ANALYZING FASHION TRENDS USING HIERARCHICAL CLUSTERING AND TEMPORAL ANALYSIS

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ABSTRACT

The fashion industry constantly evolves where art, culture, and commerce intersect, shaping how people express themselves through clothing. As Blair Waldorf famously stated, Fashion is the most powerful art. It's movement, design, and architecture all in one. It shows the world who we are and what we want to be. This sentiment captures fashion's role as both a creative and cultural force. Given its dynamic nature, analyzing fashion trends over time provides valuable insights into how styles emerge, evolve, and fade. Data from Vogue Runway was collected to explore these trends, covering Spring and Fall collections from New York and Paris between 1988 and 2024. Hierarchical clustering was used to categorize fashion trends, identifying distinct style patterns across the years. Next, time series analysis was applied to track the evolution of Ready-to-Wear and Couture collections. By integrating fashion analysis with machine learning techniques, this study highlights how data-driven approaches can enhance the understanding of fashion's ever-changing landscape while preserving its creative essence.

KEYWORDS

Fashion Industry, Trend Evolution, Machine Learning Applications, Hierarchical Clustering, Temporal Analysis, Runway Collections, Ready-to-Wear, Menswear, Couture, Pattern Recognition

1. INTRODUCTION

Fashion operates at the intersection of cultural expression, artistic creativity, and market economics. Over the years, it has become a global industry where trends transcend borders and influence consumer behavior worldwide [1]. As a result, understanding and analyzing fashion trends is critical for designers, retailers, and researchers alike [2, 3]. Among the many aspects of the fashion industry, **Ready-to-Wear**, **Menswear**, and **Couture** collections serve as key markers of stylistic evolution. While Ready-to-Wear symbolizes mass accessibility [4], Menswear traditionally reflects conservative tailoring, and Couture represents the pinnacle of luxury craftsmanship [4, 5].

This study uses hierarchical clustering [6, 7] and time-series analysis [8, 9] to uncover patterns in fashion collections, with a particular focus on understanding the thematic clusters that have emerged over the years [10, 11]. We explore the stylistic interplay between regional influences and global trends by examining data from Paris and New York— two major fashion capitals [12, 13, 14]. The dataset from historical Vogue Magazine archives provides a rich foundation for examining how fashion responds to cultural, technological, and economic changes [15, 16].

Beyond creative expression, fashion trends have significant economic and environmental implications. The patterns set on runway shows often trickle down to department stores and eventually shape casual wear, driving global consumer behavior and retail strategies. Ma-

Machine learning (ML) can help forecast these trends, leading to more sustainable production cycles and reducing waste by aligning manufacturing with predicted demand. Furthermore, designers frequently use color to narrate stories, convey emotions, or highlight socio-political issues, influencing the industry's aesthetic and commercial success. Understanding these dynamics allows brands to better adapt to shifting consumer preferences, blending artistic innovation with market demands.

The primary objectives of this study are:

1. To identify stylistic clusters across Ready-to-Wear, Menswear, and Couture collections.
2. To explore temporal patterns and correlations between Paris and New York as fashion hubs
3. To provide actionable insights for understanding the evolution of thematic styles in fashion.

This paper is organized as follows. First, we collected data from Vogue Runway and processed it to extract relevant features. Next, we clustered the collected data to identify meaningful patterns. Following this, we created time series plots to visualize trends overtime. Finally, we analyzed relationships and trends using a distance matrix and further statistical analysis to derive insights 2.

2. DATA COLLECTION AND PREPROCESSING

2.1. Data Source

The dataset used in this study was carefully compiled from Vogue Magazine's Runway website https://www.vogue.com/fashion-shows extensive archive of fashion collections spanning several decades. This dataset focuses on shows from Paris and New York, two of the most influential fashion capitals in the world, offering a rich foundation for comparing regional trends over time. Each entry in the dataset includes attributes such as collection type (Ready-to-Wear, Menswear, Couture), location, and various stylistic elements like colors, patterns, fabrics, accessories, and themes. These well-defined attributes provide a systematic framework for analyzing how fashion has evolved.

The Vogue Runway platform organizes its content by season, with each season showcasing multiple designer collections. Every collection was manually reviewed to construct a consistent dataset, and critical details were recorded to ensure accuracy. This manual process helped capture the nuanced variations between design elements across diff t collections while maintaining the dataset's structure and coherence for analysis.

Organizing the dataset using clearly defined attributes allowed for tracking shifts in fashion trends across time and location. While it was possible to identify overarching trends—such as prevailing styles within a particular decade—this structured approach enabled more granular observations, including shifts in fabric choices and color palettes. Additionally, the dataset offers cultural insights into how artistic movements and market dynamics have shaped fashion trends globally.

