



Serendipitous Recommendations for Handicraft Store Discovery in Social Commerce Using a Genetic Algorithm with Adaptive Selection

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Abstract

In social commerce, particularly among small and medium-sized handicraft enterprises (SMEs), personalized recommender systems (RS) are crucial for enhancing store and product discovery. Conventional content-based filtering (CBF) often overemphasizes accuracy, leading to over-specialization and limiting exposure to novel or diverse items, an issue in the handicraft sector where uniqueness is valued. This study proposes a serendipitous recommendation approach using a Genetic Algorithm (GA) with adaptive selection strategies, Roulette Wheel Selection (RWS), Tournament Selection (TnS), and Rank-Based Selection (RBS), to balance relevance and unexpectedness. Handicraft store attributes, such as product types, materials, and services, are encoded in a 19-bit chromosome and evaluated via a hybrid fitness function. Tested on real data from West Sumatra SMEs, the model is assessed using Precision, Recall, Novelty, and Serendipity metrics. Results show that the GA-based adaptive selection approach outperforms baseline CBF in producing more diverse and surprising recommendations, fostering exploratory shopping experiences and supporting the discovery of unique local products in social commerce ecosystems.

Keywords: adaptives selection; content-based filtering; handicraft SMEs; genetic algorithm; serendipity

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1. Introduction

In social commerce (s-commerce), particularly among small and medium-sized handicraft enterprises (SMEs), personalized RS are essential for helping users discover relevant stores and products [1]. The dynamic and unstructured nature of s-commerce platforms poses challenges for recommendation models [2], as users increasingly expect not only accurate suggestions but also novel and diverse experiences. Traditional CBF, which recommends items based on a user’s search history and previously selected items [3-6], often lead to overspecialization [7], [8] and filter-bubble effects [9] repeatedly exposing users to similar content. This limits discovery and reduces satisfaction—especially in handicraft domains where uniqueness and variety are critical. Serendipity has thus emerged as a valuable “beyond-accuracy” metric, combining relevance with unexpectedness to enable discovery of items users may

not have explicitly searched for but still find valuable [10], [11]. Achieving this balance, however, is challenging. GAs, with their population-based search and exploration capabilities, offer a promising approach for optimizing RSs on multi-objective criteria such as relevance, novelty, and diversity [12-14]. Prior studies show that GAs can be adapted for RS contexts, particularly when combined with selection strategies that maintain diversity while guiding convergence [15], [16].

Building on this, the present study proposes a serendipitous RS for handicraft store discovery using GA with adaptive selection strategies, RWS, TnS, and RBS. Store attributes such as product types and materials are encoded in a hybrid fitness function balancing relevance and unexpectedness. Experiments on real data from West Sumatra SMEs evaluate the model using Precision (P), Recall (R), Novelty, and

Serendipity, with results showing that the GA-based approach outperforms baseline CBF in generating diverse and serendipitous recommendations. Serendipity in RSs refers to suggesting items that are both relevant and unexpected, combining novelty and surprise [17], [18]. An MLLM-based hierarchical model [19] balances relevance and surprise, while Sparks of Surprise [20] demonstrates that novelty and diversity can be optimized alongside serendipity; a comprehensive review [21] confirms it as a key “beyond-accuracy” dimension that enriches user experience. GAs have proven effective in addressing the lack of diversity and novelty in content-based recommenders [22], for example through multi-objective optimization that combines relevance and novelty to reduce overspecialization [23-25], overcoming limited content issues [22], optimizing precision and novelty simultaneously [26], [27], and improving serendipity in cold-start scenarios through ontology-based hybridization [28], [29]. Selection strategies in GA such as RWS, TnS, and RBS influence convergence speed [30] and solution diversity [31], and adaptive approaches are increasingly important for dynamic user preferences [32], which combines GA with novelty search, and multi-strategy adaptive selection [33], which switches mechanisms based on performance, with adaptive GA in multi-criteria RS [14], [34] showing gains in accuracy, precision, and novelty. GA has also been applied in various business domains to enhance accuracy, convergence speed, and user experience [22], [34], [35], with adaptive models adjusting parameters from user feedback to boost

