.g., oily skin with acne), the system reasons over the ontology to identify suitable ingredients, which are then mapped to products containing those ingredients. This reasoning process ensures that the recommendations are personalized and semantically grounded.

D. Evaluation

The evaluation phase focused on both functional testing and user experience assessment. Functional testing was conducted to verify that each component of the system performed as expected, particularly in terms of the accuracy and reliability of the product recommendations. Additionally, user acceptance was evaluated using the Technology Acceptance Model (TAM), a widely used framework for assessing system usability and perceived value [22]. Two key constructs were evaluated: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). The TAM framework has been found to significantly influence technology adoption, where PU typically exerts a stronger impact than PEOU [23].

Ten participants with diverse age, gender, and skin type profiles interacted with the system and completed a Likert-scale questionnaire to assess their satisfaction and the perceived value of the system. The results from this evaluation provided valuable insights into user acceptance and the practical utility of the system in real-world scenarios.

E. Methodological Rationale

The methodology chosen for this study combines structured system development with formal knowledge representation. By embedding reasoning capabilities into the system architecture, the proposed solution aims to deliver personalized, accurate, and explainable skincare recommendations that exceed the capabilities of conventional recommendation methods. The approach leverages the power of semantic reasoning to move beyond simple keyword matching or user behavior-based recommendations, offering a more scientifically grounded and personalized solution. This methodology ensures that the system not only provides more relevant and accurate recommendations, but also builds trust with users through transparency and explainability.

IV. RESULTS

The data for this study were collected from three publicly accessible skincare platforms: Sociolla, Beautyhaul, and Skinsort. Sociolla and Beautyhaul were chosen due to their prominence and extensive product coverage in the Indonesian market, offering a diverse catalog of skincare products from both local and international brands. Skinsort, on the other hand, was selected for its detailed and structured information on cosmetic ingredients, including descriptions, functions, and potential effects. Among various ingredient databases, Skinsort was also the most accessible for data extraction.

Data scraping was conducted using the BeautifulSoup Python library, which was selected for its efficiency in parsing and navigating HTML/XML structures. On Sociolla and Beautyhaul, data was extracted from skincare-specific pages that contain rich product catalogs. The extracted data included product name, brand, description, image URL, ingredient list, and usage instructions. In contrast, the scraping of Skinsort involved traversing multiple ingredient index pages, retrieving each ingredient's name, function, and explanation. In total, the dataset comprises more than 3,800 skincare product entries from Sociolla and Beautyhaul and over 28,000 ingredient records from Skinsort.

This study resulted in the development of a web-based skincare recommendation system that leverages an ontology-driven approach. The system was designed to provide personalized product suggestions by considering users' skin types and specific skin concerns. The ontology was developed to represent the relationships formally between skincare products, ingredients, skin types, and conditions [24]. In this section, we present the implementation results of both the ontology and the recommendation system, as well as the outcomes of system testing using the Technology Acceptance Model (TAM).

A. Ontology Implementation

The ontology was constructed using Protégé and followed the Methontology methodology. The structure of the ontology was designed based on real-world product and ingredient data collected from Sociolla and Beautyhaul, both of which categorize skincare products based on skin type and skin concerns. These categories formed the foundation for modeling the domain knowledge. The ontology comprises 12 main classes: User, Product, Brand, Product Category, Allergen Type, Ingredient, Benefit, Formulation Trait, Key Ingredient, Skin Concern, Skin Type, and What It Does. Relationships among these classes were defined through object properties such as belongsToBrand, connecting Product to Brand, and containsIngredient, linking Product to specific Ingredient instances. These connections allow the system to reason not just by product labels but by the functional and dermatological implications of ingredient compositions. Figure 2 shows the high-level ontology structure that connects core entities through well-defined object properties that enable logical reasoning.

