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APPLICATION OF DEVELOPING CLOTHING RECOMMENDATION SYSTEM WITH ARTIFICIAL INTELLIGENCE TECHNIQUES

YAPAY ZEKA TEKNİKLERİ İLE GELİŞTİRİLEN GİYİM ÖNERİ SİSTEMİNİN UYGULANMASI

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APPLICATION OF DEVELOPING CLOTHING RECOMMENDATION SYSTEM WITH ARTIFICIAL INTELLIGENCE TECHNIQUES

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***ABSTRACT*:** This study aims to develop a clothing recommendation application for users who possess a large number of clothes but have limited time due to their intense work tempo. This application aims to assist them in using their clothes effectively, reducing the time spent on selecting outfits, and dressing fashionably. In the process of developing this application, firstly, the criteria influencing the user's clothing preferences were determined. Subsequently, a wardrobe dataset was created based on the established criteria. Following this, methods for suggesting clothes were explored. As a result of the research, it was decided to utilize association rule analysis, multidimensional clothing representation coding, and weighted L1 distance methods for clothing recommendation in this study. In the application phase, experiments were conducted using the dataset associated with the chosen methods. It has been determined that the application developed in this study gives successful results in suggesting clothes suitable for user preferences.

Keywords: Recommendation system, Clothing, Selection Criteria, Artificial Intelligence Techniques.

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***ÖZ*:** Bu çalışmada, yoğun iş temposunda çalışan çok sayıda giysiye sahip olan ancak zamanı kısıtlı olan kullanıcılar için bir giyim önerisi uygulaması geliştirilmesi amaçlanmıştır. Bu uygulama, kullanıcıların kıyafet seçimi ve şık giyinmeye harcadıkları zamanı azaltmak ve kıyafetlerini etkili bir şekilde kullanmalarına yardımcı olmayı amaçlar. Bu uygulamanın geliştirilmesi sürecinde ilk olarak kullanıcının giyim tercihlerini etkileyen kriterler belirlendi. Daha sonra belirlenen kriterlere göre bir gardırop veri seti oluşturuldu. Daha sonra kıyafet önerme yöntemleri araştırıldı. Araştırma sonucunda bu çalışmada giyim önerisi için ilişki kuralı analizi, çok boyutlu giyim temsil kodlaması ve ağırlıklı L1 uzaklık yöntemlerinden yararlanılmasına karar verildi. Uygulama aşamasında, seçilen yöntemlerle, ilgili veri seti kullanılarak deneyler gerçekleştirildi. Bu çalışmada geliştirilen uygulamanın, kullanıcı tercihlerine uygun kıyafet önermede başarılı sonuçlar verdiği tespit edilmiştir.

Anahtar Kelimeler: Öneri sistemi, Giyim, Seçim Kriterleri, Yapay Zeka Teknikleri.

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1. INTRODUCTION

The variety and quantity of clothing have increased due to factors like technological advancements, socio-cultural changes, economic growth, and enhanced knowledge of clothing design [1-4]. Consequently, consumers are buying more clothing. For example, in 2014, about 100 billion pieces of apparel were available on the market, averaging 14 pieces per person, with the number continuing to rise [5]. For consumers with many clothes, efficiently managing them requires remembering various details daily, such as each item's status (clean, dirty, etc.), location (wardrobe, laundry basket, etc.), compatibility with other clothes, last worn date, and inventory to avoid duplicate purchases. This is challenging and can lead to some clothes being overused and worn out faster, while others are rarely used. This can also result in economic waste when users forget they own certain items and buy similar ones again [6,7]. However, with the internet and the widespread use of smart devices, technologies like mobile applications have been developed to make life easier and save time. These applications are designed to run on mobile devices like smartphones and tablets, integrating with their main operating systems [8,9].

Globally, the number of mobile application users is increasing due to greater access to smartphones [10]. In Turkey, there were 68.7 million smartphone users in 2022, who downloaded 3.73 billion applications, with the number of downloads rising. Turkish users have spent a total of 44.4 billion hours on mobile apps [11]. Some apps address clothing-related problems by offering clothing suggestions and developing algorithms that recommend suitable outfits from a wide variety of options [1,12,13]. The present research differs from other studies as it emphasizes the efficient utilization of clothing already purchased, enabling users to buy fewer items and ultimately contribute to both environmental protection and the reduction of economic waste. Unlike existing studies, this study does not aim to propose the best design. In contrast to the literature, it offers suggestions based on predefined fashion combinations from the user's existing wardrobe and the user's previous preferences. It is the first study to make recommendations based on the user's clothing by combining clothing style and user activities. The subsequent chapters of this study are structured as follows: Chapter 2 reviews the literature on clothing recommendation systems. Chapter 3 introduces the research architecture and the methods employed. Chapter 4 contains the results and performance evaluation, while Chapter 5 presents the conclusions.

