Style in the Age of Instagram

Predicting Success within the Fashion Industry using Social Media

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ABSTRACT

Fashion is a multi-billion dollar industry with social and economic implications worldwide. To gain popularity, brands want to be represented by the top popular models. As new faces are selected using stringent (and often criticized) aesthetic criteria, *a priori* predictions are made difficult by information cascades and other fundamental trend-setting mechanisms. However, the increasing usage of social media within and without the industry may be affecting this traditional system. We therefore seek to understand the ingredients of success of fashion models in the age of Instagram. Combining data from a comprehensive online fashion database and the popular mobile image-sharing platform, we apply a machine learning framework to predict the tenure of a cohort of new faces for the 2015 Spring/Summer season throughout the subsequent 2015-16 Fall/Winter season. Our framework successfully predicts most of the new popular models who appeared in 2015. In particular, we find that a strong social media presence may be more important than being under contract with a top agency, or than the aesthetic standards sought after by the industry.

Author Keywords

Social Media; Fashion Industry; Science of Success

ACM Classification Keywords

Human-centered computing: Collaborative and social computing—*Social media*; Information systems: World Wide Web—*Social networks*

INTRODUCTION

The success of cultural artifacts is characterized by inherent unpredictability and inequality [40], posing fundamental problems for a proper understanding of markets based on the production of cultural goods. Fashion, and fashion modeling in particular, are typical examples [2, 32]. When trying to cast a model for the upcoming seasons, a casting director is faced with a seemingly impossible task: predicting whom, out of the hundreds of new faces she may see at the go-see calls, will become the top model of the next season.

Modeling has in fact a very special meaning in fashion, a multi-billion dollar industry with strong social and economic implications worldwide [24]. Models play the main role in advertisements and runways, which are, historically, the main ways brands communicate with their customers. They contribute to frame consumer experience and promote consumption, as their attractiveness becomes associated to the brands they work for [46]. This is especially true for luxury goods, whose aesthetic value is more important than practical usage. Only those who appeal the aesthetic sensibility of fashion designers stand chances to become popular [10].

Ethnographic studies show in fact that casting directors consider both objective physical characteristics — such as body size, height — and subjective considerations — the reputation of the agency representing the model — to be important decision-making criteria for casting [33, 19, 32]. However, the same studies also uncover how information cascades are a critical part of what makes a model successful. Similarly to the careers of scientists [34], fashion models also benefit from strong cumulative advantage effects, by which small differences in prestige between competing individuals get amplified, for example by means of word of mouth [39, 42, 19].

The job market for fashion castings has strong seasonal components, revolving around week-long trend-setting industry events (“Fashion Weeks”), during which a dense calendar of shows is organized in various locations in a major city. The four most prominent Fashion Weeks worldwide take place twice a year and, as of 2015, are hosted in the cities of New York, London, Paris, and Milan. These events facilitate networking and information sharing, and are seen as a crucial part of the process by which the fashion industry collectively decides what will be the new trends and the next top models.

Social media and mobile image-sharing platforms, Instagram in particular, are revolutionizing the fashion industry worldwide, as interest toward new trends, designers, and products increasingly unfolds online [25, 7, 26]. This has obvious implications on the job of fashion models too. Traditionally, models were not meant to interact directly with their customers [33]. It is instead now customary for spectators to use Instagram to upload photos or videos during runways events. This, in turn, has been argued to influence the way fashion designers design, shoot, and showcase their runways, especially for the case of luxury brands [41]. Famous designers such as Tommy Hilfiger and Kenneth Cole have been reported to take advantage of Instagram for customer engagement [14].

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As social media become for fashion models a far more important showcase than magazines and billboards, we wonder if popularity on such platforms can be used as a proxy to predict success, and seek to answer these research questions:

RQ 1. *Given data about measurable physical and professional characteristics of a models, can we predict whether she will be casted for the upcoming fashion season?*

RQ 2. *Does the addition of relevant signals of social media activity improve the predictability of success of models?*

We tackle these questions using a quantitative approach, with a mix of exploratory statistics and machine learning experiments. To rule out possible explanations in terms of cumulative advantage [42], we focus on data about a group of newcomers, who just started their career in the fashion world. As a simple and reasonable measure of success, we employ the number of catwalks a model walked.