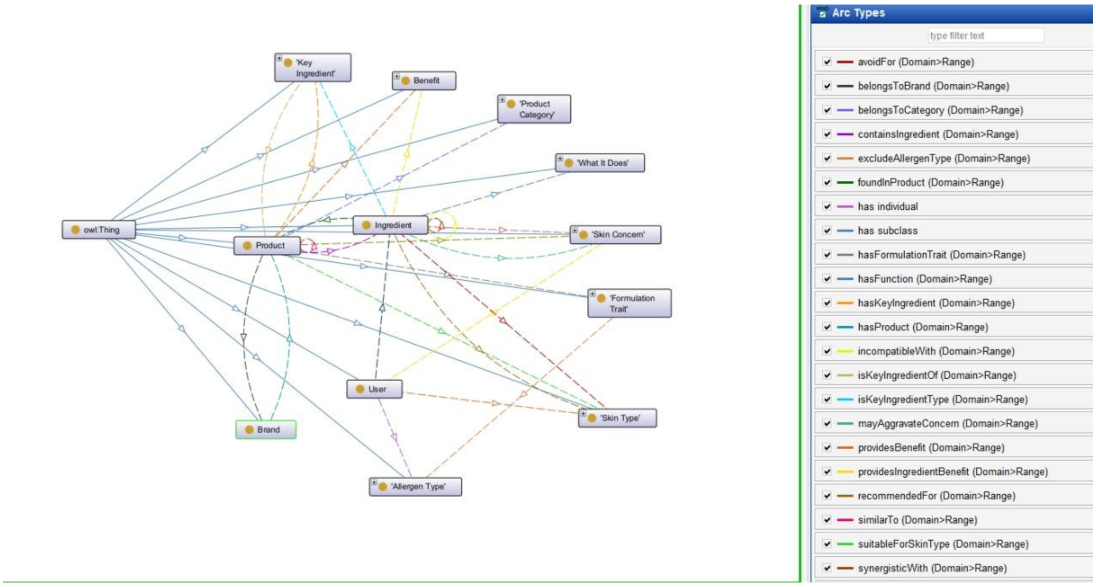


Fig. 2 High-level ontology structure of skincare domain showing main classes and relationships

Figure 2 illustrates the ontology structure designed for the skincare recommendation system. This ontology models essential concepts such as Product, Ingredient, Skin Type, Skin Concern, and Allergen Type, among others, and maps their semantic relationships through well-defined object properties. Each class in the ontology represents a core entity in the skincare domain:

1. Product and Ingredient are the most central classes, linked through the property containsIngredient.
2. The Skin Type and Skin Concern classes help model user-specific needs, connected via relationships such as recommendedFor, incompatibleWith, and mayAggravateConcern.
3. Brand and Product Category allow further classification of products through belongsToBrand and belongsToCategory.
4. Additional domain knowledge is encoded using properties like providesBenefit, hasFunction, and hasFormulationTrait, which capture the functional characteristics of ingredients.
5. The class User is used to represent personalized user input, which can be aligned with entities such as Skin Type and Allergen Type.

The arrows in the diagram represent object properties that connect one class (domain) to another (range), enabling inference over product suitability. For instance, the system can infer that a product should be avoided if an ingredient is incompatibleWith a user's skin type, or that it may be recommended if it providesBenefit for a particular concern.

The ontology, built using Protégé, leverages 25+ object properties as shown on the right side of the figure, including foundInProduct, avoidFor, synergisticWith, and suitableForSkinType. These relationships form the foundation of the recommendation logic, ensuring the output is not only personalized but also explainable and semantically valid.

This structure empowers the recommendation engine to perform more advanced reasoning, allowing it too beyond basic keyword matching and instead deliver recommendations based on conceptual understanding of skincare science.

To demonstrate the depth and completeness of the semantic modeling, Figure 3 presents the full OntoGraph generated using Protégé. This visualization includes all relevant classes, individuals, and object properties, illustrating how the domain knowledge is represented and interlinked. The OntoGraph highlights the ontology's ability to support nuanced reasoning by mapping both hierarchical and associative relationships across the skincare ecosystem. This robust semantic structure forms the foundation of the recommendation engine implemented in this study.