2. LITERATURE REVIEW

Suresh et al. propose a fashion recommendation system that uses association rule mining to suggest clothing items [14]. This system is based on the popular algorithm known as the Apriori algorithm. Association rule is an expression that describes the relationship between two items. The association rules generated by the Apriori algorithm are later used to recommend clothing items to users. The system first identifies the products that the user has purchased in the past. It then utilizes association rules to create a list of clothing items that may be of interest to the user. In their study, Zhang, Ma, and Zhang have developed a novel approach to fashion recommendation by utilizing multi-modal data, which includes data from multiple formats such as text, images, and audio [15]. They employed a deep learning model capable of learning relationships between different data modalities. As a result, they argued that the use of such data can enhance the accuracy and personalization of fashion recommendations. Chen et al. have developed a model that generates clothing recommendations for users by incorporating contextual data such as weather conditions, time of day, and user location [16]. In their study, they argued that utilizing such information can improve the accuracy and personalization of fashion recommendations. Wu et al. propose a fashion style recommendation approach that leverages user-item, item-item, and user-user similarities [17]. In their study, user-item similarity is measured based on user ratings, item-item similarity is calculated using product attribute similarity, and user-user similarity is determined based on the similarity of their product ratings. The proposed approach focuses on recommending fashion products that align with the user's interests and preferences. Wang et al. have developed a fashion recommendation system that takes into account the user's body shape and size [18]. In this recommendation system, deep learning methods are employed to estimate the user's body shape and size. Human images are used as training data for this purpose. Based on the predicted body shape and size, fashion products that are suitable for the user are filtered and identified for recommendation. Wu et al. have proposed a new approach for fashion compatibility prediction based on convolutional neural networks [19]. Their proposed method aims to learn the compatibility of fashion products by utilizing both local and global relationships between the products. The method consists of a Graph Convolutional Network (GCN) and a pairwise discriminator. The GCN is used to learn the local relationships between fashion products, while the pairwise discriminator is utilized to learn the global relationships between fashion products.

The literature on clothing recommendation systems typically employs collaborative filtering and content-based strategies. Some of these systems primarily focus on predicting the wearer's clothing preferences based on extensive historical data [20]. Examples of clothing recommendation systems include those that analyse large amounts of historical data on clothing purchases by users in the past [12, 21]. Other systems examine every pixel of clothing images found while browsing the web, periodically storing them in a database, and then suggest clothing based on the user's body type and skin tone [22]. Some define customer needs and the characteristics of each clothing item (brand, cost, material, and color), utilizing technologies to determine the degree of similarity between users to provide apparel choices based on criteria requested by clients [23]. Another approach involves using the user's photographs to extract numerous attributes to learn about the user's preferences and clothing style, then suggesting a fashion style to the user [24]. There are also systems that automatically propose garments based on the weather [25], as well as those that advise clothing based on personal preferences [26].

The utilization of artificial intelligence technologies and a comprehensive dataset of fashion has proven highly successful in studies developing clothing recommendation systems [27]. However, upon reviewing the literature on recommendation systems, it becomes evident that they typically rely on grouping items into separate categories to identify relevant products that would appeal to consumers with similar interests. Existing studies, which do not take into account the user's current clothing, recommend clothing that users may find appealing based on past purchases or ratings [21]. Consequently, upon analysis of the literature, it becomes apparent that research on clothing recommendations often encourages users to purchase specific clothing items.

Considering the studies in the literature, it is observed that all recommendation systems are designed for the acquisition of new products. Although the user's past preferences are taken into account, these are used to identify purchasable items. Systems that make recommendations from existing clothing filter based on criteria affecting clothing usage conditions, such as weather. Systems that use clothing similarity or user similarity also make inferences based on scenarios involving the purchase of new products.

Unlike the aforementioned studies in the literature, this study aims to design a system that recommends outfits by combining only the clothing items users already own, rather than acquiring new products. The designed recommendation system is intended to suggest outfits to users based on both predefined fashion designers' perspectives and user preferences. It is the first study to combine user preferences with fashion design templates to create combinations from existing clothing. The dataset used in the system architecture is designed to be easily expandable, covering various scenarios, and capable of recommending different clothes. Unlike other studies, the developed algorithm in this study has the ability to incorporate the fashion designers' perspective while also learning user preferences and making selections based on the user's existing clothing items. Considering its unique features, this study can be considered as the first of its kind in the literature with these capabilities.

3. METHODOLOGY

In this present study, the clothing recommendation system was implemented in stages. Below is a detailed explanation of these stages.

