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Visual Intelligence in Metaverse Environment for E-commerce using Group Recommendation

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Abstract

As the digital landscape evolves, the metaverse is emerging as a critical platform for e-commerce, highlighting the need for hyper-personalization and marketing automation. This study proposes an intelligent Group Recommender System (GRS) integrated into a metaverse-based e-commerce platform, tailored to provide visual intelligence for enhancing customers purchasing experience in e-commerce activities. The recommendation is determined based on user group profiling using demographic characteristics and product preferences. A case study is conducted using a virtual showroom for furniture products to demonstrate the applicability of the proposed GRS. The results indicate that the approach can effectively identify heterogeneity within groups in terms of demographic variables and preferred product attributes. The findings reveal that the integrated GRS in a metaverse e-commerce platform not only enhances the retailing experience by accurately matching products with group preferences but also serves as an effective decision-support tool for optimizing marketing strategies for consumers.

Keywords: Group Profiling; metaverse; E-commerce; Group Recommender System; *k*-means Clustering; Decision Support

1 Introduction

In recent years, the rapid evolution of metaverse technology has significantly reshaped various facets of digital interaction including personalized consumer interactions [1]. This shift created opportunities in the field of visual intelligent which are common in today's customer retailing and e-commerce [2,3]. Traditional visual intelligent approach provides recommendation focusing on suggestions of individual users [4,5]. While these systems have primarily facilitated personalized experiences through direct interactions, they often fall short when addressing the needs of groups. Groups with shared preferences are left to navigate items and make purchase decisions independently, often failing to fully capture group preferences. Group recommender systems (GRSs) are particularly relevant in such scenarios where recommendations need to cater to collective preferences rather than individual ones, such as in choosing TV shows for a group of users with shared interests [6].

As the digital landscape expands into the metaverse, the focus is increasingly shifting towards hyper-personalization within the context of digital interactions including shopping [7]. Real-time social interactions are central in the metaverse, creating opportunities for group recommender systems (GRSs) that provide collective recommendations [8]. Automated recommender systems in the metaverse can address the shortcomings of traditional recommender systems. Implementing a metaverse requires the design of a virtual store, crafting virtual salesperson dialogues, displaying product information, and more, which makes individualized recommendations costly. In contrast, GRSs can be more economically implemented by aggregating individual user profiles [9]. Moreover, the metaverse offers a unique and personalized shopping experience for groups through virtual interactions that emulate the physical shopping experience. This allows groups to receive guidance and personalized recommendations, thereby enhancing the overall shopping experience.

Despite being a better fitting approach for a metaverse environment, GRSs pose two significant implementation challenges: i) aggregating individual users' preferences [9] and ii) making uniform recommendations to groups of users [10]. Consequently, there is a need to investigate user characteristics when developing a recommender system. To this end, previous studies have focused on developing algorithms used for user grouping [11–13] and the aggregation methods used for generating recommendation lists [10,14,15]. However, these studies have not accounted for in-group homogeneity and out-group heterogeneity in terms of demographic characteristics and preferred product attributes.

This study aims to address these limitations by proposing intelligent group profiling for GRSs in a metaverse environment. It also investigates the relationship between differences in demographic variables within a target group and observed product preferences. The results of this investigation will provide valuable insights into marketing decision-making. Furthermore, the study will explore the evaluation criteria used by a target group when purchasing items and the common attributes of their preferred items. The major contributions of this study can be summarized as follows:

- i. Design and implementation of an intelligent GRS. This study proposes metaverse-adapted GRS that utilizes k-means clustering and user preference aggregation. This system is designed to enhance the shopping experience by providing personalized recommendations tailored to group preferences. Additionally, it provides strategic insights for optimizing marketing approaches.
- ii. Contributes to the theoretical understanding and practical application of GRS for e-commerce within the context of the metaverse. This study offers novel insights into effective aggregation methods, demographic considerations, and strategies for group-based recommendations within the metaverse e-commerce.

The remainder of this paper is structured as follows: Section 2 provides a review of related studies. The proposed methodology framework is discussed in section 3. Section 4 presents a case study, and section 5 offers discussions of the empirical findings. Finally, the conclusions of the research are presented in section 6.

2 Literature Review

2.1 Applications of metaverse in E-commerce

The integration of metaverse technology into e-commerce presents a transformative shift in how consumers interact with brands and products in digital spaces [16]. Several studies have explored how consumer behavior is influenced by the immersive experience of the metaverse [17,18]. Shen et al. [19] systematically reviewed consumer behavior research and virtual commerce application design, identifying key factors that promote user purchases in metaverse environments. Their findings suggest a strong alignment between immersive technology applications and consumer behavior. Tsai [20] investigated how the metaverse's immersive environments can enhance marketing strategies within the travel and tourism industry. Their findings emphasized the importance of social connections and immersive experiences in improving consumer loyalty. Park & Lim [21] analyzed consumer perceptions and sentiments toward digital fashion and brand equity. They identified three key strategies utilized by fashion brands within the metaverse: launching NFT-based brand assets, attracting customers via games and developing distinctive brand experiences using immersive technologies. Similarly, Chen et al. [22] investigated how augmented reality features influence impulsive buying intentions in the metaverse. The study emphasized the role of multimodal sensory interaction across three dimensions: image, motion, and touchscreen interactions. Furthermore, Payal et al. [23] reported interactivity within a metaverse significantly impacts consumers' experience of brand trust.

2.2 Influence of form styles on visual perception

Form styles, characterized by elements such as shape, material, color, joining relationships, texture, and other product form features, play a significant role in the visual perception of a product [24]. Shape, material and color are three major elements that influence the visual perception of a physical product [25]. As these form styles can evoke emotional responses and

affect the overall impression of a product, they can significantly impact the effectiveness of a GRS. Configuration design principles also emphasize balancing form style elements in developing product variants [26]. Thus, understanding the impact of these components on visual perception can provide valuable insights for product design and recommender systems. Through tailoring recommendations that not only match the group's preferences but also align with their perceived form styles, GRS can effectively enhance user satisfaction.

2.3 Group recommender systems

Conventional recommender systems rely on users' past preferences to generate recommendations tailored to individual needs. However, many real-life situations involve group interactions, such as watching a movie with family, dining with colleagues, or planning holidays with friends [27]. These instances underscore the significance of providing recommendations that satisfy groups of people. GRS aggregates the preferences of individual users to provide personalized recommendations tailored for the group rather than just individuals [9]. Two common recommendation algorithms used in GRS are collaborative filtering and content-based filtering [28,29]. Some examples of collaborative GRS include Polylens [30], Social Playlist [31], and Netflix's group recommender [32]. Polylens and Netflix's group recommender leverage collaborative filtering to provide movie recommendations to groups that align with the aggregate preferences of the users. Similarly, Social Playlist was designed to recommend songs by analyzing current activities and states of mind of group members [31].

