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Introduction

The fashion industry is a typical supply and demand business model where current trends determine sales, making demand forecasting important for business success. In this age of technology and social media, consumer preferences have become more dynamic than in the past resulting in shorter product life cycles. Brands need to be able to keep up with popular styles and trends, designing and producing pieces faster than before (Bhardwaj, 2010). Many fashion companies are forced to deviate from the classic bi-annual supply chain in order to meet market demand (Rudniy, 2024).

At the top of the industry, luxury fashion houses present their seasonal collections twice a year in New York, London, Milan or Paris (CFDA, 2024). Fall-Winter collections are presented in the month of February and Spring-Summer collections are presented in the month of September. The looks, or outfit presentations, that are shown on the runway are largely for photographs or celebrity events, not for everyday use by the everyday consumer, especially with the factor of price. However, based on specific styles of colors, textures, and types of accessories, that season's "trendy styles" trickle-down into mass-market and fast-fashion brands at a much more affordable price and practical use. In industry terms, haute couture is presented first, followed by ready-to-wear, and later into mass market clothing. The everyday consumer buys these products because the market and social media pushes the popularity of it, and for these same reasons it influences the products that brand produces. This shows how important it is to be able to predict what is going to be popular and desired.

The goal of this project began by trying to analyze “what are the current trends”, but has shifted into analyzing how much influence the power luxury fashion houses have on the mass consumer. Even though some dynamics have shifted, based on the “trickle-down” process, I still expected there to be an influence on consumer behavior by the events of Fashion Month. To do this, a dataset of trends was collected from a range of articles that have summarized the styles of 2025 Spring-Summer fashion weeks. The change in popularity of these trends was then analyzed over time through looking at search history data from mass consumers. Google Trends was used as the source for this search history data. I used this sample of data that was collected to analyze the predictability power that luxury fashion brands have on the clothing industry. This was done through the presentation of search history of the sample trends. I also performed an event study to be able to statistically analyze the sample. Ultimately, I determined that fashion trends do not rise collectively after Fashion Month, and they instead display unpredictable patterns of search interest. I commented on what these results might mean about the shifted dynamics of the industry, especially due to the impact of social media, as well as potential measurement errors that could have contributed to these results.

The ethical implications of this project and the data collection are also discussed. The analysis has low privacy risk, since all the data that is used is publicly available. The main concerns arise from the effect of trend forecasting on the fast-fashion supply chain, which has implications for labor conditions and environmental harm. I also need to acknowledge the bias that is created through the creation of the dataset, both in the biases in the fashion publications and my subjective judgement when cleaning the dataset. This shows how the application of data science to cultural topics can inherit bias from both media sources and the researcher.

Data Collection

The data for this project was collected through internet scraping and downloading data from Google Trends. The data that was scraped was cleaned and used as the inputs for collecting data from Google Trends. The first step of the data collection process was to aggregate the articles that would be scraped. Since the goal of the project was to analyze the behavior of an everyday consumer and attempt to explain the bridge between fashion houses and the public, the articles were chosen from a Google search. They mostly include fashion publications such as Vogue or Elle. There was a time filter on this search for the month of September 6th, 2024 - October 1st, 2024. Keywords such as “fashion trends” and “SS2024 fashion month” were used to make sure all relevant articles were included in the source of the dataset. Thirty total articles were analyzed. In many instances, images are used on social media to discuss what is going on in the industry, given that it is highly visual. Fashion publications were the best social media source to collect written data, as their content is mostly text-based rather than visual.

Once the sources were aggregated, I used RStudio for the scraping process. Most of the articles presented their summarized trends as the subtitles, which has the element of “h2”. An example of the code I wrote for the scraping process is shown in Figure 1. After the discussed fashion trends were scraped from each article, I cleaned the aggregated list to remove features of the website that were captured unnecessarily in the scraping process, such as section titles like “More articles like this”. Not every article in the list of sources was able to be scraped or added to the dataset due to issues of file permissions or text being presented in an image format.

```{r}
source2 <- read_html("https://www.elle.com/fashion/trend-reports/a62280344/london-fashion-week-spring-2025-trends/")
elle2 <- source2 |>
  html_elements("h2") |>
  html_text()
elle2 <- elle2[1:8]
```

Figure 1: Elements scraped from Elle's "London Fashion Week Spring 2025 Trends" article.

