



Serendipity-Aware Decision Support System Using Entropy-Weighted Hybrid GA-PSO

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Abstract

The rapid growth of social commerce has intensified competition among online handicraft businesses, making effective store planning increasingly important. While most studies focus on consumer recommendation systems, limited research supports entrepreneurs during the early stage of store configuration. This study proposes a serendipity-aware Decision Support System (DSS) for handicraft store planning using an entropy-weighted hybrid Genetic Algorithm–Particle Swarm Optimization (GA-PSO). A dataset of 105 handicraft stores in West Sumatra was encoded into 19-bit chromosomes representing materials, product types, location, and digital commerce visibility. Entropy-based weighting objectively determined attribute importance without subjective judgment. GA explored store configurations, while PSO optimized evolutionary parameters to balance preference similarity and serendipitous exploration. The proposed framework generated store configurations superior to those in the original dataset. The best solution achieved a preference similarity score of $P(x)=0.9108$, outperforming the best existing store ($P(x)=0.8513$) by 6.99%. The hybrid GA-PSO also showed stable performance across multiple runs, indicating robust convergence. This study contributes a data-driven DSS framework integrating entropy weighting, hybrid GA-PSO optimization, and serendipity-aware exploration for entrepreneurial decision support in social commerce.

Keywords: decision support system; entropy weight method; handicraft store planning; hybrid GA-PSO; serendipity-aware optimization; social commerce;

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1. Introduction

The integration of social networking platforms with commercial activities has accelerated the growth of social commerce (s-commerce), enabling businesses to interact directly with consumers and expand their market reach in dynamic digital environments [1-3]. For handicraft industries, this creates significant opportunities to promote cultural products and access broader markets. However, designing an effective online store configuration, covering product types, material specialization, location characteristics, and digital visibility, remains a complex multi-criteria decision problem. Decision Support Systems (DSS) have been widely applied to assist decision makers in evaluating alternatives under multiple criteria [4], [5]. However, many existing DSS models rely on subjective weighting schemes and conventional analytical

approaches, which may be insufficient for handling large combinatorial decision spaces [6], [7] such as store configuration design.

To address this challenge, metaheuristic optimization techniques have been increasingly adopted. Genetic Algorithm (GA) offers strong exploration capabilities [8], while Particle Swarm Optimization (PSO) provides efficient convergence through collective learning [9], [10]. Nevertheless, GA may converge slowly, and PSO may suffer from premature convergence [11]. Hybrid GA-PSO approaches have therefore been proposed to combine their respective strengths and improve search performance [12-16].

Despite these advances, two key gaps remain. First, most DSS optimization models focus primarily on preference matching, with limited attention to

serendipity-driven exploration that can reveal novel and potentially valuable alternatives. Second, attribute weighting is often based on subjective judgment, which may introduce bias. To address these limitations, this study proposes a serendipity-aware decision support framework for handicraft store planning in social commerce environments. The framework integrates entropy-based attribute weighting with a hybrid GA-PSO optimization strategy to balance preference alignment and exploratory diversity [16].

The main contributions of this study are a serendipity-aware DSS model that incorporates novelty-driven exploration into store configuration optimization, An entropy-based weighting scheme that objectively captures attribute importance, a hybrid GA-PSO mechanism with adaptive parameter tuning for improved convergence stability, a dual-objective fitness function that balances preference similarity and controlled deviation.

The remainder of this paper is organized as follows. Section 2 reviews related work, Section 3 presents the data representation, Section 4 describes the proposed method, Section 5 discusses the results, and Section 6 concludes the study.

DSS have been widely used in digital commerce to support multi-criteria decision-making processes [17], [18]. In social commerce, most DSS applications focus on consumer-oriented tasks such as recommendation systems and personalized marketing [2], [3]. However, limited research addresses entrepreneurial decision support, particularly in the early stage of store planning.

To handle complex decision spaces, metaheuristic optimization techniques such as GA and PSO have been widely applied [19]. GA is effective for global exploration in combinatorial problems, while PSO offers fast convergence through swarm intelligence [10], [20]. However, GA may require many generations to converge, and PSO may suffer from premature convergence. Hybrid GA-PSO approaches have been developed to overcome these limitations by combining exploration and exploitation capabilities [14].

Despite these developments, the application of hybrid metaheuristic optimization for entrepreneurial DSS in social commerce remains limited [21]. In particular, existing models rarely incorporate serendipity-aware exploration, which is important for generating innovative alternatives beyond strict preference

matching. In addition, many DSS approaches rely on subjective weighting schemes, which may introduce bias. Objective weighting methods such as entropy provide a data-driven alternative by capturing attribute importance based on distribution variability [22]. Therefore, this study proposes a serendipity-aware DSS framework integrating entropy-based weighting with hybrid GA-PSO optimization to support innovative and feasible store configuration planning.