precision, novelty, and satisfaction. Building on this, the present study applies GA with adaptive selection strategies (RWS, TnS, RBS) to the handicraft SME sector, benchmarking against CBF and evaluating relevance, novelty, and serendipity using real business data from West Sumatra, Indonesia. Unlike conventional CBF, which represents item content as unstructured text processed via TF-IDF and cosine similarity but suffers from overspecialization [1], [6], [18], the proposed model employs a structured 19-bit binary chromosome encoding semantically meaningful attributes from domain knowledge, enhancing diversity and serendipity. This domain-driven representation captures multidimensional aspects of user preferences beyond shallow textual features. For example, a preference for fabric-based stores offering traditional services in specific cities can be directly encoded, making filtering and evaluation semantically richer. Within this framework, GAs evolve candidate recommendation sets [36], with the 19-bit chromosomes serving as input to selection, crossover, and mutation operators [37], [38] as shown in Table 1. A multi-objective fitness function balances relevance, novelty, and serendipity, enabling the system to address qualitative aspects of recommendation quality in addition to accuracy. The integration of three adaptive selection mechanisms, facilitates a balance between exploration and exploitation across generations. This ensures that while fitter candidates are prioritized, population diversity is maintained, preventing premature convergence to suboptimal or overly homogeneous solutions.

Table 1. Composition of the 19-bit chromosome representing handicraft store features used in GA encoding

Feature Category	Description	Bit Length
Price availability	Whether the store provides price info (yes/no)	1 bit
Location type	Whether the store is located in a traditional market or on a street	1 bit
Business type	Handicraft or non-handicraft	1 bit
Primary material	Categorized: fabric, wood, metal, or others	2 bits
Secondary material	Categorized: brass, stone, plastic, or others	2 bits
Geographical location	Encoded based on major cities in West Sumatra	3 bits
Main product category	e.g., clothing, food, accessories, décor, art, mixed	3 bits
Type of service offered	Custom orders, rentals, tailoring, or none	2 bits
Business age	Based on estimated operational years	2 bits
Price quality label	Subjective: cheap, competitive, high-quality, or unspecified	2 bits
Total		19 bits

2. Methods

This section outlines the methods, covering system architecture, data preparation, encoding, and optimization.

2.1 System Architecture and Fitness Function Design

Data preprocessing involves the collection and cleaning of store-related attributes, including store names, material types, product categories, price ranges, geographic locations, and special services (e.g., custom orders, exports, rentals). The cleaned data are subsequently transformed through a feature encoding process, where categorical attributes such as material types (fabric, wood, metal, rattan) and product

categories (clothing, jewelry, musical instruments, wall decorations) are represented using binary vectors or weighted numerical scores. This representation ensures uniformity and computational efficiency within the optimization framework.

The proposed system employs a Hybrid Fitness Function formulated as a multi-objective model that balances relevance, novelty, and serendipity. The fitness value is defined as a weighted linear combination of objectives: $\text{Fitness} = \alpha \cdot \text{Relevance} + \beta \cdot \text{Novelty} + \gamma \cdot \text{Serendipity}$, where $\alpha = 0.4$, $\beta = 0.3$, and $\gamma = 0.3$. These parameter settings provide a balanced emphasis between recommendation accuracy and exploratory discovery. The GA iteratively evolves a

population of candidate store recommendations through selection, crossover, and mutation operators. To improve search effectiveness, three Adaptive Selection Methods are incorporated to enhance diversity preservation and convergence stability.

2.2 Chromosome Representation

We compiled data from 51 handicraft stores in West Sumatra. Each store was transformed into a fixed-length 19-bit chromosome to ensure consistent representation within the optimization framework.

This encoding scheme enables structured processing by the GA and supports efficient comparison, selection, and evolution of candidate solutions. The chromosome structure encodes key business attributes, including price availability (1 = listed, 0 = not listed) ; Location type, 1 = market, 0 = street ; Business type, 1 = handicraft, 0 = non-handicraft ; Primary material, 11 = fabric, 10 = wood, 01 = metal, 00 = other ; Secondary material, 00 = brass, 01 = stone, 10 = plastic, 11 = other ; Geographic location, 111 = Padang, 110 = Solok, 101 = Bukittinggi, 100 = Batusangkar, 011 = Pariaman, 010 = Painan, 001 = Payakumbuh, 000 = others ; Main product category, 000 = clothing, 001 = food, 010 = accessories, 011 = home goods, 100 = art, 111 = mixed ; Service type, 00 = none, 01 = embroidery/ tailoring, 10 = custom orders, 11 = rental/others ; Business age, 00 = <5 yrs, 01 = 5–15 yrs, 10 = 16–30 yrs, 11 = >30 yrs ; Price quality label, 00 = cheap, 01 = competitive, 10 = high quality, 11 = unspecified.