3.1. Determining Clothing Recommendation Criteria

People's lifestyles, daily activities, professions, and expectations of style or comfort determine their clothing styles [28]. Consequently, numerous fashion styles have emerged, including Italian, retro, vintage, basic, classic, boho, and casual styles for men [29]. The purpose of these styles is to meet various expectations of clothing. Clothing styles differ based on attire components such as pattern, color, fabric, fiber, length, collar, sleeve, waist, leg, closure material, pocket, iron mark, textile printing, and embellishment, as well as combinations of worn garments and other influencing factors.

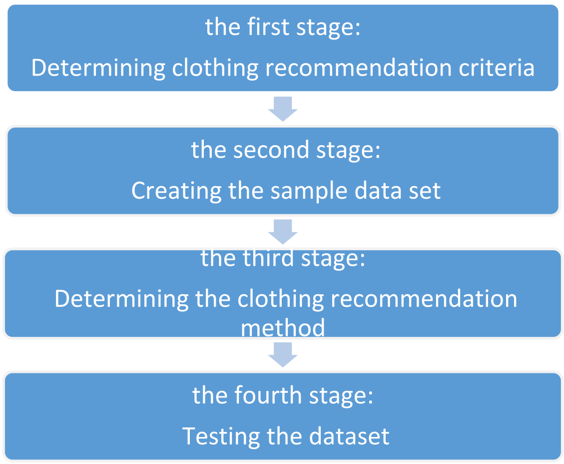

Figure 1. Stages of Creation of Clothing Recommendation System

Clothing recommendation systems suggest suitable garments to be worn together according to selected fashion styles. These systems require predefined recommendation criteria, which include identifying the fundamental components of each style, determining compatible garments, and considering other influencing factors specific to each style. For instance, the width of the leg opening is a fundamental criterion that varies significantly between styles, being very narrow in some and very wide in others. Thus, the system can recommend different garments based solely on this criterion, tailored to the specific fashion style. To represent style and recognize harmony in clothing combinations, one needs to have definite criteria. The study's selection criteria were as follows.

Basic Clothing Components. The basic components of clothing and the types of each component are also given in Table 1.

In clothing suggestions, the appearance and usage of the garment can be differentiated by changing the types of its components. Let's explain with a few examples; due to its high moisture absorption, cotton fiber is commonly used for innerwear [30]. Knitted fabrics are much more flexible compared to woven fabrics; they are widely used in the production of casual and sportswear (shirts and trousers etc.) [31, 32]. The number and the type of pockets used in the garment are effective in transforming the garment into a classic, office, sports, or daily form.

Clothing Recommendation Criteria Based on Combinability of Garments. According to fashion styles, not every garment can be worn with every other garment. Therefore, the combinability of garments is another important clothing recommendation criterion.

Table 1. Basic Clothing Components and Types of Clothing Components

Basic Clothing Components	Clothing Components Types
Pattern	slim fit, normal fit, oversize, classic etc.
Color	reds, oranges, yellows etc.
Fabric	knitted and woven
Fiber	natural fibers: cotton, wool, linen, bamboo etc. synthetic fibers: polyester, polyamide, acrylic etc. blends fibers: cotton/ polyamide, bamboo/ polyester etc.
Length	short, medium, wrist-length, and long lengths
Collar	shirt collars, turn-down collars, upright collars, mandarin collars, jacket collars, polo collars, crew neck, hooded etc.
Collar Extra	buttoned, pointed, ribbed, snap fastener, dovetail collar, buttoned, zipper, lace-up etc.
Sleeve Characteristics	mini/short/medium/long, slit/rib cuff, 2 buttons/3 buttons/5 buttons, Standard/Raglan Sleeve etc.
Waist Height	low, normal, and high
Waist	belts, elastic etc.
Leg Type	Spanish, straight, tight leg, elastic, double etc.
Closure Material	zipper, button (plastic, metal, etc.), rivet, etc.
Pocket	with/without pockets, appliqué flap/fletto flap/fletto zipper fillet, one pocket/two pockets/three pockets, inner pocket/ handkerchief pocket/handkerchief pocket, back/front/side pockets etc.
Ironing Mark	with or without iron marks
Textile Printing	plain, plaid, batik, etc.
Embellishment	sports, basting, quilting, embroidery, roving etc.

Combination. Clothing selection and combination involve considering details such as colors, textures, fabrics, accessories, shoes, and scarves [33]. Even if individual garments are fashionable on their own, their function and setting can change when combined with other clothes. This combination, known as a clothing set, is achieved by analyzing clothing information distribution [34]. For example, women's clothing combinations could include a coat, tunic, and trousers, or a tunic, skirt, and scarf [35]. Additionally, a quilted, padded coat might be used for everyday activities and sportswear, while a single-button linen jacket with a crewneck t-shirt and denim slacks can suit both office and casual wear. The user's choice of combinations influences the clothing recommendation.