This organization enables meaningful comparisons of styles across time and regions while revealing patterns in design choices. Subsequent sections will delve into clustering andtime-series analysis to further explore these evolving trends. The source of the data is illustrated in Figure 1.

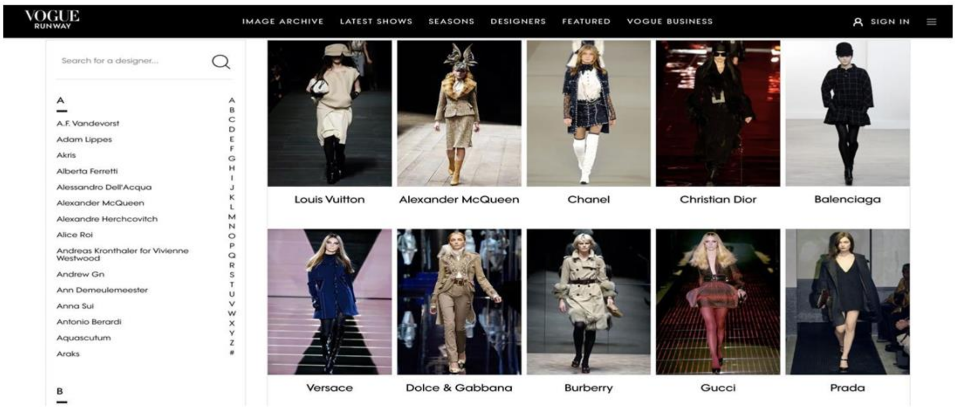

Figure 1: Vogue Runway.

Figure 1 is a screenshot of the Vogue Runway page, which served as the primary data source for this study. It covers fashion shows from 1989 to 2024, and collections from each show were comprehensively analyzed to ensure a well- rounded under standing of fashion trends during this period.

These runway collections also serve as the foundation for broader fashion trends, with their influences gradually trickling down from luxury fashion houses to department stores and eventually shaping casual wear.

2.2. Data Cleaning, Preprocessing, and Feature Extraction

Since the dataset was manually curated, there was no need for imputation techniques. However, standardization was carried out to maintain consistency across categorical attributes. Similar or overlapping terms, such as ‘baby blue,’ ‘powder blue,’ ‘mint green,’ ‘peach,’ and ‘lavender,’ were grouped under a unified category labeled ‘Pastels’ to simplify the analysis and ensure coherence throughout the dataset.

Preprocessing Steps:

- The dataset was fi to focus exclusively on shows from Paris and New York Fashion Weeks, given their significant influence in the global fashion industry.
- Categorical features, including Color, Patterns, Shoes, Accessories, Fabric, and Theme, were one-hot encoded using the MultiLabelBinarizer method. This transformation enabled the algorithm to process categorical variables numerically.
- To enhance the influence of dominant stylistic features, weighted encoding was applied, assigning a weight of 80 to each feature.

