IMPLEMENTATION OF A HYBRID FUZZY SAW AND PARTICLE SWARM OPTIMIZATION ALGORITHM FOR A DYNAMIC LAPTOP RECOMMENDATION SYSTEM BASED ON USER PREFERENCES

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Abstract - Recommendation systems often struggle to balance personalization with fairness, particularly in addressing the marginalization of minority brands caused by data and algorithmic biases. This study tackles that challenge by developing a dynamic laptop recommendation system tailored to user preferences, leveraging a hybrid algorithm that combines Fuzzy Simple Additive Weighting (Fuzzy SAW) and Particle Swarm Optimization (PSO). Fuzzy SAW is employed to manage uncertainties in subjective preferences such as budget and intended use, while PSO dynamically optimizes the weight of each criterion to enhance personalization. Evaluation was conducted using primary data from 27 respondents in Lhokseumawe, Aceh, collected via surveys and interviews, alongside secondary data on laptop specifications retrieved from the Tokopedia API. The resulting match accuracy reached 74.1%, with Asus accounting for 85.0% of the successful recommendations. In contrast, brands like Lenovo and Advan were significantly underrepresented, underscoring the system's limited sensitivity to minority brands. This research contributes to the field of recommendation systems by empirically demonstrating the trade-off between optimization and fairness, as well as proposing strategies to mitigate algorithmic bias. Practical implications include better-informed user decisions and fairer brand exposure for e-commerce platforms. Future improvements will focus on expanding data sources and refining PSO parameter tuning to better accommodate underrepresented brands.

Keywords: Hybrid recommendation system, Fuzzy SAW, Particle Swarm Optimization, algorithmic fairness, brand bias, sensitivity analysis, minority brands

I. INTRODUCTION

The rapid advancement of technology has driven manufacturers to offer a highly diverse range of laptop products in terms of specifications, features, and price. Consequently, many consumers, especially in local contexts like Lhokseumawe, who may lack in-depth technical knowledge, face difficulties in choosing the most suitable laptop for their specific needs. This challenge is reinforced by previous research highlighting consumer confusion amidst the abundance of market options. The research problem is rooted in the difficulty faced by non-expert users in translating their functional needs (e.g., "for graphic design work" or "for online lectures") into relevant technical specifications (e.g., processor type, RAM capacity, or graphics card type). This difficulty often leads to choice paralysis or suboptimal purchasing decisions, which ultimately reduces user satisfaction and the product's utility value [1]. To address this issue, an intelligent recommendation system becomes a relevant solution. This study proposes the use of a hybrid algorithm that combines Fuzzy Simple Additive Weighting (Fuzzy SAW) and Particle Swarm Optimization (PSO) [2]. Fuzzy SAW was chosen for its ability to handle multi-criteria evaluation involving uncertainty, such as subjective user preferences [3]. Meanwhile, PSO is used to dynamically optimize the criteria weights, allowing the system to adapt to changing user preferences.

The scope of this research includes the collection of primary data from 27 respondents in the Lhokseumawe area to understand user preferences, as well as the use of secondary data from the Tokopedia e-commerce API as the sole source of product specifications. This limitation inherently affects the variety of brands and data available for the system to analyze.
Explicitly, the contributions of this research are as follows:

1. To implement and evaluate the performance of the hybrid Fuzzy SAW-PSO algorithm for a laptop recommendation system within a specific local user and market context.
2. To present a critical analysis of the model's performance that not only measures accuracy but also uncovers significant brand bias, thereby offering valuable insights for the future development of fairer and more balanced recommendation systems.