The rest of the paper is organized as follows. We give a brief overview of the work related to predicting success in cultural markets, and fashion in particular, in the next section. We then describe the two datasets used in the study: the “new faces” section of the Fashion Model Directory (FMD) website¹ and Instagram.² We then present the main results of this study. We start with a descriptive analysis of the FMD data, and estimate the degree of association between the tenure of a model and a number of standard industry metrics using a regression framework. Finally, we describe the machine learning approach we employed, and the evaluation metrics used to assess the quality of the predictions of our statistical framework. The paper concludes describing the broader relevance of our findings to the emerging “Science of Success” research field, and potential future directions.

RELATED WORK

In this study we are looking at predicting popularity of fashion models using data from social media activity. The study of trends in cultural markets has a long-standing tradition [5], and various researchers have exploited social data from a wide range of backgrounds. For example, Asur and Huberman [4, 3] used Twitter data to predict the box-office performance of newly-released blockbuster movies, and later Mestyán et al. [35] improved these results using data from Wikipedia. Ferrara et al. [12, 13, 23] studied the emergence of information trends in social media settings, and the rise to popularity of Instagram users in photography contexts [11].

In contrast, in the context of fashion, it is worth noting that practical application of trend-detection technologies has started to become possible only in recent years, thanks to the increasing availability of online user-generated data about fashion apparel trends [30, 29, 31, 20].

Instagram was the platform selected in our study. It is a mobile image-sharing service that specializes in instant communication of trends and visual information in general [11], in a way similar to Twitter, Pinterest, and Flickr. Besides the detection of trends, a wide range of aspects related to image

¹<http://www.fashionmodeldirectory.com>

²<http://instagram.com>

Figure 1: Example of a FMD profile page. Image © FMD – The Fashion Model Directory

sharing have received attention from the research community, such as depression and online behavior [1, 43], situated usage in museums [21, 44], or organization of information through tags [37, 27, 18].

METHODS

Fashion Model Directory

We collected data from the Fashion Model Directory (FMD) website, one of the largest fashion databases of professional female fashion models [45]. Figure 1 shows the profile of one of the fashion models on FMD as an example. As can be seen from the figure, FMD profiles, similarly to a résumé, provide a mix of biographical, physical, and professional experience information, notably casting agencies and walked runways.

While the database claims to include profiles for over 10,000 models, our analysis focuses only on its recent additions, which are listed under the category “New Faces”. We collected our dataset in December 2014, finding $N = 431$ new faces for the 2015 Spring / Summer (S/S) season.

For each model the FMD data thus consists of the following attributes: name, hair color, eye color, height, hip size, dress size, waist size, shoes size, list of agencies, nationality, and details about all runways the model walked on (year, season, and city). We discarded the data about hair and eye color, as the color coding was not reliable enough to allow for a meaningful characterization of these features. For similar

Figure 2: Distribution of walked runways by new faces of the S/S prior to the Fashion Week season.

reasons, we also discarded nationality information. All body sizes (height, hips, dress, waist, shoes) were converted in the metric system. For shoe size we used the Paris point units system. Furthermore, the data were cleaned, substituting, in two cases where the data about shoe and waist size were missing, the missing values with the group average. Before running regressions, any non-categorical variable was also centered around the mean and standardized.

To account only for a homogeneous set of runway experiences, we considered only runways occurred during the fashion weeks for the 2015 S/S season in New York, London, Paris, and Milan. These occurred during the period of September 2014 and were the most recent major fashion weeks at the time of our data collection (December 2014). We found that, collectively, the new faces in our sample had performed $W = 1402$ runway walks (3.25 walks per model on average) for $B = 313$ distinct branded runway events.

Finally, we annotated each agency to reflect its reputation in the fashion industry. We use a simple binary classification system, by which high-prestige agencies are assigned to the “top agency” category. Since FMD does not provide this information, we retrieved a list of all top agencies from another online fashion database, Models.com,³ which collects experts knowledge to determine the reputation and influence of casting agencies. As a result, 329 out of 431 models were hired by at a least one top agency, 87 models were not hired by any top agency, and 15 had no agency information in their profile (which could indicate that either the model was not using any agency, or that the information was simply missing from the database; see Table 1).

The majority of new models did not perform even a single runway during the four fashion weeks in September 2014; only around 24% of models (102 out of 431) performed at least one runway, with a small minority having participated to several runways (see Figure 2). This is not surprising, and further suggests that there exists a strong popularity bias in castings, in line with previous work [19].