2.3 GA Workflow

The initial population consists of a number of chromosomes (store candidates) randomly selected from a dataset containing 51 stores. Each recommendation set (chromosome) is evaluated using Equation 1.

$$Fitness = 0.4 \times Relevance + 0.3 \times Novelty + 0.3 \times Serendipity \quad (1)$$

Relevance is computed as average similarity (cosine) between selected store features and user preference, Novelty is measured as the inverse popularity index, and Serendipity is high for stores that are low in similarity but relevant to preferences.

Selection by one of three adaptive schemes (RWS, TnS, RBS), Single-point crossover with probability (pc), and Bit-flip mutation with probability (pm). Repeat selection, crossover, and mutation for G generations, tracking fitness improvements.

3. Results and Discussions

This section reports the results and analysis of the applied selection strategies.

3.1 RWS

Concept: Each individual is selected probabilistically based on its fitness. The higher the fitness, the greater the chance of being selected [39], [40].

Steps: - Calculate the total fitness of the entire population and the probability of each store. The selection probability is calculated using Equation 2.

$$P_i = \frac{Fitness(i)}{\sum_{j=1}^n Fitness(j)} \quad (2)$$

Calculate the expected count (the number of individuals expected to be selected):

$E(i) = P(i) \times N$; where N is the population size, and randomly select individuals based on cumulative. Stores selected through RWS showing chromosome codes, fitness scores, and selection probabilities have presented in Table 2.

Table 2. Stores selected through RWS showing chromosome codes, fitness scores, and selection probabilities

Store – Chromosome	Fitness	Expected Count	Actual Count
SilviaPiobang – 1010011100000111110	0.760	1.04	1
Howlin Hand M – 0010111010011110111	0.854	1.17	1
Mansiang A R – 1010110010011111110	0.652	0.89	1
Eco – Paliko – 0110011100011101101	0.975	1.33	1
Working -Arts – 0010110010011110111	0.728	1.00	1
Camelia SBord – 1010011100111111110	0.762	1.04	1
RendangKatuju – 0010011000000111110	0.985	1.35	2
BefiFentiOkma – 0010111010011111110	0.549	0.75	1
Istri -Sultan – 1010011100011110111	0.983	1.34	2
Nuntarasashop – 1010011000011111110	0.585	0.80	1

Based on the single-point crossover pattern applied at position 12, the offspring generated from five selected parent pairs are presented in Table 3 and the offspring matching results are shown in Table 4.

The following is a semantic decomposition according to Table 1, and an interpretation of five derivative products that do not correspond to any store (meaning a new store with unique characteristics → (serendipity): 0010111010010111110, A street-side handicraft store using wood as the primary material, located in region 010, focused on food products, older than 7 years, offers

no specific service, and labeled as high-quality without displaying price ; 1010110010011101101, A wood/plastic-based handicraft shop offering accessories, located on the street, with rental services, 4–7 years in operation, and competitively priced ; 0010110010011111110, A long-established street-side handicraft shop specializing in accessories, using wood and plastic materials, with no service options, no price info, but considered high-quality ; 1010011100111110111, A long-standing street-based handicraft shop that sells a mix of product categories

made of fabric and miscellaneous materials, provides rental services, and has price quality left unspecified ; 0010111010010111110, This chromosome appears

twice in the list of 10 offsprings. The interpretation is already provided above.