This research has practical and theoretical significance that can be elaborated as follows:

1. For End-Users: Practically, this system offers a tool that can measurably improve users' purchasing decisions. By translating often ambiguous preferences (e.g., "flexible budget" or "need for multitasking") into concrete, data-driven product recommendations, the system has the potential to reduce post-purchase dissonance and ensure the chosen laptop better aligns with actual needs.
2. For E-commerce Platforms: The implication for platforms like Tokopedia is the highlighting of an opportunity to integrate more sophisticated and fair recommendation engines. The analysis of brand bias shows that algorithms focusing solely on accuracy optimization can inadvertently reduce the visibility of minority brands. By implementing bias mitigation strategies, platforms can enhance the user experience, guide purchasing decisions more equitably, and potentially increase conversion rates across a wider variety of products.
3. For Laptop Manufacturers: The brand sensitivity analysis in this study provides insights for manufacturers, especially minority brands. The research findings illustrate the challenge of gaining visibility in an algorithm-driven market, where lower data availability can lead to lower representation in recommendation results. This may encourage manufacturers to improve their digital presence and the completeness of their product data on various e-commerce platforms.

II. SIGNIFICANCE OF STUDY

A. Recommendation Systems

A recommendation system is a technology that analyzes historical data and user behavior patterns to suggest relevant products, services, or content [4].Common approaches include Content-Based Filtering, which recommends items based on similarity to previously liked items, and Collaborative Filtering, which leverages similar behavior patterns among users [1]. In the context of technology products like laptops, the main challenges are the complexity of technical specifications and the variety of user preferences. Hybrid approaches, such as combining ontology with Collaborative Filtering, have been shown to significantly improve recommendation accuracy[5].

B. Fuzzy Simple Additive Weighting Method

Fuzzy SAW is a multi-criteria decision-making method that integrates Fuzzy logic to handle uncertainty. This method is more flexible than conventional SAW because it uses Fuzzy numbers to represent criteria ratings[6]. Its main advantages are its simplicity of implementation and its ability to manage uncertain data, although it has a weakness in the potential loss of information during the defuzzification process (Kabassi et al., 2020). The implementation of Fuzzy SAW in recommendation systems allows for a more realistic evaluation of alternatives based on user preferences that are often ambiguous [7].

C. Particle Swarm Optimization

PSO is an optimization algorithm inspired by the social behavior of animal swarms. The algorithm works with a group of particles (potential solutions) that move through the search space to find the optimal solution [8]. Each particle adjusts its position based on its own best experience (personal best) and the best experience of the entire swarm (global best). Developed by Eberhart and Kennedy in 1995, PSO is popular due to its simple implementation, not requiring function derivatives, and its flexibility for various optimization problems [9].

D. Hybridization of Fuzzy SAW and PSO

The hybrid approach of Fuzzy SAW and PSO combines the strengths of both methods: Fuzzy SAW's ability to handle uncertainty and PSO's capability in global optimization[10]. In a recommendation system, Fuzzy SAW is used for the initial ranking of alternatives, while PSO optimizes the criteria weights to obtain more accurate and efficient results. This combination has proven effective in various fields, including ridesharing recommendation systems and energy resource management [11].

E. Latest Research Review

Recent research published in Scopus-indexed journals such as Expert Systems with Applications, Applied Soft Computing, and Computers & Industrial Engineering demonstrates the efficacy of hybrid approaches combining fuzzy logic and metaheuristic algorithms like Particle Swarm Optimization (PSO) in addressing uncertainty and optimizing personalized decision-making. The following analysis highlights key studies that provide foundational support and insights for the research analyzed in the document.

