We Are What We Watch: Movie Plots Predict the Personalities of Those who “Like” Them

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We Are What We Watch:

Movie Plots Predict the Personalities of Their Fans

ABSTRACT

How do movie contents relate to the psychological makeup of the audiences they attract? We explore this question by employing advanced analytical tools to a rich dataset combining detailed characterizations of movies and their plots with personality measures of their social-media fans. We identify novel associations between movie features such as quality and genre, and the personalities of their fans. We then show that movie plots—captured via text—predict the aggregate personalities of their fans beyond all other variables studied. We further quantify how different psychological themes (e.g., leisure) and unique concepts that organically emerge from the data (e.g., adultery) relate to fans' personalities, and show that movie plots align with the characteristic ways in which their fans think, feel, and behave (e.g., social films attract extraverted fans). Our findings provide fine-grained mappings between personality dimensions and movie preferences, facilitating automated assessment of audience psychographics at scale.

Keywords: personality, movie preferences, text analysis, machine learning.

The rise of on-demand streaming services has transformed our media consumption, offering an unprecedented variety and volume of content tailored to individual tastes. This digital evolution presents a unique opportunity to explore uncharted territories in the landscape of psychological science. While it's evident that individual preferences shape media consumption, the relationship between these preferences and the psychological makeup of audiences have remained largely unexplored. Here, we bridge this knowledge gap by employing advanced analytical methods for mapping the links between movie plots and the collective personality traits of their fans.

Interactionist psychological theories posit that individuals seek out occupations, hobbies, and relationships that reinforce and verify their needs and dispositions. A natural prediction of the theory is that individuals are drawn to content that converges with their psychological profiles. Some previous research has empirically investigated this prediction, revealing correlations between personality traits and preferences for different content types (Golbeck & Norris, 2013; Hall, 2005; Möller & Karppinen, 1983; Rentfrow et al., 2011; Weaver, 1991, 2003; Weaver et al., 1993).

Despite these previous works, several important questions remain. First, the generalizability and external validity of past findings is not well-established, as previous work has relied on small-scale studies with limited statistical power, that measured media preferences via self-reports. Such measures might be susceptible to demand effects, and could systematically differ from behavior in more naturally occurring environments. For example, participants of laboratory studies might feel compelled by social norms to downplay their liking of violent or sexual content.

A second limitation concerns how media preferences have been assessed—via self-reported liking of a small number of broad genre categories. This approach has important drawbacks. First, genres are very broad categories, and there is no consensus about how many and which genres should be represented, with some researchers using as few as six categories (Weaver, 1991) and others as many as eighteen (Rentfrow et al., 2011). Second, reducing complex and multidimensional media content into a few broadly defined genres might eliminate important and potentially valuable information. For example, the films Good Morning Vietnam (1987) and The Big Short (2015) belong to the same genre (Biography, Comedy, and Drama), according to the Internet Movie Database (IMDb). However, the former tells the story of an irreverent DJ broadcasting on the US Armed Forces Radio station during the Vietnam War, where the latter is about a group of investors betting against the housing market before the 2008 financial crisis. Relying solely on genre fails to account for substantial differences between these films' content and precludes the possibility of capturing more nuanced information.

Third, the broadness of genres makes it difficult to assess more general content attributes, such as quality and popularity. Consequently, studies have not examined how such characteristics impact preferences. For example, it may be the case that extroverts prefer popular content. In turn, popularity may differ by genre (e.g., historical documentaries are less popular than action films). Thus, failing to consider popularity might confound observed relationships between personality and preferences for content.

We address the limitations above on two studies, using data collected via myPersonality, a Facebook app through which roughly 3.5 million users completed personality questionnaires and consented to share their Facebook data with researchers. We use this data to capture a five-dimensional Aggregate Fan Personality Profile (AFPP) of movies, by averaging the Big Five scores of all myPersonality users who 'like' them on Facebook. We also obtain rich representations of movies from IMDb (www.imdb.com), an online database containing over 5 million titles of movies and TV episodes. Each IMDb entry represents a title and includes genre information and user-generated plot keywords that describe *"any notable object, concept, style or action that takes place during a title."* IMDb also includes general information about movies, such as revenue and critics ratings, which we call "metadata."

Figure 1 summarizes the method of constructing the variables used in the two studies. Study 1 employs a large diverse sample, measures movie preferences via active expressions of attitudes towards content in the field, and accounts for previously unaccounted factors such as movies' quality and commercial success. We systematically investigate how high-level movie characteristics—including metadata, their genre, and their fans' demographics—relate to their fans' personalities, identify associations between several such attributes and AFPPs and interpret them based on previous research findings. Study 2 goes beyond the boundaries of genre categorization, to investigate if considering movie plots allows capturing more nuanced information about fan personalities. We train machine-learning test-based models to predict the AFPPs from plot keywords and find that plots are predictive of aggregate fan personalities above genre and all other attributes considered. To further illuminate the underlying mechanism, we rely on plot keywords to quantify the presence of various psychological themes and other concepts that organically emerge from the data in the movies. We identify manifold links between these themes and personality dimensions—which confirm that movie plots align with the characteristic ways in which their fans think, feel, and behave. For example, fans of angry movies have lower Agreeableness, movies emphasizing social themes have extraverted fans, and fans of movies with anxiety are more neurotic. Taken together, our findings provide fine-grained mappings between dimensions of personality and externally-valid expresions of preferences for content, and demonstrate how these links enable automated psychographic assessment of audiences at scale.

Study 1: Mapping General Movie Characteristics and Genre to Fan Personalities

Study 1 conceptualizes movies via general characteristics such as quality ratings and revenue, their fans' demographics, and genre classifications. We map these features to the aggregate personalities of the movies' fans, and interpret the results based on previous research.

Data Sources and Measures

myPersonality Database. *myPersonality* is a Facebook app that ran from 2007 to 2012 (Kosinski et al., 2013). It presented users the opportunity to take scientific research questionnaires and get feedback on their results. Overall, about 7 million users took at least one questionnaire, and roughly half of them shared their personal Facebook data with the app for research purposes. myPersonality data includes "Likes"—digital records of users' positive attitude expressions towards content (e.g., friends' status updates, photos, and pages of various entities, including movies). When liking a movie's page, users opt to receive communications that relate to the movie (e.g., short clips, pictures, and marketing messages) directly to their Facebook newsfeed (John et al., 2017). The myPersonality sample is geographically diverse, with 42% of the participants residing outside the US and 44 countries that are represented by more than 1,000 respondents. The average participant age was 23.5 years at the time of data collection, and 63% were female (Stillwell & Kosinski, 2012).

Movie Personality Dataset. Our main study dataset (or Movie Personality Dataset) includes information on 846 movies. It combines (1) aggregate psychographic and demographic profiles of the movies' social media fans from myPersonality, with (2) movie characteristics such as quality ratings, genre, and plot keywords from IMDb. To select the set of movies included in the study, we excluded all of the Facebook Likes in the myPersonality database that were either not categorized by Facebook as movie-related or liked by fewer than 250 users. We then searched for each of the remaining Likes on IMDb (based on the movie's name, using an automated process) and included only movies that appeared on the website's database. Finally, we manually inspected the movies that were not found in the automatic search and (a) included movies whose corresponding IMDb entries were not found due to differences in spelling and typos (e.g., *"singing in the rain"* was matched with the IMDb entry of "singin' in the rain"; (b) included movie series, in which case we associated the value with the IMDb entry of first movie in the series (e.g., "*the twilight saga*" was matched with the title "*twilight*"); (c) in case we found more than one IMDb ID corresponding to the same Facebook Like, we linked the Facebook Like to the entry that had the greatest number of reviews (e.g., *"Phantom of the opera"* was linked to the IMDb ID of the 1998 production; (d) excluded movie quotes (e.g., *"supercalifragilistic"*) and characters (e.g., "*Eeyore*"). The final dataset includes M = 846 feature films whose Facebook pages were liked a total of 994,175 times by myPersonality users. The average movie was liked by U=1,172 unique users (SD = 1,829; Max: 18,597; Min: 252).

Aggregate Fan Personality Profile (AFPP). The myPersonality app measured the Big Five traits of its users via the International Personality Item Pool (IPIP) questionnaire, which quantifies a Five-Factor Model (FFM) of personality (20 to 100 items; (Goldberg et al., 2006/2). We z-score these measures across the entire myPersonality database and calculate a five-dimensional AFPP for each movie in the dataset, by averaging the z-scored Big Five measures of all users who liked its page. Supplemental Figure 1 displays the distributions of the five AFPP dimensions across all movies. Compared to the average myPersonality user, the average film has fans that are comparatively high on Openness and low on Conscientiousness and Extraversion. This pattern was expected because Openness is related to liking arts, and as watching movies is a leisure activity that does not require social interaction (which therefore may appeal to people low in Conscientiousness and Extraversion). The correlations between the five AFPP dimensions in the Movie Personality Dataset are summarized in Supplemental Figure 2. While the pairwise correlations between the Big Five traits are typically small when measured across people, the AFPP dimensions are correlated across movies. Openness and Neuroticism positively correlate with one another and negatively correlate with Conscientiousness, Extraversion, and Agreeableness, where the latter three dimensions positively correlated with one another. The correlations are of medium size, indicating that each of the AFPP dimensions captures a unique variance of interest. Finally, Supplemental Table 1 displays the ten movies with the highest and lowest values of each of the AFPPs dimensions in the dataset.

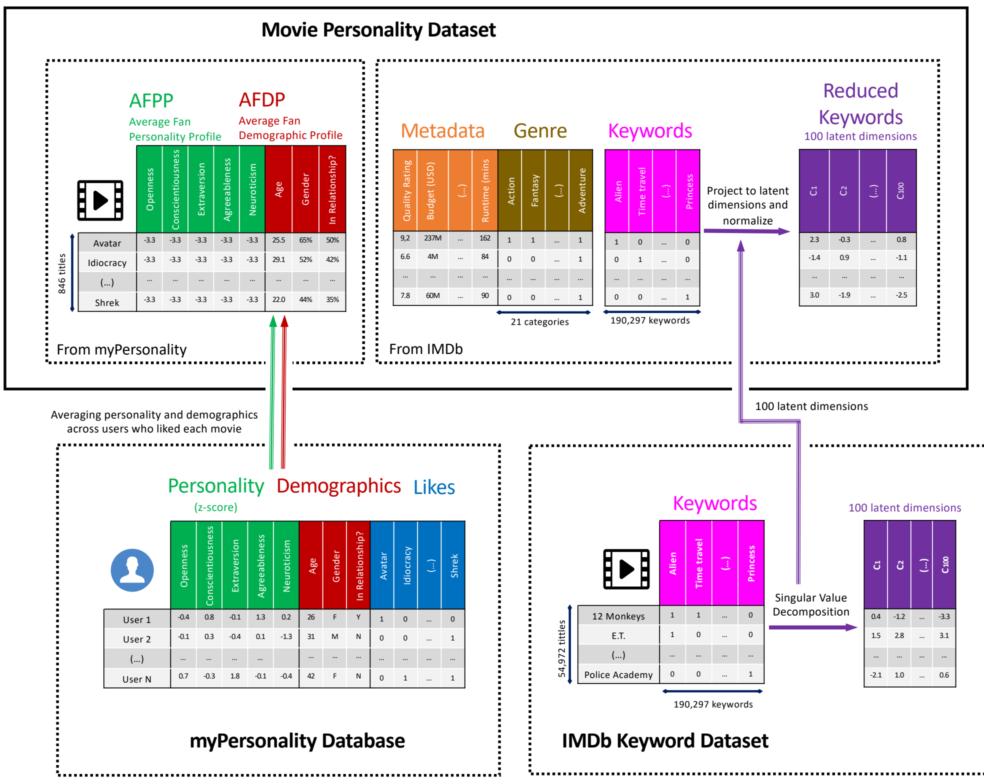
Aggregate Fan Demographic Profile (AFDP). We generate the AFDP for each movie by calculating the average age, proportion of females, and proportion of users who reported being in a relationship among the myPersonality users who liked its page. Supplemental Figure 3 shows the distributions of the different AFDP dimensions across movies.

