Uncovering the Personality of Human Brands Through Deep Learning

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Abstract for PhD

Uncovering the Personality of Human Brands Through Deep Learning

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Brands today are built around people as much as products. Human brands invite social reading, audiences respond to traits, intentions, and authenticity, not just to functional attributes. Thus, tools designed for products do not fully capture how audiences read and respond to people, especially celebrities. I develop a text-based personality measure for human brands by integrating Aaker's brand personality framework with the Big Five personality traits. The measure is trained on multiple language corpora using LIWC-style features and transformer embeddings and evaluated with five-fold cross-validated mean accuracy scores. The results show significant improvement over existing methods.

Chapter 2 of this study applies this measure to the film industry, testing the hypothesis that persona-role congruence can serve as a predictor of box office revenues, particularly with respect to recognition- and genre-specific influences. Outcomes are estimated for opening weekend and domestic totals with rich controls and clustered standard errors. The results show that persona-role congruence, on its own, is not predictive; it becomes informative only when contextualized by genre and artistic recognition, which frame audience expectations. Genre sets which traits matter (some reward congruence, others favor incongruence, some are indifferent), while artistic recognition tends to reward stretch over sameness, reducing the payoff to holistic congruence for recognized actors. In that context, congruence works chiefly as an early heuristic: effects are stronger at opening weekend and often fade over the full run.

In summary, the rigorous methodological framework developed throughout this work proposes an innovative method to measure human brands on Big Five personality traits with greater efficiency and accuracy and represents a substantial rethinking of how personality assessments are conducted for human brands, particularly in the film industry. By combining empirical measures with established psychological theories, the study provides an operational tool and actionable insights for filmmakers and marketers on casting, positioning, and communication decisions in an expectation-driven and time-sensitive market.

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I owe special thanks to my brother, whose constant support and patience carried me through difficult moments. Finally, I am deeply grateful to my parents for their unconditional support, trust, and sacrifices throughout this long and demanding journey.

Dedication

This dissertation is dedicated to my mother, **Manijeh**, my father, **Mohammad**, my brother, **Meisam**, and my friend **Shiva**, in recognition of their support, patience, and presence throughout this journey.

Table of Contents

List of Tables

List of Figures

Chapter 1: Development of a Personality Extraction Measure

1. Introduction

Brands have long been central to marketing practice and research, traditionally defined as names, terms, symbols, or designs intended to identify and differentiate the goods or services of one seller from those of others (D. A. Aaker, 1991; Brodie & De Chernatony, 2009; Keller, 1993; Rowley, 2004; Webster et al., 2004). Within this classic view, brands serve primarily as identifiers of products, encapsulating associations related to quality, value, and functional benefits.

Over time, however, branding theory evolved to recognize that brands also carry symbolic and emotional meanings that shape consumer perceptions and relationships (Escalas & Bettman, 2005, p. 2006; Hammerl et al., 2016; Jamal & Goode, 2001; Thompson et al., 2006; Xara-Brasil et al., 2018). Building on this evolution, scholars began conceptualizing brands as possessing human-like characteristics, a development that led to the notion of brand personality (J. L. Aaker, 1997; Grohmann, 2009). This framework posits that consumers perceive brands as having distinct personality traits, much like individuals, which influence consumer preferences, trust, and loyalty (J. L. Aaker et al., 2001; Brakus et al., 2009; Johar et al., 2005; Thomas & Sekar, 2008; Udomkit & Mathews, 2015). Parallel to this development, the digital era and the rise of social media have transformed branding practices by allowing individuals, such as celebrities and influencers, to be marketed as human brands (Lunardo et al., 2015; Calvo-Porral et al., 2021; Parmar & Mann, 2021, 2024).

This paradigm shifts from traditional product brands to human brands, exemplified by celebrities, movie stars, sports icons, and influencers, has become increasingly prevalent in marketing strategies. These emerging brands embody personal values and narratives that resonate on a relational level with consumers, blurring the boundaries between professional and private spaces (Eng & Jarvis, 2020; Kennedy et al., 2021; Morhart et al., 2015). This demonstrates that branding is no longer merely about superior functional, tangible attributes; it also encompasses the subjective, emotional connections consumers form with a brand representative. Effective celebrity endorsements, for instance, can enhance the perceived value of brands by transferring positive associations from the celebrity to the brand (Kutlu, 2022; Özer et al., 2022; Jun, 2024; Jabbar et al., 2024). Likewise, the notion of "being true to oneself," often articulated through personal branding strategies, shown to cultivate consumer attachment by fostering an image of sincerity and relatability that appeals to consumers' desire for connection and authenticity (Ilicic & Webster, 2016).

Taken together, this evolution underscores a broader shift in which human brands not only cultivate their own reputations but also their decisions, public personas, and interactions form part of a deliberate personal branding strategy that can directly affect perceived brand equity, consumer attachment, and loyalty (Thomson, 2006; Wohlfeil & Whelan, 2012; Wohlfeil et al., 2019; Osorio et al., 2020). This shift also transforms how I conceptualize brand meaning and measurements, since existing methods often fail to capture the distinct, dynamic characteristics of human brands adequately (Rushton & Irwing, 2008; Eisend & Stokburger-Sauer, 2013; Eisend & Stokburger-Sauer, 2013).

Despite the growing prominence of human brands, no existing study has yet thoroughly investigated the application of brand-personality frameworks to human brands. Given the proven impact of such frameworks on brand extensions, co-branding, and customer attachment in product brand context, this gap motivates a tailored measure that accounts for the unique aspects of human brands. Classic brand-personality scales (Aaker), although extensively applied and validated within product-centric setting, encounter limitations when adapted to human brands. Thus, adapting and refining traditional brand personality framework for use with human brands becomes not just relevant but essential.