³<http://www.models.com>.

	Top agency	Non-top agency	No agency	Total
with Instagram	214	33	6	253
w/o Instagram	115	54	9	178
Total	329	87	15	431

Table 1: New faces of the 2015 S/S season under contract with at least one top agency and their presence on Instagram.

Instagram

We collected data about the social media presence of our FMD new faces using Instagram. We found $N_i = 253$ Instagram accounts (59%), accounting for $W_i = 1181$ runway walks (4.67 walks per model on average). Models under contract with a top agency are more represented on Instagram (65%) than those with a non-top agency (41%), and no agency at all (40%), see Table 1.

Using the media endpoint of the Instagram API, we collected all media posted by any FMD new face in the three-month period before September 4th, 2014, the beginning of the New York Fashion Week. Metadata of each posted media include the number of likes and comments, as well as the the metadata of the first 125 likes of each post (*e.g.*, time stamp of the like, name of the liking user, etc.). We then computed the minimum, maximum, median, and average number of likes and comments of all posts uploaded by each new face, as well as the number of posts during the period, for the three months before and after the fashion week events. Similarly to the FMD data, all variables were standardized before using them in regressions.

Sentiment Analysis

We supplement the analysis of social media activity with sentiment analysis. To do so, we selected only comments written in English. Language was detected using a simple Naive Bayes classifier [36]. We extracted the comments on posts uploaded before the Fashion Week season, and calculated the average sentiment score of each model using *Vader*, a state-of-the-art, rule-based algorithm [22]. We included only those models who received at least one comment written in English to any of their posts, finding a subset of $N_s = 198$ models, who account for $W_s = 1052$ runway walks (5.31 walks per model on average). *Vader* is designed to deal with social media data, as it is based on a manually-defined vocabulary that encodes grammatical and syntactical conventions common to online documents. It is capable of capturing sentiment intensity with an accuracy of 84%, which outperforms other algorithms as well as individual human raters.

Predictive classification of success

To forecast success within the new faces cohort, we performed a binary classification exercise. Since most models in the cohort did not walk any runway, to avoid further class imbalance we consider two classes: models with zero walks (unpopular) and models with one or more walks (popular). To learn the predictive score distributions, we applied three widely-used machine learning algorithms, based on ensemble methods and boosting: Decision Tree (DT) (baseline), Random Forest (RF) [6], and AdaBoost (AB) [16]. We used the

	Height (cm)	Hips (cm)	Dress	Waist (cm)	Shoes
Mean	177.48	87.98	33.36	60.49	39.44
Std. Dev	2.49	2.33	1.36	2.17	1.19
Min.	167.00	80.00	30.00	53.50	36.00
Median	178.00	88.00	33.00	60.00	39.00
Max.	183.00	104.00	40.00	77.00	43.00

Table 2: Body size measures of new faces of the 2015 S/S season ($N = 431$).

implementations of scikit-learn [38], optimally tuning the parameters as follows: entropy is used to measure the quality of the decision splits; all statistical models employ 25 estimators; DT and RF have a pruning setting of max-depth to 5, and RF adopts a maximum of 5 features. This framework allows us to evaluate the forecasting power of the various sets of features presented above using standard performance metrics, such as AUROC (Area Under the Receiver Operating Characteristic curve), and accuracy scores. We report results obtained by averaging one thousands iterations of k -Fold Cross Validation ($k = 5$) in which 80% of data is used to train the statistical models and the remainder 20% is used for prediction. The last experiment of this paper, however, represents a “real” prediction task in which we train the machine learning models with the previous fashion season (2015 S/S) data, and use them to predict the upcoming 2015-16 Fall/Winter (F/W) season.

RESULTS

Descriptive analysis

We first analyzed height, hips, dress, waist, and shoe size of the new faces group and assessed whether there is any obvious association with the number of walked runways. Figures 3(a)–(e) show the distribution of body size measurements and, where available (Figures 3(a)–(c)) how these features compare to the US female population for the closest age group (20–29 y.o. for height and waist size [17]; 18–25 y.o. for hip size [47]). Here the data have been plotted before rescaling. The variables are all distributed within narrow ranges, following approximately normal distributions. Unsurprisingly, even the shortest model in our dataset is much taller than the US female average. In general, as far as body measures are concerned, our group of new faces seems to represent a very biased sample of the general female population. Table 2 reports standard descriptive statistics of the sample.