Table 3. Offspring chromosomes generated from five parent pairs through single-point crossover (position 12) in RWS method

Parent 1	Parent 2	Offspring 1	Offspring 2
SilviaPiobang	Howlin Hand M	1010011100001110111	0010111010010111110
Mansiang A R	Eco – Paliko	1010110010011101101	0110011100011111110
Working -Arts	Camelia SBord	0010110010011111110	1010011100111110111
RendangKatuju	BefiFentiOkma	0010011000001111110	0010111010010111110
Istri -Sultan	Nuntarasashop	1010011100011111110	1010011000011110111

Table 4. Matching results of 10 offspring chromosomes from RWS against 51 handicraft store data

Offspring Chromosome	Status	Matched Store	Offspring Chromosome	Status
1010011100001110111	Match	SilviaPiobang	0010111010010111110	Serendipity
0110011100011111110	Match	Nuntarasashop	1010110010011101101	Serendipity
0010011000001111110	Match	RendangKatuju	0010110010011111110	Serendipity
1010011100011111110	Match	Istri – Sultan	1010011100111110111	Serendipity
1010011000011110111	Match	Nuntarasashop	0010111010010111110	Serendipity

The RWS method effectively biases selection toward chromosomes with higher fitness while preserving population diversity [41] [42]. By assigning probabilities proportional to fitness, it balances exploration and exploitation, producing recommendations that align with user preferences while allowing for serendipitous discoveries. This stochastic mechanism enhances the GA's adaptability, enabling the identification of unexpected yet valuable handicraft store alternatives in the social commerce context [43].

3.2 TnS (Tournament Size = 3)

Tournament selection is used in this study to identify the most relevant handicraft stores by randomly selecting a subset of three candidates (tournament size = 3) and choosing the one with the highest fitness value as the winner (parent) for the GA crossover process [44]. This process is repeated until the required number

of parent pairs is obtained. The fitness function incorporates the relative importance of store features through a weighted evaluation [40]. Each store chromosome is a 19-bit string representing 10 features as summarized in Table 5, with normalized weights totaling 1.0. Feature values are extracted based on their bit positions and assigned semantic scores (e.g., handicraft = 1, others = 0). The final fitness score, ranging from 0 to 1, is calculated using the weighted fitness evaluation and is presented in Table 6 is calculated by multiplying each feature score by its corresponding weight and summing the results. The chromosome feature structure and their corresponding weights are presented in Table 5.

The stores selected under the TnS strategy based on their fitness scores are shown in Table 6.

Table 5. Weight values assigned to chromosome features according to their priority in GA fitness evaluation

No.	Feature Name	Bit Length	Weight	Justification
1	Price availability	1 bit	0.05	Useful, but not a major factor
2	Location type	1 bit	0.05	Helps distinguish market vs roadside
3	Business type	1 bit	0.15	MUST be handicraft-focused
4	Primary material	2 bits	0.15	Focus on rattan, wood, silver filigree
5	Secondary material	2 bits	0.05	Secondary importance
6	Geographical location	3 bits	0.15	User prefers same-city stores
7	Main product category	3 bits	0.15	Mixed/multiple item types preferred
8	Type of service offered	2 bits	0.05	Extra service like customization helps
9	Business age	2 bits	0.10	Older stores are more trusted
10	Price quality label	2 bits	0.10	Affordable or premium preferences
	Total	19 bits	1.00	—

Table 6. Stores selected through TnS based on fitness scores of handicraft store chromosomes

Store Name	Chromosome	Fitness Score	Notes
HasHus Ribuna	1010011101000111111	0.55	Strong in all core features
Nuntarasashop	0111001101101111110	0.50	Excellent location, material, category
Am ski – shop	0110111011011111000	0.45	Strong material, fair on service
Achi CraftGal	0100100101011111101	0.45	Matches business, service, age
Istri -Sultan	0010011100000111100	0.45	Good match in category and location
Adelia Craft	1110101010011110111	0.45	High on service, type, and age
SilviaPiobang	1010011100000111110	0.40	Strong business type and location
A -Sutan Mudo	0010111000011110001	0.40	Good match in business and location
Intan Parmato	0001101101101111110	0.40	Balanced in age, pricing, and service
Howlin Hand M	0010111010011110111	0.40	Moderate match across features

The next step is to perform a crossover at one point, namely at position 12, resulting in three offspring, namely 0100100101011110001 Match (Puti –Sariau), 0010111000011111101 Match (Adelia Craft),

0010111010011110111 Match (BefiFentiOkma), and The remaining offspring exhibiting serendipitous characteristics are summarized in Table 7.