Before the second portion of data collection could begin, the list of fashion trends had to be further cleaned for analysis. Consumers rarely Google the runway or journalism terms directly. Instead, they search e-commerce words, so I had to perform this transformation in my code. Here, a personal lens was used. Because the initial data source were articles, authors may have added descriptive words to enhance the writing, but that didn't contribute to the name of the trend. For example, the trend of kitten heels was scraped as "Hello Kitten Heels". I used the command "str_detect" to clean each of these instances, as shown in Figure 2. Another issue that was resolved in the cleaning phase was making sure searchable terms were correlated strictly to fashion related subjects. Otherwise, there would be a high signal-to-noise ratio, where many search spikes within Google came from unrelated events rather than fashion related topics. For example, a search for the scrapped term "double belt" would likely occur from users interested in car seat belts, not just those interested in the trend of people wearing two belts at the same time, one of the trends from last year. In these instances, I added words like "fashion" or "clothing" to the end of the search term as an attempt to eliminate irrelevant results that would cloud the dataset. On the website for Google Trends, there is a section for related topics. To make sure the appropriate edits were made to each search term, this section was checked to make sure it primarily includes apparel and fashion related search terms. Finally, overlapping search trends were combined by dropping repeated terms. "Fringe" and "suede" seemed to be really popular during SS2024 fashion week shows, as they were each present in the initial data collection more than three times. I began with 80 singular observations and ended up with 50 searchable terms after the cleaning process. An example of this is shown in Figure 3.

```
cleanedtrends <- cleanedtrends %>%
  mutate(
    search_term = case_when(
      str_detect(trend_clean, "1920s") ~ "1920s fashion",
      str_detect(trend_clean, "bohemian|boho") ~ "boho fashion",
      str_detect(trend_clean, "american") ~ "americana fashion",
      str_detect(trend_clean, "white") ~ "all white outfit",
      str_detect(trend_clean, "bold colour") ~ "pop of color fashion",
      str_detect(trend_clean, "buckled") ~ "buckles on clothes",
      str_detect(trend_clean, "denim") ~ "denim on denim",
      str_detect(trend_clean, "hello") ~ "kitten heels",
```

Figure 2: Commands used to transform the trends into searchable terms.

A tibble: 51 × 3

trends <chr>	trend_clean <chr>	search_term <chr>
1920s Inspirations	1920s inspirations	1920s fashion
A Bohemian Mood	a bohemian mood	boho fashion
All American	all american	americana fashion
All White Everything	all white everything	all white outfit
Bold colours	bold colours	pop of color fashion
Buckled Up	buckled up	buckles on clothes
Daydream Sheers	daydream sheers	sheer clothing
Deconstructed and Distressed	deconstructed and distressed	distressed clothing
Denim on denim	denim on denim	denim on denim
Ditsy florals	ditsy florals	floral clothing

1–10 of 51 rows

Figure 3: Original scraped trends and their cleaned search terms.

For the final step of the data collection process, I attempted to use the package gtrendsR on R and a for loop on the cleaned trends table to download data from Google Trends. This would eliminate manually downloading each trends' Google Trend search data, writing code to do it instead. However, a roadblock here was reached due to Google Trends not officially having an API for public use. The package in R was working for my first few iterations of data collection; however, it seems to no longer be a functioning package after receiving error messages even after trying several workarounds. At this stage, each search term was manually entered into trends.google.com with consistent filters. These filters included geographic and time period restrictions. Search data was only analyzed from US search history, even though there is European influence of the origination of the data. This decision was made because the goal here is to look at the effects of a single market, the U.S. Google Trends provides data in periods of one week, Sunday-Saturday. The chosen time period was Sunday, March 24, 2024 – Saturday, March 22, 2025. This is 52 weeks of data with the presentation of fashion shows in the middle four weeks. The goal here was to capture the social media attention that each show received and see if there was any variation or shift in the interest of a type of product once it was pushed to the consumer on a runway and subsequently a publication. Each search history was downloaded and merged into one table for analysis. Google Trends reports search data on a scale of 0-100 based on a topic's relative search history to itself over all of its search history. The table contains the start date of each week (a Sunday) followed by the score of 0-100. Some inputs had more than one peak date, as they hit peak search popularity on the scale several times in the designated time period. Figure 4 presents the aggregated search history results for seven trends over the first six weeks of the analyzed period.