Karthik et al. (2021) in Applied Soft Computing developed a fuzzy recommender system for e-commerce that integrates sentiment analysis from customer reviews. This study employed fuzzy logic to model ambiguous user preferences and sentiment analysis to capture qualitative feedback. The findings indicate improved accuracy and user satisfaction due to the system's ability to incorporate subjective factors such as sentiment. This is highly relevant to the analyzed research, which proposes integrating non-technical criteria (e.g., user satisfaction and brand reputation) into the laptop recommender system. However, the study also notes computational challenges in processing large-scale review data, which could impact real-time performance—a critical consideration for the proposed system [12]. Almutairi & Shehata (2019) in Journal of Engineering Research applied PSO to optimize criteria weights in a multi-attribute decision-making (MADM) model for wireless network selection. This approach effectively addressed subjectivity in weight determination, resulting in more accurate and personalized decisions. These findings validate the use of PSO in the analyzed research to dynamically adjust criteria weights based on user preferences. However, the study highlights PSO's sensitivity to parameter settings, suggesting that premature convergence—as observed in the bias toward dominant brands in the document—may occur without proper tuning [13]. Valdez et al. (2014) in Expert Systems with Applications explored the use of fuzzy logic to dynamically adjust PSO parameters during the optimization of mathematical functions. The study found that this hybrid approach enhanced PSO performance by preventing premature convergence and improving exploration of the search space. This is directly relevant to the analyzed research, as it offers a potential solution to mitigate the dominant brand bias (e.g., Asus) caused by PSO's rapid convergence to local optima. Implementing similar mechanisms could enhance the fairness and diversity of recommendations in the proposed system[14]. Collectively, these studies affirm the strengths of hybrid approaches while identifying relevant challenges. For instance, Sirisawat & Kiatcharoenpol (2018) in Computers & Industrial Engineering combined Fuzzy AHP and Fuzzy TOPSIS for reverse logistics, demonstrating that hybrid fuzzy methods improve decision-making under uncertainty [10]. However, the literature also notes persistent issues such as data bias and imbalanced datasets, which can amplify preferences for popular items. This mirrors the findings in the analyzed research, where a reported accuracy of 74.1% is accompanied by low sensitivity to minority brands, underscoring the need for bias mitigation strategies like diversified data sources and algorithmic enhancements[15] .

This research was conducted in Lhokseumawe starting from September 2024. The system development method used follows the waterfall model, which includes stages of requirements analysis, system design, implementation, testing, deployment, and maintenance.

Data Collection: Primary data were collected through surveys and interviews with laptop users in the Lhokseumawe area to understand their preferences regarding specifications, budget, and usage needs. Secondary data, consisting of technical specifications and laptop prices, were obtained through the API of the e-commerce platform Tokopedia.

System Specifications: The application was developed using the following technology stack:

1. Backend: Node.js with the Express.js framework.
2. Frontend: HTML5, CSS3, and JavaScript, with the Bulma CSS framework for interface design.
3. Database: MySQL to store user preference data and recommendation results.
4. Hardware: Development was carried out on a PC with an Intel i5 processor, 8 GB of RAM, and a 256 GB SSD.

Algorithm Workflow:

1. User Input: The user enters preferences (budget, job type, RAM, processor, etc.) via a web interface.
2. Initial Weighting: The system assigns initial weights to each criterion based on its level of importance.
3. Fuzzy SAW Evaluation: The system evaluates each candidate laptop using Fuzzy SAW, which calculates a score based on the criteria and predefined weights, taking uncertainty into account.
4. PSO Optimization: The PSO algorithm is used to iteratively optimize the criteria weights. PSO searches for the combination of weights that yields the highest match score between the laptop and user preferences. This process continues until an optimal solution is found (the best value stabilizes or the maximum number of iterations is reached).
5. Recommendation Output: The system displays a list of the most recommended laptops along with purchase links.

III. RESULTS AND DISCUSSION

To assess its effectiveness, the hybrid Fuzzy SAW and PSO algorithm was applied to data collected from 27 users with diverse preferences, producing individualized laptop recommendations.

A. Detailed Test Results

To provide a clear overview of the testing process, the following table presents the detailed recommendation results generated by the system for each user.