2.4 Aggregation methods in recommender systems

In GRSs, the aggregation of diverse preferences of group members to achieve consensus and fairness among recommendations is of paramount importance [33]. Aggregation functions for GRSs can be categorized into majority-based, consensus-based, and borderline methods [34]. The choice of method depends on the specific goal, with each method maximizing a different aspect of group satisfaction. Majority-based aggregation functions such as Plurality Voting and Borda Count (BC) methods focus on recommending items popular among group members [35]. However, these methods might overlook the diverse preferences within a group, potentially leading to dissatisfaction among some group members.

Consensus-based aggregation functions, such as Additive Utilitarian (ADD), Average (AVG), and Multiplicative (MUL), consider the preferences of all group members to establish collective group preferences [9,36]. While these strategies can lead to a consensus, the items recommended may not completely satisfy every individual within a group. On the other hand, borderline functions, such as Least Misery (LM), Most Pleasure (MPL) and Majority Voting (MAJ) focus only on the subset of user preferences and aim to minimize disappointments [35]. However, these methods often lead to a compromise when considering the overall group satisfaction [9]

The choice of a specific strategy depends on the desired objective. For instance, methods like MUL and AVG are used when the goal is to maximize the average level of satisfaction. In a study conducted by [37], the accuracy of various aggregation methods, including the MU, LM, FA, BC, PV, MP, and AM methods was examined. The study found that the AU method, where all individual ratings for each item are summed to form a group rating, is the optimal technique for providing accurate group recommendations. However, it should be noted that the AU and the AVG methods yield the same results, given that other parameters, like the number

of groups identified, remain constant. Hybrid aggregation methods have also been used in several studies [15]. These hybrid methods could offer a more adaptive approach to GRS in a metaverse context, accounting for the diverse and dynamic nature of user interactions and experiences.

2.5 Clustering methods in group recommender systems

Previous studies have focused on clustering methods for segmenting users into groups according to their product preferences. Notable among them is the work of [37], who proposed the automatic detection of groups using clustering methods. This approach is particularly effective when providing personalized recommendations to every individual user is impractical or costly. Prominent clustering methods used for recommender systems include the Weighted User Similarity network (WUSN), K-Means clustering and the Gaussian Mixture Model (GMM) [12,37,38]. The WUSN method clusters users into neighbourhoods based on similarity measures, including Cosine similarity and the Pearson correlation coefficient [38]. However, the WUSN method can be time-consuming and complex, especially when dealing with a large number of users [12]. In contrast, the K-Means clustering and GMM, form groups using item preference vectors, thus proving to be more efficient than the WUSN method [12,37].

2.6 Demographic variables and consumer behaviours in recommender system

Exploring group characteristics such as demographics, and their influence on the efficacy of the group recommender system, deserves attention. Demographic variables are known to account for many individual differences in consumer behaviors [39]. For instance, factors like gender and age have been identified as impactful and provide valuable insights into consumer behaviors [40,41]. Thus, it's important to investigate the relationship between demographic variables and consumer behavior. However, despite the continuous research interest in refining clustering and aggregation methods, there has been little effort to broaden the scope of information provided by GRSs [9].

Previous studies indicated gender influences multiple aspects of consumer behaviors, including information processing, personal interactions, emotional responses, reactions to price promotions and health-consciousness. Female consumers tend to treat all available information as equally important, processing it thoroughly before making a purchase decision, while male consumers often process only the information that they deem noticeable or important [42]. Moreover, gender has been shown to significantly impact visual attention during online shopping. A study by Hwang and Lee [43] has found that females are more visually attentive to various pieces of information available than males are. Males' attitudes towards products are strongly influenced by visual attention to product information and consumer opinions, both of which are deemed critical. This aligns with the Selectivity Theory, which characterizes females as comprehensive processors and males as selective processors [44]. A study by Mehta [45] indicates that women score higher than men on dimensions such as hedonism, novelty orientation and price value consciousness related to consumer decision-making styles. Moreover, a study by Hwei & Youngsook [46] suggested females tend to develop continuous purchase intention due to positive social media interactions.

Consumer behaviors are also influenced by age in several ways, including emotional responses, attention span, brand loyalty, and health awareness. Older adults often experience a decrease in attention, particularly towards factual details, a change that can be linked to cognitive decline [47]. Research also suggests that brand loyalty increases with age, with older

adults considering fewer brands and preferring long-established brands [48]. Moreover, older adults typically display more health-consciousness leading them to seek health-related information more frequently [49]. The variations in behavior due to age and gender differences provide valuable insights that can help shape marketing strategies for different user demographics [50,51]. Thus, consideration of demographic factors is essential to enhance the design of GRSs.

3 Methodology

The primary objective of this study is to develop an effective strategy for clustering users into distinct groups and determining the optimal size of each group for a GRS within a metaverse context. This involves considering factors such as shared interests, virtual communities, collaborative experiences etc. that are intrinsic to the metaverse. The proposed GRS architecture comprises the following 5 key components as illustrated in Fig. 1. Each of the key components handles specific functionalities within the system.