Table 7. Serendipitous offspring (non-matching chromosomes) generated from TnS crossover results

Chromosome	Parent Combination	Interpretation
0110111011010111110	Am ski – shop – SilviaPiobang	Non-handicraft (0), Materials: Strong match, Location: Matches target area, and potentially suitable store that is not currently in the dataset; could indicate untapped inventory
1010011100001111000	SilviaPiobang - Am ski – shop	focus on mixed products and customization, but lacking in trusted age and type, and may suggest emerging stores with potential but currently overlooked
0010011100001111110	Istri -Sultan - Intan Parmato	excellent business orientation and primary material, but mismatched in age and service, and could inspire new combinations of trusted features not yet found in one store
00011011011001111100	Intan Parmato - Istri -Sultan	reasonable location and category, but deviates in price and service offerings, and may appeal to users with flexible budget/service needs
1110101010011110111	Adelia Craft - Howlin Hand M	affordable, but lacks in material type and business focus, and Indicates possibility of niche users seeking affordability over specialization
1010011101001111110	HasHus Ribuna – Nuntarasashop	close to HasHus Ribuna, but deviates slightly in final bits, and possible variant or evolution of a known store profile
0111001101100111111	Nuntarasashop - HasHus Ribuna	high location and category match, but with novel combinations in price and type, and interesting hybrid; could represent a store model not yet present but desirable

3.3 RBS

RBS is a GA parent selection method in which individuals are ranked by fitness rather than chosen solely on absolute scores. This ranking-based approach maintains diversity by giving all individuals a chance of selection while still favoring higher-ranked candidates, thus helping to prevent premature convergence [45] [46]. The same weighted fitness function used in TnS is applied, as shown in Table 8 is applied, with each 19-

bit chromosome representing 10 store features weighted according to their relevance to user preferences. After evaluating all stores, individuals are ranked in descending fitness order. Selection probabilities are assigned inversely to rank, ensuring fitter individuals are more likely to be chosen without guaranteeing their selection. Using this probabilistic strategy, ten parents (five pairs) are obtained for crossover. The ranking results of stores selected using the RBS method are presented in Table 8.

Table 8. Stores selected through RBS ranked by fitness score

Rank	Store Name	Chromosome	Fitness Score	Notes
1	HasHus Ribuna	1010011101000111111	0.55	Strong in all core features
2	Nuntarasashop	0111001101101111110	0.50	Excellent in location, material, category
3	Am ski – shop	0110111011011111000	0.45	Strong in material and fair in service
4	Achi CraftGal	0100100101011111101	0.45	Matches business type, service, and age
5	Istri -Sultan	0010011100000111100	0.45	Good match in product category and location
6	Adelia Craft	1110101010011110111	0.45	High on service, business type, and age
7	SilviaPiobang	1010011100000111110	0.40	Strong on business type and location
8	A -Sutan Mudo	0010111000011110001	0.40	Good on business type and location
9	Intan Parmato	0001101101101111110	0.40	Balanced in age, pricing, and service
10	Howlin Hand M	0010111010011110111	0.40	Moderate match across features

Subsequently, a single-point crossover was performed on the 12th bit of the chromosome. The resulting offspring chromosomes and their matching status after

comparison with the dataset are presented in Table 9. The offspring evaluation outcomes under the RBS strategy are summarized in Table 9.

Table 9. Offspring chromosomes resulting from RBS crossover, showing matched stores and serendipitous outcomes

Offspring Chromosome	Parent Combination	Status	Matching Store
1010011100000111110	HasHus Ribuna – SilviaPiobang	Match	SilviaPiobang
1010011101000111111	SilviaPiobang - HasHus Ribuna	Match	HasHus Ribuna
010010010101111101	Achi CraftGal - Howlin Hand M	Match	Achi CraftGal
0010011100001111110	Istri -Sultan - Intan Parmato	Match	Puti – Sariau
1110101010011110111	Adelia Craft – Nuntarasashop	Match	Adelia Craft

The serendipitous offspring represent novel combinations that do not match any known store in the dataset but may represent stores with appealing feature mixes. Offspring 0110111011011110001 combines strong materials and business type (from Am ski – shop)

with a different service and age profile (from A-Sutan Mudo), potentially surfacing an undiscovered store profile. Offspring 0010111000011111000 highlights a strong alignment in location and service, but lacks a match in primary material or product category.