A tibble: 6 × 51

Week <date>	floral clothing <dbl>	double belt fashion <dbl>	oversized clothing <dbl>	luxury scarves <dbl>	fringe clothing <dbl>	slip dresses <dbl>	kitten heels <dbl>
2024-03-24	81	0	46	0	45	89	62
2024-03-31	100	0	39	0	59	100	61
2024-04-07	87	0	47	0	72	87	54
2024-04-14	100	0	34	0	37	92	60
2024-04-21	94	0	40	0	0	95	56
2024-04-28	95	0	49	0	0	82	55

Figure 4: Weekly Google search history by trend

Methods

To present the collected data in a digestible manner, I first created a simple heat map. Using "ggplot", I used a color gradient to visually present the weekly scores for each trend. These results are shown in Figure 5. This allows us to visualize the range of search history, comparing patterns across trends.

Figure 5: Google Trend search history from March 2024 - March 2025

One goal of this project is to look at the effect Fashion Weeks shows have of interest on the promoted styles. I created a second visualization to present the week when each trend hit its peak search popularity over the course of a year. Peak search popularity is defined as having a Google Trends score of 100. The peak scores are presented in Figure 6. The trends are organized alphabetically. To validate the hypothesis that there is increased search history immediately following the analyzed events of Fashion Week, we would see peaks for each trend during the weeks of October and November.