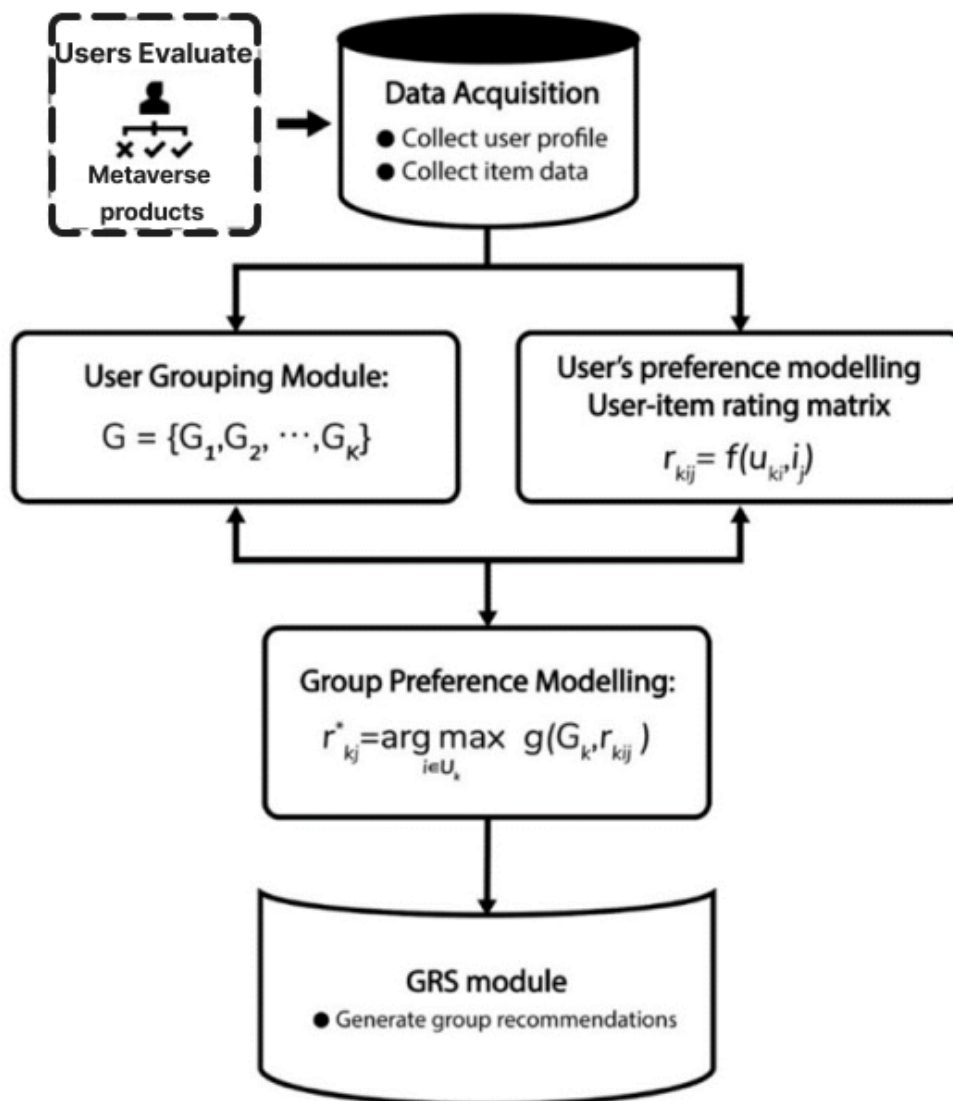


Fig. 1 Architecture of proposed GRS

- i. Data Acquisition Module: Responsible for collecting and preprocessing user and item data from the metaverse platform. Data concerning demographic variables and user ratings are collected via an electronic questionnaire administered within a simulated virtual shopping environment.
- ii. User Grouping Module: Utilizes the K-Means clustering algorithm to segment users into distinct groups based on the similarity of their item ratings. K-Means is chosen for its efficiency and effectiveness in forming distinct, non-overlapping clusters [10,37].
- iii. Preference Modelling Module: Constructs individual user preference models using recommendation techniques such as collaborative filtering and content-based filtering.
- iv. Group preference modelling: Aggregates individual user preferences to formulate group profiles that represent the collective preferences of each group.
- v. Recommendation Module: Generates personalized recommendations for each group based on the group profiles and item characteristics. Utilizes methods such as average, least misery, and multiplicative aggregation to ensure that the group's collective preferences are represented.

3.1 System architecture

The proposed GRS methodology involves providing recommendations to a set of distinct user groups. These groups are denoted as $G = \{G_1, G_2, \dots, G_K\}$. Each group G_k represents a specific subset of users who share similar preferences and demographic profiles. More formally, each group G_k consists of N users, represented as $U_k = \{u_{k1}, u_{k2}, \dots, u_{kN}\}$. All items that can be recommended within the metaverse are represented as $I = \{i_1, i_2, \dots, i_M\}$. The system ensures that each group, G_k , receive unique recommendations, maintaining the exclusivity of each group, i.e., $G_k \cap G_{k'} = \emptyset, \forall k, k' \in \{1, 2, \dots, K\}, k \neq k'$. The objective of the GRS is to determine group profiles and items with the highest predicted ratings for each group.

The objective of the GRS is to recommend items that maximize the ratings of each group (Eq. 1). The function aims to find the item with the highest aggregated rating according to the chosen aggregation method, thus maximizing group satisfaction.

$$r^*_{kj} = \operatorname{argmax}_{i \in U_k} g(G_k, r_{kij}) \quad (1)$$

Equation 2 defines the function to predict rating r_{kij} that user u_{ki} in group G_k would assign to item i_j , based on the characteristics of both the user and the item.

$$r_{kij} = f(u_{ki}, i_j) \quad (2)$$

3.2 User segmentation

This study uses user-to-item rating data to segment users into groups based on the similarity of item ratings. K-means clustering is employed, which has proven effective in grouping users in prior studies [10,37]. In K-Means, users are segmented into 'k' clusters according to the ratings they provide for a set of items. The objective function 'J' of the K-Means clustering is formulated as shown in Eq. (3).

$$J = \sum_{g=1}^k \sum_{u=1}^N \left\| x_u^{(g)} - c_g \right\|^2 \quad (3)$$

Where N is the sample size, $x_u^{(g)}$ is the rating given by a user u in the user group G_k and c_g is the centroid of G_k . The number of user groups 'k' is a critical parameter in K-means clustering.

To determine the optimal value of k , the clustering process is repeated multiple times considering different numbers of user groups.

3.3 Aggregation of Individual Ratings into Group Ratings

Once users are segmented into groups, individual ratings are aggregated into a group rating, combining ratings from all N users in the group G_k for each item. This study utilizes the average (AVG) method (Eq.4) due to its simplicity and effectiveness in reflecting the group consensus [36]. The group rating r_{kj} is computed by taking the arithmetic mean of the individual ratings r_{kij} from all users i in group k .

$$r_{kj} = \frac{1}{N} \sum_{i=1}^N r_{kij} \quad (4)$$

Other aggregation methods considered include:

- Least Misery: This method selects the minimum rating given to an item by any user in the group (Eq.5). It is useful in scenarios where the goal is to avoid disappointing any group member [36].

$$r_{kj} = \min(r_{k1j}, r_{k2j}, \dots, r_{kNj}) \quad (5)$$

- Multiplicative: This method calculates the product of all individual ratings (E.q 6), significantly penalizing low ratings. This approach is suitable where unanimous approval is required [36].

$$r_{kj} = \prod_{i=1}^N r_{kij} \quad (6)$$

3.4 Determining preferred product attributes for user groups

Product attributes are defined using form styles, which are subsequently used to extract attributes from selected products. In this study, we define two form styles using shape, material, and color. These styles, along with their corresponding pairwise adjectives, can be generalized to various physical products. Product design experts rate each item in terms of its form styles, using a score range of -1.0 to 1.0 at 0.1 intervals. The item's final score for a particular form style is determined by averaging the scores it received for that form style. To establish the relationship between the form styles and the group ratings, we use the Pearson correlation coefficient. The calculation for this coefficient, represented as R , is detailed in Eq. (8).

$$R = \frac{I(\Sigma x r_{kj}) - (\Sigma x)(\Sigma r_{kj})}{\sqrt{[n\Sigma x^2 - (\Sigma x)^2][n\Sigma r_{kj}^2 - (\Sigma r_{kj})^2]}} \quad (8)$$

Where I denote the number of rated items, x denotes the score of an item on a form style and denotes the rating of an item j by group G_k .