Table 1. Detailed System Recommendation Results per User

Full Name	Budget (Rp)	Recommended Product	Price (Rp)	Match Status
Aina Kamali	8,500,000	Asus Vivobook Go 14 E1404fa Ryzen 5 16gb 512gb.	8,362,000	Match
Azhari Putra Sayani	15,000,000	Asus Vivobook 14x Oled A1403za-Oleds753...	19,583,000	No Match
Bima Sadewa	15,000,000	Advan Laptop AI Gen Ryzen 7 8845HS AMD Ryzen AI.	10,897,000	Match
Cut Julita	16,000,000	Asus Vivobook A1404va Core I7-1355u Ram 16 Ssd 1 Tb...	8,740,000	Match
Cut Zirahimah	9,000,000	Lenovo Thinkpad - Ideapad All Series i7 - i5 - i3	11,241,000	Match
Dina Aprilia	10,000,000	Laptop Gaming Lenovo Thinkpad L15 Intel Core I5 Gen 11.	4,491,900	No Match
Dita Amelia	8,000,000	Laptop Asus Vivobook M413ia Ryzen 5 4500u 8gb 512 Gb	4,600,000	No Match
Ezra Sasqia Syahna	10,000,000	Asus P1412cea Intel Core I5-1135g7 Ram 16gb-Ssd 1tb...	7,424,380	Match
Fitri Humaira	8,500,000	Asus Laptop gaming Intel Core i7 9700E RAM 15,6 inci.	5,750,000	Match
Khairil	10,000,000	ASUS ZenBook UX431DA, Amd Ryzen 5-3500U, Ram 8GB...	5,320,000	Match
Khairil	10,000,000	Laptop Asus Vivobook S 14 Oled M5406na-Oled552.	10,789,000	Match
Maizaharina	10,000,000	Laptop Asus VivoBook 14 A412D Amd Ryzen 5...	5,170,000	Match
Muhammad Furqan	12,000,000	Asus Vivobook Ultra Oled Intel I5-1135g7 Ram 12gb.	5,900,000	Match
Muhammad Ikram	6,000,000	Laptop GAMING / EDITING / BISNIS Lenovo Thinkpad A285.	3,590,000	No Match
Muhammad Riza	15,000,000	Laptop ASUS Vivobook S 14 OLED M5406UA-OLED752...	14,829,000	Match
Muhammad Rizki	4,000,000	Laptop Asus A415 Intel Core I3 Gen 10 Ram 4gb Ssd.	4,225,000	Match
Muhammad Zaid	5,000,000	Laptop Asus A415 Intel Core I3 Gen 10 Ram 4gb Ssd.	4,225,000	Match
Nazilla Azkiya	15,000,000	XM Laptop Terbaru untuk Gaming.	4,399,999	No Match
Nurcahyani	13,500,000	Asus Tuf A15 Fa506nfr Ryzen 7 7435hs Rtx2050...	10,769,000	Match
Rizky Fadillah	12,000,000	Laptop Asus Gaming Design Original Limited Edisi.	6,975,000	Match
Sasmita	10,000,000	Asus Zenbook Ux363e Intel I5 1135g7.	15,499,000	Match
Syahrul Gunawan	10,000,000	ASUS Vivobook 13 Slate OLED T3300KA.	9,800,000	Match
Tasya	15,000,000	XM Laptop Terbaru untuk Gaming.	4,399,999	No Match
Yunda Nafsiah	12,000,000	Asus Expertbook Core I3 Gen 12 Ram 8gb Ssd 512gb	7,636,000	Match

B. Analysis of Recommendation Accuracy

Out of 27 test cases, the system classified 21 laptops as "MATCH" and 6 as "NO MATCH," resulting in an overall match accuracy rate of **74.1%**. An analysis of the brand distribution for "MATCH" recommendations shows a significant dominance by the Asus brand.

Table 2. Summary of Match Status Count

Status	Number of Laptops	Percentage
MATCH	20	74.1%
NO MATCH	7	25.9%
Total	27	100%