Year	Collection	Collection Type	Location	Gender	Colour	Patterns	Shoes	Accessories	Fabric	Theme
1988	FALL	READY-TO-WEAR	NEW YORK	Women	black, grey, crimson red, beige	crunched waist, vertical stripes	pumps, high knee boots, pointed heels	stalkings	fur, satin	tomboy, powerful
1988	FALL	COUTURE	NEW YORK	Women	red, pink, grey, black, beige	abstract, floral	pointed heels	big hats, sunglasses, chunky jewelery	fur, satin	antique, medival
1988	SPRING	COUTURE	PARIS	WOMEN	yellow, orange, blue, whites	floral, small polka dots	stilettos	big headwear, big hats	brushed cotton, cotton crosswear	ostentatious
1989	FALL	READY-TO-WEAR	NEW YORK	Women	black, mustard yellow, white	plain	pointed boots	gloves	woollen, velvet	modest, workforce
1990	FALL	READY-TO-WEAR	NEW YORK	Women	black, grey, lavender, blue	vertical stripes, checks, abstract	ballet flats	blazer	leather, nets, linen	sexy, boardroom
1990	SPRING	READY-TO-WEAR	PARIS	Women	metallic, green, white	abstract, vertical stripes	ballet flats, loafers	shrugs, jackets, beads, big belts	mesh, satin	feminine, splashy
1991	FALL	READY-TO-WEAR	NEW YORK	Women	blue, pink, white, beige, black, neons	vertical stripes, leopard print, small checks, vertic	pumps, boots	chucky gold jewelery, buttons, gloves, jackets	sheer, mesh, fleece	hip-hop, sexy
1991	SPRING	READY-TO-WEAR	PARIS	Women	neons, yellow, pink, orange, black, white	big polka dots, horizontal stripes, big checks	stilettos, flats	flowers in headgear	khaki, cotton, flowy, sheer, mesh	pop
1992	SPRING	READY-TO-WEAR	PARIS	Women	black, blue, red	straps	boots	gloves	leather, velvet, sheen	sophisticated, strong
1992	FALL	READY-TO-WEAR	NEW YORK	Women	red, yellow, white, black	strapless, leopard, vertical stripes	pumps, stilettos, flats	headgear, chunky gold jewelery	nylon, rayon, carbon	low-cut, provocative
1993	SPRING	COUTURE	PARIS	Women	black, white	cross, ruffles	pointed pumps, pointed boots	pearls	mesh, flannel	haute couture, silhouette
1993	FALL	READY-TO-WEAR	NEW YORK	Women	black, white, brown, pastels	horizontal stripes, diagonal stripes, pleated skirts,	loafers, boots, ballets	metallic headgear, beret, gold jewellery, huge hats	fleece, mesh, woollen	grunge, flashy
1993	SPRING	READY-TO-WEAR	PARIS	Women	red, yellow, white, black, pastels	horizontal stripes, leaves, small checks, abstract	sports shoes, ballets	big chockers, beads, corsets, tassels	mesh, flannel	thrift, sportswear, cool, feminine
1994	SPRING	COUTURE	PARIS	Women	black, white, brown, yellow	vertical stripes, checks	pumps	hats	silk, canvas	medival
1994	SPRING	READY-TO-WEAR	PARIS	Women	black, white, red brown	vertical stripes, abstract, ruffles	barefot, shoes, chuncky heels	no	denim,cotton, flowy, mesh	pop, summer
1994	FALL	READY-TO-WEAR	NEW YORK	Women	metallic, black, white, red, yellow	loosely fit, checks	square toe boots, loafers	fur hats, gold, bows, buttons	fur	chique
1995	FALL	COUTURE	NEW YORK	Women	black, white	plain	pumps	headgear, chunky gold jewelery	chenille, woollen	unique, classy, fierce, bold
1995	FALL	READY-TO-WEAR	NEW YORK	Women	black, white, grey	plain, checks	pumps	hats	georget, linens, velvet	simple, funk
1995	SPRING	READY-TO-WEAR	PARIS	Women	pink, white, black	vertical stripes, checks, big polka dots	stilettos	bags, brooch, belts, diamonds, gold	synthetic, satin, rayon	classy, chique
1996	FALL	COUTURE	NEW YORK	Women	black, blue, maroon, red	plain	pointed heels	headgear, gold, button	tweed, woollen	mob wife
1996	FALL	READY-TO-WEAR	NEW YORK	Women	black, brown, lavender, maroon, purple, re	plain	square toe heels, loafers	none	tweed, velvet	mob wife, professional
1996	SPRING	READY-TO-WEAR	PARIS	Women	pastels, brown, white, black, yellow	checks, verticasl stripes, plain	ballets	sunglasses, headgear	sheer, polyster	simple, professional
1996	SPRING	COUTURE	PARIS	Women	white, black,orange	animal print, plain	stilettos	headgear	organza, silk	cabaret
1997	FALL	READY-TO-WEAR	NEW YORK	Women	black	plain	pointed boots	gloves, headbands	woollen, leather	classic
1997	SPRING	READY-TO-WEAR	PARIS	Women	black, brown, blue, maroon, red, yellow	leopard print, floral, fishnets	stilettos, flats	small handbags	mesh, velvet, silk, linen	bossy, mob wife
1997	FALL	COUTURE	NEW YORK	Women	black, grey, magenta	embroidery	pointed heels, pointed boots	none	woollen, polyster	professional, work
1997	SPRING	COUTURE	PARIS	Women	black, white, pink, gold	embroidery, vertical stripes	pointed stilettos	headgear	mesh, viscose, rayon	mobwife
1998	SPRING	MENSWEAR	PARIS	MEN	black, white, beige	plain, fishnet	square toe oxfords	none	mesh, linen, polyster	classic, minimlastic
1998	FALL	READY-TO-WEAR	NEW YORK	Women	black, white, grey	plain	pointed loafers, pointed boots	none	silk, polyester, tuxedo	silhoutte, feminne
1998	SPRING	COUTURE	PARIS	Women	black, white, grey	plain	pointed stilettos, pointed pumps	none	ploystar, silk, flowy	feminine

Figure 2: A snippet of the dataset.

Feature Extraction The feature extraction process emphasized six categorical variables—Color, Patterns, Shoes, Accessories, Fabric, and Theme. Each of these attributes was one-hot encoded, transforming them into binary vectors suitable for numerical analysis. Feature weights were then applied based on their significance in shaping fashion trends, ensuring that essential stylistic elements carried more influences during clustering.

Due to the categorical nature of most attributes in the dataset, encoding the features was a necessary preprocessing step. The use of weighted encoding allowed for prioritizing more impactful elements, such as patterns and fabrics, within the clustering algorithm. This approach improved both the accuracy and interpretability of the clustering outcomes.