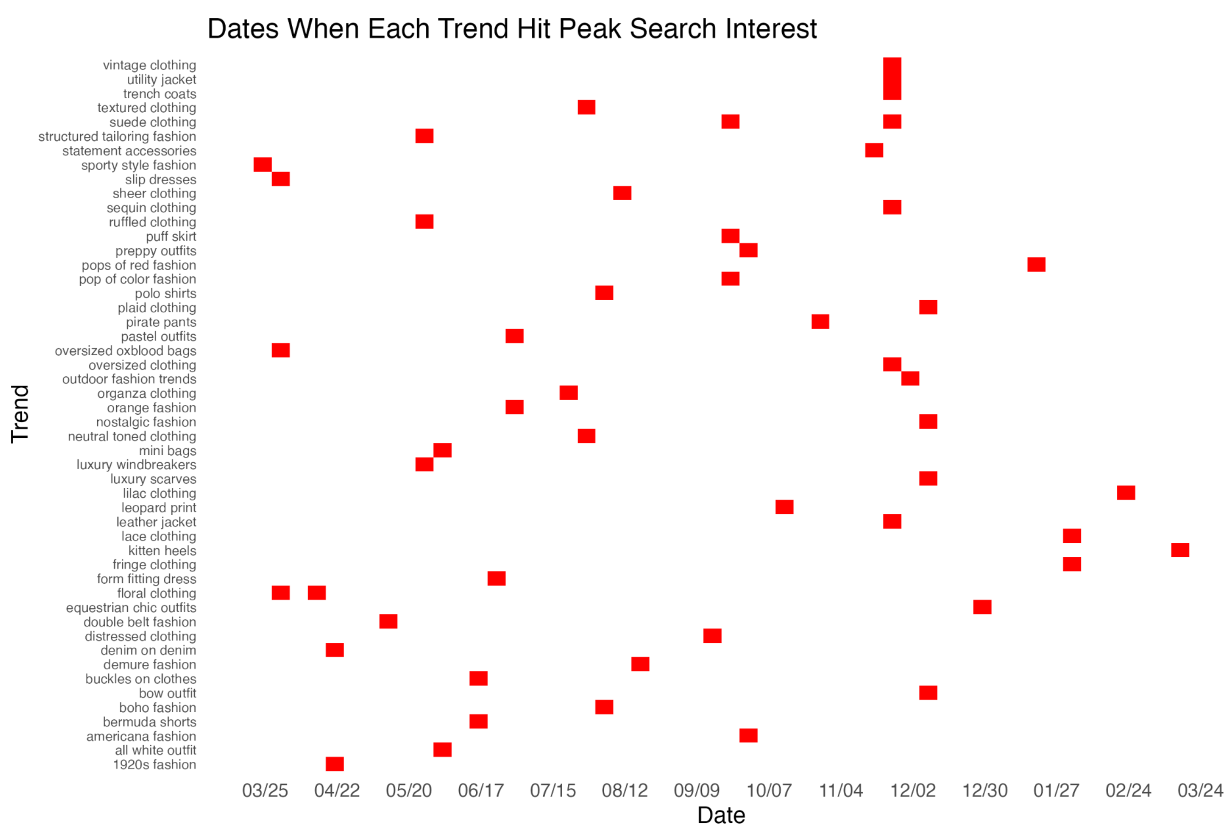

Figure 6: Trend peak search history from March 2024 – March 2025

Finally, to statistically evaluate whether Fashion Month generates changes in consumer search behavior, I estimated week specific differences in search history using an event study. This study specifically looks at search behavior for consumers who are interested in fashion and what the designers from these fashion houses are creating, being influenced in the styles they are seeing. This is due to the time period I am analyzing, and its shorter length would mean that any trickle-down effects would only apply to the subset consumers who are aware and interested in the events of the industry. The baseline comparison value was computed as an eight-week average of Google Trends search history before September 8th, 2024. Using this sample window reduces overall noise and provides a stable estimate of normal search behavior. The difference between hits in the baseline period and hits in the testing weeks was then calculated. Hits are defined as the weekly value of Google search history on a scale of 0-100. The testing weeks consisted of the eight weeks after Fashion Month ended, after October 5th, 2024. I then took the testing weeks and ran a paired t-test to look at the average of these differences, across all 50 trends, and determine if the average is equal to zero. The resulting average differences are shown in Figure 8.

I conducted a paired t-test on each test week to statistically assess whether these differences reflected meaningful changes. I define meaningful changes to be an increase or decrease in search history relative to the baseline. The paired t-test evaluates the null hypothesis, $H_0: \mu_d = 0$, where d_i is the within-trend difference between baseline search interest and search interest in week t+k. K is defined as the post-period week, 1 through 8. Here, μ_d represents the population mean difference across all fashion trends. Under this hypothesis, Fashion Month has no effect on the population of trends and the average change should be zero. Within the sample, I am looking to see if the mean difference increased or decreased from the baseline to the post-period. I also calculated an adjusted p-value for each of the paired t-tests. Doing a multiple comparison test is necessary because I ran 8 hypothesis tests. To correct for this, we multiply each p-value by the number of tests, 8.

A tibble: 8 × 8

week_index <int>	week_date <date>	n_trends <int>	mean_diff <dbl>	t_stat <dbl>	p_value <dbl>	p_adj <dbl>	week_label <chr>
1	2024-10-06	50	−0.6725	−0.2417672	0.80996952	1.0000000	t+1
2	2024-10-13	50	−1.2325	−0.4017046	0.68964820	1.0000000	t+2
3	2024-10-20	50	1.1675	0.3991302	0.69153150	1.0000000	t+3
4	2024-10-27	50	2.0475	0.7113643	0.48023144	1.0000000	t+4
5	2024-11-03	50	7.0475	2.5596361	0.01361445	0.1089156	t+5
6	2024-11-10	50	−0.6125	−0.2084801	0.83571830	1.0000000	t+6
7	2024-11-17	50	−0.5925	−0.1653718	0.86933179	1.0000000	t+7
8	2024-11-24	50	−6.0925	−1.4933759	0.14175054	1.0000000	t+8

Figure 7: Paired t-test results comparing each post-event week to the pre-event baseline

