Preprint

Personality structure predicts story preferences across 23 countries

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Abstract

Why do people prefer certain fictional stories over others? Personality traits capture stable individual differences in motivational sensitivities: Openness reflects exploration, Neuroticism reflects threat-reactivity, and so on. If so, these traits should systematically predict preferences for narrative features that engage the corresponding motivational systems. We test this hypothesis across three preregistered studies. In Study 1, we directly measured individual preferences for motivationally salient narrative features in a cross-cultural survey of 9,201 participants from 23 countries. Personality traits predicted preferences and the overall pattern replicated in 22 of 23 countries. In Study 2, we confirmed these predictions using ecologically valid data from 574 movies, annotated by large language models for the same narrative features and linked to the Big Five profiles of 3.5 million Facebook users. The predicted associations replicated at the population level. In Study 3, we tested a complementary structural prediction: if story preferences reflect an underlying motivational architecture, then the co-occurrence structure of narrative features in stories should mirror the co-preference structure across individuals. Using Mantel tests, we found strong structural correspondence, replicated across all 23 countries. Together, these findings support a model in which story preferences arise from universal motivational systems whose sensitivities vary across individuals.

Keywords: Personality, Preference, Narratives

Introduction

One of the most robust findings in psychology is that human personality is structured. Decades of research have converged on a model in which individual differences in behavior, emotion, and cognition can be described by a small number of broad traits, most notably the Big Five: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (1–4). These traits are remarkably stable across the lifespan (5–8), substantially heritable (9–12), and replicated across cultures and languages (13–16). Importantly, they predict a wide range of real-world outcomes, from occupational choice and academic achievement to relationship satisfaction and health behaviors (17–20).

Here, we ask whether personality structure also shapes the fictional stories people consume, and, by extension, the structure of fiction itself. If personality traits capture stable individual differences in motivational sensitivities (21–23), then people who differ in personality should be drawn to stories that activate different motivational systems. For instance, someone high in Openness should prefer narratives involving exploration and discovery; someone low in Agreeableness should be more drawn to stories of revenge and conflict. More ambitiously, if these motivational sensitivities are what drives both individual preferences and the cultural supply of stories, then the structure of personality (i.e., the way traits co-vary across individuals) should be mirrored in the structure of fiction (i.e., the way narrative features co-occur in stories).

Previous work has begun to establish links between specific personality traits and specific aspects of fiction. Openness, for example, has been associated with preferences for imaginative and fantastical worlds (24, 25); other studies have linked individual Big Five traits to broad genre preferences such as horror, romance, or comedy (26–29). However, these studies have typically examined one or a few traits in isolation, focused on coarse genre categories rather than fine-grained narrative content, and have never tested whether the observed associations hold across cultures.

In this article, we generalize this approach in three ways. First, we systematically map all five personality traits onto a comprehensive set of minimal narrative features: not broad genres, but specific motivationally salient narrative features of stories (hereafter 'narrative ingredients'; e.g., revenge, parental care, exploration, romantic attraction, humor; see **Table 1**), each grounded in a specific psychological mechanism. Second, we test these associations across 23 countries spanning all inhabited continents, and we predict that personality-fiction associations should be universal as well. Third, we test a structural prediction: if both story preferences and story content are shaped by the same underlying motivational systems, then the co-preference structure across individuals should mirror the co-occurrence structure of narrative features in stories.

Table 1. All models testing preregistered directional predictions linking Big Five personality traits to such narrative features derived from Dubourg et al. (2023)'s Table of Ingredients, designed to capture features of stories with specific cognitive appeal (see Supplementary Materials for full definitions). Each prediction specifies a trait-feature association, its expected direction (positive or negative), and supporting references from the personality psychology literature. See Supplementary Materials for the full wording of the narrative features used for annotation. (*References do not directly test the association between the personality trait and the narrative feature listed in each row. Rather, they document established findings in personality psychology (e.g., that individuals higher in Openness tend to explore more in real life) from which we derived our directional predictions about story preferences. Each row thus represents a theory-driven prediction: if a trait is associated with a given real-world behavior or motivation, we predict a corresponding preference for stories featuring that narrative element.)

Narrative ingredients: A character…	Personality Trait	Prediction	References*
… explores unknown	Openness	Positive	(30–33)
… trains and improves		Positive	(34–36)
… debates or outwits		Positive	(37)
… protects the vulnerable		Positive	(38, 39)

… commits romantically		Positive	(40–45)
… nurtures a child		Positive	(42–45)
… feels proud	**Conscientiousness**	Positive	(46, 47)
… defends their values		Positive	(48)
… condemns wrongdoing		Positive	(48, 49)
… is celebrated as hero		Positive	(48, 50)
… gains influence		Positive	(46, 51)
… commits romantically		Positive	(42–45)
… faces sexual violation		Positive	(52, 53)
… nurtures a child		Positive	(42–45)
… explores unknown	**Extraversion**	Negative	(54)
… endures suffering		Negative	(55, 56)
… shows empathy		Positive	(57, 58)
… bonds with friends		Positive	(59, 60)
… creates humor		Positive	(61, 62)
… gains influence		Positive	(46, 51)
… acts on rage		Positive	(63)
… falls for someone		Positive	(64, 65)
… commits romantically		Positive	(40–45)
… nurtures a child		Positive	(42–45)
… faces monsters	**Agreeableness**	Negative	(21, 22, 66, 67)
… faces enemies		Negative	(21, 22, 66, 68)
… confronts shame		Negative	(69)
… seeks redemption		Positive	(70)
… shows empathy		Positive	(57, 58)
… condemns wrongdoing		Positive	(48, 49)
… is celebrated as hero		Positive	(48, 50)
… seeks vengeance		Negative	(71, 72)
… lets go of hatred		Positive	(71, 72)
… protects the vulnerable		Positive	(38, 39)
… bonds with friends		Positive	(59, 60)
… defends their values		Negative	(48)
… acts on rage		Negative	(63)
… commits romantically		Positive	(40–45)
… faces sexual violation		Positive	(52, 53)
… nurtures a child		Positive	(42–45)
… faces monsters	**Neuroticism**	Positive	(21, 22, 66–68)
… faces enemies		Positive	(21, 22, 66, 68)
… faces contamination		Positive	(21, 73)
… endures suffering		Positive	(55, 56)
… creates humor		Negative	(61, 62)
… defends their values		Negative	(48)
… acts on rage		Positive	(63)
… commits romantically		Negative	(40–45)
… fears romantic rival		Positive	(74, 75)
… nurtures a child		Negative	(42–45)