3.5 Effect of demographic characteristics on group profiling

To determine significant differences in categorical and numeric variables among independent groups, we employed chi-square tests and one-way Analysis of Variance (ANOVA). Both the chi-square (X^2 statistic) and F-statistic are calculated, as outlined in Eq. (6) for the chi-square test, and Eq. (7)-(9) for the ANOVA. A larger X^2 value indicates a larger difference among the groups. Conversely, the F statistic measures the extent of variance in means among groups. If a significant difference is identified, the pairwise comparison will be performed using Tukey's honestly significant difference (HSD).

$$X^2 = \sum \frac{(O_i - E_i)^2}{E_i} \quad (6)$$

$$F = \frac{MSB}{MSW} \quad (7)$$

$$MSB = \frac{\sum_{g=1}^k (T_g^2 / N_g) - G^2 / N}{k - 1} \quad (8)$$

$$MSW = \frac{\sum_{g=1}^k \sum_{u=1}^{N_g} Y_{g,u}^2 - \sum_{g=1}^k (T_g^2 / N_g)}{N - k} \quad (9)$$

Where O_i refers to the observed value and E_i is the expected value. MSB denotes the sum of squares between groups and MSW is the mean sum of squares within groups. T_g is group total, and G represents the total for the whole sample. $Y_{g,u}$ denotes an observation, in this case, the age of a user.

3.6 Performance evaluation of group recommender system

The Normalized Discounted Cumulative Gain (nDCG) and precision, which are widely used in GRS research [12], are used to evaluate the appropriateness of the groups formed. The nDCG metric assesses each user's level of satisfaction with the recommended items. The nDCG is computed for the top 'M' item recommendations based on the items' group ratings. Assuming an ordered recommendation list [i_1, i_2, \dots, i_M] is given to user 'u', the Discounted Cumulative Gain (DCG) of the user is computed as shown in Eq. (3).

$$DCG_M^u = r_{u,i_1} + \sum_{m=2}^M \frac{r_{u,i_m}}{\log_2(m)} \quad (3)$$

Where m denotes the ranking of the recommended items within the recommendation list. Next, nDCG is computed as shown in Eq. (4).

$$nDCG_M^u = \frac{DCG_M^u}{IDCG_M^u} \quad (4)$$

The $IDCG_M^u$ represent the maximum possible gain for user 'u' obtained by rearranging the 'M' recommended items into the most ideal order. The resulting nDCG values are then plotted against the different values of 'k' with varied number of items in the recommendation list 'M'. In the study, 3.5 is used as the rating threshold, meaning if the group rating of an item is above 3.5, the item is labelled as recommendable. Thus, the actual rating of a recommended item given by a user needs to be 4 or 5 for the recommendation to be regarded as satisfactory. The precision metric used in this study is given in Eq. (5).

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

'TP', and 'FP' represent the true positive and false positive values, respectively. In our context, if both the group rating and the actual rating of a user in the group are higher than 3.5, the group rating is regarded as true positive (TP). On the other hand, if the group rating is higher than 3.5 but the actual rating of the user is not, the group rating is regarded as false positive (FP).

Finally, the optimal value of 'k' is chosen based on nDCG and precision results. This optimal value leads to a relatively high nDCG and precision while ensuring that each group has a reasonable size. Very small group sizes are not ideal since user-to-item rating data are likely to be sparse in real-life situations. It thus requires enough group members to aggregate representative group ratings. As such, we limit the value of 'k' to the 2-10 range, meaning that k-means clustering is performed 9 times. By plotting the nDCG and precision values for each grouping, we aim to find a value of 'k' that best satisfies the requirement.

4 Results and analysis

4.1 Case Study: Virtual Shopping Environment

This section presents a case study to demonstrate the applicability of the proposed methodology framework and evaluate its performance within a metaverse environment. The case study is set in a virtual shopping experience focused on furniture products. We developed a virtual reality (VR) application using Unity. This application simulates an immersive metaverse shopping environment tailored specifically for furniture items. Each user group receives recommendations that are customized based on their collective characteristics and preferences. Fig. 2 provides a screenshot of the developed VR application, showcasing the user interface. This immersive environment allows users to interact with the recommended products, providing feedback on user preferences.