The Internet Movie Database (IMDb). IMDb (www.IMDb.com) is an online database that contains information about movies, TV shows, home videos, video games, and internet streams. As of 2024, IMDb is the most popular movie website worldwide, with over 250 million unique visitors monthly. It includes information about cast, production crew, plot summaries, trivia, trailers, photo galleries, and box office revenue of over 5 million titles.

Metadata. We extract the following about each movie in the Movie Personality Dataset from IMDb: (1) Average quality rating; (2) number of ratings; (3) release year; (4) budget (log transformed); (5) gross box office income (log transformed); (6) return on investment (ROI), calculated as the net profit divided by the budget and multiplied by 100; and (7) runtime duration

FIGURE 1

OVERVIEW OF DATA STRUCTURES AND MAIN STUDY VARIABLES



NOTE.— Our study dataset ("Movie Personality Dataset") combines information about 846 movies, coming from two sources: myPersonality—a Facebook app through which about 3.5 million users completed psychological questionnaires and shared their profile data for research purpose, and IMDb— the most popular movie website worldwide. The dataset includes the following variables: (1) Average Fan Personality Profile (AFPP) is a five-dimensional vector denoting the average z-scored Big Five traits of all myPersonality users who Liked each movie. (2) Average Fan Demographic Profiles (AFDP) is a three-dimensional vector denoting the average age, proportion of females and proportion of people who reported being in relationship of all myPersonality users who Liked each movie. (3) Metadata variables are general movie characteristics such as quality ratings and revenue. (4) Genre is a 21-dimensional binary vector representing each movie's genre classifications. (5) Keywords are binary vectors representing each movie's plot keywords. (6) Reduced Keywords are 100-dimensional vectors, calculated by projecting each movie's Keywords vectors onto 100 latent dimensions, and normalizing these projections' magnitudes. The latent dimensions were computed by performing single value decomposition (SVD) on an IMDb Keyword Matrix, which represents 54,972 IMDb titles and their associated keywords.

(minutes). We refer to this group of variables as "Metadata." Supplemental Table 2 displays the summary statistics of these variables, and their distributions are in Supplemental Figure 4. Missing values are inferred using the means of the remaining values.[1]

Genre. IMDb includes $G = 21$ unique movie genre categories (e.g., Adventures, Drama), where the average film in the Movie Personality Dataset is associated with three genre categories (SD: 1.26). We assign each genre an integer between 1 and G and represent each movie's genre information using a G-dimensional binary vector (or "Genre"). The value of the Genre vector's g^{th} dimension equals one if the corresponding genre g is associated with the movie on IMDb, and zero otherwise. Supplemental Table 3 summarizes all genre categories and the number of titles associated with each in the Movie Personality Dataset.

Data Availability. Data are available in the study's OSF page: https://bit.ly/2IgijkS.

Statistical Analyses

We estimate, for each of the five AFPP dimensions (e.g., Extraversion) in the Movie Personality Dataset, an ordinary least squares (OLS) regression model with the corresponding dimension as the outcome. All models include the movies' AFDP dimensions (age, gender, relationship status), non-categorical Metadata variables,[2] and Genre as explanatory variables. We account for multiple hypothesis testing using Bonferroni correction, by setting the alpha level of statistical significance to $\alpha = 0.05/31$, where 31 is the number of explanatory variables in each model. Because most movies are associated with multiple genres, we can include all of the Genre vector dimensions in the model without introducing collinearity. The regression coefficient for each dimension can be

[1] Metadata variables with missing values include budget (85 missing), income (236), ROI (258), and runtime (31).
[2] We do not include categorical metadata variables (e.g., country) because these variables are represented via a large number of dummy-coded variables, which generates overfitting.

interpreted as the change in the corresponding AFPP dimension related to each genre category, relative to a movie with no genre information.

Results

We estimate five OLS regressions with the movies' AFPP dimensions as outcomes and their respective Metadata, AFDPs, and Genre as explanatory variables. Figure 2 displays the standardized beta coefficients of all variables that have at least one statistically significant effect after Bonferroni correction (for the full model, see Supplemental Tables 4 and 5). The results show unique patterns of association between movie attributes and their fans' personalities.

We identify several novel associations between general movie characteristics, quantified as Metadata variables, and personality dimensions. The factors showing the strongest relationships with AFPP dimensions are quality ratings, box office revenue, and budget. Openness is associated with liking movies that receive greater quality ratings [standardized $\beta = 0.32$, 95% confidence interval (CI) = (0.24, 0.39), $t(814) = 8.33$, $p<.001$], but yield less revenue [standardized $\beta =-0.17$, 95% CI = (-0.22, -0.11), $t(815) = -5.68$, $p< .001$]. These findings may reflect the trait's previously identified relationships with aesthetic sensitivity and the needs for cognition and uniqueness (Dollinger, 2003). On the other hand, fans of popular movies are more conscientious [standardized $\beta =0.14$, 95% CI = (0.08, 0.20), $t(815) = 4.75$, $p<.001$] and agreeable [standardized $\beta =0.12$, 95% CI = (0.06, 0.18), $t(815) = 3.81$, $p< .001$]—in line with these traits' well-established links with conformity (Roccas et al., 2002). Extraversion, is also positively associated with liking movies that succeed at the box office [standardized $\beta =0.11$, 95% CI = (0.04, 0.17), $t(815) = 3.29$, $p< .001$].

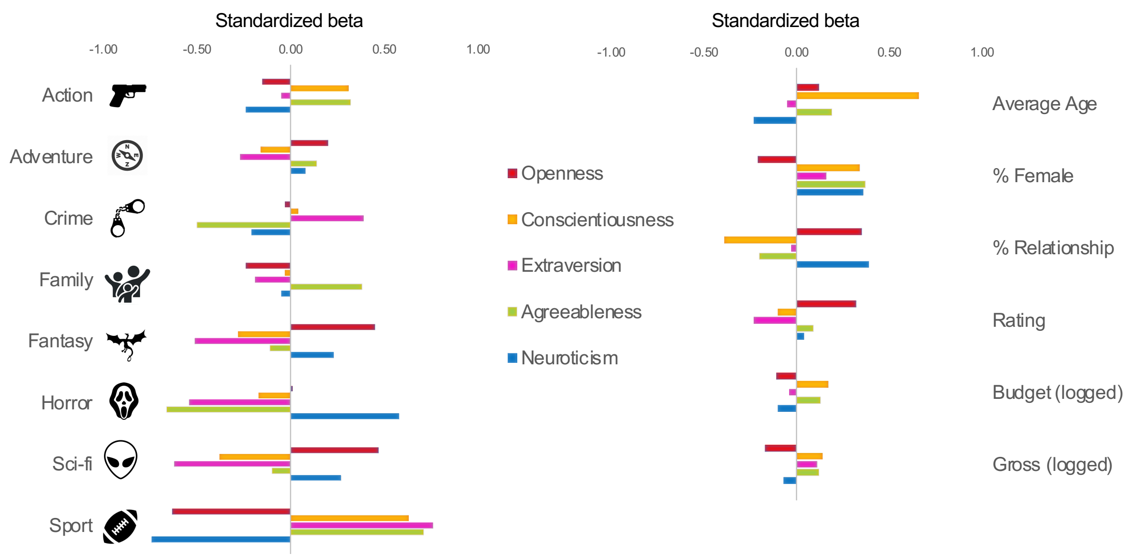
We also identify several links between personality dimensions and demographic factors across films. The proportion of females among a movie's fan base correlates with all five AFPP dimensions: negatively with Openness and positively with the remaining traits. The positive associations with Agreeableness, Extraversion, and Neuroticism are consistent with previous findings that females tend to score higher on these traits (e.g., (Weisberg et al., 2011). The pattern of associations between AFPPs and age mirrors a typical evolution of the Big Five within individuals during adulthood (Soto et al., 2011). Most notably, movies liked by older people also have more conscientious fans [standardized $\beta = 0.66$, 95% CI = (0.59, 0.73), $t(815) = 18.40$, $p < .001$]. Age also shows weaker positive relationships with Agreeableness and Openness, and a negative relationship with Neuroticism. According to Social Investment Theory, such changes reflect people's psychological adaptations to their normative roles at particular life phases (Roberts et al., 2005). For example, as people mature, they become parents, pursue careers, and attain financial independence. As a result of these roles and responsibilities, individuals adapt by becoming more conscientious.

Eight genre categories have significant relationships with personality dimensions. Each genre has a unique pattern of relationships with the Big Five, where most effects are small to medium in size (Figure 2).[3] The genre with the strongest links to personality traits is Sports, whose liking has not been assessed in any previous studies of the links between movie preferences and personality. Fans of Sports movies are lower on Openness and Neuroticism, and are higher on Conscientiousness, Extraversion, and Agreeableness. These associations mirror the relationships of the Big Five and actual physical activity among people, for all traits except Agreeableness (Wilson & Dishman, 2015). However, Agreeableness tends to be higher among supporters of sports teams (Donavan et al., 2005).

[3] Due to the small number of Documentaries ($N = 6$) and Westerns ($N = 9$), our analysis has low statistical power to detect associations between personality and liking of these genres (Supplemental Table 3).

FIGURE 2

RELATIONSHIPS BETWEEN MOVIE CHARACTERISTICS AND FAN PERSONALITIES



NOTE.—The relationships are estimated as standardized coefficients of five regression models, with AFPP dimensions as outcomes. Explanatory variables included genre, ADFPs and meta-data.

Crime movies have fans that are more extroverted and less agreeable, akin to people who gravitate towards crime in real life (e.g., (O'Riordan & O'Connell, 2014)). Devotees of Sci-fi and Fantasy movies have greater Openness, lower Extraversion, and lower Conscientiousness—indicating that movies of these genres attract imaginative, reflective, and spontaneous people. Family movies have fans that are higher on Agreeableness, a trait which is high among people who value close relationships and family ties (e.g., (Laakasuo et al., 2017)). Finally, fans of Horror movies are more Neurotic, perhaps because Horror provides anxious individuals a means to experience their anxiety in a nonthreatening and controllable setting (Scrivner & Christensen, 2021). Fans of Horror films are also less Agreeable and less Extraverted. Of note, Horror has been shown to generate stronger fear responses among individuals higher in either Neuroticism or Agreeableness (Clasen et al., 2020). However, these two traits show the opposite relationship with liking Horror, suggesting that the psychological mechanism underlying these links might differ between the two traits, as we explore in the next study.

STUDY 2: Movie Plot Keywords Predict Aggregate Fan Personalities

Study 2 characterizes movies via their plots, quantified using text keywords, and investigates whether this representation facilitates more accurate predictions of aggregate fan personalities. We further use text analysis to quantify how different psychological themes appear in the movies, and link these themes, as well as other concepts that organically emerge from the data, with personality dimensions—in order to generate additional insight into the underlying mechanisms. Similar to Study 1, we rely on data from myPersonality and IMDb and include all movie titles in the Movie Personality Dataset. In addition to the variables described in Study 1 (AFPPs, AFDP, Metadata, and Genre), Study 2 relies on additional data structures, described in detail below and illustrated in Figure 1.

Materials and Measures

Plot Keywords. A keyword is a single lower-case word (e.g., 'police') or a phrase of several words (e.g., 'time travel') attached to a movie title. IMDb users generate these keywords to facilitate easy search and discovery of titles by other users. According to the IMDb website, keywords describe "any notable object, concept, style or action that takes place during a title." The average movie in the Movie Personality Dataset has 168 keywords (SD = 100.1; Max: 865 Min: 7).