We study the association between body size measures and the main dependent variable, the number of runways the models walked *prior* to the 2015 S/S fashion week season, using a regression framework.

Since our measure of success is based on the count of walked runways, we used a Poisson regression model to estimate the chances of walking a single runway as a function of various regression features. We start by only considering physical attributes as regressors. The results are reported in Table 4 (see Model 1). The expected number of walked runways for the baseline new face is 2.25. Height is positively associated to increased chances of walking a runway — specifically, 2.27

	Height	Hips	Dress	Waist	Shoes
Height	1.00				
Hips	0.01	1.00			
Dress	−0.06	0.25	1.00		
Waist	0.02	0.58	0.28	1.00	
Shoes	0.36	−0.01	0.00	0.07	1.00

Table 3: Pairwise correlations between body size measures of the new faces of the 2015 S/S season ($N = 431$)

times for each additional standard deviation (2.49 cm, approximately one inch), relative to the group average baseline. Larger dress, hips, and shoe sizes are all negatively associated with the chances of walking a runway, while waist size seem to be not associated in either way.

In Table 3 we also report correlations between all body size regressors, as a simple test for possible source of multicollinearity. We find that dress, waist, and hip size are pairwise correlated with each other, as well as shoe size with height. All correlations appear to be of moderate entity.

Adding the information on agencies (see Model 2), we find a strong association between having a top agency and the number of walked runways: models with a top agency have, everything else being equal, nearly ten times higher chances ($\exp(2.29) = 9.87$) of walking a runway, than their counterparts represented by non-top agencies. The chances of walking for models without a prestigious agency drop substantially, as the expected count for the baseline is now only 0.28 walks. This is consistent with previous research [19], and highlights the role of agencies in setting fashion models trends in the fashion industry.

We then focus on models with an Instagram account ($N_i = 253$) and assess how the average number of posted media, received likes, and comments is associated to the count of walked runways. Figures 3(g)–(i) show distribution histograms (log10-scaled) of these variables.

Model 3 and Model 4 replicate the above findings on the subset of new faces with an Instagram account. In particular, within this subset the gap between those with a top agency and those without is even more marked. Adding the Instagram-related variables does not change much the association with height, hip size, and agency. Instagram activity seem to have mixed associations with runway walks. Additional posts over the average activity yield a 15% higher chances of walking a runway but, surprisingly, more likes tend to *lower* the chances of walking a runway (about 10% less). The average number of Instagram Likes is highly correlated with the average number of comments ($r = 0.82$) yet it has a negligible correlation with the number of posts ($r = 0.15$). The number of received comments does not seem to be correlated with the number of posts ($r = 0.00$).

The overall picture does not change significantly when we look at the sentiment expressed by Instagram users when commenting on the media posted by our new faces (Model 6, 7, and 8 of Table 4). The sentiment itself appears to be

Figure 3: Distribution of body size measures and Instagram activity of new faces of the 2015 S/S season ($N = 431$). Dashed lines, where shown, indicate averages computed on the closest matching age group in the US female population.

positively associated to better chances of walking a runway (23% more), together with the overall number of comments.

Including the information about agency and all Instagram-related variables yields better statistical models for both the overall sample of new faces and those with an Instagram account, as shown by both the Akaike (AIC) and Bayesian Information criterion (BIC) scores. This indicates that all variables potentially provide useful predictive signals. In the next section we describe the results of the prediction tasks in detail.

Forecasting success in fashion

For each classification algorithm (DT, RF, and AB) we learned three distinct predictive models: (i) with only body size measures (height, hips, dress, waist, and shoes) (BODY); (ii) with physical attributes and the binary information about whether the fashion model has a top agencies or not (BODY+AGENCY); and, (iii) with body size measures, agency information, and Instagram-related signals—number of posts, average number of likes and comments received—(BODY+AGENCY+INSTA). For the latter statistical model, we restrict the training data to use only the media posted in the three months *before* the fashion week. As shown in Table 5, and consistently with results from the previous section, when trained on 2015 S/S runway walks data, social media features improve accuracy of the statistical model. According to t -tests, all improvements are statistically significant. We also tried other statistical models [38] (SVM, Logistic Regression,

Naive Bayes, etc.): none yielded AUROCs or accuracy above 60%.