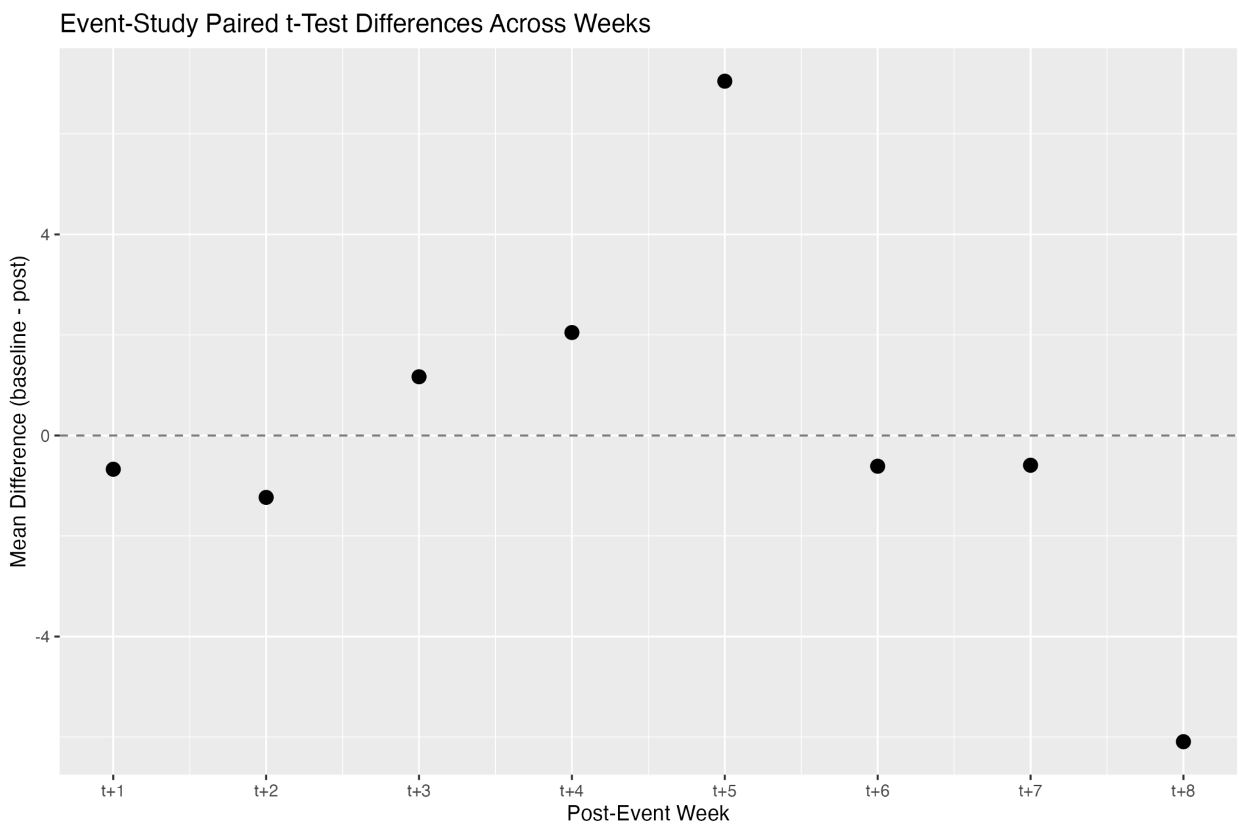

Figure 8: Mean difference in search history in each post-event week

Results

Figure 5 displays weekly Google Trends scores for all fashion trends over the full year. Darker blue values indicate higher search interest. This figure reveals that many trends are consistently very popular over the period, while others peak once and at very sporadic dates. Among the more popular terms were “vintage clothing”, “floral clothing” and “preppy clothing”, indicating that these trends have longer lifecycles and wouldn’t be considered microtrends. Microtrends are defined as short-lived and highly-specific trends that are intensely popular but quickly fade, usually lasting only weeks or months. The mentioned popular terms were trends that were likely present in prior Fashion Week presentations, so they would have already had heightened popularity. This heatmap supports the idea that consumer search interest is not synchronized across trends.

Figure 6 plots only the dates on which each trend reached its maximum search interest over the study period. The results of the visualization show highly scattered and asynchronous peak timing across trends, rather than clustering around any specific period, which is not what I expected. Several trends peak during the summer months, while others peak in mid-fall or winter, with no meaningful concentration around Fashion Month. It is also important to note that many trends only peak once and at completely different points in the calendar. This tells us that there is no coordination around the lifecycle of a trend; they instead follow individualized trajectories. If runway activity drove consumer searches, we would expect peaks to cluster shortly after September.

Through the events study, across all 50 trends, the results show only one week with statistically significant changes in search interest out of the eight weeks following Fashion Month. The results of the paired t-test are displayed in Figure 7. Week t+5 exhibits the largest deviation from the baseline with a mean difference of 7.05. The p-value is .014, which is statistically significant at a 5% significance level. This suggests a delayed response five weeks after the event. Since the mean difference is positive, this is interpreted as a decrease in search interest. However, to adjust for multiple comparisons, I multiplied the p-value by 8. The p-adjusted is .109, which is no longer statistically significant, so we cannot reject the null hypothesis. The remaining weeks have mean differences that are both smaller and inconsistent, and none of them have significant p-values both on their own and after adjusting for multiple comparisons. The range can be visualized in Figure 8. Overall, I cannot reject the null hypothesis at any week, so I cannot conclude that the sample of fashion trend data holds predictive power on consumers by the events of Fashion Week.