IMDb Keywords Matrix. Our analysis employs the dataset of (Bhatia & Stewart, 2018), which scrapped the IMDb website in 2014 to obtain 160,322 unique keywords associated with 44,972 titles. We updated this dataset in 2018, by adding the keywords of the 9,067 additional movies (the most voted feature film titles on IMDb at that time, with the exception of movies that were already in the myPersonality database and movies that did not have plot keywords on IMDb). The number of unique keywords in the updated dataset, which we call "IMDb Keywords Dataset," is K = 190,297. We assign each of these keywords an integer between 1 and K, and represent the keywords associated with each title using a K-dimensional binary vector (or "Keywords"), where the value of the k^{th} dimension equals one if keyword k appears as a descriptor of the movie on IMDb, and zero otherwise. We rely on the Keyword vectors of the titles in the IMDb Keywords Dataset to construct an IMDb Keyword Matrix. Each row of the matrix represents an IMDb title, and consists of its Keywords vector. This resulted in a 54,972 (titles) x 190,297 (keywords) dimensional matrix.

Reduced Keywords. We reduce the dimensionality of the IMDb Keyword Matrix by performing single value decomposition (SVD) and keeping the first 100 SVD components, similar to previous work (Bhatia & Stewart, 2018; Kosinski et al., 2013). We then project the Keywords vectors of all titles in the Movie Personality Dataset onto these 100 latent dimensions, and normalize the projections' magnitudes (L2). We refer to the normalized projection vector of each movie's Keywords vector as its Reduced Keywords vector.

Metadata. In addition to all Metadata variables used in Study 1, we include the following measures: (1) Number of keywords; (2) Language (86 languages, dummy coded); and (3) Country (40 countries, dummy coded). The language and country variables were not included in Study 1 as they are represented via a large number of variables, which generates overfitting.

Data Availability. Data are available in the study's OSF page.

Statistical Analyses

Predicting Fan Personalities from Plot Keywords. For each of the five AFPP dimensions, we conduct a "leave one out" cross-validated prediction exercise. We carry out predictions for each title in the Movie Personality Dataset by fitting regularized linear regressions with the Least Absolute Shrinkage and Selection Operator (LASSO) to the data of all other movies in this dataset, and recording the models' predictions. We train our models using different combinations of the movies' (1) Reduced Keywords vectors; (2) AFDPs; (3) Metadata; and (4) Genre. We define predictive accuracy as the Pearson correlation between the actual and predicted values across movies (Kosinski et al., 2013; Nave et al., 2018). The main results that we report are obtained using a LASSO with a regularization parameter value of $\lambda = 0.001$. We also report LASSO results with other parameter values and results of Ridge regressions with various parameter values, as robustness tests.

Estimating the associations between aggregate fan personalities and unique plot keywords. We project the 1,000 most common keywords on IMDb onto the 100-dimensional reduced keyword space and denote the k^{th} keyword loading on the d^{th} SVD dimension by $L_{k,d}$. Next, we fit LASSO regressions (as described above) to predict the AFPPs of all titles in the Movie Personality Dataset from these Reduced Keywords vectors, controlling for all AFDP and Metadata variables. We denote the beta coefficients for the d^{th} dimension and trait t by $b_{d,t}$, and quantify the relationship between each personality traits t and a keyword k by

$$(1) \qquad b_{0,t} + \sum_{d=1}^{100} b_{d,t} \cdot L_{k,d}.$$

We interpret this relationship as the predictive score of trait t for a movie with only one keyword, and this keyword is k.

Associations between aggregate fan personalities and the movies' psychological themes. We estimate how the plot keywords of each movie are related to 33 word categories from the

Linguistic Inquiry and Word Count (LIWC).[4] LIWC is a language analysis program commonly used to study relationships between language and psychological variables, including personality (e.g., (Yarkoni, 2010). We estimate these associations by calculating the semantic similarity between each movie's plot keywords and the LIWC dictionary words. To this end, we obtain a 300-dimensional word2vec embedding representation (Mikolov et al., 2013) for each plot keyword in a movie and average across keywords to get a single 300-dimensional vector representation for each movie. We then calculate the cosine similarity between each movie and each LIWC category by summing the movie's similarities with all the words in that category. Finally, we estimate the links between LIWC categories and the AFPPs via partial linear correlations between the two across movies, adjusting for the AFDP dimensions and non-categorical metadata variables. We account for multiple hypotheses testing using Bonferroni correction that sets the alpha level of each coefficient's statistical significance tests to $\alpha = 0.05/33$, where 33 is the number of partial correlations computed for each trait.

Pre-registration. Before analyzing the data, we registered our analysis on the Open Science Framework (OSF): https://bit.ly/2IgijkS. Our pre-registration included ten hypotheses, predicting that Reduced Keywords vectors would be predictive of all five AFPP dimensions above chance, and that Reduced Keywords vectors would be predictive of all five AFPP dimensions above AFDPs and Metadata variables. The tests of all pre-registered hypotheses yielded statistically significant effects. The main findings reported in the paper include several deviations from the pre-registered analyses, summarized in detail in the study's OSF page.

Results

[4] LIWC has more than 33 categories, but we exclude grammatical categories (e.g., pronouns) and only keep those with thematic/semantic content.

Predicting Fan Personalities from Plot Keywords. As a first step, we train five machine-learning models that predict the movies' AFPPs from their Reduced Keyword Vectors. Figure 3 plots the actual values against the out-of-sample predicted AFPPs across movies. The most accurate predictions are for Extraversion ($r(846)=.67$, 95% CI = (.63, .71), $p<0.001$), followed by Neuroticism ($r(846)=.67$, 95% CI = (.62, .70), $p<0.001$), Agreeableness ($r(846)=.64$, 95% CI = (.60, .68), $p<0.001$), Openness ($r(846)=.64$, 95% CI = (.60, .68), $p<0.001$), and Conscientiousness ($r(846)=.55$, 95% CI = (.50, .59), $p<0.001$). Thus, the models leverage information contained in the movie plots to predict all of the Big Five dimensions, explaining out-of-sample variance between R^2=30% to R^2=45%.

Figure 4 displays the out-of-sample variance explained (R^2) of models using Genre, Metadata, AFDPs, Reduced Keyword Vectors, and different combinations of these variables. Models that rely on Reduced Keyword Vectors alone are significantly more accurate than models that use either Metadata or Genre for all traits (all p's<0.001) and are significantly more accurate than models that rely on AFDPs for three traits (Openness $p<0.017$; Extraversion and Agreeableness $p<0.001$). The gain in predictive accuracy relative to genre is particularly notable for Openness, where models trained using plot keywords increase the out-of-sample variance explained by 200% (ΔR^2 =27%). The gain is notable for the other traits as well, with increases in out-of-sample variance explained ranging from 35% to 55% (ΔR^2 between 10% and 15%). Furthermore, adding plot keywords to the models that include all other variables significantly improves predictive accuracy of all dimensions (all p's < 0.01, Williams z-test), with additional out-of-sample variance explained ranging from ΔR^2=4% to ΔR^2=12%.

We conducted several analyses to investigate our conclusions' sensitivity to specific analytical choices. First, we repeat the analyses using LASSO regressions with λ = {0.0001, 0.001.

0.01}, Ridge regressions with α = {0.01, 0.1, 1, 10, 100}, and OLS regressions. The results confirm that keywords are predictive of all five AFPP dimensions and are informative above all other variable groups under these specifications (Supplemental Table 6).[5] Second, we investigate if our conclusions hold when there is no overlap between the data used to compute the SVD dimensions and the data used to train and test the predictive models. To this end, we repeat our analysis using a different set of Reduced Keyword Vectors, composed by projecting the Keyword Vectors of the movies in the Movie Personality Dataset onto a different set of 100 latent dimensions. We calculated these dimensions by performing SVD on the keyword matrix of the 10,000 most voted feature film titles on IMDb up to 2018, excluding the titles in the Movie Personality dataset[6]. Our conclusions hold under this alternative specification (Supplemental Table 7).

Predicting Personality in a New Set of Movies. Using our models, we generate predictions for the AFPPs of 9,067 additional movies that were not included in the original Movie Personality Dataset. These movies include the 10,000 most rated films on IMDb as of 2018, except for titles that already appear in the Movie Personality Dataset and titles that do not have keywords. We make these predictions publicly available (https://bit.ly/2IgijkS), and they can be used in future studies that further test the generalizability of our models' insight to different settings.

Associating Movies' Themes and Concepts and Fan Personalities. Plot keywords predict the AFPP dimensions above all the other variables included in our analyses. Our reliance on text keywords as explanatory variables allows us to conduct more nuanced analyses to understand the

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[5] OLS regression models (expectedly) yielded poor performance in analyses that had a large number of variables, due to overfitting. Overfitting was driven by the large number of Metadata variables, which included dummy variables indicating the movies' country and language.

[6] We excluded the entire Bhatia and Stewart (2018) dataset from the SVD calculation in this analysis, because we could not identify every title in this dataset, since IMDb's title-naming scheme had changed since its assembly in 2014. As a result, we could not ensure that all titles in the Movie Like dataset were excluded from this dataset.

relationships between movies' psychological themes and the personality traits of fans. To do this, we quantify the degree that each movie contains 33 different psychological themes, and calculate the partial correlations between these themes and the AFPPs across movies (adjusting for AFDPs and Metadata). We substantiate this analysis by isolating keywords that emerge as the strongest predictors of the Big Five traits in the dataset.

Figure 5 displays the correlations across movies between the AFPP dimensions and a subset of the psychological themes studied (for all themes, see Supplemental Table 8). Table 1 lists the top 20 keywords that most positively and negatively predict each of the Big Five dimensions. In total, we quantify 165 correlations between the Big Five and 33 psychological themes. After Bonferroni correction, 74 (44.8%) remain statistically significant at the α=.05 level and 67 (40.6%) are significant at the α=.01 level. Although not all observed correlations have a straightforward interpretation, their general pattern indicates that movie plots align with the psychological tendencies of their fans.

The themes that most strongly correlate with AFPP dimensions are from the Affective Processes and Personal Concerns categories (Figure 5). For Affective Processes, the largest positive correlations are between Neuroticism and Negative Emotions, Anxiety, and Anger. Further underscoring these findings, keywords such as 'unrequited love,' 'nightmare,' and 'screaming' are among the strongest predictors of Neuroticism. Neuroticism also correlates with the themes of Body, Health, and Death. The keywords 'fainting,' 'mental illness,' and 'serial killer,' which are also highly predictive of Neuroticism, suggest that these links arise as neurotic audiences are drawn to movies that involve psychological hardship. Conversely, the keywords that most strongly predict low Neuroticism denote appearances of weapons ('uzi,' 'ak 47') and combat personnel ('sniper,' 'FBI-agent'), which typically occur in action-loaded films with easygoing protagonists (e.g., *Mission Impossible*, *James Bond*). Taken together, these findings suggest that neurotic people prefer movies that mirror their negative emotions, rather than seek out movies that distract these emotions away.

Openness shows associations with themes in the Affective Processes and Personal Concerns categories, which are qualitatively similar to the patterns observed for Neuroticism, but with smaller effects. These findings were expected, as these AFPP dimensions correlate across movies (Supplemental Figure 2). The only two themes for which Openness has stronger correlations than Neuroticism are Religion and Power—which tend to appear in dark comedies, political satires, and movies about taboo topics (e.g., *Monty Python and the Holy Grail*, *Dogma*, *I Care a Lot*). This interpretation is supported by the list of keywords that predict high Openness, which includes 'cult director,' 'dark comedy,' 'adultery,' and 'satire.' Openness also correlates with Cognitive Processes (most strongly with the Insight theme), where other keyword predictors ('surrealism,' 'hallucination,' 'record player') reflect the trait's association with aesthetic sensitivity and creativity. The keywords that most strongly predict low Openness often appear in lighthearted mainstream films (e.g., 'college student,' 'gym,' 'baseball')—suggesting that high-Openness individuals, who have greater needs for cognition and uniqueness (Dollinger, 2003), avoid such movies.

Agreeableness, which is characterized by affiliative behavior and conflict avoidance (Vliert et al., 1994) positively correlates with Positive Emotions and themes that are lighter and optimistic, including Family, Friends, Achievement, Leisure, Money, and Work. The keywords that most strongly predict Agreeableness are indicative of functioning relationships ('marriage proposal,' 'wedding,' 'grandmother-grandson relationship'), leisure ('fishing,' 'baseball,' 'waterfall') and 'feel good' action ('hero,' 'hand-to-hand combat'). On the other hand, Agreeableness shows strong negative correlations with Anger and the themes of Sexuality, Body, and Health. The keywords that most strongly predict low Agreeableness are terms that indicate violence (‘attempted rape,’ ‘gore,’ ‘sadism,’ ‘self-mutilation’) and sexual imagery (‘bare breasts,’ ‘female nudity’).