In Study 1, we designed and validated a questionnaire aimed at directly measuring individual preferences for these specific narrative ingredients (see Methods and Supplementary Materials). Crucially, in a preliminary validation study reported in the Supplementary Materials, participants' self-reported interest in each narrative feature (**Table 1**) reliably predicted the presence of those ingredients in their reported favorite books and movies. We then administered this instrument to participants from 23 countries spanning all inhabited continents, encompassing substantial cultural, linguistic, and socioeconomic diversity (**Figure 2**). Participants also completed a short Big Five personality questionnaire, enabling us to test all preregistered trait-ingredient models at the individual level.

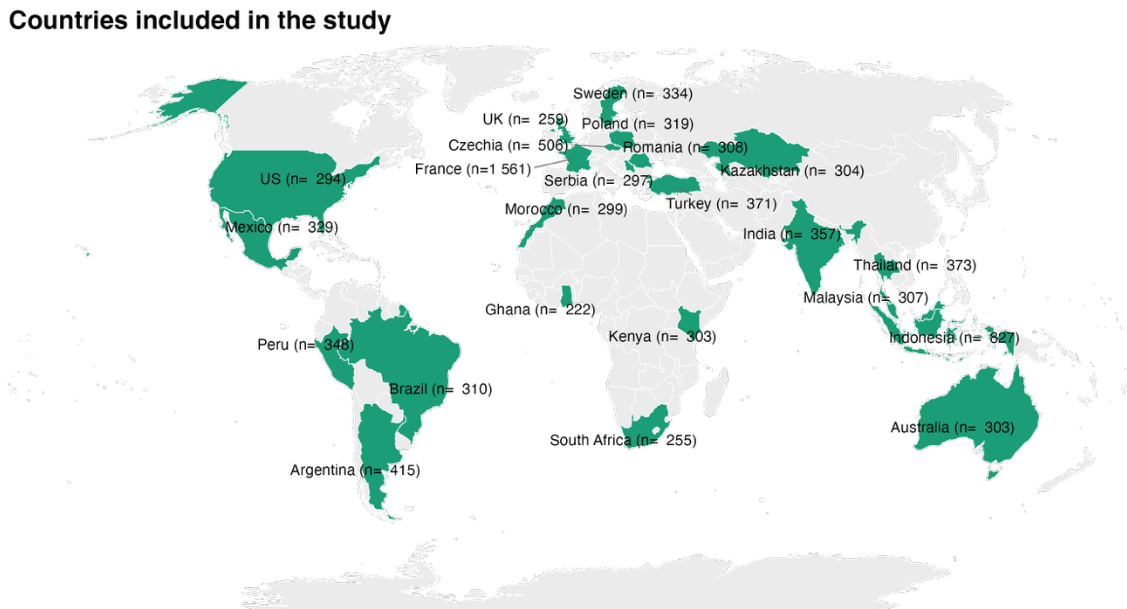

Figure 2. The 23 countries included in the study (green), with sample sizes indicated in parentheses.

In Study 2, we leverage a large-scale, ecologically valid dataset comprising 574 movies for which personality information is available for approximately 3.5 million Facebook users. For each movie, personality scores reflect the average Big Five profile of users who expressed liking the movie on Facebook, providing a population-level estimate of the psychological characteristics associated with each film. We automatically annotated these movies for the presence and narrative importance of each ingredient and tested whether the preregistered predictions linking personality traits to narrative ingredients (**Table 1**) hold in this real-world dataset. This study thus provides a large-scale test of the hypothesis that personality traits systematically shape narrative preferences, using naturally occurring cultural choices.

In Study 3, we tested a structural hypothesis. If narrative preferences and cultural products both reflect the same underlying motivational architecture, then the way ingredients cluster in stories should mirror the way they cluster in preferences. To test this, we compared the inter-ingredient correlation matrix derived from movie annotations (from Study 2) with the inter-ingredient correlation matrix derived from individual preference ratings (from Study 1), using Mantel tests (76). We also replicated this analysis with a dataset of 877 novels (see Supporting Information). We performed this analysis both on the pooled sample and separately within each of the 23 countries. A positive correspondence would indicate that ingredients which tend to co-occur in the same films are also the ingredients that tend to be co-preferred by the same individuals, as expected if both patterns are shaped by the same motivational systems.

Results

Are ingredient preferences shaped by personality traits?

In Study 1, we tested each preregistered association using linear mixed-effects models that predicted ingredient preferences from personality traits while accounting for baseline differences between countries (see Method). Across the 49 models, 41 associations (83.6%) were in the predicted direction, 4 were in the opposite direction, and 4 were non-significant (**Figure 3**).