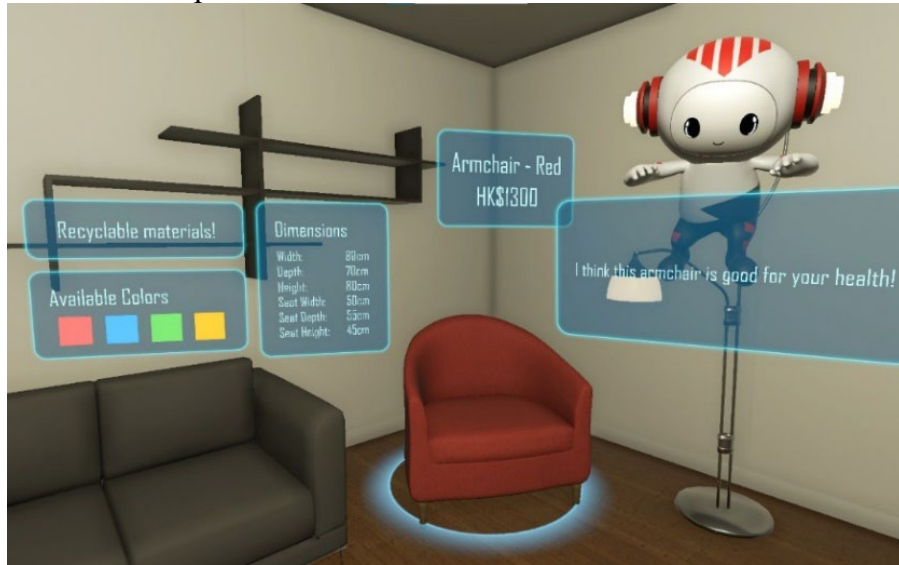


Fig. 2. Screenshot of the metaverse shopping experience

4.2 Data collection

Data collection was conducted through an electronic questionnaire within a simulated virtual shopping environment, structured into two sequential stages as illustrated in Fig. 3. To the best of our knowledge there are no established benchmark datasets for evaluating GRS. Hence, we procedurally generated a robust simulated dataset which overcomes the limitations of small real-world samples and allows comprehensive assessment. The simulation was designed to model the participation of 10,000 virtual subjects, with simulated demographics set at approximately 5,500 (55%) male and 4,500 (45%) female. The simulated mean age of the participants was set at approximately 32 years, with a standard deviation of about 10 years; ages were adjusted to fall within the 18 to 65-year range. This data was generated using a normal distribution for age and a biased random choice for gender, reflecting realistic demographic variations.

For item rating data, virtual participants were assumed to have been placed in a simulated room where they were presented with various item features as abstract models. These models are automatically rotated to allow viewing from different perspectives. Ratings of virtual participants for each item were simulated on a 5-point Likert scale, where 1 indicated the lowest preference and 5 the highest. After each rating, a simulated 3-second countdown commenced to signal the transition to the next item.

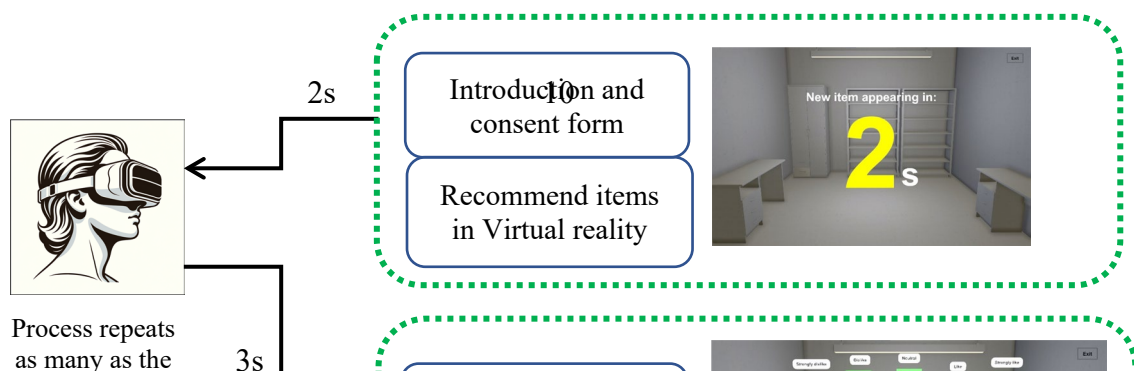












Fig. 3. Experimental protocol for the data acquisition in a metaverse

4.3 Virtual Furniture Product Evaluation

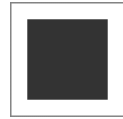
4.3.1 Product screening and selection

Furniture was chosen as the product category because it is familiar to most people, and participants are likely to have a similar level of expertise in evaluating these products' merits. Initially, we collected 50 items spanning four subcategories: chairs, lamps, storage units, and tables, sourced from online shopping platforms. We then applied a screening process based on the list of form styles shown in Table 1. Following this process, 20 items were selected for the study while ensuring each form style was adequately represented (Table 2).

Table 1
Pairwise adjectives describing form styles

Form style	Pairwise adjective	
Shape Irregularity		
	Geometric	Irregular
Complexity		
	Simple	Complex
Material Softness		
	Hard	Soft
Roughness		
	Smooth	Rough
Color Contrast		
	Harmonious	Contrasting

Lightness



Dark



Light

Table 2
Selected items for case study

Chair			
Item 1	Item 2	Item 3	Item 4
Item 5	Item 6	Item 7	Item 8
Lamp			
Item 9	Item 10	Item 11	Item 12
Storage			
Item 13	Item 14	Item 15	Item 16
Table			
Item 17	Item 18	Item 19	Item 20

We invited seven product design experts to evaluate the form styles of 20 selected items across six dimensions (Appendix A). These ratings were used to compile the recommendation lists for each group, focusing on the items with the highest ratings.

4.4 User grouping and optimization

The k-means clustering algorithm was applied to the user-item ratings matrix to identify user groups. The number of clusters k varied from 2 to 10, and Normalized Discounted

Cumulative Gain (nDCG) and precision metrics for each configuration were computed. Fig. 4 illustrates the variations in nDCG and precision values corresponding to the number of groups, with varied sizes for the recommendation list (M set as 1, 3, or 5). The analysis revealed that $k=4$ is the optimal number of groups. This is evidenced by a significant increase in both nDCG and precision metrics between $k=3$ and $k=4$, which then begin to decline for larger values of k .