Among all traits, Extraversion—which is characterized by energetic social interactions—has the strongest associations with the Friends theme, where the trait’s most predictive keywords include social interactions of all types (e.g., ‘best friend,’ ‘flirting,’ ‘dating,’ ’break-up,’ ‘roommate,’ ‘bar-fight,’ ‘raised middle finger’). Extraversion also positively correlates with the Sexual theme and negatively correlates with Negative Emotions and Anxiety—in line with previous reports of high sexual drive and low anxiety among extraverts (Jylhä & Isometsä, 2006; Schenk & Pfrang, 1986). Other themes that correlate with Extraversion are Ingestion and Leisure, where the predictive keywords list—which includes terms such as ‘beer,’ ‘bar,’ ‘singing in a car,’ ‘motel,’ and ‘strip club’—hints that these relationships stem from the social aspects of dining and vacations.

Introverted AFPPs, on the other hand, are most strongly associated with Cognitive Processes and serious themes, like Death and Religion. The strongest keyword predictors of introversion point to three unique topics: (1) fantasy (‘monster,’ ‘creature,’ ‘surrealism,’ ‘fictional war’)—in line with findings that introverts score higher on measures of imagination and fantasy (Feist & Barron, 2003); (2) science (‘laboratory,’ ‘scientist,’ ‘doctor’)—consistent with introverts’ interest in scientific professions (Feist, 2012); and (3) World War II (‘tunnel,’ ‘gas-mask,’ ‘German’)—which is among the more serious topics appearing in award-winning movies over the past decades (e.g., *Saving Private Ryan*, *Life is Beautiful*, *Schindler’s List*).

Finally, Conscientiousness is the only trait that negatively correlates with all the types of Emotional Processes, as well as the themes of Sexuality, Body, and Health. Contrary to our expectations, we do not observe correlations between Conscientiousness and the Work and Achievement themes, though several of the trait's predictive keywords may reflect career aspirations ('businessman,' 'Manhattan New York City,' 'Chicago Illinois'), or characteristics of an organized and predictable lifestyle ('marriage,''church,' 'prayer,' 'fishing,''baseball'). Conscientiousness reflects the degree to which individuals conform to social norms (Roccas et al., 2002), so it is conceivable that plot themes that appeal to the status quo might be more enjoyable among people who have traits that encourage such compliance. The keywords that are most predictive of low Conscientiousness mirror these findings, with terms related to instability ('disfigurement,' 'transformation'), moral conflict ('good versus evil'), and fantasy ('reverse-footage,' 'spoof,' 'monster,' 'creature').

Discussion

To date, all knowledge on how content features relate to the psychological tendencies of their audience has relied on findings from small-scale studies that correlated personality traits with self-reported preference measures for few broad genre categories. We push the boundaries of knowledge by obtaining fine-grained representations of movie features and plots and use advanced analytical techniques to link these features to the psychological profiles of social media users who expressed their movie preferences behaviorally, in a large diverse sample.

Study 1 reveals that general movie features—such as quality, revenue, and fan demographics—are associated with aggregate fan personalities, demonstrating the importance of appropriately controlling such factors. We also identify links between the Big Five and liking of specific genres (e.g., Agreeableness correlates positively with liking family movies and negatively with liking crime movies). Study 2 goes beyond genres, representing movies via plot keywords. This approach facilitates more accurate predictions of aggregate fan personalities, above genres and all other variables considered. Reliance on plot keywords also allows quantification of various concepts and psychological themes appearing in the movies, and relating them to the Big Five of their fans. We find that audiences are drawn to movies that align with their own psychological dispositions. For example, social movies have extroverted fans, and violent movies have fans low on Agreeableness. Such insights, (Table 2 and Table 3) can guide production of movies whose target audiences have known personality types.

While our analyses focused on themes from the widely used LIWC dictionary, a similar approach can be used to quantify the presence of any other theme in the movies. To this end, researchers can rely on semantic categories from other existing lexicons (e.g., (Nielsen, 2011), or manually construct new dictionaries for any given theme (e.g., Environmentalism, The Cold War) by asking participants to list phrases associated with them. Once such dictionaries are constructed, researchers can follow our method to compute the degree that these themes appear in the movies using word embeddings, and investigate their relationship with fan characteristics.

Our study leaves several open questions for future research. First, while we link movie preferences to stable traits, preferences are also influenced by situational context. For example, people seem to prefer romantic movies when it is colder (Hong & Sun, 2012). Continuous investigation of how context influences movie preferences may benefit from studying interactions between personality and situational variables. For example, cold weather may have stronger effects on Neurotic individuals, who have greater needs for psychological warmth in the winter.

Second, although Facebook Likes are active, naturalistic expressions of attitudes, they do not necessarily reflect what people de facto watch and could be affected by impression-management concerns. Furthermore, specific types of people may have a greater disposition to like movies on Facebook or become research participants online. In general, such selection bias would be expected to attenuate the associations we quantified, as it restricts the range of personality that we observe and constrains the variance that could potentially be explained by our models (Yarkoni, 2010). We hope that the growing availability of video-streaming services will facilitate further investigations of how personality relates to actual watching behavior, and with less selection bias.

Third, our findings are silent about causal relations. Personality is partially heritable, and it is reasonable that one's personality influences their taste for movies. However, research within the ‘‘media effects’’ paradigm (Adorno & Horkheimer, 1997) suggests that media exposure can also generate lasting effects on one's internal world. For example, violent media consumption has been shown to increase aggressive thoughts (Anderson et al., 2003). Moreover, although our analyses include covariates that were not accounted for in earlier studies, we cannot control for all possible factors that might affect both personality and movie preferences, and generate non-causal correlations between them (e.g., SES, culture).

Fourth, associations between personality and psychological themes of movie plots are expected to evolve over time, due to cultural change. High-Openness individuals, for example, appear to be interested in topics that are considered taboo. Yet, topics that were taboo in the past may become a part of mainstream culture. For example, consider the topic of sexual harassment before and after the emergence of the *#metoo*. Likewise, San Francisco was mostly associated with Hippy culture in the 1960s, but became synonymous with Tech in the 2000s. Thus, movies taking place in San Francisco in the 1960s are expected to have fans that are less Conscientious, relative to movies taking place in the city in the 2000s.

Fifth, although we have no reason to believe that our results depend on the characteristics of the participants, materials, or context, continuous exploration of their generalizability is worthwhile. In particular, while the set of movies used in the current study represents a wide array of genres, most movies are relatively popular, produced in Western countries, and were released before 2012, the year when myPersonality concluded data collection. To allow further exploration of our findings' generalizability across movies, we provided AFPP predictions derived from our models for 9,067 additional movies (see Study 2 Results). We hope that further research will study the generalizability of our findings to non-Western movies released after 2021. Relatedly, we hope that future work will evaluate our findings' relevance for other media types, such as TV shows and radio podcasts.

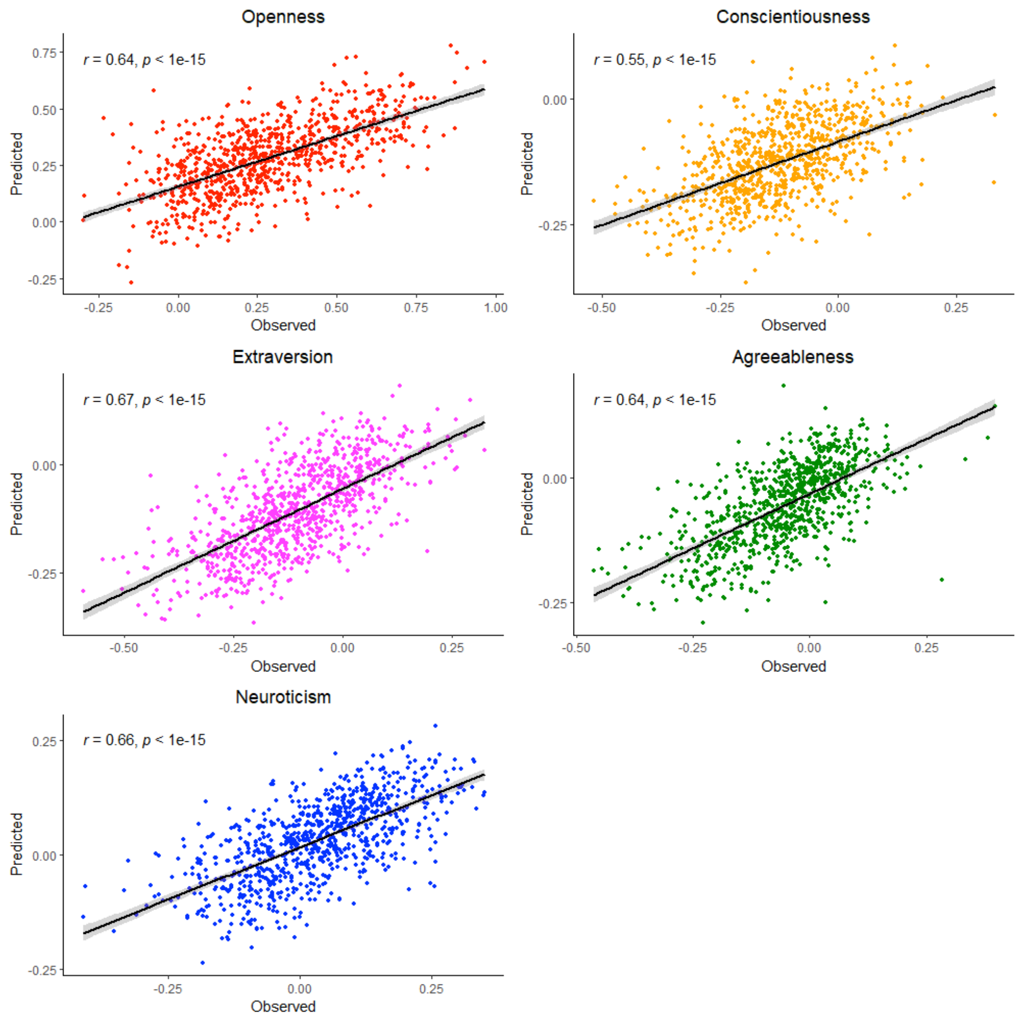
Finally, we recognize that the complexity of movies is far greater than what is captured by plot keywords. We therefore see our results as a lower bound for the predictive accuracy that can be achieved when predicting fan personalities from movie content. Predictive accuracy will likely rise with incorporation of additional movie characteristics, such as information about the cast, auditory features retrieved from movie scores, and visual features obtained from video frames. We look forward to future work that combines data driven machine learning techniques with rich datasets of movie content to better understand and predict the personalities of target viewers.

Research Transparency Statement

Data, analysis scripts and pre-registration (study 2) are available in the study's OSF page: https://bit.ly/2IgijkS.

FIGURE 3

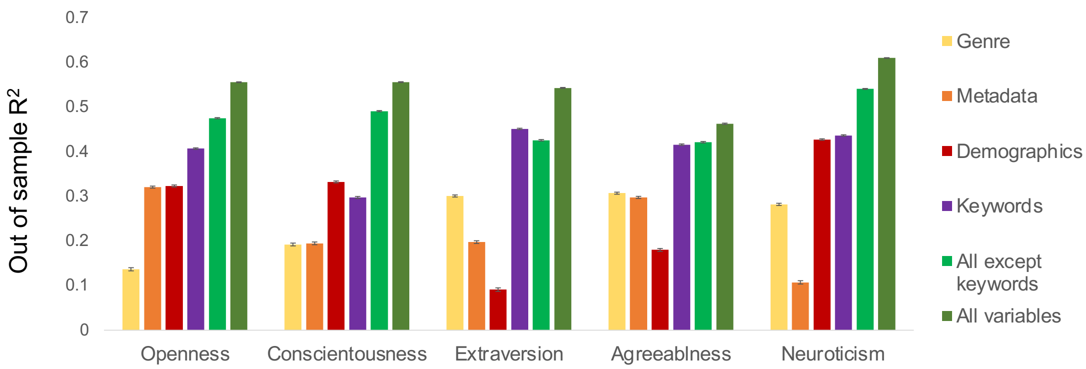
OBSERVED VERSUS PREDICTED AGGREGATE FAN PERSONALITIES



NOTE.—Each data point represents a movie. Lines represent fitted regressions and their associated 95% confidence intervals.