Several associations matched our hypotheses. For instance, individuals higher in openness showed stronger preferences for stories involving characters exploring ($\beta = 0.13$) and debating ($\beta = 0.14$); conscientiousness predicted greater preference for stories with characters defending their moral values ($\beta = 0.11$); and agreeableness was associated with stronger preferences for stories featuring warm characters ($\beta = 0.14$) showing empathy ($\beta = 0.15$). As pre-registered, traits also predicted aversions; for instance, more agreeable individuals showed reduced preference for stories involving anger ($\beta = -0.06$). A few associations diverged from predictions. Most notably, stories involving sexual disgust were predicted to correlate positively with Agreeableness and Conscientiousness, yet both links were negative ($\beta = –0.09$ and $\beta = –0.12$, respectively).

To evaluate the overall pattern, we averaged the sign-adjusted coefficients across all 49 models, as pre-registered (i.e., reversing the sign of negatively predicted associations so that higher values consistently indicate support for the prediction). A stratified bootstrap analysis (1,000 resamples) yielded a mean effect of 0.068, with a 95% confidence interval of [0.062 - 0.074] (**Figure 3.A**). This aggregate effect size is comparable to typical findings in the personality-behavior literature, supporting the conclusion that personality traits predict preferences for stories featuring different narrative ingredients (77).

Study 2 leveraged an ecologically valid dataset of popular films in which each movie is characterized by the average Big Five profile of Facebook users who "liked" it (approximately 3.5 million users in total across the dataset). To test our predictions in this setting, we automatically annotated each movie for the narrative ingredients (see Method) and focused on cases where an ingredient was sufficiently important to plausibly structure the narrative. As pre-registered, for each ingredient we split movies into those in which the ingredient was dominant (score ≥ 5, out of 6) versus not dominant (score ≤ 4), and for each preregistered trait-ingredient association we estimated the difference in mean personality between these two groups. Effects were sign-aligned so that positive values always indicated support for the preregistered direction, and confirmatory tests were restricted to ingredients with adequate prevalence (at least 30 movies in both groups). All these criteria were preregistered (see Supplementary Materials for sensitivity analyses).

Across the confirmatory set of 45 preregistered predictions (4 excluded due to low sample size, as pre-registered), 26 (57.7%) were validated (significant and in the predicted direction), 5 were rejected (significant but in the opposite direction), and 14 were non-significant, including 5 that were nonetheless in the predicted direction but did not reach significance. At the aggregate level, the observed mean sign-aligned effect across predictions was 0.0289. A movie-level bootstrap procedure (1,000 resamples) yielded a 95% confidence interval of [0.0243, 0.0333], excluding zero. In terms of effect size, the descriptive mean sign-aligned Cohen's d across predictions was 0.24, indicating a small-to-moderate aggregate association.