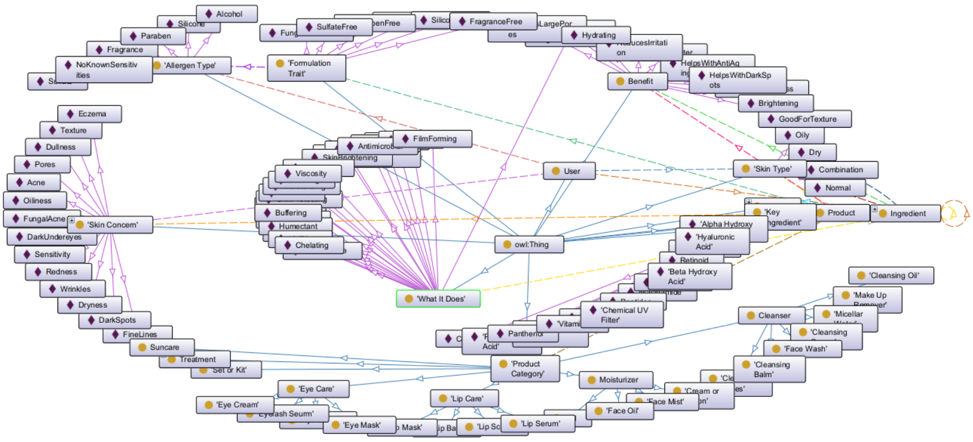


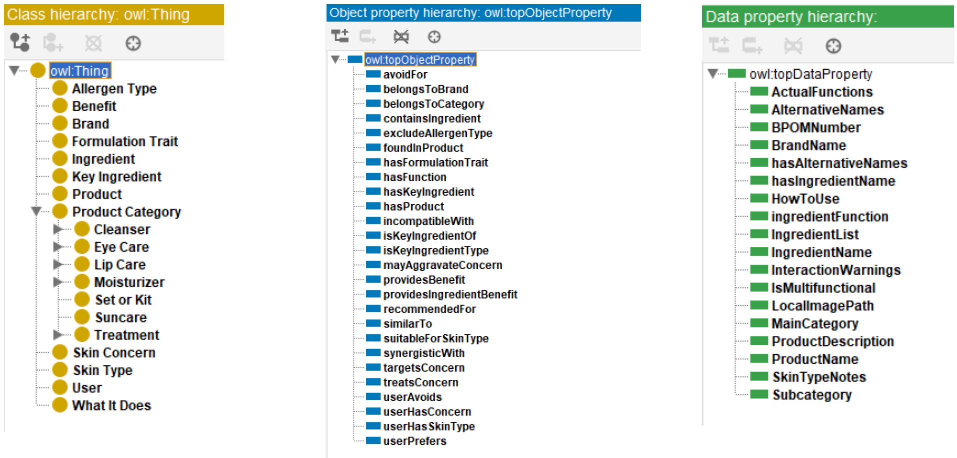
Fig. 3 Complete OntoGraph of the skincare ontology showing subclasses, individuals, and object properties

Figure 3 presents the complete OntoGraph view of the skincare ontology, offering a detailed visualization of all classes and individuals along with their semantic interconnections. This diagram showcases the rich structure of domain knowledge curated in the ontology, including instances of ingredients, skin types, skin concerns, formulation traits, product categories, and the functional relationships among them. In this graph:

1. Individual ingredients such as *Alcohol*, *Paraben*, and *Niacinamide* are linked to specific formulation traits and benefits.
2. The Skin Concern class contains various instances such as *Acne*, *Dryness*, *Redness*, and *Hyperpigmentation*, each of which may be influenced or treated by ingredients based on properties like providesBenefit, mayAggravateConcern, or incompatibleWith.
3. Product categories such as *Toner, Moisturizer, Serum, and Cleanser* are organized under the Product Category class and connected to the Product class.
4. The What It Does class connects multiple functional descriptions (e.g., *Hydrating*, *Soothing*, *Brightening*) that are semantically linked to both product and ingredient classes.
5. User personalization is incorporated through the User class, which interacts with other entities via their associated preferences, skin characteristics, and concerns.