FIGURE 4

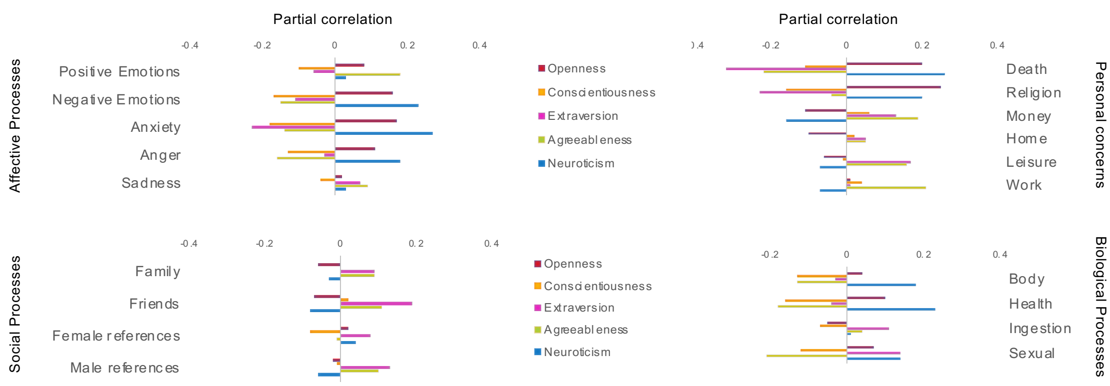
OUT OF SAMPLE AGGREGATE FAN PERSONALITY VARIANCE EXPLAINED



NOTE.—Values represent the R^2 between actual and predicted values across movies. Each color denotes a model trained using a different subset of the study's variables.

FIGURE 5

RELATIONSHIPS BETWEEN MOVIE THEMES AND FAN PERSONALITIES



NOTE.—Relationships are estimated via partial correlations, controlling for AFDP and metadata. The figure displays a subset of the correlations. For all correlations and their significance, see Supplemental Table 8.

TABLE 1

TOP 20 POSITIVE AND NEGATIVE PREDICTIVE KEYWORDS OF THE BIG FIVE

Trait	Opennesss	Percentile	Conscientiousness	Percentile	Extraversion	Percentile	Agreeableness	Percentile	Neuroticism	Percentile
High	cult director	11%	marriage proposal	19%	dating	13%	baseball	16%	insanity	22%
	surrealism	15%	wedding	21%	gay slur	17%	wedding	16%	obsession	22%
	recording	17%	new york city	21%	break up	18%	training	17%	self mutilation	22%
	cult film	18%	fistfight	21%	ex boyfriend ex girlfriend relation	18%	hand to hand combat	17%	based on novel	22%
	tea	22%	new york	21%	roommate	19%	fishing	17%	doll	24%
	cynicism	22%	manhattan new york city	21%	bar fight	19%	fireworks	17%	fainting	24%
	mirror	23%	church	22%	beer	19%	marriage proposal	17%	key	25%
	record player	23%	chicago illinois	23%	basketball	19%	competition	17%	necklace	25%
	satire	24%	semiautomatic pistol	23%	best friend	20%	action hero	17%	mental illness	26%
	key	26%	fishing	24%	machismo	20%	construction site	17%	ghost	26%
	cigarette smoking	26%	prayer	25%	motel	20%	waterfall	18%	screaming	26%
	dark comedy	26%	rural setting	25%	gym	20%	ak 47	19%	dream sequence	27%
	older man younger woman relation	26%	divorce	25%	obscene finger gesture	20%	hero	19%	poison	27%
	insanity	26%	love	25%	bar	21%	mixed martial arts	19%	drawing	27%
	memory	27%	marriage	25%	stripper	21%	product placement	19%	serial killer	28%
	shaving	27%	businessman	25%	flirting	22%	blockbuster	20%	unrequited love	28%
	destiny	29%	grief	25%	strip club	22%	grandmother grandson relation	20%	nightmare	28%
	adultery	29%	baseball	25%	raised middle finger	22%	speech	20%	disfigurement	28%
	hallucination	29%	river	26%	singing in a car	23%	village	20%	flower	28%
	radio	29%	hairy chest	26%	hit in the crotch	23%	terrorist	20%	incest	28%
Trait	Opennesss	Percentile	Conscientiousness	Percentile	Extraversion	Percentile	Agreeableness	Percentile	Neuroticism	Percentile
Low	laptop	98%	cult director	79%	laboratory	83%	female frontal nudity	75%	machine gun	86%
	wedding	95%	surrealism	79%	skeleton	81%	female rear nudity	73%	ak 47	82%
	bikini	95%	cult film	76%	scientist	81%	female nudity	70%	shootout	82%
	product placement	94%	disfigurement	76%	self sacrifice	81%	gore	70%	american flag	82%
	basketball	94%	good versus evil	72%	creature	80%	covered in blood	70%	sniper	80%
	baseball	93%	monster	72%	nurse	80%	murder	70%	uzi	80%
	gym	93%	creature	72%	evacuation	80%	blood splatter	70%	rocket launcher	80%
	helicopter	93%	fictional war	72%	radio	80%	nudity	69%	sniper rifle	80%
	college student	93%	insanity	72%	german	80%	self mutilation	69%	exploding car	80%
	2000s	92%	nurse	68%	monster	78%	bare breasts	69%	bulletproof vest	78%
	fishing	92%	transformation	68%	surrealism	78%	female full frontal nudity	68%	hand grenade	78%
	accident	91%	reverse footage	68%	key	78%	attempted rape	68%	target practice	78%
	scene during end credits	91%	skeleton	68%	statue	78%	nipples	67%	fbi	78%
	church	91%	destiny	68%	map	78%	cult director	66%	gunfight	78%
	cell phone	90%	robot	68%	attack	78%	insanity	66%	press conference	78%
	internet	90%	self mutilation	68%	destruction	78%	breasts	66%	silencer	78%
	2010s	89%	hallucination	68%	fictional war	78%	sadism	65%	machismo	74%
	ak 47	89%	laboratory	68%	surgery	78%	pubic hair	65%	exploding building	74%
	singing in a car	89%	spoof	68%	doctor	78%	lust	64%	fbi agent	74%
	lake	89%	virgin	68%	gas mask	78%	topless female nudity	64%	shotgun	74%

NOTE.—Percentile denotes the predicted percentile of a movie that only has the keyword in the corresponding trait, relative to the movies in the Movie Personality Dataset (e.g., a movie that only has the keyword ‘cult director’ would be in the top 11% of Openness in our dataset).

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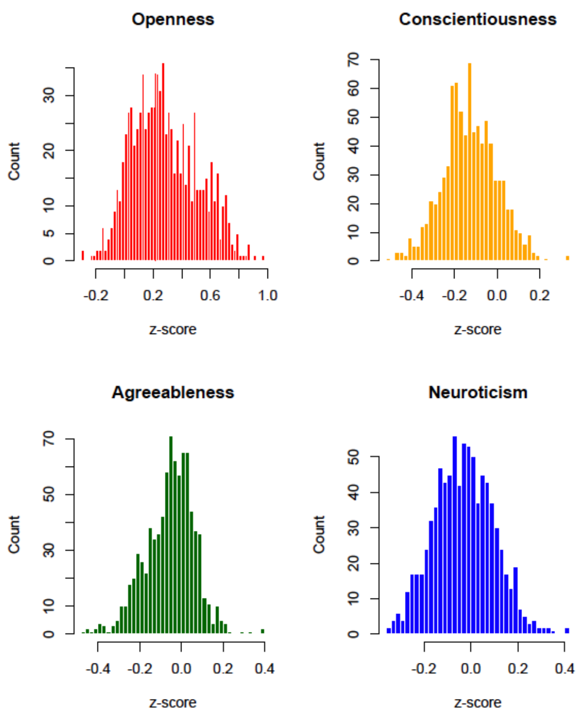
We Are What We Watch: Movie Plots Predict the Personalities of Their Fans