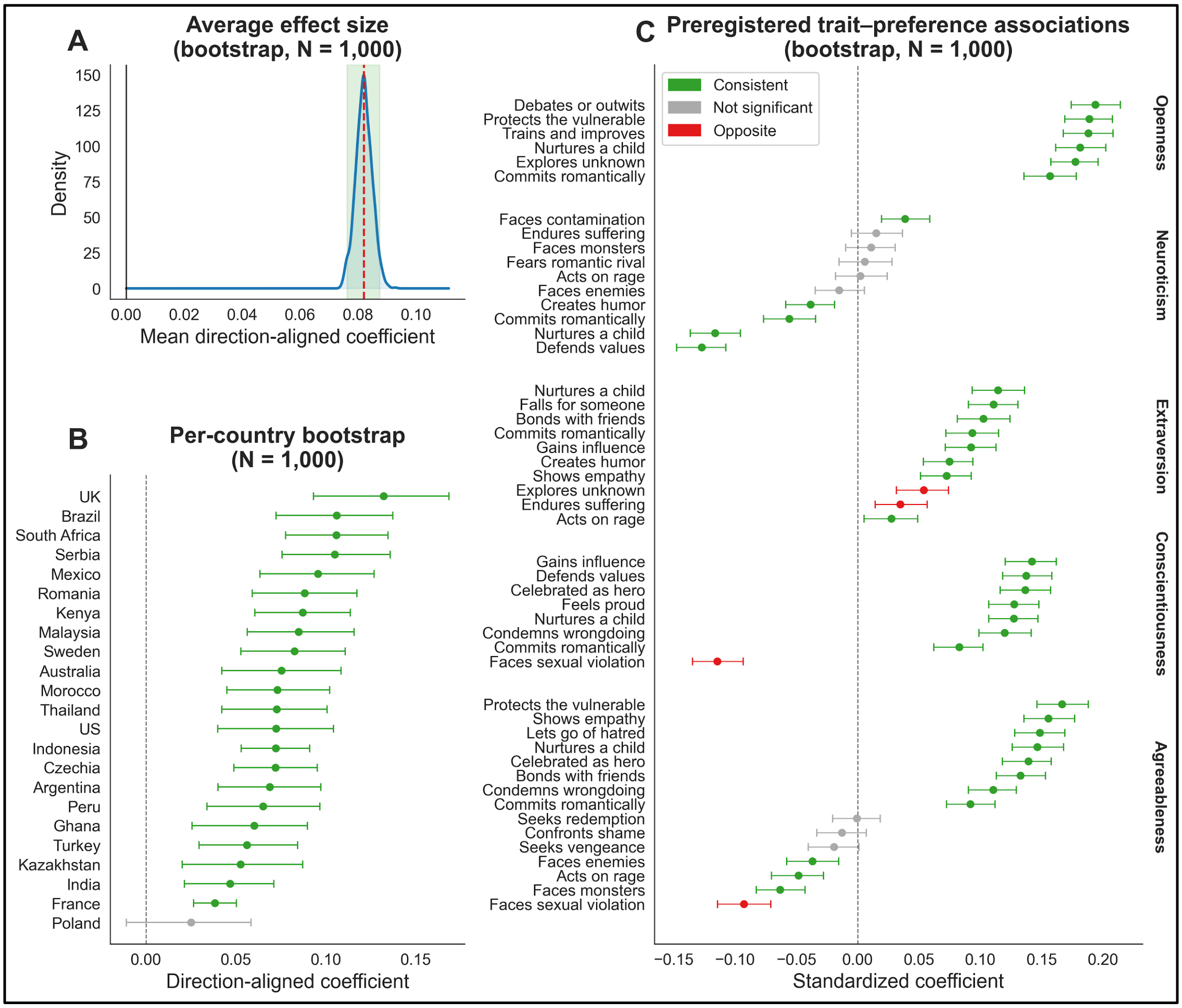

Figure 3. A. Distribution of the average effect size across all preregistered tests, obtained via within-country stratified bootstrap (N = 1,000 resamples) on linear mixed-effects models (trait predicting ingredient, random intercept for country). The x-axis shows the mean direction-aligned standardized coefficients (β), with the dashed red line marking the bootstrap mean and dotted green lines showing the 95% confidence interval. **B.** Cross-cultural consistency of the preregistered associations, showing the average effect size (direction-aligned standardized coefficient, β) estimated separately in each country (N = 1,000 bootstraps per country). Points indicate country-specific means, and horizontal bars indicate 95% confidence intervals. **C.** Forest plot of preregistered trait–ingredient associations, estimated with linear mixed-effects models and bootstrapped within countries (N = 1,000). Each point represents the bootstrapped mean standardized coefficient (β) for a trait-ingredient pair, with horizontal bars indicating 95% confidence intervals.

Results are organized by trait (left axis). Green points denote significant effects in the predicted direction, red points denote significant effects in the opposite direction, and grey points indicate nonsignificant results.

Together, these results provide evidence that personality traits are systematically associated with the narrative ingredients that characterize the stories people choose, in the preregistered directions.

Are trait–preference effects stable across countries?

To test cross-cultural stability, we repeated the preregistered analysis within each country independently (see Method). The results showed that the predicted trait-preference alignment was robust across cultures: in 22 of the 23 countries, the confidence interval excluded zero, indicating that personality systematically predicted preferences for narrative ingredients within each national sample (**Figure 3.B**). This means that individuals in very different cultural contexts—across continents, languages, and socioeconomic settings—tended to enjoy the same kinds of stories for the same psychological reasons. Only Poland yielded a mean effect whose confidence interval overlapped with zero, suggesting weaker evidence for the predicted associations in that country. Overall, these findings provide strong evidence that the links between personality and story preferences are not confined to specific populations but instead reflect universal patterns in the co-variation between psychology and culture.

Does the co-occurrence structure of ingredients in stories mirror the co-preference structure across individuals?

Study 3 tested whether the motivational architecture revealed by individual preferences is also reflected in how stories are constructed. If narrative ingredients engage related motivational systems, then ingredients that tend to co-occur in the same films should also tend to be co-preferred by the same individuals. As preregistered, we computed two 32×32 Spearman correlation matrices: one capturing co-preferences across 9,201 individuals (Study 1) and one capturing ingredient co-occurrence across 574 movies (Study 2). We converted both into distance matrices and assessed their correspondence using a one-sided Mantel test. We predicted a positive Mantel statistic both in the pooled sample and separately within each of the 23 countries (see Method).

The Mantel test revealed a strong positive correspondence between the two matrices ($r = 0.391$, $p < .001$; **Figure 4**). Ingredients that structurally co-occur in films are also more likely to be co-preferred by the same individuals. Inspection of both matrices reveals coherent motivational clusters (threat and self-protection, mating, social conflict, prosocial and moral evaluation, and cognition and achievement) appearing consistently in both the film co-occurrence and the individual preference structures.

This structural correspondence replicated across all 23 countries. Country-level Mantel statistics were all significant (all $p < .001$), with values ranging from 0.243 (France, Thailand) to 0.463 (Argentina; **Figure 4.C**). The robustness of this pattern across cultures that differ widely in their narrative traditions provides strong evidence that a shared motivational architecture shapes both the stories people prefer and the stories cultures produce. This structural correspondence also replicated when using novels instead of movies (rM = .41, p < .001; all 23 countries significant; see Supporting Information for details). An exploratory factor analysis on the preference data further confirmed that narrative ingredients cluster into interpretable motivational dimensions (see Supporting Information for full EFA results).