Offspring 0010111010011110001 has a balanced feature distribution across business type, materials, and moderate age, but doesn't match any real store. Offspring 0111001101101110111 shows strong location and category relevance from Nuntarasashop, but deviates in pricing and service compared to any existing store. These serendipitous results highlight the GA's ability to explore new combinations that may lead to potentially valuable store recommendations outside known options.

3.4 Performance Evaluation of the GA-Based RS

To comprehensively evaluate the performance of the proposed content-based RS enhanced by GA, a comparative analysis was conducted across three different selection methods: RWS, TnS, and RBS. Each method produced 10 offspring through crossover operations using parent pairs derived from real handicraft store data. The effectiveness of each method was assessed using standard evaluation metrics in RS: Precision, Recall, and F1-Score. Precision indicates the proportion of offspring that successfully matched actual relevant stores; Recall reflects the system's ability to

retrieve all possible relevant stores based on the number of parent pairs (maximum of 5 relevant matches); while F1-Score provides a harmonic mean between precision and recall. Table 10 summarizes the performance of each method. The evaluation metrics are computed using Equations 3–5.

$$\text{Precision} = \frac{\text{Number of matched stores}}{\text{Total number offspring}} \quad (3)$$

$$\text{Recall} = \frac{\text{Number of matched stores}}{\text{Maximum number of relevant stores that can be discovered}} \quad (4)$$

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (5)$$

Table 10 summarizes the precision, recall, and F1-score for each method. Precision measures the proportion of successful (matched) recommendations among all recommendations made. Recall represents the ability of the method to recover potential matching stores from the dataset, and F1-score provides a harmonic mean of precision and recall, giving a balanced view of the method's performance. The comparative performance results of the three GA selection methods are summarized in Table 10.

Table 10. Precision, Recall, and F1-Score of GA-Based RS Using Different Selection Methods

Selection Method	Precision	Recall	F1-Score
GA+Roulette Wheel (RWS)	0.50	1.00	0.67
GA+Tournament (TnS)	0.40	0.80	0.53
GA+Rank-Based (RBS)	0.50	1.00	0.67

Precision and Recall were calculated based on the proportion of offspring that matched actual store data out of the total offspring produced per selection method. The similarity in F1-scores between RWS and RBS suggests that both strategies effectively maintain population diversity while emphasizing fitness proportionally. Both GA + RWS and GA + RBS achieved the highest F1-score (0.67) due to a combination of perfect recall (1.00) and moderate precision (0.50), indicating strong retrieval capability while maintaining acceptable recommendation accuracy. Conversely, GA + TnS recorded the lowest performance across all metrics (precision: 0.40, recall: 0.80, F1: 0.53), suggesting that its exploratory nature increases the inclusion of irrelevant items, thereby reducing matching accuracy. Overall, RWS and RBS demonstrate greater reliability for producing relevant and high-quality store recommendations in a GA-based content-based RS.

4. Conclusions

In the evolving landscape of social commerce, the ability to guide users toward unexpected yet relevant discoveries has become a defining benchmark of intelligent recommendation systems. This study introduced a serendipitous recommendation model that integrates GA with adaptive selection strategies—RWS, TnS, and RBS—to uncover novel handicraft stores beyond the reach of conventional CBF. While

traditional CBF succeeded in generating relevant recommendations, it lacked the capacity for serendipity. In contrast, all GA-based methods demonstrated a remarkable ability to produce serendipitous recommendations that introduced users to stores previously unseen in the dataset, thereby enriching the discovery process. Among the three selection strategies, RWS and RBS showed a strong balance between matching accuracy and serendipitous diversity. The TnS method leaned more toward exploration but often at the expense of recommendation precision. Overall, the integration of evolutionary search with structured semantic encoding offers a compelling framework for serendipitous discovery in RS. This work underscores the value of serendipity as a core design principle for the next generation of intelligent social commerce platforms.

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