The framework was designed with flexibility in mind, allowing for the adjustment of weights to emphasize specific data aspects as needed. For time-series analysis, equal weights were applied to ensure balanced trend representation across the years. This balanced approach ensures consistency while allowing for future adjustments if certain attributes, such as color trends or material usage, need to be emphasized. The effects of these weighting strategies on clustering outcomes are discussed in later sections.

3. METHODOLOGY

To apply machine learning and analyze temporal patterns in fashion, we need to design a distance metric. The challenge is that for each year, the description of fashion trends could contain both numerical and categorical data. As a result, we need to design a flexible metric that would allow us to assign different significance to features.

3.1. Hierarchical Clustering

Hierarchical clustering is an unsupervised machine-learning technique used to build a hierarchy of clusters by grouping similar data points based on their distance or similarity [17]. It operates through two primary approaches: agglomerative clustering, which starts with each data point as an individual cluster and iteratively merges the closest pairs of clusters, and divisive clustering, which begins with all data points in a single cluster and recursively splits them into smaller clusters. The process relies on distance metrics, such as Jaccard's Distance, and linkage criteria, like single, complete, average linkage, or Ward's method, to determine how clusters are formed. The results are often visualized using a dendrogram, a tree-like diagram that illustrates the relationships and arrangement of clusters. Hierarchical clustering is widely applied in fi such as market segmentation, biological taxonomy, image processing, and social network analysis due to its ability to reveal nested structures within data [18] To identify patterns and group similar fashion collections, hierarchical clustering was employed. This method was chosen for its ability to reveal nested relationships, and provide insights into the hierarchy of stylistic similarities. Using the *Ward linkage method*, the clustering algorithm minimized the variance within clusters while maximizing the distance between them. This approach allowed us to form distinct stylistic groups that encapsulate recurring themes and trends in fashion.

3.2. Cluster Validation and Visualization

The dendrogram, a key output of hierarchical clustering, was instrumental in visualizing the relationships between clusters (Figure 3). By examining the dendrogram, we identified five distinct clusters, each representing a unique thematic style. These clusters were validated by domain experts to ensure that the groupings were both meaningful and representative of the data.

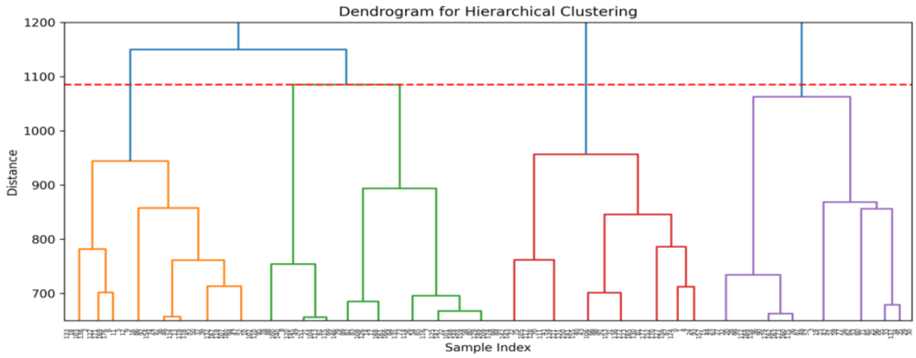

Figure 3: A sample dendrogram for hierarchical clustering.

4. Temporal Analysis and Results

One of the advantages of the proposed approach is that we can represent an evolution of highly dimensional objects (describing fashion) in terms of cluster trajectories over time. Clusters represent typical fashion collections and differences and similarities in fashion trends over time can be computed by examining the commonality of cluster trajectories,

4.1. Cluster Distribution and Interpretation

We illustrate the above ideas by clustering our objects into 5 clusters. The distribution of collections across the fie clusters is shown in Figure 4. Cluster 4 emerged as the largest group, characterized by universally appealing designs with neutral tones and minimalist aesthetics. In contrast, Cluster 2 represented avant-garde collections that pushed the boundaries of conventional fashion. The diversity of styles within these clusters highlights the multifaceted nature of fashion trends.

- Cluster 1: Funkand Denim Vibes. This cluster of 41 items captures bold, youthful energy with a love for ”funk,” ”chunky jewelry,” and ”denim,” with statement accessories paired with cool, casual outfits—perfect for streetwear lovers.

- Cluster 2: Winter Luxe. Withjust 17 items, thisisanichegroup for those whoadore the cozy elegance of winter. ”Rich” textures, ”hound smooth” patterns, ”boots,” and ”woolen” fabrics create a look that is both stylish and warm.