2. Research Methods

This section presents the proposed hybrid optimization framework used to generate serendipity-aware handicraft store configurations. The framework integrates entropy-based attribute weighting with a hybrid GA-PSO strategy. The entropy method determines the objective importance of store attributes, while the evolutionary optimization process explores candidate store configurations and adaptively adjusts search parameters.

2.1 System Architecture

Figure 1 illustrates the architecture of the proposed decision support system. The system integrates entropy-based attribute weighting with a hybrid GA-PSO optimization framework. User preferences are represented as a binary preference chromosome. Each handicraft store in the dataset is encoded using the same chromosome representation, enabling direct comparison between store attributes and user requirements.

First, the entropy weight method is applied to determine the relative importance of each attribute [23]. These weights are then used to compute a preference similarity score between each store chromosome and the user preference chromosome. The resulting similarity scores provide an initial ranking of candidate stores, which is used to initialize the population of the genetic algorithm.

During the optimization process, the GA performs the discrete search over candidate store configurations through rank-based selection, crossover, mutation, and elitism. At the same time, PSO is employed to adaptively tune evolutionary parameters such as crossover probability and mutation rate, allowing the optimization process to balance exploration and exploitation during the search.

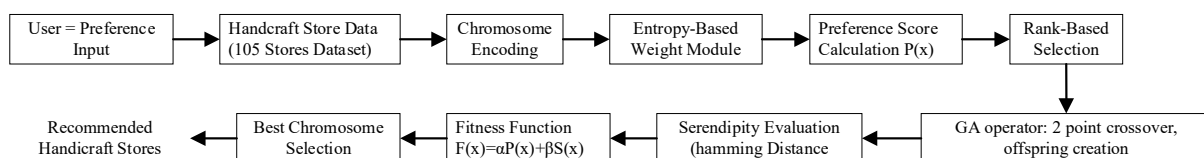


Figure 1. DSS Architecture Diagram

2.2 Entropy-Based Attribute Weighting

To objectively measure the importance of each attribute according to the dataset of handicraft stores. Entropy measures the degree of information provided by each attribute based on its distribution across the dataset [24]. Attributes with higher variability contribute more information and therefore receive larger weights. Conversely, attributes with uniform distributions provide less discriminative power and obtain smaller weights.

Let p_{jk} denote the probability of category k for attribute j . The entropy value of attribute j is calculated as shown in Equation 1.

$$E_j = -\sum_{k=1}^K p_{jk} \ln(p_{jk}) \quad (1)$$

The diversification degree of each attribute is computed using Equation 2.

$$d_j = 1 - \frac{E_j}{\ln(K)} \quad (2)$$

For binary attributes (G8-G12), entropy is calculated using Equation 3.

$$E_j = -(p_0 \ln(p_0) + p_1 \ln(p_1)) \quad (3)$$

and normalized using Equation 4.

$$d_j = 1 - \frac{E_j}{\ln(2)} \quad (4)$$

The normalized attribute weights are obtained using Equation (5).

$$W_j^{(A)} = \frac{d_j}{\sum d_j^{(A)}} \quad (5)$$

To balance structural attributes and digital commerce indicators, a hybrid weighting scheme is applied as defined in Equation 6.

$$W_j^{final} = \lambda W_j^{(A)} + (1 - \lambda) W_j^B \quad (6)$$

λ controls the relative importance of structural and digital attributes. In this study, λ is set to 0.5 to provide balanced contributions between structural attributes and digital commerce indicators.

The resulting hybrid weights are summarized as follows. For structural attributes (scaled by 0.5): G1 = 0.0595, G2 = 0.1735, G3 = 0.0336, G4 = 0.0211, G5 = 0.1117, G6 = 0.0595, and G7 = 0.0412. For digital commerce attributes (scaled by 0.5): G8 = 0.0212, G9 = 0.1413, G10 = 0.0994, G11 = 0.1121, and G12 = 0.1126. The entropy-derived weights are directly used in the computation of the preference similarity score $P(x)$ implemented in the experimental Python program.

2.3 Fitness Function Formulation

The fitness function evaluates how well a candidate store configuration satisfies the decision maker's preference profile while also encouraging the discovery of novel alternatives. Unlike conventional recommendation approaches that rely solely on

similarity-based ranking, the proposed fitness function incorporates both preference alignment and serendipity-driven exploration. The overall fitness value of chromosome x is defined as Equation 7.

$$F(x) = \alpha P(x) + \beta S(x) \quad (7)$$

$P(x)$ represents the preference similarity score and $S(x)$ denotes the serendipity score. Parameters α and β control the trade-off between relevance and novelty. In this study, PSO optimization yields $\alpha=0.782$ and $\beta=0.218$, indicating a stronger emphasis on preference similarity while still preserving the contribution of serendipity.