Other Criteria Influencing Clothing Recommendations. Factors like gender, identity, societal values, economic status, and religious beliefs influence clothing recommendations. For instance, in Turkey, women traditionally did not wear trousers due to religious and cultural reasons [36]. However, this study focuses on different criteria for clothing recommendations, specifically the intended activity and the weather conditions at the location where the garment will be worn. These criteria are elaborated below.

Where to Wear (Choice of Location). People want to be stylish and comfortable when engaging in activities such as sports, walking and exercising, socializing, attending meetings and parties, traveling, vacationing, at home, sleeping, etc. The user's status affects the clothing recommendation. For example, athletes' clothing is generally recommended to be in sharp-contrast, bright, and light colors to enhance excitement and motivation for explosive and power-demanding activities [37]. During travel, however, it is more suitable to wear travel-appropriate and aesthetically pleasing clothes [38].

Ambient Temperature. Weather conditions significantly influence clothing recommendations [39]. For instance, linen trousers are ideal for summer, while velvet trousers are better for winter. The activity's location—indoors or outdoors—also affects recommendations. For outdoor activities in heat, thin, light-colored, short-sleeved garments are advised. Conversely, for cold outdoor conditions, thicker, dark-colored, long-sleeved garments are more suitable.

3.2. Creating The Sample Data Set

The data set used in this study has been created by the fashion designer. While creating this data set, the fashion designer took into consideration the clothing recommendation criteria and casual men's clothing style determined in this research. The dataset consists of basic garments found in a men's wardrobe with a Classic clothing style and has been created from three clothing categories. These are bottom wear (trousers, shorts, etc.), top wear (shirt, sweatshirt, t-shirt) and outerwear (jacket, coat, etc.). The distribution of the data set as bottom wear, top wear and outerwear products is given in Table 2.

Table 2. Distribution Table of the data set according to clothing types

Top Wear		**Bottom Wear**		**Outerwear**	
Clothing Type	Quantity	Clothing Type	Quantity	Clothing Type	Quantity
Trousers	10	Shirts	10	Jackets	5
		Sweaters	10	Coats	5
		T-shirts	5		
		Sweatshirts	5		

Table 3. Examples of the characteristics and Criteria for evaluating outerwear

	Where to Wear	**Wearable Temperature Range (°C)**	**Wearable Environment**	**Pattern**	**Color**	**Fabric**	**Fabric Fiber Content**	**Print Weave Feature**
Jacket 1 (C1)	O/I	10-30	DO	S	NB	Cotton Polyester	55% Polyester,40% Viscose,5% Elastane	
Jacket 2 (C2)	O	10-25	D	R	BR	Velvet	80% Cotton 18% Polyamide 2% Lycra	ribbed
Jacket 3 (C3)	O/I	15-30	DO	S	BE	Linen Woven	%100 Keten	
Jacket 4 (C4)	O/I	10-25	DO	S	BR	Polyester	38% Viscose 2% Lycra 60% Polyester	
Jacket 5 (C5)	O	15-25	D	R	W	Cotton 3 Yarn Knitting	100% Cotton	
Coat 6 (C6)	O	10-20	S	S	K	Suede	80% Cotton - 20% Polyester.	
Coat 7 (C7)	O	10-20	D	R	B	Faux Leather		
Coat 8 (C8)	O	10-20	D	R	BE	Polyester	100% Polyester	
Reefer jacket 9 (C9)	O	5-15	DO	R	B	Stamp	20% Polyester 80% Wool	
Reefer jacket 10 (C10)	O	5-15	DO	R	DG	Stamp	78% Polyester 20% Viscose 2% Lycra	

Only the outerwear group is presented in the tables that follow as an example of the data set. The common criteria for outerwear are shown in Table 3, and the technical and specific features of outerwear are listed in Table 4. These features are combined separately for each type of clothing for shirts, t-shirts, sweatshirts, sweaters, and trousers in other data sets, and sample information about the recommended combinations is presented in Table 5.