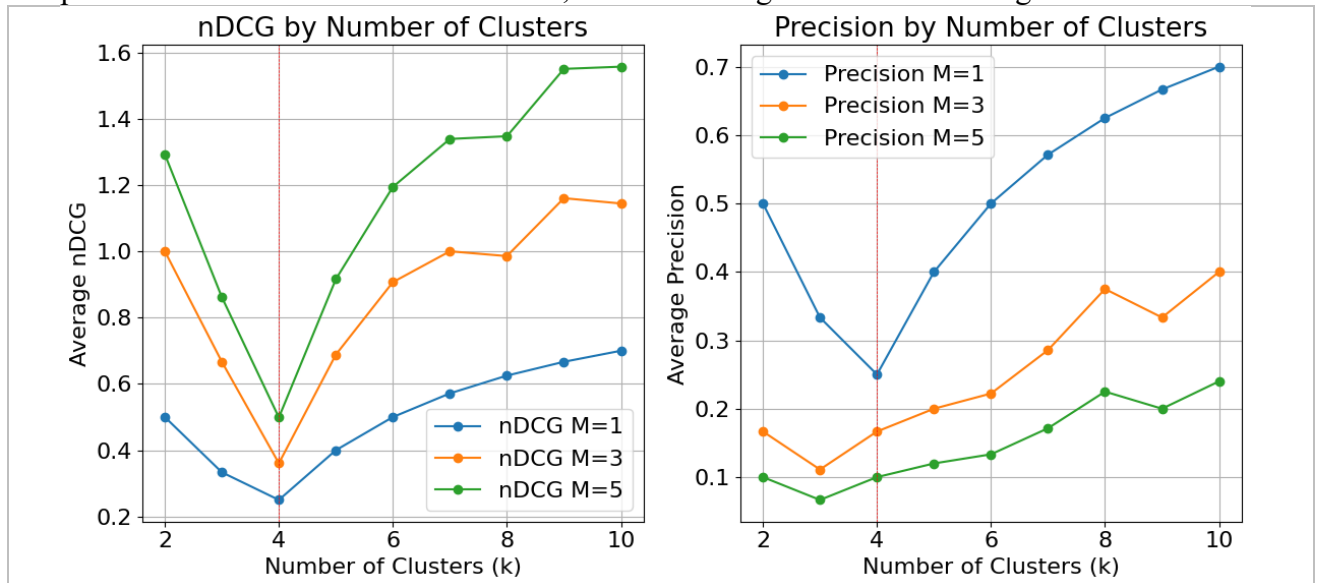
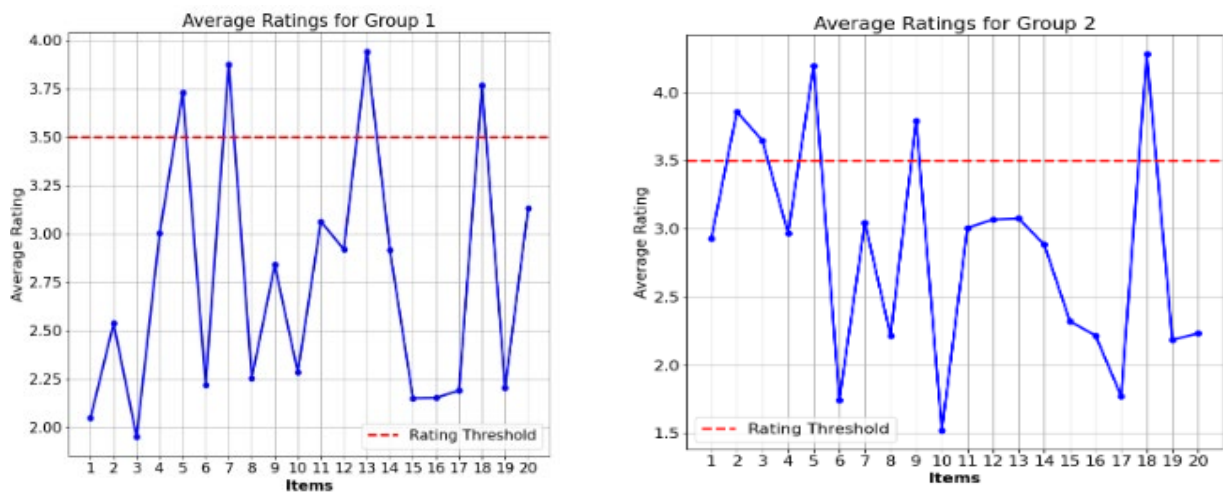


Fig. 4. nDCG and precision with different values of k

After determining the optimal grouping, we examined the group ratings for all items within each identified group. Fig. 5 depicts these ratings, highlighting clear variations in product preferences across different groups. For example, Group 2 and Group 4 generally exhibit higher group ratings, while the opposite is true for Group 3. There are also notable differences among the groups in terms of the number of items liked or disliked. For instance, Group 2 and Group 4 each liked 5 items, in contrast to Group 3 who liked 1 item only. This underscores the necessity of personalized group recommendations in enhancing user satisfaction.



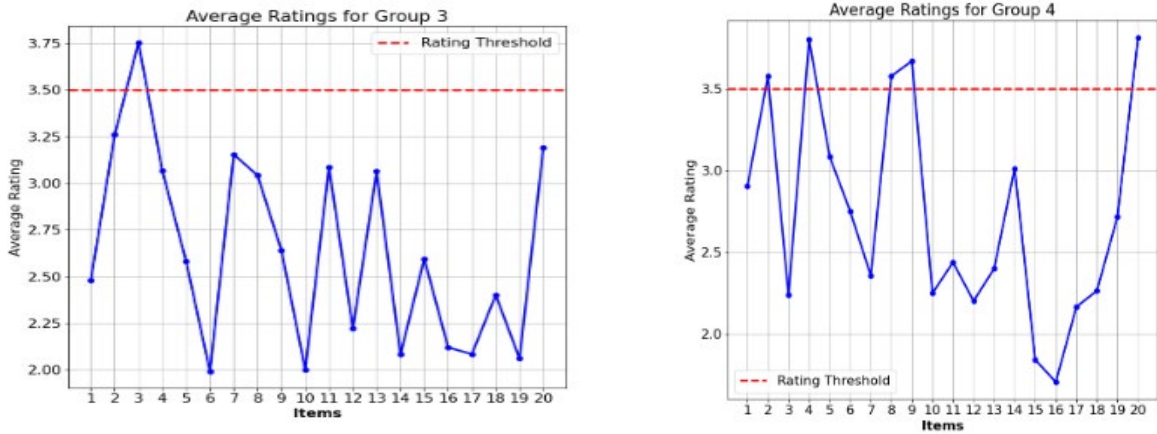


Fig. 5. Group ratings of the user groups

The recommendation list for each group includes the five items with the highest group ratings. Fig. 6 illustrates the mean values of the form styles recommended for each group.