- Cluster 3: Playful and Creative, This 35-item cluster is all about fun, creativity, and a little edge. ”Pop” colors, ”abstract” designs, ”flats,” and ”organza” fabrics give off a modern, artsy vibe that is both practical and unique.

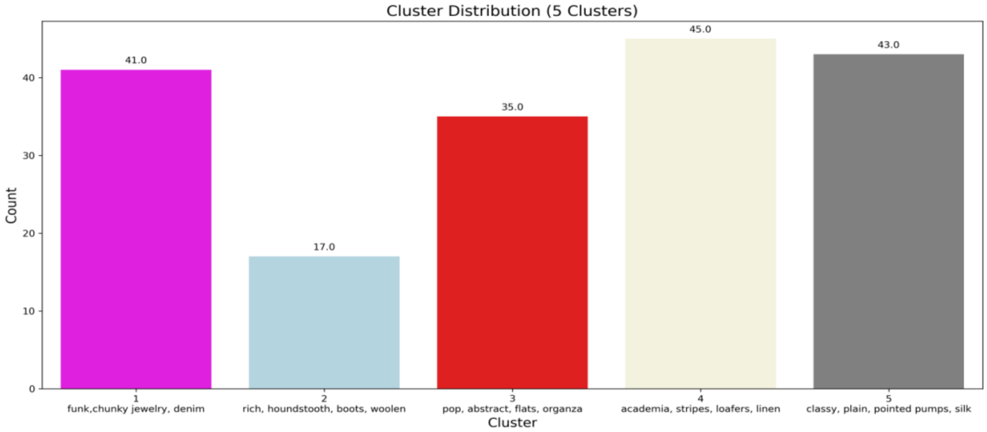

Figure 4: Cluster Distribution Across Collections (A bar chart showing the size of each cluster.)

- Cluster 4: Smart and Minimalist. The largest cluster, with 45 items, speaks to the classics: ”academia,” ”stripes,” ”loafers,” and ”linen.” It’s a timeless, polished style perfect for work or anyone who loves clean, minimalist fashion.

- Cluster 5: Classy Elegance. With 43 items, this cluster oozes sophistication. ”Classy” silhouettes, ”plain” designs, ”pointed pumps” and ”silk” fabrics make it the go-to choice for formal events or professional chic.

4.2. Temporal Trends Across Fashion Capitals

Time-series analysis revealed significant insights into the evolution of fashion trends in Paris and New York. The analysis highlighted how Ready-to-Wear, Menswear, and Couture collections evolved over time, with distinct crossovers and divergences between the two cities.

Accurate trend prediction through machine learning also offers practical benefits for both the fashion industry and the environment. Retailers can use these insights to manage inventory more effectively, reducing overproduction and minimizing waste. Furthermore, the globalization of fashion trends reflects how runway styles from Paris and New York gradually influence mass-market clothing, making high fashion accessible to a broader audience while promoting sustainability through better resource management.

4.3. Ready-To-Wear

As shown in Figure 5, Ready-to-Wear exhibited a moderate correlation (0.36) between Paris and New York, driven by the globalization of trends through digital platforms and fast fashion retailers.

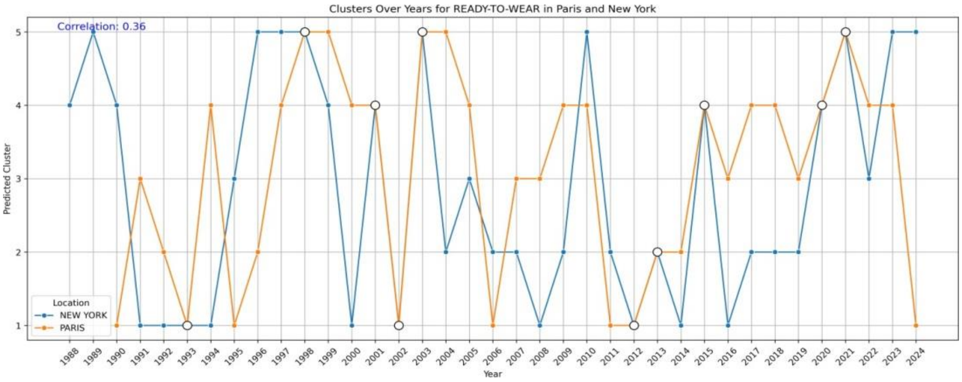

Figure 5: Clusters Over Years for Ready-to-Wear (Time-series trends in Paris and New York.)

The periodic alignment of trends between Paris and New York indicates a growing globalization in this segment. Unlike Menswear and Couture, Ready-to-Wear trends seem to blend regional influences more cohesively, which may be due to its accessibility and adaptability.

The rise of digital influence and cross-regional marketing efforts has also helped merge the styles between the two cities. However, certain years show some sporadic diff which likely points to the persistence of regional preferences in Ready-to-Wear fashion.