What the abbreviations in Table 3 mean for each component: Where to Wear (Outdoor =O, Outdoor/Indoor=O/I), Wearable Environment (Diary=D, Diary /Office=DO), Pattern (Slim Fit=S, Regular=R), Color (Black=B, Dark grey=DG, Brown=BR, Navy blue=NB, White=W, Khaki=K, Beige=BE)

What the abbreviations in Table 4 mean for each component: Ornament (Basting=B, Spor=S, Quilting=Q, Plaid pattern=P), Collar Type (Jacket=J, Turn down= T, Lapel=L, Neckband=N, Grandad=G, wide jacket=WJ,), Collar Detail (pointed collar=P, Rib collar=R, snap=S, dovetail=D), Closing Technique (Button=B, Zipper=Z), Sleeve Wrist Detail (slit=S, rib cuff=R), Sleeve Detail (4 button=4B, zipper=Z), Sleeve Type (Standart=S, Reglan=R), Sleeve length (Long Sleeve=L), Clothing Length (Regular=R, Slim=S, hip height=H), Pocket Type (Flap pocket with flap=FWF, applique pocket=A, Zippered flat pocket=ZWF, zippered pocket=Z, upright vest pocket=UVP), Extra pocket (handkerchief pocket=H, inner pocket=I, Zippered ornamental pocket=ZO), With/Without Pocket (with pockets=P, unlined=UL), Lined/Unlined (lined=L, unlined=UL), Lining Material (silk satin=SS, Fleece Fabric=FF, satin filled=SF), Back Slit (single slit=SS, without slits=WS, double slit=DS)

Table 4. Technical Details and Features of Outerwear

	Ornament	Collar Type	Collar Detail	Number of Front Closure Buttons	Closing Technique	Sleeve Wrist Detail	Sleeve Detail	Sleeve Type	Sleeve length	Clothing Length	Pocket Type	Number of pockets	extra pocket	Number of Extra Pockets	With/Without Pocket	Lined/Unlined	Lining Material	Back Slit
Jacket 1 (C1)	B	J		2	B	S	4B	S	L	R	FWF	2	H	1	P	L	SS	SS
Jacket 2 (C2)	S	T		5	B			S	L	R	A	3	I	1	P	UL	SS	WS
Jacket 3 (C3)	B	L		2	B	S	4B	S	L	R	FWF	2	H	1	P	L	SS	DS
Jacket 4 (C4)		L	P	1	B	S	4B	S	L	R	FWF	2	H	1	P	L	SS	SS
Jacket 5 (C5)		N	R		Z	R		R	L	R	ZWF	2			P	L	FF	WS
Coat 6 (C6)	Q	G	S		Z	S	Z	S	L	S	ZWF	2	ZO	2	P	L	SF	WS
Coat 7 (C7)	Q	G	S		Z	S	Z	S	L	S	Z	2	ZO	2	P	L	SF	WS
Coat 8 (C8)	Q	N			Z			S	L	R	Z	2			P	L	SF	WS
Reefer jacket 9 (C9)		WJ	P	2	B	S	4B	S	L	H	FWF	2	H	1	P	L	SS	SS
Reefer jacket 10 (C10)	P	J	D	3	B	S	4B	S	L	H	UVP	2	H	1	P	L	SS	

Table 5. Various Outerwear Combination Suggestions

	Shirt	**T-shirt / Sweat**	**Jumper**	**Pants**
Jacket 1 (C1)	G5	T1,T4,T5	K3,K6,K9,K10	P5,P4,P2,P6
Jacket 2 (C2)		T1,T3,T4,T5	K1,K7,K9,K10	P4,P6
Jacket 3 (C3)	G5,G1	T4,T5	K3	P6,P2,
Jacket 4 (C4)	G7,G5		K10	P1,P9
Jacket 5 (C5)	G1,G10	S1,T1,T2,T3, T4,T5	K1	P1,P2,P3,P6, P7
Coat 6 (C6)	G5,G9,G10	S1,T1,T2,S3, T3,T4,T5	K1,K2,K3,K6, K7,K9,K10	P1,P2,P5,P6, P7,P10
Coat 7(C7)	G1,G2,G3,G8, G9,G10	S1,T1,T2,S3,T3, T4,T5	K1,K2,K3, K5, K6,K7,K8, K9,K10	P1,P2,P4,P5, P6,P7, P10
Coat 8 (C8)	G1,G2,G3,G5, G8,G9,G10,G4,G6	S1,T1,S2,T2, S3,S4, S5,T3, T4,T5	K1,K2,K3,K4,K5,K6, K7,K8,K9,K10	P1,P2,P3,P5, P6,P7
Reefer jacket 9 (C9)	G5,G7,G9,G10	T1,T2	K1,K2,K3,K4,K5,K6, K7,K8,K9,K10	P1,P2,P4,P5,P6,P7, P8,P9
Reefer jacket 10 (C10)	G1,G2,G3,G5,G7,G8,G9 ,G10	T1,T2	K1,K2,K3,K4,K5,K6, K7,K9,K10	P1,P2,P5,P6,P7,P8,P9

3.3. Determining The Clothing Recommendation Method

In this research, for determining the clothing recommendation method, Association Rule Analysis, Clothing Encoding and Similarity Measurement, and Clothing Recommendation Algorithm have been developed. These processes are detailed below.