Web Appendix

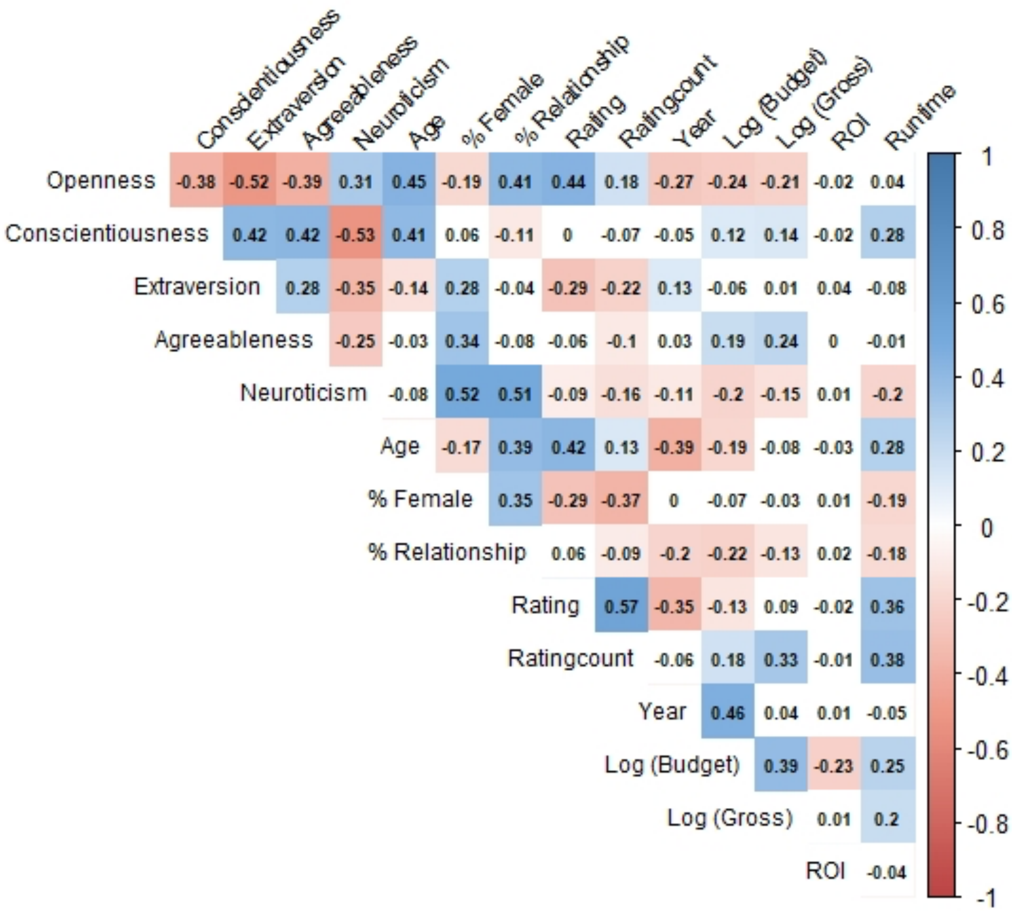
SUPPLEMENTAL FIGURE 1

HISTOGRAMS OF THE AVERAGE FAN PERSONALITY PROFILE (AFPP) DIMENSIONS ACROSS MOVIES



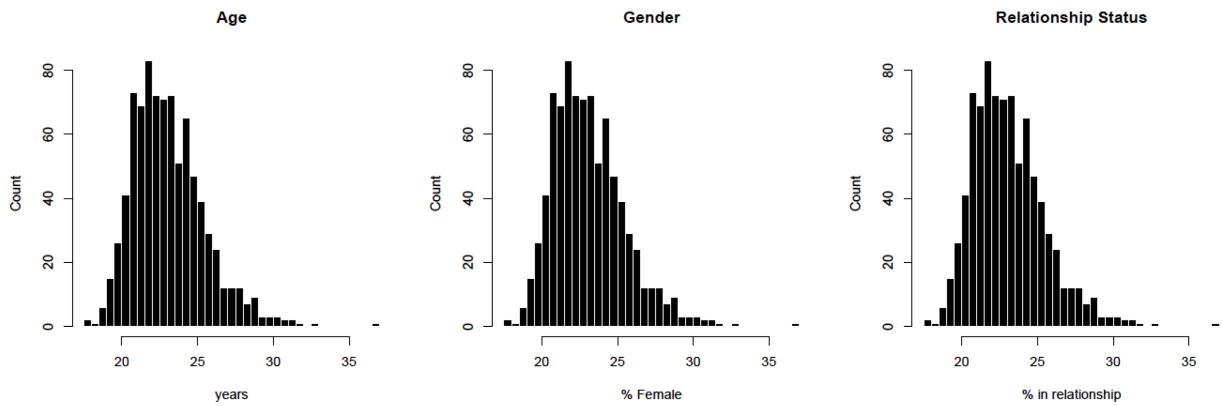
SUPPLEMENTAL FIGURE 2

CORRELATIONS BETWEEN MAIN STUDY VARIABLES



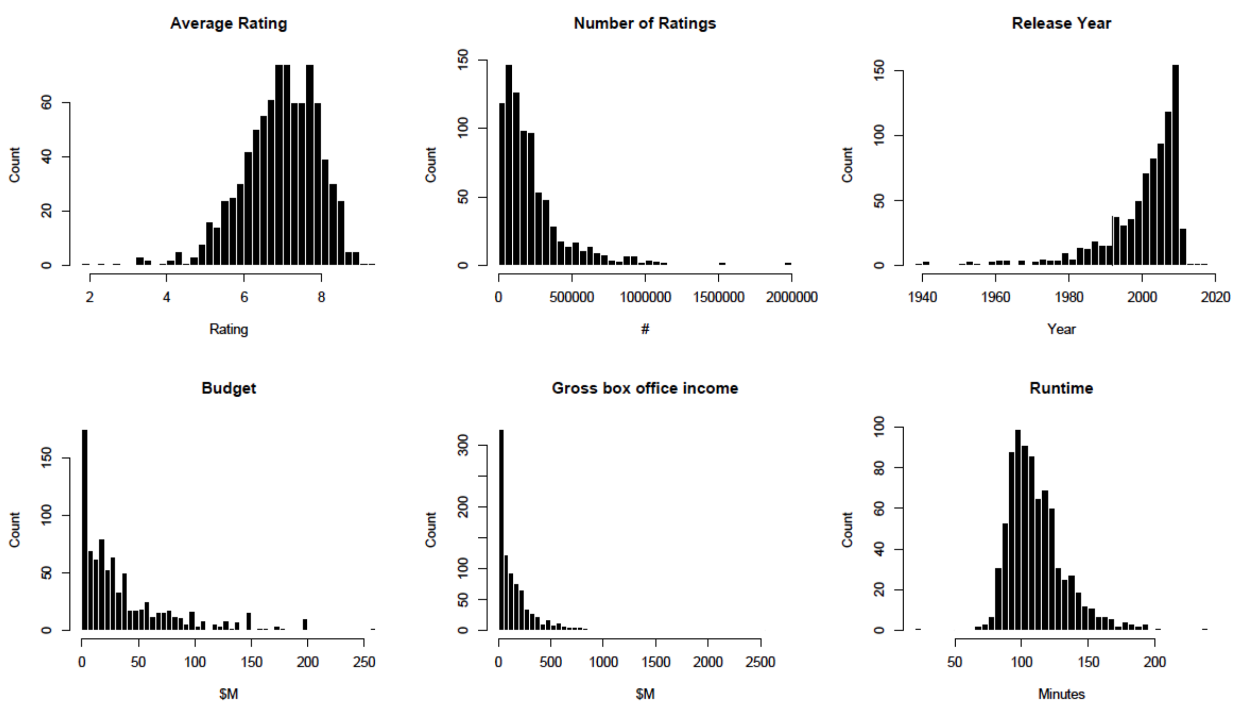
SUPPLEMENTAL FIGURE 3

DISTRIBUTIONS OF THE AVERAGE FAN DEMOGRAPHIC PROFILES



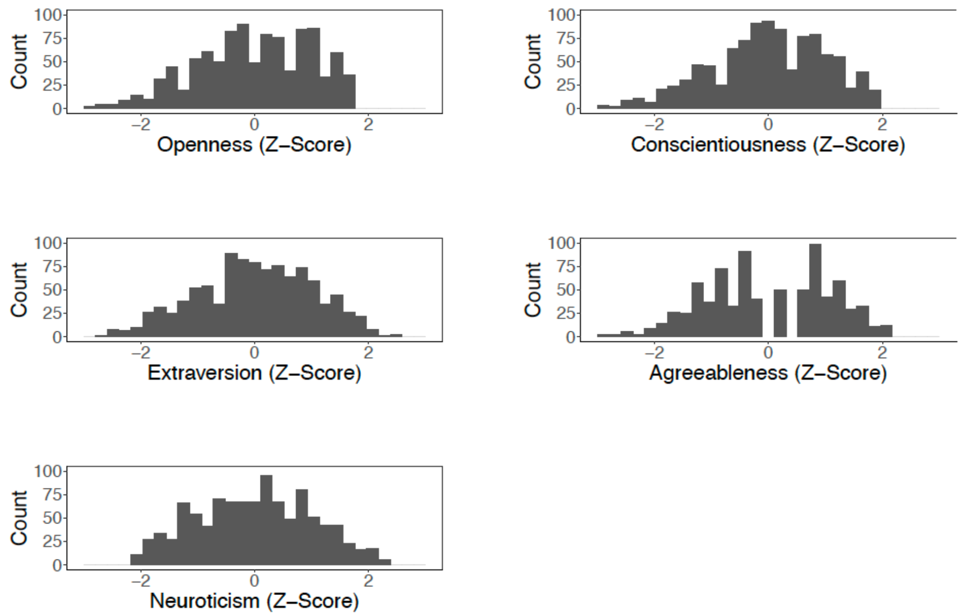
SUPPLEMENTAL FIGURE 4

DISTRIBUTIONS OF METADATA VARIABLES



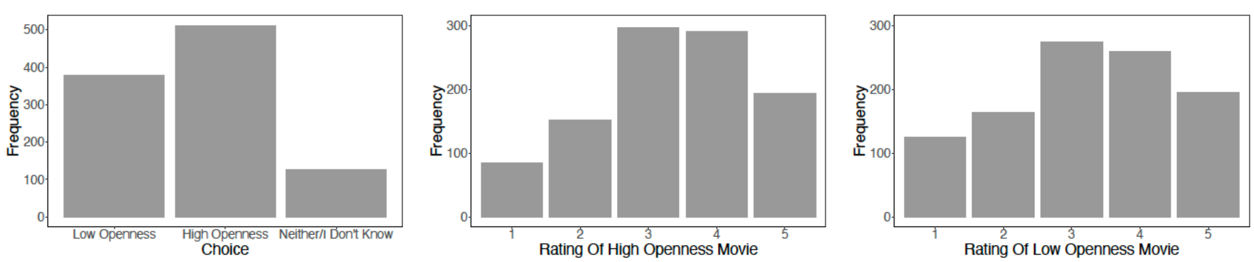
SUPPLEMENTAL FIGURE 5

DISTRIBUTIONS OF THE BIG FIVE TRAITS ACROSS STUDY 3 PARTICIPANTS



SUPPLEMENTAL FIGURE 6

DISTRIBUTIOTNS OF BEHAVIORAL OUTCOMES ACROSS STUDY 3 PARTICIPANTS



SUPPLEMENTAL TABLE 1

THE MOVIES WITH THE TOP/BUTTOM 10 AVERAGE FAN PERSONALITY PROFILES FOR EACH PERSONALITY DIMENSION

Title	Year	Genre	Z
Openness – high			
Waking Life	2001	Animation | Drama | Fantasy	.96
Pi	1998	Drama | Horror | Mystery | Sci-Fi | Thriller	.91
A Scanner Darkly	2006	Animation | Crime | Drama | Mystery | Sci-Fi | Thriller	.88
The Science of Sleep	2006	Comedy | Drama | Fantasy | Romance	.87
The Fountain	2006	Drama | Sci-Fi	.87
Mulholland Drive	2001	Drama | Mystery | Thriller	.86
The Darjeeling Limited	2007	Adventure | Comedy | Drama	.84
Being John Malkovich	1999	Comedy | Drama | Fantasy	.81
The Buddha	2010	Documentary	.80
The Life Aquatic with Steve Zissou	2004	Adventure | Comedy | Drama	.79
Openness - low			
Anjaana Anjaani	2010	Comedy | Drama | Musical | Romance	-.30
Shrek Forever After	2010	Animation | Adventure | Comedy | Family | Fantasy | Romance	-.29
Get Rich or Die Tryin'	2005	Biography | Crime | Drama | Music	-.23
8 Seconds	1994	Biography | Drama | Sport | Western	-.21
Step Up 3D	2010	Drama | Music | Romance	-.19
Hannah Montana: The Movie	2009	Comedy | Drama | Family | Music | Romance	-.18
Boy	2010	Comedy | Drama	-.16
Another Cinderella Story	2008	Comedy | Family | Music | Romance	-.16
Kuch Kuch Hota Hai	1998	Comedy | Drama | Musical | Romance	-.15
Facing the Giants	2006	Drama | Sport	-.15
Conscientiousness – high			
Ladder 49	2004	Action | Drama | Thriller	.33
Love Jones	1997	Drama | Romance	.33
Steel Magnolias	1989	Comedy | Drama | Romance	.22
Brown Sugar	2002	Romance | Comedy | Drama | Music	.19
National Lampoon's Christmas Vacation	1989	Comedy	.18
The Guardian	2006	Action | Adventure | Drama	.18
The Wedding Planner	2001	Comedy | Romance	.18
Patch Adams	1998	Biography | Comedy | Drama | Romance	.18
To Kill a Mockingbird	1962	Crime | Drama	.15
The Best Man	1999	Comedy | Drama	.15
Conscientiousness – low			
Yellow Submarine	1968	Animation | Adventure | Comedy | Family | Fantasy | Musical	-.52
Party Monster	2003	Biography | Crime | Drama | Thriller	-.47
The Human Centipede (First Sequence)	2009	Horror	-.47
My Neighbor Totoro	1988	Animation | Family | Fantasy	-.47
This Is England	2006	Crime | Drama	-.45
Hard Candy	2005	Crime | Drama | Thriller	-.44
Battle Royale	2000	Adventure | Drama | Sci-Fi | Thriller	-.44
Wristcutters: A Love Story	2006	Comedy | Drama | Fantasy | Romance	-.43
Monster High	1989	Comedy | Horror | Sci-Fi	-.42
Spirited Away	2001	Animation | Adventure | Family | Fantasy | Mystery	-.41
Extraversion – high			
8 Seconds	1994	Biography | Drama | Sport | Western	.32
ATL	2006	Comedy | Crime | Drama | Music | Romance	.29
The Wood	1999	Comedy | Drama | Romance	.28
Old School	2003	Comedy	.26
Friday Night Lights	2004	Action | Drama | Sport	.26
Unforgivable	2011	Drama	.26
Love & Basketball	2000	Drama | Romance | Sport	.25
Baby Boy	2001	Crime | Drama | Romance | Thriller	.25
Friday	1995	Comedy | Drama	.24
Juice	1992	Action | Crime | Drama | Thriller	.24
Extraversion - low			
Ghost in the Shell	2017	Action | Drama | Sci-Fi | Thriller	-.59
Kiki's Delivery Service	1989	Animation | Adventure | Drama | Family | Fantasy	-.55
My Neighbor Totoro	1988	Animation | Family | Fantasy	-.52
Akira	1988	Animation | Action | Drama | Sci-Fi | Thriller	-.50
Silent Hill	2006	Horror	-.50
Battle Royale	2000	Adventure | Drama | Sci-Fi | Thriller	-.49
Princess Mononoke	1997	Animation | Adventure | Fantasy	-.47
Aliens	1986	Action | Adventure | Sci-Fi | Thriller	-.47
Howl's Moving Castle	2004	Animation | Adventure | Family | Fantasy	-.45