The OntoGraph representation helps validate the integrity and coverage of the ontology model, ensuring that the system has sufficient semantic context to reason about complex user needs and product suitability. It also reveals the depth of representation by highlighting how various subclasses, object properties, and instances interact in a meaningful hierarchy. This structure allows the ontology to go beyond static classification by supporting dynamic inference during recommendation generation.

Through this visual model, the system can infer, for example, that a moisturizer containing Niacinamide may benefit a user experiencing hyperpigmentation, while also warning users with sensitivities to specific allergens or ingredients. This ability to represent both positive and negative interactions gives the ontology a significant advantage over traditional flat data structures.



(a) (b) (c)

Fig. 4 (a) Class structure; (b) Object Properties; (c) Data Properties

Figure 4(a) presents the class hierarchy, including twelve top-level classes, where the ProductCategory class branches into specific types such as cleansers, moisturizers, and serums. Figure 4(b) shows the object properties defined to connect domain entities, with 25+ object properties implemented to capture complex semantic relationships. These structured definitions enable the ontology to serve as a rich knowledge base for semantic reasoning, thus enhancing the relevance of the recommendation output. In addition to the object properties that define semantic relationships between classes, the ontology is enriched with a set of data properties that provide specific literal information for each individual within the domain. These data properties describe attributes such as product metadata, ingredient details, and usage guidelines. For instance, ProductName, BrandName, ProductDescription, and LocalImagePath are used to store textual and visual representations of each skincare item. Properties such as IngredientName, ingredientFunction, and InteractionWarnings are designed to capture the function and potential reactions of active ingredients, supporting the reasoning process during recommendation.

Other supporting properties include BPOMNumber, which indicates product registration in the Indonesian regulatory body, MainCategory and Subcategory for product classification, and SkinTypeNotes to document specific considerations for different skin types. The presence of IsMultifunctional, ActualFunctions, and HowToUse further enhances the ontology's capacity to deliver informative and personalized recommendations. The full list of data properties used in this ontology is shown in Figure 4(c), reflecting a comprehensive structure for both knowledge representation and user-facing data delivery.

B. System Implementation

The recommendation engine was implemented using Apache Jena Fuseki as the primary reasoning engine and SPARQL as the query language. This setup was selected for its robustness in handling semantic reasoning tasks over structured domain knowledge.

The recommendation system was developed as a web application using React for the frontend interface and Node.js for the backend. The system interacts with the ontology to infer suitable products based on user input. Users can either answer a quiz to determine their skin type or directly input their specific concerns and preferences. The reasoning engine processes these inputs and queries the ontology to retrieve a curated list of product recommendations.

The system begins by converting the user's skin quiz inputs into RDF triples compatible with the ontology. For example, a user with "Skin Type: Dry", "Skin Concern: Acne", and "Sensitivity: Alcohol" is represented semantically within the knowledge base. Through defined object properties—such as `suitableForSkinType`, `treatsConcern`, `incompatibleWith`, and `avoidFor`—the system performs logical inference to determine a list of safe and suitable product recommendations.

The ontology backend was integrated using OWL APIs, while PostgreSQL was employed to store complementary data such as user feedback and interaction logs. The user interface (Figure 5) was designed to be intuitive, offering clear navigation and product descriptions enriched by ontology-derived metadata.