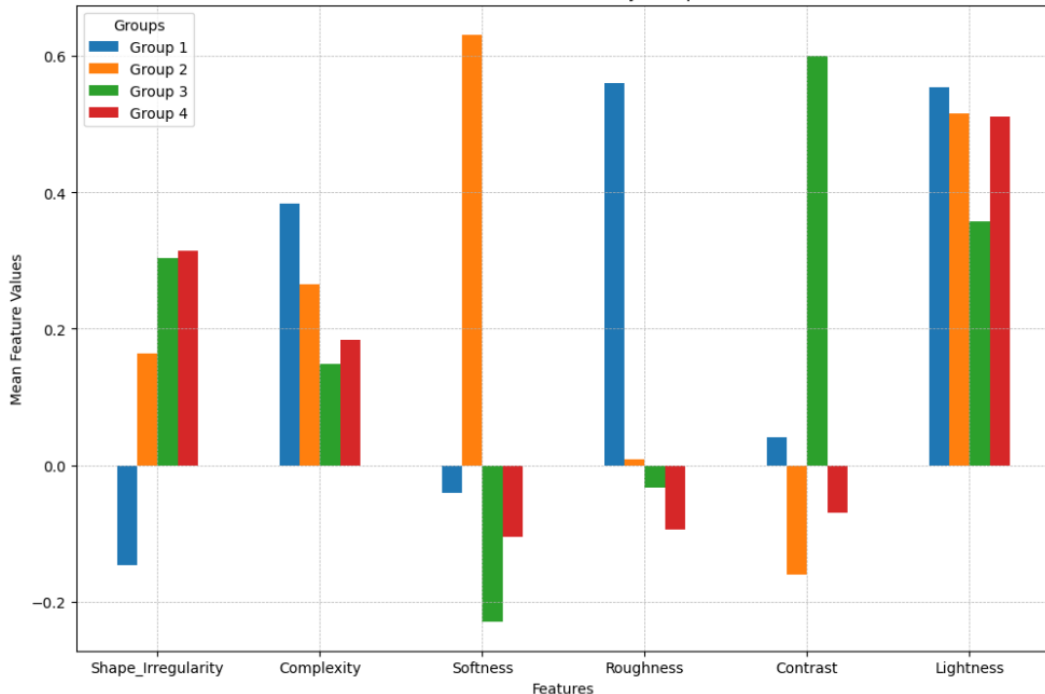


Fig. 6. Mean feature values of form styles of top five recommended items

4.5 Analysis of group profiles

To investigate how demographic variables influence group preferences, we conducted statistical tests on gender and age differences across groups. A chi-square test was performed to assess the significance of gender and age bias on group preferences. The results are presented in Table 3, which shows the intergroup differences regarding gender and age across four different clusters. The pairwise comparison of the chi-square test reveals significant differences in preferences between groups with varying gender and age compositions. In terms of gender, Group 3 (69.3% female) and Group 4 (66.9% female) have a significantly higher percentage of females compared to Groups 1 (22.0% female) and 2 (25.9% female). This suggests that

gender composition significantly influences group preferences. On the other hand, the age distribution shows that Group 2 has a remarkably high percentage of individuals in the 18-24 age category (61.0%) compared to other groups. Conversely, Group 4 has a substantial proportion in the older age categories (42.9% in 35-44 and 28.1% in 45-54). These age preferences suggest that different age groups may also significantly influence the preferences and behaviors of each cluster.

Table 3
Intergroup differences regarding gender and gender

Variable		Group 1	Group 2	Group 3	Group 4	Chi-Square Test	
						X^2	p
Gender	Female	22.0%	25.9%	69.3%	66.9%	2000.47	0.0001*
	Male	78.0%	74.1%	30.7%	33.1%		
Age category	18-24	4.2%	61.0%	24.7%	5.9%	4506.22	0.0001*
	25-34	60.7%	24.6%	38.1%	20.2%		
	35-44	32.3%	12.8%	27.5%	42.9%		
	45-54	2.3%	1.2%	9.0%	28.1%		
	55-64	0.5%	0.3%	0.8%	2.9%		
	65+	0.1%	0.0%	0.0%	0.0%		

* $p < .05$

4.6 Group preferences of product attributes

To quantify the relationship between these form styles and the group ratings, Pearson correlation coefficients were calculated (Table 4). The results show Group 2 and Group 3 show strong preferences for specific features (Roughness and Lightness respectively), with high statistical significance. Group 1 and Group 4 have a significant preference only for certain features (Contrast for Group 1, Softness for Group 4).

Table 4
Correlation between form styles and group ratings

Form style	Pearson correlation coefficient (R, p)			
	Group 1	Group 2	Group 3	Group 4
Irregularity	(0.23, 0.34)	(-0.26, 0.27)	(-0.05, 0.84)	(0.23, 0.32)
Complexity	(0.09, 0.70)	(0.47, 0.035*)	(0.44, 0.05*)	(0.34, 0.15)
Softness	(-0.19, 0.42)	(-0.19, 0.42)	(-0.19, 0.43)	(0.74, 0.00*)
Roughness	(0.07, 0.78)	(0.75, 0.00*)	(0.29, 0.22)	(0.16, 0.51)
Contrast	(0.65, 0.02*)	(0.07, 0.76)	(-0.38, 0.10)	(-0.19, 0.42)
Lightness	(0.33, 0.15)	(0.66, 0.001*)	(0.90, 0.00*)	(0.34, 0.14)

* $p < .05$

The results of the Pearson correlation analysis reveal that Group 1 members place significant emphasis on contrast while Group 4 focuses on softness. Similarly, a strong correlation was observed between preferences of Group 2 and specific features (complexity, roughness, and lightness). Group 3 has a strong correlation with complexity and lightness.

4.7 Insights from Group Preferences

The comprehensive analysis of demographic data and product attribute preferences has enabled the creation of detailed profiles for each user group. Formed group profiles provide a foundation for targeted marketing actions tailored to each segment's characteristics. Table 5 outlines potential marketing strategies for each of the four groups. Each group's marketing strategy is designed to leverage their unique preferences and demographics, ensuring that the marketing efforts are more effective and efficient.

Table 5
Marketing strategies for each cluster

Group	Group profile	Preferred attribute	Marketing strategy
1	Predominantly male (78.0%)	Strong preference for contrast ($R = 0.65$, $p = 0.02^*$)	Focus on bold, contrasting designs that stand out visually.
2	Young demographic predominance (61.0% in 18-24 age category)	High preference for roughness ($R = 0.75$, $p = 0.00^*$) and lightness ($R = 0.66$, $p = 0.001^*$)	Incorporate modern, minimalist designs with rough textures and light visual appearance
3	Majority female (69.3%)	Significant preference for lightness ($R = 0.90$, $p = 0.00^*$)	Offer products with lighter colors and materials that enhance spatial perception
4	Predominantly female (66.9%)	Strong preference for softness ($R = 0.74$, $p = 0.00^*$)	Design and promote furniture that emphasizes comfort and plushness.

5 Discussion

This study contributes to the evolving field of GRS and demonstrates its potential to deliver personalized recommendations within a metaverse context. Based on product preferences and demographic similarities, distinct user groups can be identified. Specifically, this study demonstrated the usage of k-means clustering to determine user groups that optimize cluster validity metrics such as nDCG and precision. This highlights the potential of machine learning techniques to determine user groups based on user-item rating data.

The study conclusively identified that user groups, differentiated by their demographic characteristics, exhibited unique product preferences. The analysis uncovered notable gender-specific differences, with female-dominant groups favoring softness ($R = 0.74$, $p = 0.00^*$) and lightness ($R = 0.90$, $p = 0.00^*$) in products. These aesthetic inclinations provide actionable insights for businesses on tailoring offerings and marketing to resonate with women in virtual spaces. Similarly, the results showed age-specific divergent needs with younger groups demonstrating distinct preferences from older groups. For instance, younger consumers may seek trendiness and fashion, while older ones tend to prioritize comfort and durability. Such

variations could be linked to various factors, such as cultural norms, social expectations, or psychological factors.