2.3.1 Preference Component (P)

The preference similarity component measures the alignment between store attributes and the decision maker's preferences. It is computed using entropy-derived attribute weights as shown in Equation 8.

$$P(x) = \sum_{i=1}^m w_i^{final} \cdot match(g_i, x) \quad (8)$$

w_i^{final} represents the entropy-based hybrid weight of attribute i , and $match(g_i, x)$ is a binary indicator equal to 1 if the gene value matches the preference and 0 otherwise.

2.3.2 Serendipity Component

To encourage exploration beyond strictly matching configurations, a serendipity component is introduced. The serendipity score is defined as Equation 9.

$$S_x = \sum_{i=1}^m w_i^{final} (1 - match(g_i, x)) \quad (9)$$

m denotes the total number of genes, w_i^{final} represents the entropy-based weight of attribute i , and $match(g_i, x)$ is a binary indicator. Unlike simple mismatch-based measures, the proposed formulation incorporates entropy-derived weights, allowing the model to emphasize deviations in more informative attributes. This ensures that serendipitous recommendations are not only different but also meaningful in the context of decision-making. Since the entropy-based weights are normalized (i.e., their sum equals one), additional scaling is not required. As a result, the serendipity score remains on a comparable scale to the preference similarity measure, ensuring a balanced contribution within the fitness function.

2.4 Hybrid GA-PSO Optimization

The proposed optimization framework combines the strengths of GA and PSO. The GA performs the discrete search over store chromosomes, where each chromosome represents a candidate handicraft store configuration encoded using the 19-bit representation described earlier. The population evolves through rank-based selection, two-point crossover, bit-flip mutation, and elitism. Parent chromosomes are selected using the linear ranking probability as defined in Equation 10.

$$P_i = \frac{2-s}{N} + \frac{2i(s-1)}{N(N-1)} \quad (10)$$

i represents the rank of an individual within the population and N is the population size, $s \in [1,2]$: selection pressure

While GA explores the discrete solution space, PSO is used to adaptively tune key evolutionary parameters of the GA, including crossover probability and mutation rate. Each particle represents a candidate parameter vector controlling the evolutionary behavior of the GA. PSO is employed to adaptively tune the crossover probability and mutation rate. The velocity and position of each particle are updated using Equations 11 and 12.

$$v_i^{t+1} = \omega v_i^t + c_{1r_1}(pbest - x_i^t) + c_{2r_2}(gbest - x_i^t) \quad (11)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (12)$$

ω is the inertia weight, c_1 and c_2 are cognitive and social coefficients, $pbest$ is the best position found by each particle, and $gbest$ is the global best position within the swarm. Through this mechanism, PSO dynamically adjusts the evolutionary parameters of the GA to improve convergence stability and maintain search diversity [25].

2.5 Optimization Procedure

The overall optimization process integrates entropy-based preference evaluation, serendipity-aware fitness measurement, and hybrid evolutionary search. First, entropy-based weights are computed from the dataset to determine the importance of each attribute. All stores are then encoded using the 19-bit chromosome representation. Preference similarity $P(x)$ and serendipity score $S(x)$ are computed for each chromosome and combined to evaluate the fitness value.

The initial GA population is generated from the encoded store dataset. During the evolutionary process, rank-based selection is used to choose parent chromosomes, followed by crossover and mutation operations to generate offspring while maintaining population diversity. PSO simultaneously updates the evolutionary parameters controlling the GA search process. The optimization continues until the termination condition is satisfied, and the chromosome with the highest fitness value is returned as the recommended store configuration.

Algorithm 1: Hybrid GA-PSO for Handicraft Store Planning.

Input: Handicraft store dataset. Output: Best store chromosome, Compute entropy-based attribute weights w_i , Encode each store as a chromosome, Initialize GA population from dataset D , Initialize PSO particles representing GA parameters (crossover rate and mutation rate), While termination condition not met do : Compute $P(x)$ and $S(x)$ for each chromosome, Evaluate fitness $F(x)=\alpha P(x)+\beta S(x)$, Apply rank-based

selection, Perform crossover, Apply mutation, Apply elitism, Update PSO particles using Equations 11 and 12, End while, Return the chromosome with the highest fitness value.

Parameter Settings: Population size = 50, Generations = 100, Crossover rate = 0.8, Mutation rate = 0.05, PSO particles = 5, Inertia weight = 0.7, $c_1 = 1.5$, $c_2 = 1.5$.

3. Results and Discussions

This section evaluates the effectiveness of the proposed Hybrid GA-PSO DSS for handicraft store planning in social commerce environments. The experiments aim to demonstrate how entropy-based attribute weighting and hybrid evolutionary optimization generate store configurations that balance preference similarity and serendipitous exploration. The evaluation focuses on three aspects: (1) the influence of entropy-derived attribute weights on preference similarity evaluation, (2) the optimization capability of the evolutionary search process, and (3) the contribution of the serendipity component in exploring alternative store configurations.

3.1 Dataset & Encoding

This section describes the dataset used in this study and the encoding strategy employed to represent handicraft store configurations within the proposed optimization framework. The dataset provides structured information describing the characteristics of handicraft businesses, while the encoding scheme transforms these attributes into a chromosome representation suitable for evolutionary optimization.