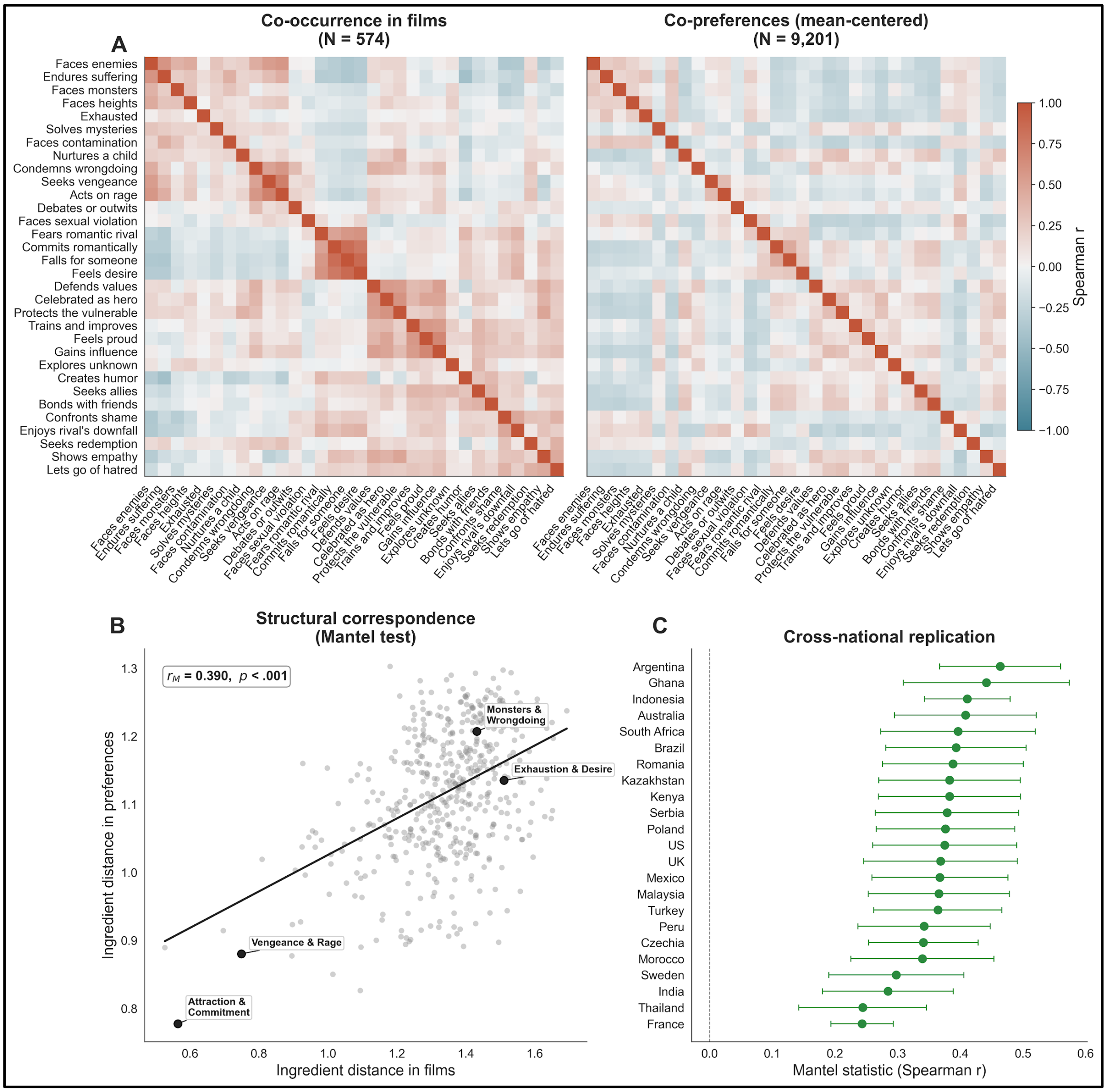

Figure 4. Structural correspondence between narrative ingredient co-occurrence in movies and co-preferences across individuals. **A.** Spearman correlation matrices for the 32 narrative ingredients: co-occurrence across 574 films (left) and co-preferences across 9,201 individuals (right). Rows and columns are ordered by hierarchical clustering; dashed lines indicate cluster boundaries (k = 5). **B.** Mantel scatter plot. Each point represents one ingredient pair; the x-axis shows the distance between two ingredients in the movie matrix, and the y-axis shows the distance in the preference matrix. For example, Vengeance and Rage are close in both spaces: films that feature one tend to feature the other, and people who enjoy one tend to enjoy the other. Conversely, Monsters and Wrongdoing are distant in both: they rarely co-occur in films, and preferences for one do not predict

preferences for the other. The positive correlation (rM = .394) indicates that the motivational structure of films mirrors the structure of audience preferences. **C.** Country-level Mantel statistics.

Discussion

Across three preregistered studies, we find converging evidence that personality traits systematically predict which narrative ingredients people find engaging. At the individual level, 83.6% of predicted trait–ingredient associations were supported, and this pattern replicated in 22 of 23 countries (Study 1). At the population level, movies dominated by a given ingredient were preferentially liked by audiences with the predicted personality profile (Study 2). Finally, the co-occurrence structure of ingredients in films mirrored the co-preference structure across individuals, with this correspondence replicating in all 23 countries (Study 3). These findings support the hypothesis that stories attract attention when they activate motivational systems whose sensitivities vary across individuals.

The fine-grained nature of these associations deserves emphasis. The predicted links were not between personality traits and broad genre categories such as horror or romance, but between traits and specific narrative ingredients tied to identifiable motivational mechanisms. Openness predicted preferences for characters engaging in exploration and reasoning, not for all aspects of science fiction or fantasy (24, 25, 78, 79). Agreeableness predicted stronger responses to characters showing warmth, compassion, and forgiveness (26–28, 78), and reduced interest in characters acting on rage and seeking revenge. This level of specificity is consistent with an account in which each ingredient activates a distinct motivational system, and personality traits modulate the sensitivity of these systems independently.

Study 3 revealed coherent motivational clusters appearing consistently in both the film co-occurrence and the individual preference structures. These clusters raise a question that our data alone cannot resolve: when two ingredients consistently co-occur in stories and are co-preferred by the same individuals, does this reflect two distinct motivations that tend to be co-activated, or a single broader system? Characters feeling proud and characters gaining influence, for instance, cluster together in our data. These two features may draw on overlapping motivational processes: the pursuit of social rank and the affective reward for achievement are plausibly part of a single status-regulation system (47, 82, 83). Yet, it seems they can dissociate in narratives: a character may climb in influence without experiencing pride or feel pride after a private accomplishment with no status implications.

Take fear of predators and fear of aggressors: they also correlate in both preferences and films. Yet these two forms of threat processing are routed through distinct neural circuits (84), and the distinction maps onto recognizable differences in fiction: stories built around monstrous creatures engage a different kind of horror than stories featuring human enemies, and critically, they are not preferred by the same individuals to the same degree. Here, the correlation between ingredients likely reflects the narrative efficiency of co-activating related but functionally independent systems, not the operation of a single motivational mechanism. More generally, determining which narrative feature correlations reflect genuine motivational unity and which reflect frequent co-activation of distinct systems is a key challenge for refining this framework.