These insights underscore the importance of incorporating key demographic variables when modelling group profiles. Recognizing how gender and age shape collective preferences is crucial for businesses exploring personalization in metaverse commerce. Blending this understanding with data-driven clustering enables more precise recommendations catered to the nuanced needs of each user segment. This relationship offers crucial insights for marketers to craft targeted strategies and accurate recommendations in a metaverse.

5.1 Implications

As metaverse platforms evolve, hyper-personalization and marketing automation have emerged as key trends shaping the digital commerce landscape. Implementing targeted strategies can lead to more effective customer engagement and satisfaction in virtual environments. However, personalization within the metaverse requires tailoring core elements like store design, product visuals, and interfaces to each user.

This research demonstrated the potential of GRS to enable such personalization in metaverse contexts. It also highlights the value of leveraging machine learning to segment users based on ratings data and demographics to develop an in-depth understanding of each group's preferences. This facilitates businesses to craft personalized recommendations, promotions, and virtual experiences tailored to each group.

The proposed approach not only enhances user engagement but also optimizes resource allocation, making the personalization process more scalable and economically viable. Integrating GRS with Web 3.0 technologies can further amplify its cross-sector potential. Web 3.0 facilitates collecting expansive datasets to dynamically adapt GRS models to evolving behaviors.

5.2 Limitations and future research

This methodology proposed in this study, while robust, has its limitations. Firstly, the scope of user information considered in the study is limited, as it assumes gender and age as the sole demographic variables. Incorporating additional demographic factors such as level of education and income could enrich the understanding of user preferences and behaviors [52]. Secondly, the inclusion of psychographic variables and user behavior data, such as order histories, loyalty card usage, and coupon redemption rates could enhance marketing decisions [53].

This study sets solid groundwork for group profiling in GRS. Future research could explore the potential of merging GRS with marketing decision support systems. With the availability of more comprehensive user data, future studies should explore automating the entire group recommender system workflow. This includes data acquisition, user grouping, and final recommendations generation integrated with marketing actions. Lastly, future research should compare advanced machine learning techniques such as deep learning and reinforcement learning for GRS. These techniques could potentially enhance the system's capability to interpret and learn from complex user behaviors and preferences, thereby improving the accuracy and effectiveness of the recommendations.

6 Conclusion

This research demonstrates a novel group profiling methodology for GRS in metaverse-based e-commerce platforms. The case study in a simulated furniture store validated the approach of using k-means clustering and average rating aggregation to identify distinct user groups based on shared demographics and product preferences. Analysis of the group profiles revealed significant gender differences between user groups, contributing to divergent preferences. The group profiling insights from this research uncover new opportunities for targeted marketing decision support. By matching product offerings and promotions to group preferences, satisfaction and engagement can be enhanced while driving better outcomes.

The proposed framework bridges intelligent recommender systems with marketing automation and highlights the integral role of GRS in the evolving virtual commerce landscape. As group recommenders are further refined, their potential to revolutionize metaverse-based e-commerce platforms through hyper-personalization is apparent. While the current findings showcase the efficacy of GRS, future work should focus on incorporating more expansive datasets, automating processes, and deep learning approaches such as reinforcement learning.

Appendix A: Rating given to form styles of selected items

Item	Form style					
	Shape		Material		Color	
	Irregularity (-1=geometric, 1=irregular)	Complexity (-1=simple, 1=complex)	Softness (-1=rigid, 1=hard)	Roughness (-1=smooth, 1=rough)	Contrast (-1=harmonious, 1=contrasting)	Lightness (-1=dark, 1=light)
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
1	-.23 (.56)	-.01 (.64)	-.80 (.21)	-.37 (.52)	-.09 (.56)	-.64 (.57)
2	-.23 (.53)	.26 (.57)	-.86 (.16)	-.09 (.66)	-.30 (.56)	.87 (.15)
3	-.74 (.28)	-.47 (.30)	-.76 (.21)	.21 (.56)	-.20 (.50)	-.51 (.18)
4	.64 (.21)	-.20 (.29)	.03 (.35)	.06 (.55)	-.57 (.22)	-.63 (.18)
5	.17 (.65)	-.01 (.48)	-.14 (.40)	.49 (.30)	-.11 (.50)	-.51 (.18)
6	.21 (.37)	-.51 (.44)	.53 (.27)	-.04 (.44)	-.30 (.52)	.00 (.42)
7	-.33 (.48)	.24 (.42)	-.77 (.26)	-.19 (.38)	-.10 (.60)	.74 (.27)
8	.17 (.36)	-.13 (.26)	.26 (.41)	.21 (.25)	.01 (.51)	-.19 (.23)
9	.34 (.49)	.09 (.25)	-.53 (.51)	-.46 (.28)	.03 (.46)	.33 (.72)
10	-.13 (.56)	-.63 (.20)	-.61 (.34)	-.17 (.63)	-.04 (.44)	-.31 (.56)
11	-.10 (.59)	-.26 (.33)	-.47 (.56)	-.49 (.38)	-.24 (.38)	-.09 (.52)
12	-.34 (.29)	-.24 (.34)	-.56 (.57)	-.37 (.55)	-.41 (.42)	.81 (.20)
13	-.51 (.41)	-.41 (.42)	-.80 (.20)	-.37 (.34)	.23 (.65)	.46 (.30)
14	-.81 (.15)	-.34 (.53)	-.79 (.19)	-.07 (.62)	-.27 (.51)	-.34 (.32)
15	-.73 (.21)	-.37 (.59)	-.74 (.23)	-.41 (.40)	.34 (.47)	.41 (.29)
16	-.70 (.22)	-.20 (.46)	-.69 (.33)	-.51 (.27)	-.06 (.49)	.76 (.19)
17	-.60 (.66)	-.16 (.40)	-.63 (.30)	-.37 (.47)	.07 (.64)	-.49 (.23)
18	-.21 (.42)	-.10 (.42)	-.71 (.25)	-.17 (.56)	-.43 (.37)	-.24 (.31)
19	-.67 (.25)	-.13 (.53)	-.67 (.24)	-.40 (.56)	.10 (.53)	.50 (.26)
20	-.03 (.50)	-.23 (.31)	-.46 (.42)	-.50 (.38)	.17 (.53)	.53 (.21)

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