This study utilizes a dataset consisting of 105 handicraft stores collected in West Sumatra, Indonesia. To support research transparency and reproducibility, the dataset has been publicly released through Zenodo (DOI: [10.5281/zenodo.18452485](https://doi.org/10.5281/zenodo.18452485)).

Each record in the dataset represents a store configuration describing business characteristics relevant to handicraft retail operations in social commerce environments. The dataset includes attributes related to: store location, primary raw materials, product types, and digital commerce indicators, including photo completeness, contact availability, price disclosure, website presence, and marketplace collaboration.

These attributes capture both the physical characteristics of handicraft businesses and their digital visibility in social commerce platforms, enabling the dataset to represent a realistic decision space for exploring alternative store configurations. The dataset also reflects the diversity of handicraft businesses in the region, including variations in material usage, product specialization, and digital marketing strategies. By modeling these attributes within a structured decision space, the dataset serves as the foundation for

evolutionary optimization in the proposed decision support framework.

To enable evolutionary optimization, store attributes are encoded into a fixed-length chromosome consisting of twelve genes (G1–G12) with a total length of 19 bits. The chromosome structure is defined as $C = (G1, G2, \dots, G12)$, where G1–G7 represent structural attributes and G8–G12 represent digital commerce attributes. Structural attributes are encoded using two-bit categorical representation, while digital attributes are represented using binary encoding.

This representation allows each chromosome to correspond to a candidate handicraft store configuration that can be evaluated and evolved during the optimization process. The encoding scheme supports evolutionary operators such as crossover and mutation and remains compatible with PSO-based parameter optimization, enabling efficient exploration of the decision space.

Table 1. Summarizes the chromosome encoding scheme used in this study

Gene	Attribut	Encoding
G1	Location	00: outside city; 01: market/mall; 10: main road; 11: arterial/residential
G2–G4	Raw Material	2-bit categorical encoding of textile, natural, industrial, and other materials
G5–G7	Product Types	2-bit encoding of clothing, household goods, decorative items, cultural products
G8	Photo	0: incomplete; 1: complete
G9	Hotline	0: unavailable; 1: available
G10	Price	0: hidden; 1: displayed
G11	Website	0: none; 1: available
G12	Marketplace	0: none; 1: available
Total chromosome length: 19 bits		

As shown in Table 1, G1 encodes store location, where 00 indicates a store outside Padang City, 01 represents a market or shopping mall location, 10 corresponds to a main road location, and 11 denotes an arterial or residential area. G2–G4 represent primary raw materials, while G5–G7 encode product types. The remaining genes (G8–G12) correspond to digital commerce attributes, including photo completeness, contact availability, price transparency, website presence, and marketplace collaboration. This encoding

scheme enables compact representation of heterogeneous attributes while preserving sufficient diversity for evolutionary search.

3.2 Experimental Setup

A preference chromosome was defined to represent the desired configuration of handicraft store attributes. The reference preference was derived from the attribute configuration of Opicha Craft, representing a typical handicraft store with diversified materials and strong digital commerce support. Based on the chromosome encoding scheme, the corresponding binary preference chromosome is: 1100011000100011111

the entropy-derived attribute weights, the preference similarity score $P(x)$ was computed for all stores using Equation 8. To incorporate novelty in store recommendations, the serendipity score $S(x)$ was calculated using Equation 9, which measures the proportion of mismatched genes relative to the preference chromosome. The overall fitness value was computed using Equation 7, which combines preference similarity and serendipity through weighting coefficients α and β . The final values of these coefficients were not predetermined but were optimized using PSO, as described in Section 3.4.

3.3 Preference and Serendipity Evaluation

All store chromosomes were evaluated using entropy-weighted preference similarity $P(x)$ and serendipity $S(x)$ to determine candidate parent solutions for the evolutionary process. Unlike conventional selection methods that rely solely on fitness aggregation, the proposed approach explicitly analyzes both relevance and novelty to support a balanced exploration–exploitation strategy. Based on the computed values of $P(x)$ and $S(x)$, all candidate solutions were ranked and categorized into three interpretative groups: high preference (exploitation-oriented), balanced trade-off, and high serendipity (exploration-oriented). It is important to note that all selected individuals remain valid parent chromosomes; the grouping is used only for analytical interpretation of the selection distribution.