Discussion

A lack of correlation in the data does not necessarily indicate that runway influence is absent. Instead, it may mean that Google Trends is the wrong source to show the effects. Runway shows may influence visual platforms such as Instagram, TikTok, or Pinterest more than text-based search engines. Although there was an attempt to clean the following factors, both of them still likely occurred. First, there is room for weakened correlations through vocabulary mismatch in the trend vs. the search term. Second, there could still be search term noise from unrelated topics and double-meanings of terms.

The absence of significance in predictability may also suggest that Fashion Month may now function more as a branding event rather than a catalyst for consumer behavior. Luxury runways increasingly speak to the industry, which includes the press, buyers, and influencers, rather than the general public, which is what Google Trends data measures. From these results, we can see that the more traditional diffusion model of haute couture to ready-to-wear to mass market appears to be weakened. There are several explanations of this, one of which could be attributed to TikTok and other social media influencer ecosystems that are bypassing this traditional hierarchy. The key difference here is that Google search behavior is reactive, while runway presentations are pre-planned cultural moments. The dynamics of the industry might soon shift to looking at how fashion brands, who put in months of detailed work for a show, can become reactive to microtrends and influence behavior, rather than influencing them first.

Further, the influence of TikTok has briefly been mentioned, but it is important to elaborate on the media ecosystem. TikTok has radically shortened trend cycles (especially microtrends) to 1-2 weeks, far faster than the weeks-long fashion calendar. Trends today don't just emerge from the top-down, but rather the diffusion model has more back and forth influence. The emergence of fast-fashion brands and their ability to compete in the industry through extremely fast production styles, as a way to meet the demand for the microtrends, further pushes this agenda.

Ethical Implications

In this project, the goal was to explore cultural diffusion and timing patterns of consumer behavior. The findings are low risk when it comes to the topic of ethics, due to the project being centered around the fashion industry and consumer behavior. This project analyzes publicly available data and does not involve any information that is personal or sensitive. Google explicitly states that their trend data is aggregated and anonymized, and it is downloadable through their site (Rogers, 2016). This allows for public research and journalism. In regards to the fashion publications, while the data is available publicly, the articles are copyrighted.

However, I didn’t extract or store the full article text. I focused on non-expressive data extraction, scraping trend labels only. Further, this project is also exploratory rather than commercial, meaning the findings aren’t supposed to influence consumer behavior or marketing decisions, but rather provide awareness to them.

The “trickle-down” process from fashion week to mass-market consumption allows for the emergence of fast fashion, which can involve exploitative labor and unsustainable practices. While this project does not directly engage with those markets, awareness and potential encouragement of participating in these trend cycles perpetuates ethical concerns that exist in the broader market. Consumers may unnecessarily purchase clothing that was produced in harsh labor conditions and then dispose of it after minimal use, harming the environment in the process. This connects to broader ethical discussions of the labor market and the environment.

Finally, the ethical implications surrounding the data set and methodology can be discussed in the context of bias. The Google Trends data is drawn from the U.S., where results represent American search interest rather than global fashion consumption. This geographic focus means the findings reflect Western media and consumer behavior more than worldwide trends. There is also bias that stems from the authors of the fashion articles that were used to create the data set. Looking at photos and videos from a personal lens or through the use of AI can unknowingly sway the choice of which trends are written about in articles. Additionally, my own role in cleaning and modifying the data set introduces subjective judgment. Deciding which terms to remove or include reflects my personal biases. These choices demonstrate how when data science is applied to qualitative topics like fashion, there is room for bias and error in the process of trying to quantify and analyze the topic.

Conclusion

This project set out to discuss trend patterns in the fashion industry, specifically investigating the meaningful influence of Fashion Month runway presentations on consumer search behavior. Using a dataset of trends identified from fashion publications and a year of weekly Google Trends scores, I examined whether search interest collectively increased in the weeks following the presentation of Spring-Summer 2024 shows. Across visualizations and hypothesis testing, the results failed to show a coordinated rise in interest following Fashion Month.

These findings reflect structural changes within this market, which can be attributed to the rise of microtrends, fast fashion, and the power of social media. Here, I used Google Trends as a representation of mass-consumer behavior, which revealed that luxury presentations no longer shaped public interest in predictable ways. Fashion houses may still have an impact on the mass consumer; however the process has likely become much more indirect and non-linear.

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