4.4. Menswear

The temporal trends in Menswear, illustrated in Figure 6, showed a limited correlation (0.28), reflecting regional differences in tailoring and the rise of streetwear influence in New York.

Paris leans more toward structured and classic tailoring, staying true to its roots, while New York's evolving menswear trends are heavily influenced by streetwear and urban culture. This divergence highlights how cultural narratives shape fashion differently in both cities, especially in menswear. The influence of functionality and casual aesthetics in New York contrasts with the timeless elegance that Paris continues to prioritize.

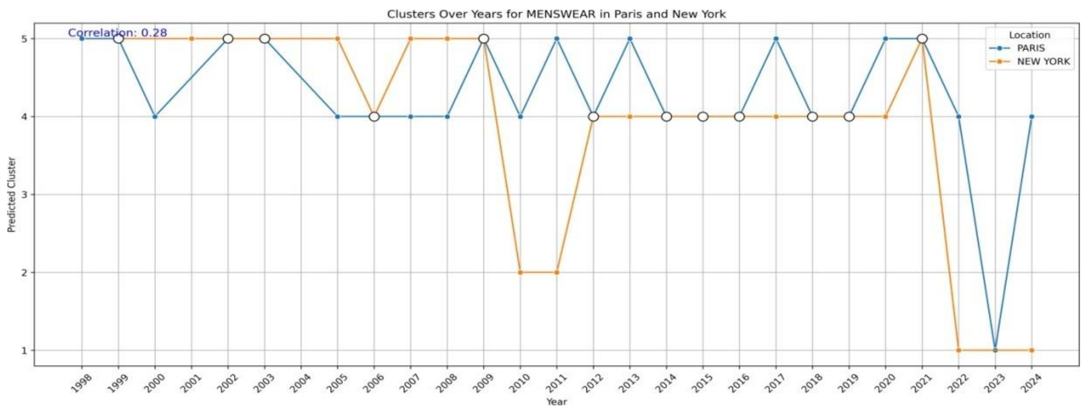

Figure 6: Clusters Over Years for Menswear (Temporal analysis of Menswear in the two fashion capitals.)

4.5. Couture

Figure 7 depicts the evolution of Couture, with Paris maintaining its dominance due to its rich heritage and the continued influence of luxury brands like Dior and Chanel.

The occasional alignment with New York might reflect efforts to bring high-fashion elements into the city's commercially driven fashion culture. Paris continues to set the standard for Couture with its focus on craftsmanship and timeless elegance. The sharp difference in certain years emphasize the distinct cultural and aesthetic interpretations of Couture between these two fashion capitals.

5. Distance Matrix and Stylistic Divergence

The distance matrix (Figure 8) provides a quantitative representation of the stylistic differences between clusters.

The Jaccard Distance Matrix quantifies the dissimilarity between clusters, offering insights into stylistic similarities and divergences. Lower distances indicate greater overlap, while higher distances signify divergence. For instance, Clusters 1 and 3 exhibit strong overlap, likely reflecting minimalist or transitional styles with shared characteristics. Clusters 2 and 5 are highly dissimilar, highlighting the contrast between experimental styles and heritage-driven luxury. Cluster 4 shows moderate distances, suggesting a hybrid style drawing elements from transitional and experimental aesthetics.

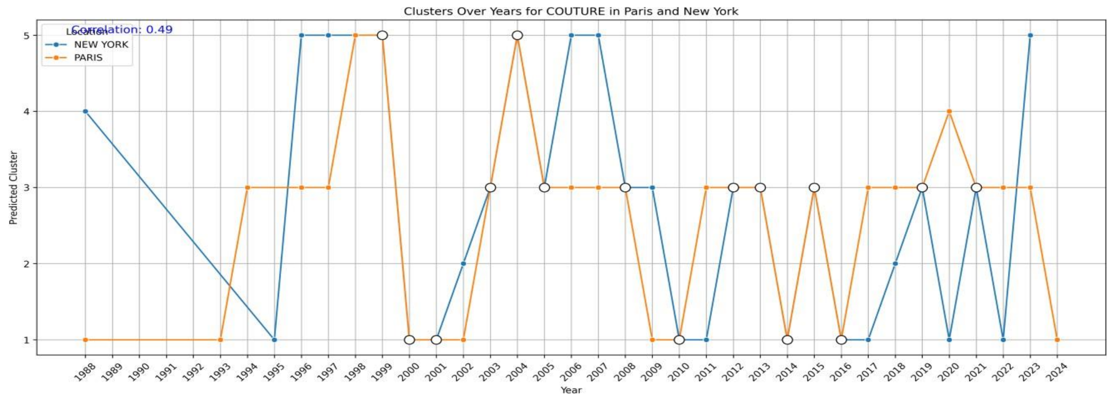

Figure 7: Clusters Over Years for Couture (Illustrating Paris's sustained dominance in luxury couture.)