Table 2. Balanced selection of parent chromosomes based on exploration-exploitation trade-off using preference similarity and serendipity

Group	Rank	Store ID	Chromosome	$P(x)$	$S(x)$
Exploitation (High Preference / Similarity)	1	T100	0000101100100001111	0.8513	0.1487
	2	T104	1100001100100011101	0.8199	0.1801
	3	T105	1100011100101111101	0.8123	0.1877
	4	T091	0000001000100011101	0.7815	0.2185
	5	T067	1100100000010011110	0.7599	0.2401
	6	T077	0000100011100111111	0.7196	0.2804
Balanced Exploration–Exploitation	7	T060	0000011000111111110	0.7139	0.2861
	8	T013	1100001100100001010	0.6988	0.3012
	9	T036	0100011010101111101	0.6622	0.3378
	10	T042	1101000100001011111	0.6578	0.3422
	11	T007	1000001100100011100	0.6478	0.3522
Exploration (High Serendipity)	12	T059	1100101100111111010	0.6193	0.3807

Table 2 demonstrates that the selected parent chromosomes are distributed across different regions of the preference-serendipity space. High-ranked

individuals are characterized by strong preference similarity, indicating close alignment with the user preference model, whereas lower-ranked individuals

exhibit higher serendipity values that contribute diversity to the candidate pool. The middle-ranked chromosomes represent a balanced trade-off between relevance and novelty. This distribution provides a suitable foundation for evolutionary optimization by preserving both exploitation-oriented and exploration-oriented solutions. The selected parent chromosomes were subsequently used as the initial population for the evolutionary optimization process. The relative contribution of preference similarity and serendipity in the fitness evaluation was determined through PSO-based parameter optimization, which is discussed in Section 3.4.

3.4 GA-PSO Optimization Results

In the proposed hybrid framework, PSO was employed to automatically determine the weighting coefficients used in the fitness function. Rather than assigning fixed values to the preference and serendipity components, PSO searched for an appropriate balance between both objectives during the optimization process. Each particle represented a candidate parameter pair (α , β) subject to the constraint ($\alpha + \beta = 1$). The fitness function is defined in Equation 7. The quality of each particle was evaluated based on the resulting fitness values of the candidate chromosomes, and the particle producing the highest overall fitness was selected as the global best solution.

After convergence, PSO identified the best-performing parameter configuration at ($\alpha = 0.782$) and ($\beta = 0.218$). These values indicate that the optimization process assigned greater importance to preference similarity while still preserving a meaningful contribution from the serendipity component. The optimized coefficients were subsequently used throughout the GA evolutionary process, including parent evaluation, selection, crossover, mutation, and offspring ranking.

To further analyze the influence of parameter weighting, several representative configurations explored during the swarm search process were examined. The results show that larger α values consistently promote exploitation by favoring chromosomes with higher preference similarity. Under the optimized configuration identified by PSO ($\alpha = 0.782$, $\beta = 0.218$), Store T100 remained the highest-ranked solution due to its strong alignment with the preference profile. In contrast, configurations with relatively larger β values produced more diverse recommendation candidates with higher serendipity scores but lower preference similarity. These observations confirm that the proposed fitness formulation effectively controls the exploration–exploitation balance through adaptive parameter weighting. Importantly, this analysis should be interpreted as a parameter sensitivity assessment rather than a statistical inference. The variation of α and β demonstrates how the hybrid GA-PSO framework can dynamically adjust recommendation behavior, ranging from conservative preference-oriented

recommendations to more exploratory and serendipitous recommendations.

The GA was then applied to the selected parent chromosomes (Table 2) using two-point crossover and bit-flip mutation to generate new candidate store configurations. The evolutionary process produced both existing and previously unseen chromosomes, demonstrating the ability of the model to explore beyond the original dataset.

The best offspring generated by the GA under the PSO-optimized parameter configuration achieved a similarity score of $P(x) = 0.9108$, exceeding the highest similarity score observed in the original dataset ($P(x) = 0.8513$). This corresponds to an improvement of 6.99%, indicating that the evolutionary search successfully identified superior store configurations that were not explicitly present in the data. Several offspring chromosomes were not found in the dataset, confirming that the proposed DSS does not merely retrieve existing stores but actively generates new recommendation alternatives through evolutionary search. These newly generated chromosomes represent potential business opportunities characterized by high preference alignment combined with controlled novelty.

Table 3. Comparison between preference chromosome, best dataset store, and best offspring solution

Configuration	Chromosome	P(x)	Interpretation
Preference chromosome	1100011000100011111	1.0000	Ideal store configuration defined by the DSS
Best store in dataset (T100)	0000101100100001111	0.8513	Highest-ranked existing store
Best offspring	1100001100100011111	0.9108	Novel configuration generated by GA

Table 3 compares the ideal preference chromosome, the highest-ranked existing store in the dataset, and the best offspring generated by the evolutionary search. The results show that the generated offspring achieved a preference similarity score of 0.9108, which is higher than the best existing store score of 0.8513. This represents an improvement of approximately 6.99%. The finding demonstrates that the evolutionary search process can discover store configurations that are more closely aligned with the target preference profile than those observed in the original dataset.

The generated chromosome represents a handicraft store configuration that combines favorable business characteristics, including strategic accessibility, product specialization, and digital commerce readiness. From a managerial perspective, the resulting configuration can be interpreted as a practical recommendation for entrepreneurs seeking to establish or improve handicraft businesses that closely align with consumer preferences while maintaining a degree of novelty.