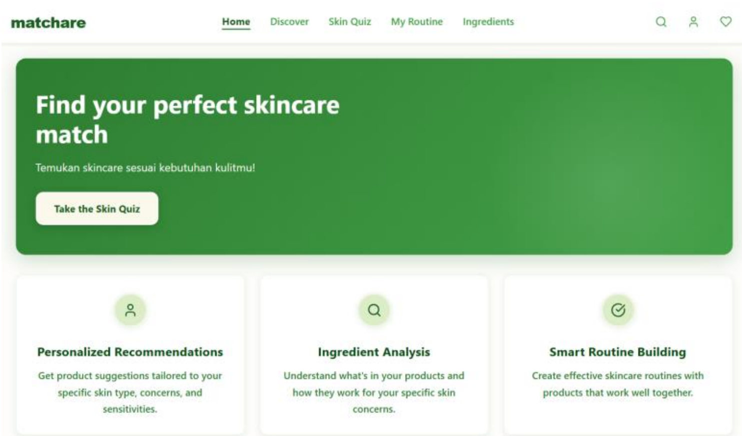


Fig. 5 Recommendation system landing page

C. System Evaluation

The Technology Acceptance Model (TAM) was adopted to evaluate the system due to its effectiveness in assessing user acceptance and intention to use [25]. System testing involved ten participants who interacted with the system and completed a TAM-based questionnaire measuring two key indicators: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), which help quantify how users perceive the practical benefit and usability of the system [26]. This approach is particularly suitable given the goal of the system to assist non-expert users in making informed skincare decisions.

To evaluate user acceptance of the developed system, feedback was gathered from ten respondents with diverse backgrounds in age, gender, and skin types. The majority of respondents were female, with a small proportion of male participants. Age distribution spanned across three categories: under 17, 17–25, and 26–35 years old. The variety in skin types included oily, dry, normal, combination, and even users who were unsure of their skin type, reflecting a realistic representation of skincare users in the target demographic. Respondents' demographic data are shown in Table 1.

TABLE 1
RESPONDENTS' DEMOGRAPHIC DATA

Respondent	Age Range	Gender	Skin Type	Average Score
Respondent 1	17–25	Female	Combination	4.5
Respondent 2	17–25	Female	Normal	4.5
Respondent 3	26–35	Female	Oily	4.3
Respondent 4	17–25	Female	Dry	4.5
Respondent 5	26–35	Male	Normal	4.5
Respondent 6	<17	Female	Normal	4.5
Respondent 7	<17	Female	Unknown	4.8
Respondent 8	26–35	Female	Combination	4.6
Respondent 9	<17	Female	Oily	4.5
Respondent 10	17–25	Male	Oily	4.1

The evaluation utilized a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Each respondent interacted with the recommendation system and provided feedback based on their experience, particularly reflecting on aspects aligned with the Technology Acceptance Model (TAM): perceived usefulness and perceived ease of use. The average rating across all participants was 4.5 out of 5, indicating a generally high level of satisfaction. Notably, even users unfamiliar with their own skin type were able to navigate the system and found the recommendations relevant, which underscores the system's usability and accessibility. The results are summarized in Table 2.

TABLE 2
TEST SUMMARY

Variable	Statement	Score
Perceived Usefulness	The system helps me find suitable products	4.8
	The recommendations are relevant to my skin needs	4.4
	It improves the efficiency of my product search	4.6
Perceived Ease of Use	The system is easy to operate	4.4
	The interface is easy to understand	4.3
	The navigation process is not confusing	4.4

The results show that all indicators received average scores above 4.0, with the highest being "*The system helps me find suitable products*" at 4.8. These findings suggest that users found the system both useful and easy to use. The semantic structure enabled by the ontology allowed the system to provide recommendations that were perceived as more accurate than traditional keyword-matching techniques.

Compared to traditional approaches like content-based (CB) or collaborative filtering (CF), the ontology-based system developed in this study offers greater adaptability and domain awareness. CB methods usually use statistical measures (like TF-IDF) to match ingredients, but they don't understand the meanings behind the ingredients or follow specific rules about how they interact or their suitability for skin. Meanwhile, the need for large historical datasets limits CF techniques and prevents them from incorporating expert dermatological knowledge, which is crucial for safety-aware recommendations.

The ontology-based system addresses these limitations by explicitly modeling domain knowledge using object properties such as treatsConcern, incompatibleWith, synergisticWith, and avoidFor. These relationships enable the system to reason about product suitability not only based on ingredient presence but also on how ingredients behave in combination and interact with different skin conditions.