To test the actual forecasting power of our framework based on the classifiers trained on the 2015 S/S data, we attempt to predict the popularity labels for the next season, the 2015-16 F/W Fashion Week, that is, on a completely separate test set. To do so, we manually collected a new and more recent dataset (May 2015) containing the *new faces* of the latest fashion season, and up-to-date information about runways performed during the 2015-16 F/W Fashion Week (February 12–March 11, 2015). We found 15 such new face profiles. This set is roughly balanced (8 fashion models ran at least one top walk, 7 did not appear in any of the four main events), and each profile links to an Instagram account, allowing us to employ all predictive features (BODY+AGENCY+INSTA).

Social media features for the validation test set were built using the meta-data of media posted in the three months before the season only (November 12, 2014 to February 11, 2015). The results for the best predictive model, Random Forest (RF), along with the true popularity labels (*became popular*), are shown in Table 6. Random Forest scores an AUROC performance above 81%: impressively, RF is able to correctly predict 6 out of 8 fashion models who became popular during the 2015-16 F/W, using training data from the past season only. Random Forest also successfully identified 6 of the 7 fashion models who did not perform in any top event. The confusion matrix in Fig. 4 summarizes these results.

	All new faces ($N = 431, W = 1402$)		w/ Instagram ($N_i = 253, W_i = 1181$)			w/ Instagram & Sentiment ($N_s = 198, W_s = 1052$)		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	0.81***	-1.27***	1.21***	-7.70*	-7.70*	1.32***	-7.59	-7.65*
Height	0.82***	0.76***	0.89***	0.85***	0.88***	0.89***	0.86***	0.90***
Dress	-0.23***	-0.17***	-0.13***	-0.05	-0.05	-0.16***	-0.13***	-0.12***
Hips	-0.35***	-0.33***	-0.24***	-0.28***	-0.29***	-0.23***	-0.33***	-0.36***
Waist	-0.04	-0.00	0.06*	0.11***	0.10***	0.10***	0.18***	0.19***
Shoes	-0.38***	-0.37***	-0.35***	-0.37***	-0.36***	-0.41***	-0.44***	-0.45***
Has Top Agency		2.29***		9.05**	9.04**		9.03*	9.07**
Inst. Posts					0.14***			0.08**
Inst. Likes					-0.18***			-0.17***
Inst. Comments					0.24***			0.21***
Inst. Sentiment								0.16***
AIC	4814.41	4531.28	3339.79	3064.96	3038.96	2734.13	2489.47	2462.77
BIC	1824.81	1545.74	1639.85	1368.52	1353.12	1426.88	1185.46	1171.92

Table 4: Poisson regression results for the new faces of the 2015 S/S season. Dependent variable is the count of runways walked. Legend: * : $p < 0.05$; ** : $p < 0.01$; *** : $p < 0.001$.

	BODY		BODY+AGENCY		BODY+AGENCY+INSTA	
	ACC	ROC	ACC	ROC	ACC	ROC
Decision Tree	0.596	0.558	0.635(+0.039)***	0.563(+0.005)***	0.694(+0.059)***	0.619(+0.056)***
Random Forest	0.643	0.549	0.656(+0.013)***	0.586(+0.037)***	0.733(+0.077)***	0.688(+0.102)***
Ada Boost	0.640	0.533	0.636(-0.004)***	0.556(+0.023)***	0.692(+0.056)***	0.640(+0.084)***

Table 5: Accuracy (ACC) and Area Under the ROC curve (ROC) values for all classifiers. Increments for the classifier with all features (BODY+AGENCY+INSTA) are computed over that without Instagram-related features (BODY+AGENCY), which is in turn computed over the baseline (BODY). All improvements are statistically significant. Random Forest is the model with the best predictive power, scoring a top accuracy of 73.3% and an AUROC of 68.8%. Legend: * : $p < 0.05$; ** : $p < 0.01$; *** : $p < 0.001$.

Figure 4: Confusion matrix of the Random Forest performance for the prediction task (2015-16 F/W Fashion Week).