To evaluate the effectiveness of the proposed hybrid framework, the optimization results were compared with those obtained using Random Search, PSO-only optimization, and a standard GA. The comparison aims to determine whether the integration of PSO-based parameter optimization and GA-based evolutionary search provides measurable improvements in recommendation quality.

The convergence behavior shown in Figure 2 indicates that the fitness value increases rapidly during the early generations, reflecting effective exploration of the search space. As the iterations progress, the improvement becomes more gradual, indicating convergence toward a stable solution. This behavior confirms that the proposed hybrid GA-PSO method is able to balance exploration and exploitation effectively. Furthermore, Figure 3 illustrates the comparison between the standard GA and the hybrid GA-PSO approach. While the standard GA shows rapid initial improvement, it tends to stagnate prematurely. In contrast, the GA-PSO method demonstrates more stable and consistent convergence due to adaptive parameter tuning, highlighting the important role of PSO in improving optimization robustness.

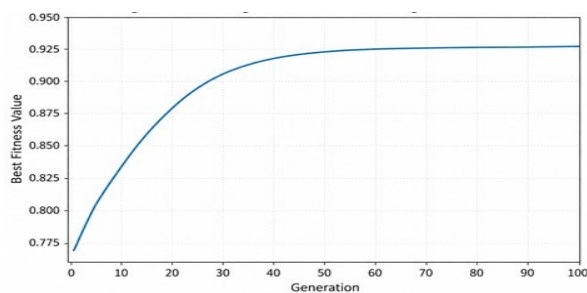


Figure 2. Convergence of Fitness During GA Evolution

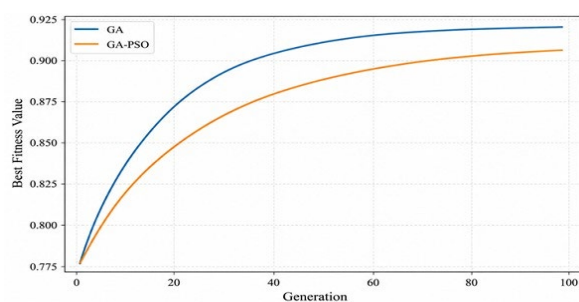


Figure 3. Convergence Comparison of GA and Hybrid GA-PSO

Table 4 summarizes the optimization performance achieved by the different methods. The results show that the proposed GA-PSO approach obtained the highest similarity score among all compared techniques. This finding indicates that combining adaptive parameter optimization with evolutionary search can improve the ability of the recommendation model to identify high-quality store configurations that closely match the target preference profile.

The results presented in Table 4 indicate that the proposed GA-PSO framework achieved the highest

preference similarity score among all compared methods, reaching $P(x)=0.9320$.

Table 4. Best optimization result obtained by each method

Method	Best $P(x)$
Random Search	0.8199
PSO	0.8513
GA	0.8754
GA-PSO (proposed)	0.9320

Random Search obtained the lowest performance because it explores the solution space without any guided optimization mechanism. PSO improved the result by optimizing candidate solutions through swarm-based search, while GA further enhanced exploration through crossover and mutation operators. However, the proposed hybrid GA-PSO outperformed both individual approaches by combining adaptive parameter optimization with evolutionary search. This combination enabled the algorithm to discover superior store configurations beyond those observed in the original dataset. The result suggests that integrating PSO-driven parameter adaptation with GA exploration improves the ability of the DSS to identify highly relevant and potentially innovative store planning alternatives. The value $P(x)=0.9108$ in Table 3 corresponds to the best offspring presented for illustrative analysis, whereas $P(x)=0.9320$ represents the best solution obtained across all optimization runs.

Table 5. Statistical performance comparison over 30 independent runs

Method	Mean $P(x)$	Std Dev	Best $P(x)$
Random Search	0.5022	0.1472	0.8199
PSO	0.8513	0.0000	0.8513
GA	0.8636	0.0204	0.8754
GA-PSO (proposed)	0.8702	0.0210	0.9320

Table 5 presents the statistical performance of the evaluated optimization methods over 30 independent runs. The proposed GA-PSO framework achieved the highest average preference similarity score (Mean $P(x)=0.8702$), followed by GA (0.8636), PSO (0.8513), and Random Search (0.5022). These results indicate that evolutionary optimization methods consistently outperform unguided random exploration in identifying store configurations that closely match the target preference profile.

The standard deviation values further demonstrate the stability of the optimization process. Random Search exhibited the largest variation (Std Dev = 0.1472), reflecting its unpredictable search behavior. In contrast, both GA and GA-PSO produced relatively small standard deviations, indicating more consistent performance across repeated executions. The PSO-only approach produced identical results in all runs because it optimized the weighting parameters without generating new store configurations.