This shift from genres to ingredients marks a substantive departure from prior work linking personality to cultural preferences. Rentfrow and colleagues (28) established that personality traits predict broad entertainment preferences (e.g., Openness correlates with preferences for "reflective and complex" music, Extraversion with "energetic and rhythmic" genres) but these categories remain descriptive clusters rather than psychologically decomposed units. Similarly, Nave et al. (78) demonstrated robust personality–movie associations at the population level using Facebook data, but at the level of entire films, leaving open which narrative features within a film drive the association. Our approach decomposes films and preferences into their constituent motivational ingredients, each linked to a specific motivation. This matters because genre categories bundle together heterogeneous ingredients: a horror film may engage threat-detection (monsters), moral outrage (wrongdoing), or disgust (contamination), and these ingredients are not preferred by the same individuals. By disaggregating genre into ingredients, we can explain why two films in the same genre attract different audiences and why a single individual may be drawn to films across ostensibly unrelated genres—provided those films share an underlying motivational ingredient.

One unexpected finding concerned sexual disgust. Based on prior work linking Agreeableness and Conscientiousness to heightened sensitivity to sexual disgust in everyday life (52, 85), we predicted that individuals higher on these traits would report stronger preferences for stories featuring sexual disgust. Instead, we observed the opposite: those more dispositionally sensitive to sexual disgust were significantly less attracted to the corresponding ingredient in stories. This dissociation suggests that motivational systems differ in whether they produce approach-oriented engagement or avoidance-oriented disengagement when activated by fictional content. Systems whose evolutionary function benefits from simulated exposure (such as threat detection, where vicariously experiencing danger may help calibrate defensive responses) may generate attraction to the corresponding narrative elements. Systems that evolved primarily to minimize exposure, such as sexual disgust avoidance, may instead produce repulsion even in fictional contexts. This framework should therefore distinguish between these two classes of motivational response. Identifying which systems promote simulated approach and which promote avoidance is a critical direction for future research (86, 87).

A methodological consideration bears on the interpretation of effect sizes across our studies. The observed associations, while consistent and replicable, are modest in magnitude (mean $\beta = 0.068$ in Study 1; mean Cohen's $d = 0.24$ in Study 2). These values fall within the range typically observed in personality–behavior research (77), but they also reflect known sources of attenuation. In both studies, personality was measured with the TIPI, a two-item-per-trait instrument whose internal consistency is substantially lower than that of longer inventories such as the BFI or NEO (107). Measurement error in the predictor mechanically attenuates regression coefficients, meaning that the true associations between latent personality dimensions and narrative preferences are likely stronger than those we report. This source of attenuation works against our predictions, making the systematic pattern of confirmed associations more noteworthy. Future work using longer personality instruments and individual-level movie preference data would provide sharper estimates of the underlying effect magnitudes.

While our results establish that personality traits systematically shape story preferences, they also raise deeper questions about the origins of these individual differences. Personality traits vary across individuals for at least two reasons. First, they are partly shaped by genetic differences (11), which explains why variation in story preferences is to some extent heritable (88). Second, personality is calibrated to ecological conditions through phenotypic plasticity (81, 89). Our study identifies the proximate pathway (i.e., how dispositional differences in motivational sensitivity predict attraction to specific ingredients) but the ultimate question remains open: why do these sensitivities vary in the first place? If personality calibration responds to ecological conditions, then systematic variation in story preferences across populations may ultimately trace back to variation in the environments that shaped those personalities. Future research can build on our findings by examining how ecological factors shape the distribution of motivational sensitivities across populations, and how these distributions in turn drive cultural variation in the kinds of stories societies produce and consume (90–93).

These findings open pathways for the scientific study of cultural preferences. By grounding narrative preferences in identifiable motivational systems, this framework moves beyond descriptive taxonomies of genre and taste toward a causal account of why specific cultural products engage specific audiences. This has practical implications. In education and clinical settings, targeting the motivational systems most responsive for a given individual could enhance engagement with narrative-based interventions (93, 94). More broadly, if story preferences reflect stable motivational tuning, then long-run changes in the distribution of personality traits within a population should predict corresponding changes in cultural demand, offering a new tool for tracing psychological diversity through cultural production over time and space (96). Finally, this study shows that fiction offers an ethically and practically unique opportunity to measure motivational engagement without real-world costs and thus acts as a diagnostic window onto latent motivational structures.

Materials and Methods

All hypotheses, data collection procedures, and statistical analyses were preregistered (https://osf.io/w493y/).

Data and automatic annotation

To test the preregistered predictions in an ecologically valid setting, we used a large-scale dataset originally compiled by Nave and colleagues (78), which links cultural preferences on Facebook to personality traits. The dataset includes 689 popular movies, each associated with the average Big Five personality profile of Facebook users who expressed liking the movie, based on approximately 3.5 million users. For each movie, personality scores therefore reflect aggregate psychological characteristics of the audience who selected it, rather than self-reports tied to a specific experimental context.

To characterize the content of these movies, we automatically annotated each film for the presence and narrative importance of the 32 narrative ingredients listed in Table 1. Each ingredient corresponds to a specific cognitive or motivational mechanism (e.g., curiosity, fear, care, status-seeking) and was operationalized using an explicit, theory-driven definition provided to the model. For convenience and readability, the narrative ingredients are referred to in abbreviated form throughout the tables and figures of this paper (e.g., "explores unknown"). However, the definitions used both in the annotation prompt and in the questionnaire administered to participants were longer and more explicit (e.g., "A story where a character explores new environments" for the ingredient derived from the motivation to explore). See Table S0 for a full correspondence table listing, for each ingredient, the underlying motivation, its short label used in tables and figures, and its long-form definition used for annotation and measurement. Movies were rated on an ordinal scale capturing the degree to which each ingredient was absent, marginal, important, or dominant in structuring the narrative.