When connected to temporal analysis, the matrix illustrates how stylistic clusters evolve over time: Clusters 1 and 3, with high similarity, align with globalized trends seen in Ready-to-Wear, where digital platforms and fast fashion foster consistent overlap between Paris and New York. Divergence between Clusters 2 and 5 reflects distinct temporal patterns, such as Paris's dominance in Couture (heritage-driven luxury) versus New York's experimental streetwear in Menswear. Over time, stable clusters like Cluster 5 act as temporal anchors, preserving traditional elements, while experimental clusters like Cluster 2 reflect disruptive fashion trends. By integrating the Jaccard Matrix with temporal trends, we see how some styles converge globally, while others maintain distinct regional identities.

6. DISCUSSION AND FASHION INSIGHTS

The findings from this study provide meaningful insights into the evolution of fashion over time. This research highlights significant shifts in stylistic preferences by examining variations in colors, fabrics, and design elements across different seasons and locations. The analysis reveals both recurring patterns and distinct transformations, offering a clearer understanding of how external factors such as cultural influences, technological advancements, and market trends have shaped fashion.

6.1. Ready-to-Wear

Over the years, Ready-to-Wear collections have undergone significant transformations, reflecting shifts in cultural, economic, and technological landscapes. Clusters 1 and 5 have consistently been dominant, with Cluster 1 representing bold and casual aesthetics, such as chunky jewelry and denim, and Cluster 5 characterized by timeless elegance with pointed

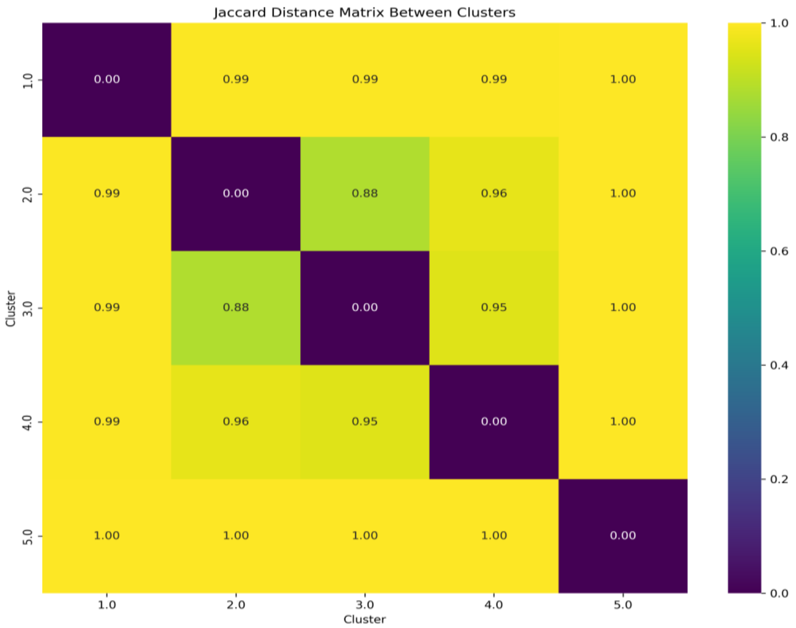

Figure 8: Distance Matrix Between Clusters (Highlighting the stylistic relationships between thematic clusters.

Pumps and silk. However, certain periods stand out due to distinct transitions, often influenced by external events.

In the early 2000s, there was a notable move toward Cluster 4, which featured academia- inspired designs with stripes, loafers, and linen. This change coincided with the rise of technology and digital innovation, which likely encouraged cleaner, more minimalist aesthetics that aligned with the forward-looking mindset of the time. By 2008, the global economic crisis brought a shift toward Cluster 3, marked by practical and conservative styles like flats and organza. During this period, designers responded to the growing demand for restrained and functional fashion choices, reflecting the cautious sentiment of the time.

In 2019 and 2020, the COVID-19 pandemic had a profound impact on the fashion industry. This period saw Ready-to-Wear collections leaning toward Cluster 4 and Cluster 3, emphasizing comfort and practicality as loungewear and work-from-home styles became prominent. The focus shifted away from bold statements to designs that catered to the need for adaptability and simplicity during uncertain times.

From 2022 to 2024, a significant shift occurred in New York as Cluster 1's funky and bold style, with its emphasis on denim and chunky jewelry, experienced a resurgence. This change was driven by global conversations around inclusivity and gender fluidity, inspiring designers to adopt more expressive, unconventional, and diverse approaches to fashion. At the same time, Cluster 5's elegant and sophisticated styles regained popularity in Paris, showcasing a renewed appreciation for classic and refined designs.