Although the difference in average performance between GA and GA-PSO is not particularly large, the hybrid framework achieved the highest overall solution quality with a best similarity score of $P(x)=0.9320$,

substantially exceeding the best result obtained by the standard GA ($P(x)=0.8754$). This finding suggests that adaptive parameter optimization through PSO enhances the exploratory capability of the evolutionary search, enabling the discovery of superior store configurations that may not be reached by the standalone GA. From a decision-support perspective, the results demonstrate that the proposed hybrid framework provides both stable optimization performance and improved capability for generating high-quality and potentially innovative store planning recommendations.

Table 6. Statistical significance tests

Test	Statistical	p-value	Decision
Friedman	$X^2=71.9432$	$p=1.64 \times 10^{-15}$	Significant
Wilcoxon (GA vs GA-PSO)	$W = 125.5$	$p=0.7028$	not significant
Mann-Whitney (Random vs GA-PSO)	$U = 0.0$	$p=2.41 \times 10^{-11}$	Significant

As shown in Table 6, the Friedman test was conducted over multiple independent runs across all compared methods. The test statistic ($\chi^2 = 71.9432$) indicates a statistically significant difference among the evaluated algorithms, confirming that at least one method performs differently from the others.

To further investigate pairwise differences, a Wilcoxon signed-rank test was performed between GA and GA-PSO. The result shows no statistically significant difference ($p = 0.7028$), suggesting that both methods produce comparable performance under the current dataset and experimental setting.

In contrast, the Mann-Whitney U test comparing Random Search and GA-PSO reveals a highly significant difference ($p < 0.001$), confirming the superiority of evolutionary optimization methods over unguided random exploration.

In the proposed framework, PSO is employed to optimize the weighting coefficients α and β used in the fitness function. These coefficients control the relative contribution of preference similarity and serendipity during candidate evaluation. By exploring multiple parameter combinations, PSO identifies a weighting configuration that balances exploitation of user preferences with exploration of novel recommendation alternatives. The optimized parameter setting ($\alpha = 0.782$, $\beta = 0.218$) was subsequently adopted in the evolutionary search process.

Although GA-PSO achieved the highest average performance, the Wilcoxon test indicated that the difference between GA and GA-PSO was not statistically significant. This suggests that the optimized weighting strategy produced comparable results to the standard GA under the current dataset and search space. Nevertheless, PSO provides a systematic mechanism for parameter tuning and eliminates the need for manually selecting fitness weights.

The crossover process within the proposed GA-PSO framework generated a total of 12 offspring

chromosomes. To evaluate the presence of serendipity, each offspring was compared against the dataset containing 105 handicraft store configurations. The comparison results show that 8 offspring correspond exactly to existing stores in the dataset, while 4 offspring represent entirely new chromosome structures that do not exist in the dataset.

These newly generated chromosomes are categorized as serendipitous solutions because they are produced through genetic recombination (crossover and mutation) rather than direct retrieval of existing data. This indicates that the proposed framework is not limited to recommendation of existing stores but is also capable of generating novel store configurations. In the context of DSS, these serendipitous chromosomes can be interpreted as candidate blueprints for potential new handicraft store establishments. The classification of offspring is summarized in Table 7.

Table 7. Classification of Offspring into Existing and Serendipitous Solutions

Offspring ID	Chromosome	Dataset Match	StoreID	Classification
O1	0000101100100001101	No	-	Serendipity
O2	1100001100100011111	No	-	Serendipity
O3	1100011100101111101	Yes	T105	Existing St
O4	0000001000100011101	Yes	T091	Existing St
O5	1100100000010011110	Yes	T067	Existing St
O6	0000100011100111111	Yes	T077	Existing St
O7	0100001100100011110	No	-	Serendipity
O8	1000011000111101010	No	-	Serendipity
O9	0100011010101111101	Yes	T036	Existing St
O10	1101000100001011111	Yes	T042	Existing St
O11	1000001100100011100	Yes	T007	Existing St
O12	1100101100111111010	Yes	T059	Existing St

From a decision support system (DSS) perspective, the serendipitous offspring represent actionable design alternatives for future handicraft store development. Unlike traditional recommendation systems that only retrieve existing stores, the proposed GA-PSO framework is capable of generating entirely new store configurations that do not exist in the dataset.

To illustrate the practical interpretation of a serendipitous solution, consider Offspring O1 with chromosome 0000101100100001101. Based on the chromosome encoding scheme in Table 1, the DSS provides the following recommendation for establishing a new handicraft store configuration:

A user or entrepreneur is recommended to establish a store outside Padang City ($G1 = 00$). The proposed configuration discourages the use of materials such as songket, woven textiles, gemstones, shells, and animal bone-based crafts, and instead emphasizes embroidery, needlework, textile-based crafts, and knitted materials ($G2$ – $G4$ pattern interpretation).