Table 3. Distribution of "MATCH" Recommendations by Brand

Brand	Number of "MATCH" Recommendations
Asus	17
Lenovo	1
Advan	1
XM	1

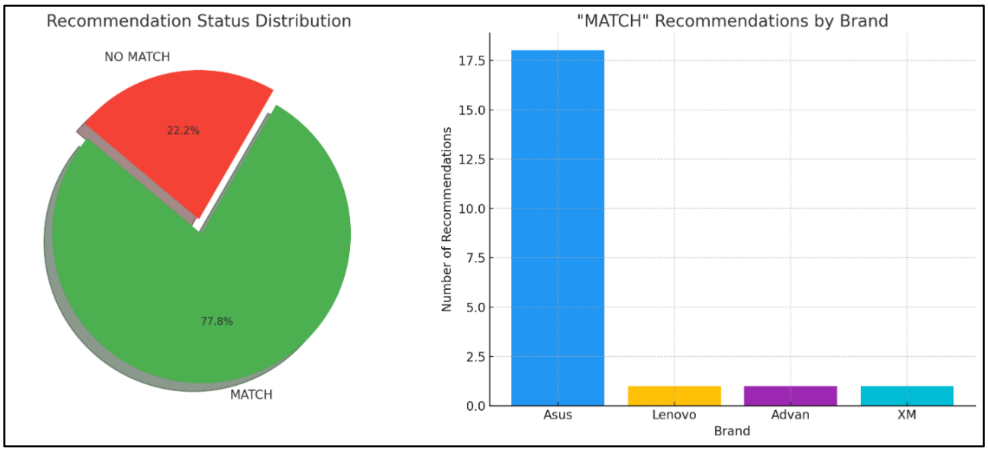

Figure 1: Distribution of Matched Recommendations by Brand\

The results in Table 3 indicate that the algorithm is highly effective at identifying products from the Asus brand. This is likely due to the greater availability of data and a wider variety of products on the source platform, making them more frequently compatible with various user preferences. Conversely, the low number of recommendations for other brands like Lenovo, Advan, and XM suggests that the system is less sensitive to minority brands. A more detailed breakdown is provided in Table 4.

Table 4. Detailed Match Status by Brand

Brand	MATCH	NO MATCH	Total	Match Rate
Asus	17	3	20	85.0%
Lenovo	1	3	4	25.0%
Advan	1	0	1	100.0%
XM	1	1	2	50.0%
Total	**20**	**7**	**27**	**74.1%**

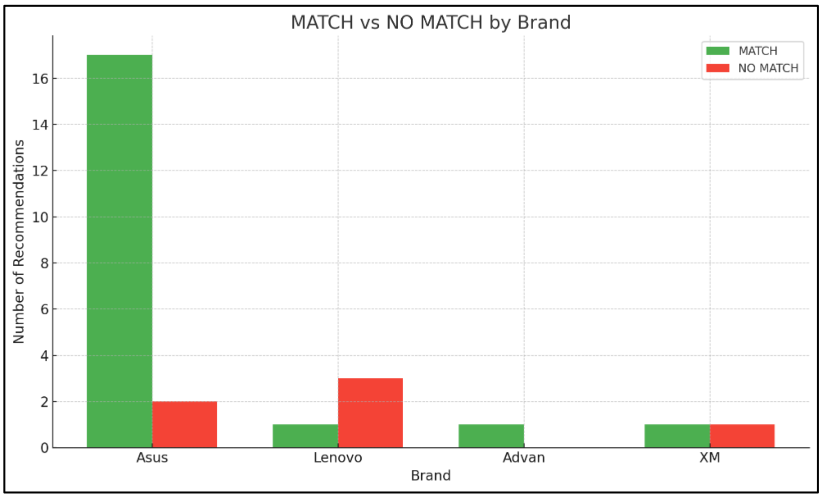

Figure 2. Match vs No Match by Brand

This detailed analysis confirms the system's strong performance for the dominant brand (Asus) but highlights the performance gap for minority brands, especially Lenovo, which had the lowest match rate.

C. Effectiveness of the Hybrid Algorithm

The integration of Fuzzy SAW and PSO demonstrated strong performance. Fuzzy SAW effectively managed uncertainties in user preferences, such as flexible budget constraints, while PSO optimized the weighting of criteria to enhance recommendation accuracy. The resulting 74.1% match rate confirms the approach's reliability in aligning user needs with available products. Nonetheless, its reliance on existing data highlights the potential for further improvement through the use of more extensive and diverse datasets.