SUPPLEMENTAL TABLE 1 (CONTINUED)

Title	Year	Genre	Z
Agreeableness – high			
Facing the Giants	2006	Drama | Sport	.40
Letters to God	2010	Drama | Family	.38
Fireproof	2008	Drama | Romance	.33
The Passion of the Christ	2004	Drama	.28
The Lake House	2006	Drama | Fantasy | Romance	.24
The Buddha	2010	Documentary	.22
Patch Adams	1998	Biography | Comedy | Drama | Romance	.21
Ever After: A Cinderella Story	1998	Comedy | Drama | Romance	.21
Pay It Forward	2000	Drama	.20
You've Got Mail	1998	Comedy | Drama | Romance	.20
Agreeableness – low			
Hellraiser	1987	Horror | Thriller	-.46
Hannibal Rising	2007	Adventure | Crime | Drama | Thriller | War	-.45
Heathers	1988	Comedy	-.44
Red Dragon	2002	Crime | Drama | Thriller	-.43
Party Monster	2003	Biography | Crime | Drama | Thriller	-.40
Get Rich or Die Tryin'	2005	Biography | Crime | Drama | Music	-.40
Hannibal	2001	Crime | Drama | Thriller	-.39
Lord of War	2005	Crime | Drama | Thriller	-.39
The Human Centipede (First Sequence)	2009	Horror	-.39
Taxi Driver	1976	Crime | Drama	-.39
Neuroticism – high			
Girl, Interrupted	1999	Biography | Drama	-.41
Thirteen	2003	Drama	-.41
The Craft	1996	Drama | Fantasy | Horror | Thriller	-.35
Silent Hill	2006	Horror	-.33
Wristcutters: A Love Story	2006	Comedy | Drama | Fantasy | Romance	-.33
The Incubus	1982	Horror | Thriller	-.31
Heathers	1988	Comedy	-.31
Hard Candy	2005	Crime | Drama | Thriller	-.29
Marie Antoinette	2006	Biography | Drama | History | Romance	-.28
Corpse Bride	2005	Animation | Drama | Family | Fantasy | Musical | Romance	-.28
Neuroticism – low			
Friday Night Lights	2004	Action | Drama | Sport	.35
Mission: Impossible	1996	Action | Adventure | Thriller	.35
Boyz n the Hood	1991	Crime | Drama	.34
Ip Man 2	2010	Action | Drama | Sport	.33
Paid in Full	2002	Action | Crime | Drama	.33
Shooter	2007	Action | Crime | Drama | Mystery | Thriller	.33
The Wood	1999	Comedy | Drama | Romance	.31
Ip Man	2008	Action | Biography | Drama | Sport	.31
We Were Soldiers	2002	Action | Drama | History | War	.31
Menace II Society	1993	Crime | Drama | Thriller	.31

SUPPLEMENTAL TABLE 2

SUMMARY STATISTICS FOR NON-CATEGORICAL METADATA VARIABLES

	Mean	**SD**	**Min**	**Max**
Rating	6.99	1.00	1.9	9.3
Rating count	240,514.57	254,013.78	137	1982609
Budget	44,827,549.90	45,068,769.27	15,000	260,000,000
Gross	216,904,282.66	231,813,657.28	252,207	2,787,965,087
ROI	28.78	531.57	-0.90	12,889.39
Num keywords	168.05	100.04	7	865
Runtime	111.54	21.88	22	238

SUPPLEMENTAL TABLE 3

GENRE CATEGORIES REPRESENTED IN THE STUDY

Genre	# of titles
Action	194
Adventure	186
Animation	76
Biography	42
Comedy	349
Crime	134
Documentary	6
Drama	402
Family	126
Fantasy	144
History	27
Horror	91
Music	42
Musical	48
Mystery	80
Romance	238
Sci-Fi	110
Sport	36
Thriller	213
War	34
Western	9

SUPPLEMENTAL TABLE 4

REGRESSION ANALYSES WITH AFPP DIMENSIONS AS DEPENDENT VARIABLES
(FULL MODEL, STANDARDIZED COEFFICIENTS)

	Dependent variable:				
	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
	(1)	(2)	(3)	(4)	(5)
Age	0.120**	0.663***	-0.049	0.193***	-0.226***
	(0.036)	(0.036)	(0.039)	(0.039)	(0.034)
Female	-0.213***	0.341***	0.155**	0.367***	0.356***
	(0.040)	(0.041)	(0.044)	(0.044)	(0.038)
Relationship	0.347***	-0.387***	-0.025	-0.202***	0.392***
	(0.033)	(0.033)	(0.036)	(0.036)	(0.032)
Rating	0.318***	-0.104*	-0.232***	0.093*	0.043
	(0.038)	(0.039)	(0.042)	(0.042)	(0.037)
Rating count	-0.022	-0.085*	0.019	-0.027	0.009
	(0.035)	(0.036)	(0.039)	(0.039)	(0.034)
Year	0.035	-0.033	0.041	0.019	-0.038
	(0.033)	(0.034)	(0.037)	(0.036)	(0.032)
Log (Budget)	-0.113*	0.167***	-0.042	0.133**	-0.103*
	(0.037)	(0.037)	(0.041)	(0.040)	(0.035)
Log (Gross)	-0.166***	0.140***	0.106**	0.122***	-0.065*
	(0.029)	(0.030)	(0.032)	(0.032)	(0.028)
ROI	-0.038	0.039	0.026	0.053	-0.044
	(0.025)	(0.026)	(0.028)	(0.028)	(0.024)
Runtime	-0.051	0.023	0.025	-0.097*	0.056
	(0.034)	(0.035)	(0.038)	(0.038)	(0.033)
Genre: Action	-0.145	0.309***	-0.047	0.315***	-0.239**
	(0.076)	(0.077)	(0.084)	(0.083)	(0.073)
Genre: adventure	0.201*	-0.161*	-0.269**	0.138	0.081
	(0.075)	(0.076)	(0.083)	(0.083)	(0.072)
Genre: animation	0.045	-0.267*	-0.184	-0.375*	0.116
	(0.127)	(0.128)	(0.140)	(0.139)	(0.122)
Genre: biography	0.074	-0.180	0.013	0.022	0.233
	(0.129)	(0.130)	(0.143)	(0.141)	(0.123)
Genre: comedy	-0.035	-0.135*	0.122	0.169*	-0.007
	(0.068)	(0.068)	(0.075)	(0.074)	(0.065)
Genre: crime	-0.029	0.043	0.391***	-0.499***	-0.210*
	(0.079)	(0.080)	(0.088)	(0.087)	(0.076)

Genre: documentary	0.013	0.055	0.175	-0.252	-0.111
	(0.299)	(0.303)	(0.331)	(0.328)	(0.287)
Genre: drama	0.158*	-0.163*	-0.127	-0.132	0.100
	(0.064)	(0.064)	(0.070)	(0.070)	(0.061)
Genre: family	-0.241*	-0.034	-0.186	0.381**	-0.053
	(0.100)	(0.101)	(0.111)	(0.110)	(0.096)
Genre: fantasy	0.453***	-0.282***	-0.513***	-0.114	0.230**
	(0.075)	(0.076)	(0.083)	(0.082)	(0.072)
Genre: history	0.282	0.321	-0.278	0.082	-0.193
	(0.162)	(0.164)	(0.179)	(0.177)	(0.155)
Genre: horror	0.008	-0.172	-0.536***	-0.663***	0.582***
	(0.097)	(0.099)	(0.108)	(0.107)	(0.093)
Genre: music	-0.022	0.095	0.155	0.151	-0.129
	(0.117)	(0.118)	(0.129)	(0.128)	(0.112)
Genre: musical	0.229	-0.223	0.025	0.158	0.066
	(0.119)	(0.120)	(0.132)	(0.131)	(0.114)
Genre: mystery	0.099	0.085	-0.153	0.160	-0.031
	(0.092)	(0.093)	(0.102)	(0.101)	(0.088)
Genre: romance	-0.035	0.155*	0.106	0.212*	-0.151*
	(0.073)	(0.074)	(0.081)	(0.080)	(0.070)
Genre: sci.fi	0.473***	-0.381***	-0.623***	-0.096	0.270**
	(0.084)	(0.085)	(0.093)	(0.092)	(0.081)
Genre: sport	-0.628***	0.630***	0.762***	0.712***	-0.741***
	(0.130)	(0.131)	(0.144)	(0.142)	(0.124)
Genre: thriller	-0.021	0.066	-0.231*	-0.080	0.126
	(0.075)	(0.075)	(0.082)	(0.082)	(0.071)
Genre: western	-0.115	-0.152	0.014	0.280	-0.270
	(0.242)	(0.244)	(0.267)	(0.265)	(0.232)
Genre: war	-0.040	0.391*	-0.227	-0.203	-0.038
	(0.140)	(0.141)	(0.155)	(0.153)	(0.134)
Constant	-0.164*	0.132	0.306**	-0.048	-0.066
	(0.083)	(0.084)	(0.092)	(0.092)	(0.080)
Observations	846	846	846	846	846
R^2	0.528	0.516	0.421	0.432	0.566
Adjusted R^2	0.510	0.498	0.399	0.410	0.549
Residual Std. Error (df = 814)	0.700	0.709	0.775	0.768	0.671
F Statistic (df = 31; 814)	29.374***	28.040***	19.130***	19.948***	34.227***

Note: *p<0.05 (uncorrected); **p<0.05 (corrected); *** p<0.01 (corrected)

SUPPLEMENTAL TABLE 5

REGRESSION ANALYSES WITH AFPP DIMENSIONS AS DEPENDENT VARIABLES
(FULL MODEL, UNSTANDARDIZED COEFFICIENTS)

	Dependent variable:				
	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
	(1)	(2)	(3)	(4)	(5)
Age	0.012**	0.036***	-0.003	0.010***	-0.012***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Female	-0.280***	0.249***	0.129**	0.253***	0.265***
	(0.053)	(0.030)	(0.037)	(0.030)	(0.029)
Relationship	1.152***	-0.716***	-0.054	-0.352***	0.736***
	(0.109)	(0.062)	(0.077)	(0.063)	(0.059)
Rating	0.072***	-0.013*	-0.034***	0.011*	0.006
	(0.009)	(0.005)	(0.006)	(0.005)	(0.005)
Rating count	-0.00000	-0.00000*	0.000	-0.000	0.000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Year	0.001	-0.0003	0.0005	0.0002	-0.0004
	(0.001)	(0.0003)	(0.0004)	(0.0004)	(0.0003)
Log (Budget)	-0.047*	0.039***	-0.011	0.029**	-0.024*
	(0.015)	(0.009)	(0.011)	(0.009)	(0.008)
Log (Gross)	-0.096***	0.045***	0.039**	0.037***	-0.021*
	(0.017)	(0.010)	(0.012)	(0.010)	(0.009)
ROI	-0.00002	0.00001	0.00001	0.00001	-0.00001
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Runtime	-0.001	0.0001	0.0002	-0.001*	0.0003
	(0.0004)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Genre: action	-0.033	0.039***	-0.007	0.037***	-0.031**
	(0.017)	(0.010)	(0.012)	(0.010)	(0.009)
Genre: adventure	0.046*	-0.020*	-0.039**	0.016	0.010
	(0.017)	(0.010)	(0.012)	(0.010)	(0.009)
Genre: animation	0.010	-0.034*	-0.027	-0.045*	0.015
	(0.029)	(0.016)	(0.020)	(0.017)	(0.016)
Genre: biography	0.017	-0.023	0.002	0.003	0.030
	(0.029)	(0.016)	(0.021)	(0.017)	(0.016)
Genre: comedy	-0.008	-0.017*	0.018	0.020*	-0.001
	(0.015)	(0.009)	(0.011)	(0.009)	(0.008)
Genre: crime	-0.007	0.005	0.056***	-0.059***	-0.027*
	(0.018)	(0.010)	(0.013)	(0.010)	(0.010)