The annotation was performed using a large language model (GPT), prompted to assess each movie based on its plot, themes, and widely available cultural knowledge. This approach builds on a growing body of work showing that GPT-based models can match or exceed human annotators in cultural and social-science coding tasks, including value classification, ideological labeling, emotion detection, and narrative analysis (97–100). Importantly, these models can perform such tasks in a zero-shot manner, without task-specific fine-tuning, while remaining sensitive to subtle conceptual distinctions defined by researchers (97, 99, 101, 102).

The use of GPT for narrative annotation is further supported by previous applications to cultural products. In the domain of video games, GPT-generated ratings of agency and exploration closely matched players' subjective experiences, providing evidence of construct validity (103). In literature, GPT has been shown to reliably identify imaginary worlds and related narrative features across large corpora, yielding results consistent with manual coding as well as alternative computational approaches such as embedding-based similarity and supervised classifiers (24, 25, 103). Moreover, earlier work established that GPT possesses sufficiently detailed knowledge of widely distributed films to support systematic annotation at scale (25, 104).

Taken together, these findings support the use of GPT as a scalable and theoretically controlled tool for annotating narrative ingredients in movies (106). This approach enables the systematic analysis of large cultural datasets while preserving fine-grained distinctions between psychological mechanisms, which would be difficult to achieve through manual coding alone.

Material

We assessed personality traits using the Ten-Item Personality Inventory (TIPI), a brief and validated measure which uses pairs of adjectives to capture each of the five personality domains (107). We also collected demographic data, including participants' age, gender, and socio-economic status (see Supplementary Materials).

We designed a questionnaire to measure story preferences using Dubourg et al.(108)'s Table of Ingredients, which identifies minimal narrative features that attract attention because they engage specific cognitive mechanisms (i.e., narrative 'ingredients'). To validate the Ingredient Questionnaire, which is a tool designed to measure story preferences across these ingredients, we first conducted a preliminary validation study (N=395 participants), prior to the pre-registration of the present article (see Supplementary Materials for the full results).

In this Ingredient Questionnaire, we asked participants, for each of these ingredients, to imagine it within a larger story and to rate how interested they would be in this element, all other things being equal and assuming the element is well executed. For example: "How interested would you be in the following stories? A story where a character explores new environments" (see Table 1 for the full Ingredient Questionnaire). Participants are then invited to respond using a Likert scale with the following values: "Uninterested", "Slightly interested", "Moderately interested", "Fairly interested", "Very interested", "Extremely interested."

In the preliminary validation study, participants reported that rating the ingredients was easy, with responses significantly above the neutral midpoint. Internal validity was supported by high consistency between original and slightly reformulated items (mean ICC = 0.72; 0.83 excluding moderate ratings), while test–retest analyses over two weeks showed moderate to good reliability (ICCs = 0.42-0.73). Crucially, external validity was confirmed by showing that ingredient preferences predicted the presence of those ingredients in participants' favorite fictions ($\beta = 0.25$, $p < .001$); in other words, participants' stated preferences reliably tracked the narrative ingredients present in the stories they actually consumed and enjoyed. Finally, we retained only the ingredients that significantly predicted their presence in participants' favorite stories. For example, participants who reported liking curiosity-related elements tended to list stories that actually had curiosity-related ingredients, so we kept curiosity; in contrast, familial love was excluded, as reported preference for family-related ingredients did not translate into significant associations with family themes in favorite stories. This procedure yielded a final set of 32 ingredients (see Supplementary Materials for detailed methods).

Participants

Participants were recruited through the CINT platform, following the preregistered plan to obtain representative samples from 23 countries. In total, 300 participants per country were targeted, but larger numbers were recruited to ensure sufficient sample sizes after exclusions. Due to a platform error, an especially large sample was collected in France. The final numbers of participants per country were as follows: France (1,626), Indonesia (855), Czechia (404), Argentina (341), Thailand (324), Turkey (310), India (306), Peru (305), Sweden (303), Mexico (302), Poland (301), Brazil (300), Romania (300), Malaysia (299), Kazakhstan (298), Kenya (294), Australia (290), Morocco (287), Serbia (285), United States (284), United Kingdom (283), South Africa (281), and Ghana (215). This selection provides coverage across all continents and a wide range of HDI levels, thereby ensuring cultural and socioeconomic diversity in the sample (see Supplementary Materials).

As pre-registered, only participants who successfully passed the Instructed Response Item (IRI), spent at least 120 seconds on the survey, and completed the entire questionnaire were retained for analysis. We also removed respondents identified by Qualtrics' reCAPTCHA system as potential automated or bot entries. This ensured that the dataset is restricted to human participants who engaged meaningfully with the survey. In addition, although not preregistered, we excluded participants who reported a height below 140 cm or above 220 cm, as such values are implausible and most likely due to input errors (i.e., selecting the first or last option in the drop-down menu). Results were only marginally different with or without this additional filtering (see Supplementary Materials).

Predictions

In this study, we hypothesized that the same psychological motivations that link personality traits to real-world preferences also shape individuals' preferences for fictional content. Research in personality psychology has consistently shown that Big Five traits predict interests and behaviors across a wide range of life domains. Here, we extended this framework to fiction by asking whether these traits similarly predict preferences for specific narrative ingredients, depending on how the underlying motivations vary with personality.