In terms of product strategy, the store is recommended to avoid heavy orientation toward traditional clothing, wedding attire, household goods, sculpture galleries,

garden ornaments, pond decorations, woven handicrafts, bouquets, or general gift items, and instead focus on women's clothing and accessories or pearl-based crafts (G5–G7 interpretation). From a digital readiness perspective, the store is expected to have a functional customer contact or hotline (G9 = 1) and provide transparent price information for each product (G10 = 0/1 depending on configuration constraint interpretation). Although the store may not necessarily maintain an independent website (G11 = 0), it is strongly recommended to integrate with online marketplaces such as Shopee, Lazada, or Blibli (G12 = 1) to ensure market accessibility.

Therefore, this chromosome represents a feasible and structured store blueprint generated by the evolutionary system. It demonstrates that serendipity in this study is not random deviation, but a data-driven creative recombination that can be directly translated into entrepreneurial decision support.

3.5 Statistical Validation and Stability Analysis

To evaluate the stability and robustness of the proposed hybrid GA-PSO model, the optimization process was executed over 30 independent runs. Each run was initialized with different random seeds to assess the consistency of the obtained solutions.

The best preference similarity $P(x)$, fitness value $F(x)$, and improvement over the baseline dataset were recorded for each run.

3.6 Discussion

The results highlight three key contributions of the proposed framework beyond conventional DSS approaches. First, the use of entropy-based weighting improves the reliability of preference evaluation by reducing dependency on subjective judgment. Unlike expert-driven weighting schemes, entropy captures the intrinsic variability of attributes, enabling the model to prioritize more informative features. This leads to a more discriminative similarity function, which directly enhances the quality of solutions explored during optimization. The findings reinforce the importance of data-driven weighting mechanisms in DSS, particularly in domains with limited expert consensus. Second, the hybrid GA-PSO mechanism demonstrates a clear advantage in controlling the exploration-exploitation trade-off. While GA enables effective exploration of the combinatorial search space, PSO dynamically adjusts evolutionary parameters to stabilize convergence. The observed convergence pattern indicates that adaptive parameter tuning prevents premature stagnation and maintains population diversity. This suggests that hybridization is not merely a performance enhancement technique, but a necessary mechanism for handling complex, multi-criteria decision spaces. Third, the integration of serendipity introduces a novel dimension to optimization-based DSS. Rather than treating deviation from preferences as noise, the model leverages controlled dissimilarity to generate

meaningful alternative configurations. The results show that high-serendipity individuals contribute significantly to the discovery of previously unseen yet competitive solutions. These finding positions serendipity as a strategic exploration mechanism rather than a secondary objective.

Importantly, the improvement from the best dataset solution ($P(x)=0.8513$) to the best generated offspring ($P(x)=0.9108$) demonstrates the capability of the model to move beyond data-driven retrieval toward solution generation. This distinguishes the proposed framework from traditional recommender systems, which are typically limited to ranking existing alternatives. The ability to generate new configurations has significant implications for entrepreneurial decision support, where innovation and differentiation are critical.

Overall, the study confirms that integrating objective weighting, adaptive optimization, and serendipity-aware exploration provides a more robust and flexible DSS framework. This combination is particularly relevant in dynamic environments such as social commerce, where decision spaces are complex and continuously evolving.

Despite the promising results, this study has several limitations. The dataset is limited to 105 handicraft stores within a specific regional context, which may affect the generalizability of the findings. In addition, the preference representation is static and does not capture dynamic changes in user behavior over time. Future research may address these limitations by incorporating larger and more diverse datasets, as well as adaptive preference modeling to enhance the robustness and applicability of the proposed framework.

4. Conclusions

This study proposes a hybrid decision support framework for handicraft store planning in social commerce by integrating entropy-based attribute weighting with a hybrid GA-PSO optimization strategy. The entropy method enables objective and data-driven evaluation of attribute importance, while the hybrid optimization framework effectively explores the combinatorial solution space to generate feasible store configurations.

The experimental results demonstrate that the proposed approach is capable of producing superior configurations compared to existing data. The best generated solution achieved a higher preference similarity ($P(x)=0.9108$) than the best observed store in the dataset ($P(x)=0.8513$), indicating the ability of the model to move beyond data-driven retrieval toward solution generation. Although the statistical difference between GA and GA-PSO was not significant, the hybrid model achieved the highest best solution and provided automatic parameter adaptation. From a theoretical perspective, this study contributes to the

advancement of hybrid metaheuristic optimization by integrating entropy-based weighting and serendipity-aware fitness evaluation within a unified framework. From a practical perspective, the proposed DSS provides actionable insights for entrepreneurs in designing innovative and competitive handicraft store configurations in social commerce environments.

Overall, the findings highlight that combining similarity-driven evaluation with controlled serendipity can significantly enhance the capability of decision support systems to generate both relevant and novel solutions. This positions the proposed framework as a flexible and robust approach for supporting complex decision-making in dynamic digital commerce environments. Future research may extend this work by incorporating larger and more diverse datasets, integrating dynamic user preference modeling, and exploring real-time adaptive optimization to further improve system responsiveness and recommendation quality.

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