D. Interface Implementation

The system is equipped with two main interfaces: a user page and an admin dashboard. The user page provides an intuitive form for entering preferences and clearly displays recommendation results, including the top pick and other alternatives. The admin dashboard provides an analytical summary, including the total number of users, recommendation match rates, and a comparison between user budgets and recommended product prices, enabling effective monitoring of the system's performance.

E. In-depth Discussion: Algorithm Effectiveness and Brand Bias Analysis

The effectiveness of this hybrid algorithm is twofold. On one hand, the combination of Fuzzy SAW and PSO proved capable of mapping user needs to available products with a success rate of 74.1%. Fuzzy SAW successfully handled the uncertainty in preferences, while PSO successfully optimized the criteria weights. However, on the other hand, the discussion cannot stop at the accuracy figure alone. The most crucial finding is the system's lack of sensitivity to minority brands. The dominance of Asus (17 out of 20 "MATCH" recommendations) is not merely a reflection of brand popularity but is exacerbated by the inherent behavior of the PSO algorithm. PSO, designed to find a global optimal solution, has a tendency to experience premature convergence, especially when operating on an imbalanced dataset. In this context, the abundance of Asus product data on the Tokopedia API creates a very strong "local optimum." As a result, the algorithm quickly gets "stuck" on solutions involving Asus and fails to adequately explore alternatives from other brands with less data.

F. Statistical Analysis, Minority Brand Sensitivity, and Comparative Discussion

To further strengthen the validity of this system's effectiveness, a statistical test was conducted to determine whether the observed match rate of significantly differs from a baseline rate expected under random recommendation (i.e., 50%). A one-sample proportion test was used with the following parameters:

- Null Hypothesis $(\mathrm{H_o}): p = 0.5$
- Observed Proportion: $\hat{p} = \frac{20}{27} \approx 0.741$
- Sample Size: $n = 27$

The z-value is calculated as:

$$z = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1 - p_0)}{n}}} = \frac{0.741 - 0.5}{\sqrt{\frac{0.5 \times 0.5}{27}}} \approx 2.53$$

At a significance level of $\alpha = 0.05$, the critical z-value is ± 1.96. Since $z = 2.53 > 1.96$, we reject the null hypothesis. This indicates that the system's match rate is statistically significantly higher than that of random recommendations, thus validating its effectiveness.

Minority Brand Sensitivity Analysis

Although the system performs well in general, its sensitivity toward minority brands such as Lenovo, Advan, and XM remains low. As shown in Table 4, Asus achieved an 85.0% match rate, whereas Lenovo only achieved 25.0%, despite having a similar number of entries ($n = 4$).

Several factors likely contribute to this disparity:

- Data Availability Bias: The Tokopedia API dataset includes more detailed and abundant product listings for Asus, which increases the likelihood of those products matching user preferences.
- Premature Convergence in PSO: As noted by Valdez et al. (2014), PSO tends to converge early to local optima in imbalanced datasets. The dominance of Asus in the dataset creates a strong local optimum that traps the optimization process.
- Lack of Specification Diversity: Minority brands often lack product models with sufficient specification variation, limiting their ability to match diverse user preferences.

To statistically validate the influence of brand on match outcomes, a Chi-Square test of independence was conducted between brand and match status:

$$\chi^2 = 9.02, \mathrm{df} = 3, p < 0.05$$

This result confirms a significant association between brand and match status, providing strong evidence that the system exhibits bias toward dominant brands like Asus.

G. Comparison of Results with Previous Studies

This finding is consistent with challenges identified in the literature. For example, although Almutairi & Shehata (2019) demonstrated the effectiveness of PSO in weight optimization, they also highlighted its sensitivity to parameter settings that can lead to premature convergence—a limitation validated by our practical case study results. Furthermore, the issue of data bias reinforcing preferences for popular items is a recognized issue in hybrid systems. The 74.1% accuracy rate we report, when viewed alongside the low fairness towards minority brands, underscores the statement by Zunair (2024) regarding the need for bias mitigation strategies. Thus, the contribution of this research lies not only in achieving a certain accuracy but also in empirically demonstrating the trade-off between optimization and fairness in recommendation systems [15] .