V. DISCUSSION

The development of an ontology-based skincare recommendation system presented in this study demonstrates the advantages of integrating structured domain knowledge with semantic reasoning to provide more personalized, safe, and explainable recommendations. Unlike traditional approaches such as content-based filtering (CB) and collaborative filtering (CF), which rely heavily on statistical similarity or user behavior history, the proposed system embeds dermatological knowledge directly into its logic using ontological representations. Semantic reasoning enables the system to infer emergent properties from dynamic interactions such as how certain ingredient combinations may synergize to enhance efficacy or, conversely, trigger adverse reactions by traversing multi-hop relationships in the ontology. This knowledge is formalized through object properties like treatsConcern, incompatibleWith, synergisticWith, and avoidFor, enabling a deeper understanding of product suitability that considers not only ingredient presence but also their interactions and appropriateness for specific skin types or concerns [7].

Compared to CB methods, which often struggle to account for the semantic relationships among ingredients or provide medically relevant justifications for recommendations, the ontology-based system enables richer inference. By modeling and reasoning over properties such as “synergisticWith” and “incompatibleWith,” the system can predict how combinations of ingredients will interact under different skin conditions, offering explanations grounded in dermatological science. This is especially valuable in skincare, where product suitability involves complex considerations such as allergen warnings, formulation traits, and contraindications. Similarly, CF approaches, which depend on collaborative patterns in user feedback, face limitations in cold-start scenarios and cannot incorporate explicit domain knowledge, reducing their reliability in contexts that demand precision and safety [9].

The evaluation using the Technology Acceptance Model (TAM) supports the effectiveness of the system. The high average rating of 4.5 across all TAM indicators reflects strong user confidence in both the system’s usefulness and usability. Notably, the highest rating was observed for “The system helps me find suitable products,” indicating that users recognized the value of the ontology-driven logic in navigating the vast skincare product space. Even users unfamiliar with their skin type were able to interact successfully with the system, showing its accessibility to novice users [22].

Additionally, the ontology structure itself comprising 12 major classes and over 25 object properties—shows a robust semantic framework that supports diverse reasoning scenarios. The visualizations (Figures 2 and 3) illustrate the system's ability to represent and interlink dermatological knowledge, product categories, and user profiles. The OntoGraph representation further validates the comprehensiveness and integrity of the ontology model, providing a strong foundation for explainable AI in skincare recommendations.

Looking ahead, the system’s capabilities could be further expanded by integrating machine learning algorithms such as reinforcement learning to adjust recommendation weights based on long-term user satisfaction, or supervised models trained on user feedback to predict outcome metrics like skin improvement scores. Implementing a continuous feedback loop, where user-reported outcomes and preferences dynamically update the ontology and inference rules, would refine personalization over time and adapt to evolving consumer needs.

Ultimately, this study not only demonstrates the technical feasibility of using ontologies for skincare recommendations but also highlights their superiority in terms of reasoning capability, safety awareness, and user trust when compared to traditional techniques.

VI. CONCLUSION

This study successfully developed an ontology-based skincare recommendation system that integrates domain-specific knowledge to offer personalized and explainable product suggestions. By embedding semantic reasoning directly into the recommendation engine through multi-hop inference over relationships such as synergisticWith, incompatibleWith, and treats Concern the system delivers recommendations with greater relevance and transparency than traditional content-based or collaborative filtering approaches, which typically rely on surface-level similarity or aggregate user behavior. Evaluated using the Technology Acceptance Model (TAM), the system demonstrated a high level of user satisfaction, with an average rating of 4.5 out of 5, highlighting its effectiveness in meeting individual skin condition and concern needs.

While the system performs well in its current form, there are several opportunities for enhancement. Future improvements could include the incorporation of user feedback loops—where real-world outcome data continuously refines both ontology structure and inference rules and the integration of machine learning models to predict long-term skin health outcomes and optimize recommendation weights. Moreover, extending this semantic-reasoning framework to other consumer health domains such as personalized nutrition, mental wellness applications, or medication adherence tools could inspire a new generation of transparent, knowledge-driven recommendation systems across the broader landscape of personalized health technologies.

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