Genre: documentary	0.003	0.007	0.025	-0.030	-0.014
	(0.068)	(0.038)	(0.048)	(0.039)	(0.037)
Genre: drama	0.036*	-0.021*	-0.018	-0.016	0.013
	(0.014)	(0.008)	(0.010)	(0.008)	(0.008)
Genre: family	-0.055*	-0.004	-0.027	0.045**	-0.007
	(0.023)	(0.013)	(0.016)	(0.013)	(0.012)
Genre: fantasy	0.103***	-0.036***	-0.074***	-0.014	0.030**
	(0.017)	(0.010)	(0.012)	(0.010)	(0.009)
Genre: history	0.064	0.041	-0.040	0.010	-0.025
	(0.037)	(0.021)	(0.026)	(0.021)	(0.020)
Genre: horror	0.002	-0.022	-0.077***	-0.079***	0.075***
	(0.022)	(0.012)	(0.016)	(0.013)	(0.012)
Genre: music	-0.005	0.012	0.022	0.018	-0.017
	(0.027)	(0.015)	(0.019)	(0.015)	(0.014)
Genre: musical	0.052	-0.028	0.004	0.019	0.009
	(0.027)	(0.015)	(0.019)	(0.016)	(0.015)
Genre: mystery	0.022	0.011	-0.022	0.019	-0.004
	(0.021)	(0.012)	(0.015)	(0.012)	(0.011)
Genre: romance	-0.008	0.020*	0.015	0.025*	-0.019*
	(0.017)	(0.009)	(0.012)	(0.009)	(0.009)
Genre: sci.fi	0.107***	-0.048***	-0.090***	-0.011	0.035**
	(0.019)	(0.011)	(0.013)	(0.011)	(0.010)
Genre: sport	-0.142***	0.080***	0.110***	0.085***	-0.095***
	(0.029)	(0.017)	(0.021)	(0.017)	(0.016)
Genre: thriller	-0.005	0.008	-0.033*	-0.009	0.016
	(0.017)	(0.010)	(0.012)	(0.010)	(0.009)
Genre: western	-0.026	-0.019	0.002	0.033	-0.035
	(0.055)	(0.031)	(0.039)	(0.032)	(0.030)
Genre: war	-0.009	0.049*	-0.033	-0.024	-0.005
	(0.032)	(0.018)	(0.022)	(0.018)	(0.017)
Constant	-0.958	-0.678	-1.045	-1.203	0.838
	(1.242)	(0.700)	(0.873)	(0.714)	(0.675)
Observations	846	846	846	846	846
R^2	0.528	0.516	0.421	0.432	0.566
Adjusted R^2	0.510	0.498	0.399	0.410	0.549
Residual Std. Error (df = 814)	0.159	0.090	0.112	0.091	0.086
F Statistic (df = 31; 814)	29.374***	28.040***	19.130***	19.948***	34.227***

Note: *p<0.05 (uncorrected); **p<0.05 (corrected); *** p<0.01 (corrected)

SUPPLEMENTAL TABLE 6

PREDICTIVE ACCURACIES FOR DIFFERENT PREDICTION MODELS

		Ope	Con	Ext	Agr	Neu
LASSO Lambda=0.0001	Genre	.37	.44	.55	.55	.53
	Metadata	.49	.42	.42	.52	.30
	Demographics	.57	.58	.30	.42	.65
	Keywords	.63	.53	.67	.64	.65
	All but keywords	.68	.68	.63	.64	.72
	All variables	.72	.72	.71	.67	.76
LASSO Lambda=.01	Genre	.36	.41	.52	.54	.51
	Metadata	.59	.43	.42	.53	.31
	Demographics	.57	.56	.28	.39	.65
	Keywords	.62	.45	.62	.60	.60
	All but keywords	.71	.66	.63	.62	.71
	All variables	.75	.69	.70	.65	.74
Linear	Genre	.37	.44	.54	.55	.53
	Metadata	.07	.03	.00	.03	.01
	Demographics	.57	.58	.30	.42	.65
	Keywords	.63	.53	.67	.63	.65
	All but keywords	-.02	-.02	-.01	.05	-.01
	All variables	.05	.03	.04	-.01	.02
Ridge Alpha=10	Genre	.37	.44	.55	.55	.53
	Metadata	.55	.41	.42	.51	.30
	Demographics	.57	.58	.30	.42	.65
	Keywords	.63	.53	.67	.63	.65
	All but keywords	.68	.68	.63	.64	.72
	All variables	.72	.71	.70	.68	.76
Ridge Alpha=100	Genre	.37	.44	.55	.55	.53
	Metadata	.56	.42	.43	.53	.32
	Demographics	.57	.57	.30	.42	.65
	Keywords	.63	.53	.67	.64	.65
	All but keywords	.69	.68	.64	.65	.73
	All variables	.74	.72	.72	.69	.77

NOTE.— simple linear regression models yielded poor performance in models that had a large number of metadata variables due to overfitting.

SUPPLEMENTAL TABLE 7

PREDICTIVE ACCURACIES FOR DIFFERENT PREDICTION MODELS

	Ope	**Con**	**Ext**	**Agr**	**Neu**
Genre	.37	.44	.55	.56	.53
Metadata	.56	.44	.44	.54	.33
Demographics	.57	.58	.30	.42	.65
Keywords	.64	.55	.67	.65	.66
All except keywords	.69	.70	.65	.65	.74
All variables	.75	.74	.73	.70	.78

NOTE.— This analysis is identical to the main analysis, except that the reduced keyword vectors were composed by projecting the keyword vectors of all titles in the Movie Likes dataset onto the 100 latent dimensions calculated by performing SVD on the keyword matrix of the 10,000 most voted feature film titles on IMDb as for 2018, with the exception of the movies that are included in the Movie Likes dataset. This analysis demonstrates that our results hold when there is no overlap between the dataset used to compute the SVD dimensions and the data used to train and test the models.

SUPPLEMENTAL TABLE 8

RELATIONSHIPS BETWEEN MOVIE THEMES AND FAN PERSONALITIES

	O	C	E	A	N	Lexical examples	Top plot keywords
Personal Concerns							
Death	**<u>.20</u>**	-.11	**<u>-.32</u>**	**<u>-.22</u>**	**<u>.26</u>**	bury, coffin, kill	death, death-of-mother, death-of-father
Religion	**<u>.25</u>**	**<u>-.16</u>**	**<u>-.23</u>**	-.04	**<u>.20</u>**	altar, church	reference-to-jesus-christ, christian, catholic-church
Money	**-.11**	.06	**<u>.13</u>**	**<u>.19</u>**	**<u>-.16</u>**	audit, cash, owe	money, pay-phone, debt
Home	-.10	.02	.05	.05	.00	kitchen, landlord	bedroom, kitchen, house
Leisure	-.06	-.01	**<u>.17</u>**	**<u>.16</u>**	-.07	cook, chat, movie	dance, singing-in-a-car, listening-to-music
Work	.01	.04	.01	**<u>.21</u>**	-.07	job, majors, xerox	teacher-student-relationship, college-student, high-school-student
Drives							
Achieve	.10	-.05	**<u>-.14</u>**	**<u>.23</u>**	-.02	win, success, better	title-at-the-end. loss-of-loved-one, falling-in-love
Power	**<u>.16</u>**	-.09	**-.12**	.06	.07	superior, bully	one-man-army, good-versus-evil, character-says-i-love-you
Reward	-.01	.00	-.04	**<u>.25</u>**	-.10	take, prize, benefit	good-versus-evil, long-take, falling-in-love
Risk	.04	-.04	**<u>-.17</u>**	-.01	**.11**	danger, doubt	danger, fear, child-in-peril
Perceptual Processes	.07	**<u>-.14</u>**	-.10	.05	**<u>.13</u>**	look, heard, feeling	scream, nipples-visible-through-clothing falling-in-love
Seeing	**.12**	**<u>-.17</u>**	**<u>-.23</u>**	.01	**<u>.17</u>**	view, saw, seen	looking-at-oneself-in-a-mirror. nipples-visible-through-clothing. talking-to-the-camera
Hearing	-.05	.01	.09	**<u>.21</u>**	-.03	listen, hearing	listening-to-music, scream. singing
Feeling	.06	**<u>-.13</u>**	**<u>-.15</u>**	.02	**<u>.15</u>**	feels, touch	bare-butt, hit-in-the-crotch falling-in-love
Biological Processes	.05	**<u>-.14</u>**	.03	**-.12**	**<u>.16</u>**	eat, blood, pain	penis, nipples, nipples-visible-through-clothing
Body	.04	**<u>-.13</u>**	-.03	**<u>-.13</u>**	**<u>.18</u>**	cheek, hands, spit	penis, nipples, bare-butt
Health	.10	**<u>-.16</u>**	-.04	**<u>-.18</u>**	**<u>.23</u>**	clinic, flu, pill	pain, doctor, vomiting
Ingestion	-.05	-.07	.11	.04	.01	dish, eat, pizza	eating, pizza, drink
Sexual	.07	**<u>-.12</u>**	**<u>.14</u>**	**<u>-.21</u>**	**<u>.14</u>**	horny, love, incest	kissing-while-having-sex, masturbation, lesbian-kiss
Affective Processes	.13	**<u>-.16</u>**	-.10	.00	**<u>.15</u>**	happy, cried	character-says-i-love-you, good-versus-evil, love
Positive Emotions	.08	-.10	-.06	**<u>.18</u>**	.03	love, nice, sweet	character-says-i-love-you, love, good-versus-evil
Negative Emotions	**<u>.16</u>**	**<u>-.17</u>**	-.11	**<u>-.15</u>**	**<u>.23</u>**	hurt, ugly, nasty	fear, panic, paranoia
Anxiety	**<u>.17</u>**	**<u>-.18</u>**	**<u>-.23</u>**	**<u>-.14</u>**	**<u>.27</u>**	worried, fearful	fear, panic, paranoia
Anger	**.11**	**<u>-.13</u>**	-.03	**<u>-.16</u>**	**<u>.18</u>**	hate, kill, annoyed	bully, evil-man, scream
Sadness	.02	-.04	.07	.09	.03	crying, grief, sad	character-says-i-love-you, crying-man, crying-woman
Social Processes	-.02	-.02	.11	.11	-.02	mate, talk, they	character-says-i-love-you, mother-daughter-relationship, little-girl
Family	-.06	.00	.09	.09	-.03	daughter, dad, aunt	mother-son-relationship, mother-daughter-relationship, father-daughter-relationship
Friends	-.07	.02	**<u>.19</u>**	.11	-.08	buddy, neighbor	friend, boyfriend-girlfriend-relationship, ex-boyfriend-ex-girlfriend-relationship
Female references	.02	-.08	.08	-.01	.04	girl, her, mom	girl. girl-in-panties, little-girl
Male references	-.02	-.01	**<u>.13</u>**	.10	-.06	boy, his, dad	uncle-nephew-relationship, father-son-relationship, brother-brother-relationship
Cognitive Processes	**.12**	**<u>-.14</u>**	**<u>-.16</u>**	.10	**.11**	cause, know, ought	character-says-i-love-you, character-repeating-someone-else's-dialogue, good-vs-evil
Insight	**<u>.17</u>**	**<u>-.15</u>**	**<u>-.21</u>**	.07	**<u>.13</u>**	think, know	character-repeating-someone-else's-dialogue, character-says-i-love-you, talking-to- camera
Causation	**<u>.16</u>**	**<u>-.16</u>**	**<u>-.26</u>**	.04	**<u>.14</u>**	because, effect	character-says-i-love-you, character-repeating-someone-else's-dialogue, lifting-someone-into-the-air

Significance level (Bonferroni corrected): **p<0.05**; **<u>P<0.01</u>**

NOTE.—Partial Correlations between the average fan personality profiles and the plots' psychological themes across movies, controlling for demographics and non-categorical metadata variables