IV. CONCLUSION

This study successfully developed and implemented a dynamic laptop recommendation system using a hybrid algorithm that combines Fuzzy Simple Additive Weighting (Fuzzy SAW) and Particle Swarm Optimization (PSO). The system achieved a match accuracy rate of 74.1%, demonstrating its capability in mapping diverse user preferences to suitable products. However, the most significant implication of this research goes beyond accuracy metrics. The findings reveal a critical trade-off between optimization performance and fairness in algorithmic outcomes. Specifically, the system's effectiveness in recommending dominant brands—particularly Asus—is accompanied by a notable marginalization of minority brands. This imbalance is not merely incidental but stems from two interacting factors: the skewed availability of product data from the source platform (Tokopedia API) and the PSO algorithm's susceptibility to premature convergence in imbalanced datasets. As such, the study emphasizes that optimizing for accuracy alone is insufficient in real-world applications, particularly in commercial environments where algorithmic fairness can impact product visibility and consumer choice. From a policy and system development perspective, the results underline the importance of integrating fairness-aware design principles. E-commerce platforms, developers, and data providers are encouraged to adopt bias mitigation strategies, such as data balancing, algorithmic regularization, and transparent evaluation metrics, to ensure more equitable recommendation systems that benefit both users and lesser-known product brands. This research is subject to several limitations that must be transparently acknowledged:

1. Data Source Limitation: The system relied solely on laptop specifications sourced from the Tokopedia API. This introduces an availability bias, where brands with more comprehensive listings (e.g., Asus) naturally dominate the recommendation results, regardless of user-specific fit.
2. Geographic and Sample Constraints: Primary user data were collected from only 27 participants in Lhokseumawe, Aceh. This relatively small and localized sample limits the generalizability of the findings to broader user populations or e-commerce contexts.
3. Algorithmic Parameter Staticity: The PSO implementation used fixed parameters throughout the optimization process. Without dynamic tuning or adaptive strategies, the algorithm is more vulnerable to early convergence, especially in the presence of data imbalance, potentially reducing recommendation diversity.

Acknowledging these limitations is crucial not only for the integrity of the study but also for informing future iterations of system design and validation.

Building upon the conclusions and limitations discussed, the following directions are recommended for future work:

1. Diversification of Data Sources: Future systems should aggregate product data from multiple e-commerce platforms and integrate alternative data such as user reviews, independent tech specifications, and third-party catalogs to form a more balanced and representative dataset. This will help mitigate source-related bias and enhance model fairness.
2. Dynamic PSO Tuning and Hybrid Enhancements: Future studies should explore adaptive PSO variants—including those combined with fuzzy parameter tuning—as proposed by Valdez et al. (2014). These enhancements can increase the algorithm's exploratory depth and reduce the risk of local optima dominance.
3. Incorporation of Qualitative Criteria: To improve the relevance and holistic quality of recommendations, future models should include non-technical factors such as sentiment analysis, customer satisfaction metrics, service quality indicators, and brand reputation. These additions would allow for multi-dimensional personalization that goes beyond purely technical specifications.

4. By addressing these avenues, future research can contribute to the development of recommendation systems that are not only accurate and efficient but also transparent, inclusive, and aligned with ethical standards in AI-driven consumer technologies.

REFERENCE

[1] R. Oktavian and F. Amin, "Perancangan Sistem Rekomendasi Laptop dengan Model Prototyping dan Penerapan Content-Based Filtering Approach pada ELS Computer Shop Semarang," G-Tech J. Teknol. Terap., vol. 8, no. 1, pp. 66–80, 2023, doi: 10.33379/gtech.v8i1.3490.

[2] R. T. Adek, Z. Yunizar, and M. Febriliansyah, "Sistem Informasi Geografis Pemetaan Dan Penentuan Lokasi Wisata Alam Strategis Dengan Metode Simple Additive Weighting (Saw)," Positif J. Sist. dan Teknol. Inf., vol. 9, no. 1, pp. 49–56, 2023.