Association Rule Analysis. Association rule mining is a powerful technique in data mining and machine learning aimed at discovering patterns and relationships within datasets by analyzing the co-occurrence of items or variables [40]. This technique assumes that certain items or variables tend to appear together more often than expected by chance. The process involves three main phases: item set generation, rule generation, and rule evaluation [41]. In item set generation, frequent itemsets are identified based on their support, which is the proportion of transactions where a specific itemset appears. Frequent itemsets surpass a predefined minimum support threshold [42]. Once frequent itemsets are identified, association rules are generated, comprising an antecedent and a consequent. These rules describe relationships between itemsets or sets of variables. Metrics such as support and confidence are commonly used to assess the quality and significance of these rules. Support measures the frequency of a rule in the dataset, while confidence gauges its reliability. Association rule mining has proven effective across various domains.

In the study, I is the item set with n attributes {i1, i2, ... in}, and D is the list of combinations containing the union of items {t1, t2, ... tn}. Each combination in D is a subset of I. A rule X=>Y is defined as X, Y⊆ I, where X is the antecedent (left-hand side) and Y is the consequent (right-hand side). The Apriori Algorithm, widely used in association analysis [43], iteratively discovers frequent items in a database. It first identifies frequent items, then generates association rules based on minimum support and confidence values. Support represents the proportion of transactions with the relationship, while confidence represents the probability of item Y occurring given item X. The algorithm uses these values to identify frequent items and generate rules [41].

$$Support = \frac{Frequency(X,Y)}{N} \quad (1)$$

$$Confidence = \frac{Frequency(X,Y)}{Frequency(X)} \quad (2)$$

Clothing Encoding and Similarity Measurement. Item encoding in data analysis refers to the conversion of qualitative or textual data into numerical codes to facilitate representation and analysis. This process enables easier processing of data by computer algorithms, transforming non-numeric information into structured formats suitable for statistical calculations and modeling. The encoded codes should be unique, meaningful, and consistent with the original data [17]. Given that many statistical and machine learning algorithms require numeric inputs, item encoding is essential for effective data analysis. In this study, a novel technique has been introduced for encoding clothing items and measuring similarity between two clothes.

The dataset features for the recommendation system are designed to yield unique results when comparing clothes. Each clothing item has a feature vector created from its combined features, with varying impacts on similarity. Weights are assigned to each feature to determine their influence on similarity, forming a weight vector. The clothing item's code is a two-dimensional vector, with one row for similarity and one for weight, and columns corresponding to the number of features.

The L1 distance, or Manhattan distance, measures the difference between two points by summing the absolute differences of their coordinates [44]. The weighted L1 distance, a variant of the L1 distance, assigns different weights to each dimension, reflecting their importance. This is done by multiplying the absolute difference of each dimension by its corresponding weight before summing them. In the clothing recommendation system, the similarity between clothing items is measured using the weighted L1 distance. This allows for recommendations among items with similar levels of similarity. The clothing similarity Gxy for items nx and ny is calculated by taking the weighted L1 norm of their feature vectors. Comparing clothing items at the same level is essential for meaningful results.

$$G_{xy} = \| \left| n_x - n_y \right| x \, \vartheta \|_1 \quad (3)$$

Clothing Recommendation Algorithm. Our algorithm for the clothing recommendation system operates in three stages. Initially, all clothing items are categorized based on the body regions they are designed for, organized into a hierarchical structure. In the second stage, transition rules between these hierarchies are established using association rule analysis, incorporating combination scenarios from fashion designers and users. Recommendations begin by selecting an initial clothing item either randomly or from a specific hierarchy. As the algorithm progresses through defined hierarchies, subsequent clothing items are chosen based on association rule analysis to suggest the most suitable options. The third stage involves assessing similarities among alternative clothing recommendations within the same hierarchy. Each clothing item is represented by two-dimensional vectors: a feature vector amalgamating all item attributes, and a weight vector (Table 6) assigning importance to these features.