To formulate predictions, we relied on the Ingredient Table (108), which identifies a set of motivations that make particular story elements appealing. For each motivation, we systematically reviewed the personality psychology literature to identify studies testing how its sensitivity varies across individuals. For example, the authors identify curiosity as a distinct motivation, and thus as a corresponding narrative ingredient that captures the appeal of curiosity-driven stories. Prior work shows that curiosity in real life is reliably higher among individuals high in Openness (31–33), leading us to predict a positive association between Openness and preference for curiosity-related ingredients in stories (92). Similarly, for revenge, prior studies demonstrate that individuals lower in Agreeableness are more likely to endorse vengeful motives (71, 72), yielding the prediction of a negative association between Agreeableness and preference for revenge-related ingredients in stories.

Following this procedure, we derived and pre-registered 49 directional predictions across 32 ingredients, each specifying an association and whether the link should be positive or negative. Table 1 presents the full set of predicted associations, along with the personality traits, the targeted motivation, the expected direction, and the supporting references.

Analyses

For study 1, our analyses addressed two complementary questions: first, whether personality traits systematically predict ingredient preferences across individuals (independent of countries); and second, whether these effects replicate consistently across countries. Together, these tests allowed us to evaluate not only the overall strength of the trait-preference link but also its universality across cultural contexts.

To test our first preregistered prediction, we fitted separate linear mixed-effects models for each trait-ingredient pair, predicting ingredient preference from the relevant personality trait (both standardized). Each model included a random intercept for country, thereby accounting for baseline country-level differences in mean ratings. From each model, we extracted the standardized fixed effect. For negatively predicted associations, we then reversed the sign of the coefficient, so that all effects were aligned in the expected direction. We then calculated the mean of these sign-adjusted coefficients across all predicted associations, which provides a global estimate of the extent to which personality traits shape story preferences.

To assess robustness, we implemented a bootstrap procedure: participants are resampled with replacement (1,000 iterations; within-country stratified bootstrap), all mixed-effects models are re-estimated, and the mean sign-adjusted coefficient is computed for each iteration. This generated a bootstrap distribution of the mean trait-preference effect, from which we derived a 95% confidence interval. As preregistered, we expected this interval to exclude zero, indicating that personality meaningfully predicted fictional preferences across individuals, even after accounting for country-level variation.

To evaluate cross-cultural stability, we replicated the same procedure within each country independently. For each country, we computed the mean of the sign-adjusted Pearson correlations across all predicted trait-ingredient pairs, again reversing the sign for negatively predicted associations. A bootstrap procedure (1,000 resamples) provides a 95% confidence interval around each country-specific mean. Our preregistered prediction was that these intervals would consistently exclude zero, supporting the view that the alignment between traits and fictional preferences reflects universal patterns in the co-variation between psychology and culture.

For Study 2, our analyses addressed whether the same preregistered associations between personality traits and narrative ingredients observed at the individual level would also be detectable in aggregate cultural choices, using movies as the unit of analysis. Because ingredient ratings are ordinal and our theoretical predictions concern cases in which an ingredient plays a sufficiently important role to plausibly structure the narrative, we relied on a threshold-based group comparison rather than assuming linearity.

For each ingredient, movies were divided into two groups: movies in which the ingredient was very important or dominant (score ≥ 5) and movies in which the ingredient was not dominant (score ≤ 4). For each preregistered trait–ingredient pair, we computed the difference in mean personality scores between the high-ingredient group and the not-high group, yielding an estimate of whether movies strongly characterized by a given ingredient tended to be liked by audiences higher or lower on the relevant personality trait. To ensure that each comparison was informative, confirmatory analyses were restricted to ingredients with sufficient prevalence, defined a priori as having at least 30 movies in both groups.

As in Study 1, effects were then sign-aligned so that positive values consistently indicated support for the preregistered prediction: for associations predicted to be negative, the sign of the mean difference was reversed. We then computed the mean sign-aligned effect across all preregistered associations, providing a global estimate of the correspondence between personality traits and narrative ingredients at the population level.

To assess robustness, we implemented a movie-level bootstrap procedure. Movies were resampled with replacement (1,000 iterations), and the entire analysis pipeline—including group assignment, computation of mean differences, and calculation of the mean sign-aligned effect—was repeated for each bootstrap sample. This yielded a bootstrap distribution of the mean aligned effect, from which a 95% confidence interval was derived. As preregistered, we expected this interval to exclude zero, indicating that personality traits systematically predict narrative ingredient preferences even when measured through large-scale, naturally occurring cultural choices rather than individual self-reports.

For study 3, we tested whether the co-occurrence structure of narrative ingredients in films mirrors the co-preference structure across individuals. We computed two 32×32 Spearman correlation matrices: a movie matrix capturing ingredient co-variation across 574 films, and a preference matrix capturing ingredient co-preference across 9,201 participants. Both were converted to distance matrices ($d_{ij} = \sqrt{2(1 - r_{ij})}$). We assessed their correspondence using a one-sided Mantel test (Spearman statistic; 9,999 permutations). To test cross-national replication, we repeated this procedure within each of the 23 countries using country-specific preference matrices. Hierarchical clustering (Ward linkage, $k = 5$) on the movie distance matrix was used for visualization only.

Note that, because each trait-ingredient association corresponds to an independent directionally preregistered prediction grounded in prior literature, we did not apply corrections for multiple comparisons.

Author Contributions: E.D., V.T., and N.B. conceptualized the study. T.B. conducted the literature review and compiled the set of preregistered predictions. R.F. drafted the preregistration and contributed to the design of the statistical analyses. G.D. and C.C. coordinated and implemented the data collection procedure. G.D. managed participant recruitment and performed the initial data cleaning. E.D. conducted the final data analyses. N.N. performed the analyses for Study 3. C.C. and N.B. provided supervision throughout the project and funded the project. E.D. wrote the first draft of the manuscript, and all authors contributed to the final version.

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