These transitions illustrate how external factors, such as technological advancements, economic challenges, global health crises, and social movements, have shaped the evolution of Ready-to-Wear fashion. The industry's ability to adapt to changing societal needs and values underscores its role as both a reflection of and response to the world around it.

6.2. Menswear

Over the years, menswear has seen constant ups and downs, moving mostly between Cluster 4, with its minimalist and classic vibe, and Cluster 5, which leans more toward formal and sophisticated styles. But in 2010 and 2011, there was a noticeable shift to Cluster 3, which had a more conservative and practical feel. This was likely due to the impact of the economic crisis, which pushed the focus toward more reserved and functional designs. Then, from 2022 to 2024, menswear took a sharp turn and embraced a funky, bold style. This sudden change was driven by the rise of inclusivity and gender fluidity, showing how much the fashion world has opened up to different and unconventional expressions in menswear.

The historically conservative, Menswear has embraced innovation in recent years, with the rise of streetwear and gender-fluid designs challenging traditional norms.

6.3. Couture

Over the years, Couture collections have undergone distinct transformations, influenced by cultural milestones, economic fluctuations, and global events. Cluster 1, with its bold and unconventional appeal characterized by chunky jewelry and denim, and Cluster 5, known for its timeless sophistication featuring pointed pumps and silk, have remained dominant. However, various years reflect unique transitions that were shaped by external influences.

In the early 2000s, there was a clear shift from Cluster 1 toward Cluster 3, defined by playful and abstract designs such as flats and organza. This period aligned with the rapid advancement of technology and the rise of digital culture, inspiring designers to embrace experimental and futuristic aesthetics. By 2009, after the global economic crisis, Couture collections leaned toward Cluster 1, emphasizing daring and statement-making designs that offered a sense of resilience and boldness amid fi uncertainty.

During the COVID-19 pandemic in 2019 and 2020 in Paris, Couture collections adapted to the realities of a changing world. The focus shifted to Clusters 4 and 3, reflecting more practical and intellectual styles with stripes, linen, and subtle textures. Designers responded to the limitations of large-scale events by embracing understated yet innovative aesthetics suitable for smaller, more intimate presentations.

From 2022 to 2024, the Couture landscape saw a resurgence in Cluster 5's elegance in New York, emphasizing luxurious and classic designs, while Cluster 1's bold and funky styles also gained traction in Paris. This period coincided with a global emphasis on inclusivity and gender diversity, encouraging more daring and expressive designs. The balance between experimental creativity and traditional sophistication during these years highlights Couture's adaptability to evolving societal norms and its role in championing diverse narratives.

These transitions in Couture reflect the interplay between external events and the creative direction of high fashion. The ability of Couture to reinvent itself while staying rooted in its essence underscores its significance as a reflection of both historical context and cultural change.

7. Conclusion

Fashion is a profound art form that reflects and shapes individual and cultural identities. Its trends are deeply embedded in cultural contexts and follow a cyclical evolution driven by design, production, and marketing innovation. Artificial intelligence and machine learning have further transformed the industry, enabling advanced trend forecasting, consumer analysis, and even AI-assisted design. Initiatives like Project Muze highlight the synergy between technology and human creativity, while clustering techniques offer deeper insights into consumer preferences. As the fashion industry continues to evolve, integrating technology and data-driven approaches unlocks new possibilities for creativity, efficiency, and consumer understanding.

Beyond aesthetic analysis, this study also highlights fashion trend prediction's broader economic and environmental significance. Accurately forecasting trends can help retailers optimize supply chains, reduce waste by aligning production with expected demand, and promote sustainability by minimizing overproduction. Additionally, understanding how runway trends influence mainstream fashion enables brands to strategically plan collections strategically, balancing creative expression with commercial viability.

This study demonstrates the efficacy of hierarchical clustering and time-series analysis in uncovering patterns and cycles in fashion. By analyzing historical collections from Paris and New York, we identified thematic clusters and temporal trends that reflect the dynamic interplay of cultural and economic forces in fashion. The findings provide actionable insights for designers, retailers, and researchers, paving the way for more data-driven approaches to understanding and predicting fashion trends.

Future research could incorporate social media analytics and consumer behavior data to enhance predictive accuracy. By integrating these additional dimensions, we can further unravel the complexities of the fashion industry and its evolving landscape, fostering a more sustainable and responsive approach to global fashion trends.

Declarations

Conflict of Interest: We declare that there are no conflicts of interest regarding the publication of this paper.

Author Contributions: All authors contributed equally to the effort.

Funding: This research was conducted without any external funding. All aspects of the study, including design, data collection, analysis, and interpretation, were carried out using the resources available within the authors' institution.

Data Availability (including Appendices): All the relevant data, Python code for analysis, detailed annual tables and graphs are available via:

https://github.com/ResearchFiles16/Fashion-Week-Analysis

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