Table 6. Weight values for clothing recommendation criteria

Criteria	**Top and Outerwear Weight**	**Bottom wear Weight**
Style	10	10
Pattern	9	9
Color	10	10
Where to wear (choice of location)	8	8
Ambient temperature	9	9
Fabric type	6	6
Fiber type	10	10
Length	10	10
Collar type	10	
Collar extra	7	
Arm lenght	9	
Arm Wrist Detail	7	
Arm Detail	7	
Arm type	10	
Waist height		6
Waist		9
Trouser leg type		10
Trouser leg detail		10
Closure material	9	
Number of Front Closure Buttons	3	
Pocket variant	8	
Number of Pockets	9	10
Front pocket		4
Back pocket		4
Extra pocket Detail	5	3
Number of Extra Pockets	5	
Iron trace		10
Print/weave capability	9	
Embellishment	6	
Back detail	4	
Lining	5	
Lining Material	2	
Back Slit	2	

Within the same hierarchy, weighted L1 distance is calculated between all clothing items for recommendations. The item with the smallest distance is the most similar. Comparing an item to itself yields a distance of zero. There are two scenarios for alternative recommendations. First, if the user doesn't own the recommended item, the algorithm suggests the most similar item from the user's collection and marks the initial recommendation as "available for purchase." Second, if the user dislikes the recommendation, the algorithm provides alternative suggestions by ranking items based on similarity, with the closest items listed first. The weight vector for features, determined by fashion designers, ensures that clothing items within the same hierarchy align with designer perspectives. During transitions between hierarchies, user preferences and designer-created combinations are considered. The system aims to curate the best options from the user's existing wardrobe. If a recommended item is not owned by the user, the algorithm finds the most similar item within the same hierarchy. Thus, recommendations always come from the user's wardrobe. User preferences are recorded and used to prioritize future recommendations. The pseudocode for the recommendation algorithm is in Algorithm 1. Attributes in the clothing feature vector are encoded as 0/1. When calculating similarity, matching attributes do not contribute to the difference, while differing attributes add a difference of +1, which is then weighted. Summing these weighted differences across all attributes gives the similarity ratio between items. An example feature vector comparison is shown in Figure 2.

```
Algorithm 1: Clothing Recommendation Algorithm
Input:
    ● feature vector, FV
    ● weight vector, WV
    ● combination table, CT
    ● renk uyumu, CH
    ● clothes list, CL
suggestion <= [ ]
levels <= [tops, bottoms, outerwear, …]
group the clothes in the combination table according to their levels
foreach level
   if  suggestion is empty
      selection = have the user choose a top or randomly select an available top
        add selection to existing combination, suggestion <= selection
      continue, switch to new level
   else
      create association analysis rules with current suggestion and CT
      list candidate clothes sorted by confidence value
      while candidate clothes not emtpy
         select the clothes with the highest confidence value and remove it from the list
         calculate similarity for CL using FV, WV, CH
         sort similar clothes by similarity value
         list the highest trust value and similar clothes to the user
         if  the user has chosen
            break, switch to new level
         else
            continue, select the next candidate outfit from the list
         end
      end
   end
end
if suggestion not in CT
  request user confirmation for adding to the list
  if confirmation
    CT <= suggestion
  end
end
```

Figure 2. Example feature vectors for clothes X and Y

To evaluate the color attribute categorically, a color compatibility table is used. Color information is stored in the clothing feature vector and converted into a 0/1 categorical format for similarity calculation. The colors in the feature vectors of clothes X and Y are checked against the table. Compatible colors receive a value of 0 (no difference), and incompatible colors receive a value of +1 (difference). This result is multiplied by the color attribute's weight to determine the final color similarity, used in the overall similarity formula. The clothing similarity Gxy is calculated using the feature vectors and the attribute weight vector for clothes X and Y. If all attributes match, Gxy is 0, indicating complete similarity. As differences increase, Gxy rises above 0 based on the number and weight of differing attributes. To select clothing based on Gxy, items are sorted by similarity, choosing those with the smallest values. Although a minimum similarity threshold can filter out less similar clothes, this study focuses on optimizing the user's existing wardrobe without such a threshold, leaving preferences to the user. However, in unrestricted scenarios, a threshold-based approach is recommended for comparisons.

3.4. Experimental Results and Performance Evaluation

The purpose of the experimental study was to evaluate our algorithm's performance. The evaluation aimed to demonstrate that our algorithm aligns with fashion designers' preferences, adapts to the user's routine preferences, and generates alternatives based on the user's owned clothing items. The experimental design included scenarios to assess these capabilities.

In our first scenario, a combination suggested by a fashion designer is added to the user's wardrobe. The user potentially has access to clothing items g1, p2, and c5 from our fashion designer dataset. Running our algorithm with these items starts by selecting g1. Moving to the next level, the algorithm generates association rules for combinations involving g1 and suggests alternatives. For instance, p2 and p6 have the highest confidence values. Therefore, the algorithm recommends p2 from the user's wardrobe. Progressing further, it ranks and suggests outerwear options with high confidence values for the combination of g1 and p2, including items like c5, c7, c8, and c10. Since the user already owns c5, it is suggested at this stage. In this scenario, as the user already possesses the clothing items suggested by the fashion designer's combination, clothing similarity is not needed. Instead, association analysis directly recommends these combinations. The study demonstrates that utilizing association analysis effectively identifies frequent combinations from alternative designs when the user already owns the necessary clothing items, making personalized recommendations.