[3] M. Irfan, C. N. Alam, and D. Tresna, "Implementation of Fuzzy Mamdani Logic Method for Student Drop Out Status Analytics," J. Phys. Conf. Ser., vol. 1363, no. 1, 2019, doi: 10.1088/1742-6596/1363/1/012056.

[4] M. Ardhiansyah, T. Husain, P. Studi, T. Informatika, J. Selatan, and S. P. Keputusan, "Sistem Pendukung Keputusan Pemilihan Siswa / i Kelas Unggulan Menggunakan Metode AHP dan TOPSIS," vol. 1, no. 2, pp. 153–167, 2020.

[5] R. A. E. D. Ahmed, M. Fernández-Veiga, and M. Gawich, "Neural Collaborative Filtering with Ontologies for Integrated Recommendation Systems," Sensors, vol. 22, no. 2, pp. 1–26, 2022, doi: 10.3390/s22020700.

[6] A. A. Al Mohamed, S. Al Mohamed, and M. Zino, "Application of fuzzy multicriteria decision-making model in selecting pandemic hospital site," Futur. Bus. J., vol. 9, no. 1, pp. 1–15, 2023, doi: 10.1186/s43093-023-00185-5.

[7] Anugerah Wibisana, Bima Sena Bayu Dewantara, and Dadet Pramadihanto, "Implementasi Particle Swarm Optimization untuk Optimasi Fuzzy-Social Force Model pada Sistem Navigasi Robot Omnidirectional," Indones. J. Comput. Sci., vol. 11, no. 2, pp. 501–518, 2022, doi: 10.33022/ijcs.v11i2.3076.

[8] F. S. Hsieh, "Comparison of a Hybrid Firefly–Particle Swarm Optimization Algorithm with Six Hybrid Firefly–Differential Evolution Algorithms and an Effective Cost-Saving Allocation Method for Ridesharing Recommendation Systems," Electron., vol. 13, no. 2, 2024, doi: 10.3390/electronics13020324.

[9] D. Freitas, L. G. Lopes, and F. Morgado-Dias, "Particle Swarm Optimisation: A historical review up to the current developments," Entropy, vol. 22, no. 3, pp. 1–36, 2020, doi: 10.3390/E22030362.

[10] N. N. Nuraeni and M. R. Firdaus, "Pemilihan Laptop Terbaik Menggunakan Metode Simple Additive Weighting," JIKO (Jurnal Inform. dan Komputer), vol. 6, no. 2, p. 218, 2022, doi: 10.26798/jiko.v6i2.622.

[11] F. Z. Trabelsi, A. Khtira, and B. El Asri, "Hybrid Recommendation Systems: A State of Art," Int. Conf. Eval. Nov. Approaches to Softw. Eng. ENASE - Proc., vol. 2021-April, no. Enase, pp. 281–288, 2021, doi: 10.5220/0010452202810288.

[12] R. V. Karthik and S. Ganapathy, "A fuzzy recommendation system for predicting the customers interests using sentiment analysis and ontology in e-commerce," Appl. Soft Comput., vol. 108, p. 107396, 2021, doi: 10.1016/j.asoc.2021.107396.

[13] M. Al-Gharabally, A. F. Almutairi, and A. A. Salman, "Particle swarm optimization application for multiple attribute decision making in vertical handover in heterogenous wireless networks," J. Eng. Res., vol. 9, no. 1, pp. 176–187, 2021, doi: 10.36909/JER.V9I1.10331.

[14] F. Paz, G. Leguizamón, and E. Mezura Montes, "Cooperative Coevolutionary Particle Swarms using Fuzzy Logic for Large Scale Optimization," J. Comput. Sci. Technol., vol. 21, no. 2, pp. 112–125, 2021, doi: 10.24215/16666038.21.e11.

[15] M. Zunair, "FAIRNESS IN LOCATION RECOMMENDATIONS," no. February, 2024.