The elements of success in fashion modeling

The analysis of the prediction task provides some interesting insights: Fashion Models 11 and 13, although having top agencies, did not rise to popularity; Fashion Model 5, however, became popular even without a top agency: both of these dynamics have been correctly captured by our prediction framework. It is worth considering when our framework failed. Fashion Models 2 and 3 represent the two *false negatives*: they both exhibit low social media activity, a signal highly regarded by our predictor (see below), which induces

Random Forest to fail. Fashion Model 10, the only *false positive*, on the other hand shows very high social media engagement levels, yet did not perform in any top runway during the 2015-16 F/W season. The FMD profile pictures of the six models whose success was correctly predicted by our framework are shown in Figure 5.

To understand which features contribute most to the predictive signal we compute feature importance. The contribution of each feature is here calculated as information gain. The results for Random Forest (RF) are shown in Table 7. For prediction purposes, we note how the three social media activity features contribute as much as having optimal physical attributes and more than being under contract with a top agency. The top 3 features used by RF are: (i) *Instagram #Likes*, (ii) *Height*, and (iii) *#Posts*. Similar results hold for other classifiers.

DISCUSSION

Social media are increasingly used as sensors of social collective phenomena [4, 13]. Increasingly, the usage of social data, often in conjunction with other data sources, proves crucial to be able to represent real-world events, trends, information diffusion, and social behavior. In this study we were concerned with understanding whether it is possible to predict fashion models popularity, complementing physical and professional information with social data.

Our methodology has of course limitations, and we here report few notable ones:

Fashion Model ID	Height	Hips	Waist	Dress	Shoes	Instagram Posts	Instagram Comments	Instagram Likes	Has top agency	Became popular	RF Prediction
1	178	86.5	58	33	41.0	59	4	148	True	True	True
2	178	86.0	60	33	40.0	24	0	32	False	True	False
3	179	88.0	61	34	39.0	0	0	0	True	True	False
4	180	89.0	60	34	41.0	52	1	93	True	True	True
5	175	86.0	58	33	38.0	163	2	70	True	False	False
6	180	89.0	60	34	41.0	2	7	48	True	True	True
7	180	90.0	61	34	40.0	10	3	116	True	True	True
8	178	87.0	61	33	39.0	34	2	90	True	True	True
9	183	86.0	62	34	41.0	16	2	61	True	True	True
10	176	87.0	59	33	38.5	17	17	647	True	False	True
11	177	86.0	60	32	38.5	38	2	51	True	False	False
12	180	90.0	60	33	40.0	29	1	59	False	False	False
13	169	88.0	60	33	38.0	49	9	570	True	False	False
14	179	94.0	65	35	41.0	58	3	52	False	False	False
15	180	83.0	62	35	43.0	11	15	546	False	False	False

Table 6: Performance of our predictive models trained on 2015 S/S data, and tested on 15 new fashion models who appeared in the 2015-16 F/W Fashion Week. Our best classifier, Random Forest, correctly predicts 6 out of 8 positive instances (became popular), and 6 out of 7 negative ones (not becoming popular) yielding 80% accuracy and an AUROC score of 81.25%.

Figure 5: FMD profiles of the six *new faces* whose success (having at least one runway during 2015-16 F/W Fashion Week) was correctly predicted by our framework. All images © FMD – The Fashion Model Directory.

- All brands during the season are equally treated. Runways of higher reputation brands, such as Hermès or Chanel, should be reflected with higher weights if compared to new and relatively unpopular brands. We plan to incorporate such prestige in future revisions of our statistical models, and observe what effects this yields.
- Our measure of popularity only takes into account the number of runways walked. This neglects several aspects of popularity within the fashion industry, such as appearance in magazines and social events. We plan to incorporate further dimensions of success in future work, to determine how these additional dimensions play along with the success measured by runways.
- Our “real” prediction task is tested on a very small dataset containing only 15 fashion models appeared during the 2015-16 F/W Fashion Week: although this limitation is due to the intrinsic scale of fashion events and to our data sources, more data in the future will be needed to determine the general performance of our framework.
- Our study is confined to one single online platform, Instagram: its peculiar characteristics (e.g., the mobile-oriented nature) might affect the dynamics of content generation and perceived popularity, as opposed to other platforms with different usage purposes, like information sharing (Twitter [28]) or befriending activities (Facebook [9]).
- Finally, our study is limited to analyze only female fashion, while male modeling is increasingly becoming more mainstream. It will be interesting to see, when data become available, whether our results apply to the male fashion modeling market as well.