In the second scenario, an additional combination, g1*-p2*-c5*, similar to g1-p2-c5 from the first scenario, is added to the user's wardrobe. This scenario aims to showcase the algorithm's ability to suggest alternatives based on the user's owned clothing items and to learn user preferences. g1*-p2*-c5* was derived from g1-p2-c5 by changing clothing colors using a color matching chart, resulting in a maximum similarity value of 0 when compared to g1-p2-c5, indicating high similarity. Therefore, g1*-p2*-c5* ranks first in alternative recommendations. Running the algorithm with these items begins by selecting g1* as the initial item. Next, the algorithm generates association rules for combinations involving g1* and suggests alternatives. Since g1* is not in the database, association rule analysis uses g1, which has the highest similarity to g1*. For instance, p2 and p6 have the highest confidence values. In this scenario, the algorithm recommends considering p2 from the user's wardrobe and p2* as the most similar alternative. Following the user's preference, p2* is chosen. Moving forward, the algorithm ranks and suggests outerwear options with high confidence values for the combination of g1 and p2. Here, c5 and c5* are available, with c5* chosen as per preference. The user opts for g1*-p2*-c5* over g1-p2-c5 initially suggested by the fashion designer, recorded in the CT (Clothing Trends) database. In subsequent runs of this scenario, after selecting g1*, the algorithm continues recommending p2* and c5* in subsequent steps. Additionally, p2 and c5 are presented as alternative options with high similarity. This scenario illustrates that through association analysis of the fashion designer's database, the algorithm can recommend the most similar clothing items to the user, even if they are not currently in their wardrobe. By integrating user preferences into the database, the algorithm learns and applies these preferences to make personalized recommendations in future uses. This learning process is crucial as it allows the algorithm to assess the frequency of alternative selections for combinations not in the user's wardrobe and prioritize previously preferred alternatives. The system's primary goal is to optimize the use of the user's wardrobe, making the algorithm's ability to suggest similar clothes aligned with fashion designers' perspectives a key factor.

4. RESULTS AND DISCUSSIONS

In the literature, there are many clothing recommendation systems based on body shapes, weather conditions, photo processing, etc. However, these clothing recommendation systems typically guide users towards purchasing new garments. This study aims to develop a system that can assist users in making clothing choices according to clothing style and preferences. The developed clothing recommendation system, unlike the existing literature, takes into account both the user's clothing style and the user's current wardrobe when making suggestions. Therefore, it enables the user to use existing clothes more effectively, causing the user to buy less clothes.

In this study, Association Rule Analysis has been adapted into the system design to enable the use of predefined fashion designs along with user preferences, allowing users to create combinations from their existing clothing. Furthermore, a literature review conducted to improve the clothing recommendation application has determined that Association Rule Analysis is the most common and suitable method. Subsequently, the experimental set for the study has been created. Finally, the clothing recommendation algorithm, which forms the basis of the recommendation system, has been developed. The developed algorithm has been applied to two scenarios.

In the first scenario, the combination recommended by the fashion designer has been successfully presented to the user. In the second scenario, it has been observed that the algorithm learned the user's preferences and suggested the most similar options from combinations that the user did not possess.

As a result of the experiments conducted with the developed algorithm, it has been determined that the algorithm can make choices by the preferences of the users. Additionally, the behavior of the algorithm adapts to the user's routine preferences, and it can generate alternatives based on the clothing items owned by the user. These results represent an important success for the algorithm in effectively utilizing the clothing in the user's wardrobe and providing personalized recommendations based on their preferences. This is significant because it demonstrates that the application developed using the algorithm can provide the most suitable clothing recommendations based on the user's style and preferences. On the other hand, it was found that in 2022, the number of applications downloaded per smartphone user in Turkey was approximately 54. This indicates that the culture of using applications in Turkey is well-developed and suggests that the clothing recommendation application developed in this study will attract interest.

In this study, one of the important features that needs to be developed for the clothing recommendation system to fulfil its function is for the user to input data regarding their clothing style, when and for what activity they will wear the clothing, and in which environment. Additionally, the practical study conducted in this research comprises limited data consisting of 10 outerwear, 30 tops, and 10 bottoms according to daily men's clothing styles. Expanding this dataset to include more clothing styles and a greater variety of apparel in future studies could lead to better results.

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