CONCLUSIONS

The ingredients to career success oftentimes remain mysterious. In the fashion industry, style is often credited as that ineffable quality all successful individuals have. The present contribution shows how a number of seemingly disconnected characteristics are actually tightly entangled: physical attributes are required for inclusion in the modeling profession, but do not suffice. The professional contribution of trend-setting top agencies play an equally important role. And, as we first show in this paper, in the new era of social networks, online presence helps succeed, as we see by the improvement in the predictive power of our forecasting models.

We submit a few possible explanation to this observation: in a world with limited attention [8], information cascades and the wisdom of the collectives are precious indicators for casting agencies, promoters, marketeers, agents, recruiters, and the fashion industry in general. The response of the online audience plays an increasingly important role in the offline fashion industry world: a rising star in the online world will hardly be ignored, and will probably be noticed by a top agency, facts that will enhance her likelihood to succeed. In other words, buzz on social media is a proxy for the buzz in the offline world, and this reduces uncertainty on the part of the industry.

Yet, it remains interesting that, in the regression models, increased activity on social media had only a weak association with heightened success (though on average fashion models with an Instagram account tended also to have done more shows). Perhaps, even these small differences have more chances of getting amplified due to word of mouth and collective attention, so that social media may be just facilitating the information cascades mentioned before. Lacking data on the word of mouth among industry professionals, in this work we did not investigate actual information cascades, but we believe that further research is needed to better elucidate this point.

We also note how fashion modeling exhibits a strong winner-takes-all component. In an industry that seems to be governed by such a *survival of the fittest* mechanism, the difference between performing a show in a premier venue or not becomes crucial: while the majority of new faces will not appear in any prestigious avenue, having even one single runway in one such venue may decree the success of a new model, bring-

ing her visibility above that of 76% of her competitors.⁴ Our analysis aimed at understanding the factors that play a role in obtaining such popularity, including physical attributes, the reputation of casting agencies, and the importance of social media presence and reactions.

Regarding our exploratory analysis (*cfr.* Table 4), we find that thinner and slender individuals are more likely to walk in runways. Compared to the general population, models are often singled out for their extremely skinny and tall looks. However, it is interesting that even among themselves, these preferences — towards skinny and tall models — are still significantly related to the number of runways they can join. Beauty is notoriously a hard-to-define quality and, in the case of the fashion industry, largely a by-product of a collective effort, rather than an inherent quality [32]. While beyond the scope of the present work, an intriguing question that follows up from it is whether Instagram and other social media are indeed changing the traditional notions of beauty.

Research on the fashion industry thus far has been largely qualitative, relying on methods such as interviews with small number of models and casting directors [33, 19]. To the best of our knowledge, this is first time a large online fashion database has been explored in a quantitative way, together with data from online social activity. As the impact of social media — especially Instagram — becomes significant in the fashion industry, predictive methods have the potential to leverage collective attention and the wisdom of the broader user population, which reflect some of the popularity of fashion models, to predict their career success.

Fashion modeling is one of the best examples of a cultural market, like music, art, and literature. In all these markets, determining quality of cultural products is hard because of inherent uncertainty, and thus market actors must rely on social conventions and buzz as a proxy for success. In the case of fashion models, here we show that the buzz going on social media (Instagram in this case) is a reliable predictor of early career success. Our results are in line with previous work that shows that social signals have a prominent role in determining success of cultural contents [40, 4], and so we can expect that similar approaches to cultural predictions will work in other markets too. Even scientific production and the stock market are, to some extent, ruled by prestige and buzz [34, 15]. Thus we expect that the essence of our findings might inform cultural producers and scholars well beyond the fashion industry.

In conclusion, computer-mediated collectives are increasingly disrupting the way culture is consumed and produced. Understanding how use of internet communication platforms affects cultural production is just an instance of the study of work in computer-mediated environments and an interesting challenge for future research.

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⁴Only 24% of fashion models ran at least one top walk in our dataset.

Feature	Type	Importance
Height	Physical	0.16
Dress	Physical	0.05
Hips	Physical	0.09
Waist	Physical	0.10
Shoes	Physical	0.09
Has Top Agency	Professional	0.05
Instagram Posts	Social	0.16
Instagram Comments	Social	0.13
Instagram Likes	Social	0.18

Table 7: Feature importance (Random Forest model) to predict fashion models' success.

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