Accordingly, the Big Five scale, which is one of the most widely used human personality model in the psychology literature, provides a rigorous basis for assessing personality traits in psychology and marketing, supported by strong reliability, validity, and cross-study comparability (Goldberg, 1990; McCrae & John, 1992; Pervin & John, 1999). Adopting the Big Five offers two advantages: (1) conceptual fit with human brands and (2) commensurability by situating human-brand personality in the same trait space as other human entities.

However, there are practical measurement constraints to employing such frameworks. For example, it is neither feasible nor scalable to ask human brands to complete standardized surveys. One innovative approach to overcome this limitation is by leveraging extensive secondary textual data (e.g., interviews, press coverage, social media, long-form profiles, scripts, and related communications) which are abundantly available online, to infer personality consistently and at scale.

To address this gap, I propose a unified, text-based deep-learning measure that maps language to the Big Five personality measures within the brand-personality framework. In this first chapter, I will delve into development of such method and proceed to validating the measure on two datasets to establish construct coverage and benchmark its performance against existing models. The significance of developing this new measure lies in its potential to enhance the strategic management of human brands in several key areas: brand alignment, market positioning, and audience engagement. By accurately assessing and articulating the personalities of human brands, marketers can achieve a deeper, more resonant connection with audiences, ultimately influencing brand loyalty and market performance. This frames my primary research question about designing and validating this integrated measure for human brands.

Research Question. To design and validate a new text-based brand personality measure that incorporate brand personality framework with the Big Five personality traits to effectively capture the essence of human brands from their secondary textual data.

The framework aims to bridge the theoretical and practical disconnect between the existing brand-personality concept and the distinctive attributes of human brands, offering a more appropriate tool for marketers and brand strategists in the growing field of human-centric branding. This chapter thus provides a reusable baseline for future applications and comparative evaluations. In the next chapter, I demonstrate a practical application of this measure in film, where actor personalities may predict audience response and impact market outcomes, providing a baseline for future applications. Together, these steps turn a conceptual gap into a testable model with clear success criteria.

2. Literature Review

Celebrities' capacity to shape consumer perceptions and behavior significantly extends their impact beyond mere entertainment into influential human brands, making them pivotal in modern marketing strategies (Keel & Nataraajan, 2012; Luo et al., 2010). Celebrities have become pivotal in endorsements, leveraging their personal credibility and popularity to shape consumer perceptions and stimulate purchase intentions and drive brand loyalty, particularly in culturally resonant markets (M. Yang & Roskos-Ewoldsen, 2007; Pradhan et al., 2016; Nnamocha & Chukundah, 2018).

The success of celebrity endorsements in elevating brand awareness and driving consumer purchase intentions hinges on several factors, including the celebrity's credibility, the congruence between the celebrity and the product, and their engagement with the brand (Thomas & Sekar, 2008; Choi & Rifon, 2012; Dikcius et al., 2013; Bang et al., 2014; Kang & Choi, 2016). Their ability to authentically engage with audiences makes them valuable assets for brands aiming to enhance visibility and loyalty (Jun, 2024; Schouten et al., 2020, 2021; Till et al., 2008).

While the effectiveness of celebrity endorsements is well documented; with companies leveraging celebrities' authenticity and expertise to shape consumer perceptions and attitudes, enhance brand popularity, and drive loyalty (Pradhan et al., 2016), a considerable research gap remains in adapting traditional, product-focused branding models to human brands.

Consequently, despite extensive research on non-human brands' personality traits and their impact on consumer responses to marketing efforts, the application of these models to human brands has not been thoroughly explored. This lack of research indicates a critical need for a deeper examination into how existing brand personality frameworks can be tailored for celebrity.

2.1. Application of Personality Models in Human Brands

The assessment of brand personality has relied on Aaker's Brand Personality Frameworks, introduced by Jennifer Aaker in 1997, which categorizes brand traits into five overarching dimensions: Sincerity (honesty and genuineness), Excitement (youthful and spirited), Competence (reliable and intelligent), Sophistication (elegant and prestigious), and Ruggedness (tough and robust). These dimensions are foundational in characterizing how consumers perceive a brand emotionally and culturally.

In the evolving landscape of brand personality assessment, traditional Aaker's framework, while foundational, is insufficient alone for capturing the depth and complexity of human-like traits effectively that are critical in today's consumer landscape. This necessitates an integrative approach, employing multi-dimensional evaluative models that encompass emotional, psychological, and personality-driven factors, fostering more effective consumer-brand relationship strategies (Marković et al., 2022; Ramaseshan & Stein, 2014).

An influential alternative highlighted in the literature is the Big Five personality traits framework (Goldberg, 1990), which is extensively used in psychology to describe human personality. The Big Five model, comprising traits of extraversion, agreeableness, conscientiousness, neuroticism, and openness, has been shown to correlate with consumer preference, trust and loyalty, offering a more nuanced approach to understanding consumer preferences (Azzahra et al., 2024; Becker et al., 2012; Cherdchu & Chambers, 2013; Fujiwara & Nagasawa, 2015; Mulyanegara et al., 2009; Tseng et al., 2022).

Additionally, studies have suggested that the Big Five traits influence numerous aspects of consumer behavior beyond loyalty, such as ad appeal engagement and the sharing of branded content (Kulkarni et al., 2019). Research also indicates that these personality dimensions significantly shape consumer behavior, particularly in terms of brand attachment and loyalty (Damaschi et al., 2025; Matzler et al., 2006). This framework captures a broader range of psychological nuances that are related to brand trust, preference, and the emotional resonance that brands evoke in individuals (Purnamabroto et al., 2022).

Consequently, developing a personality assessment tool grounded in the Big Five theory has the potential to enhance celebrity brand assessments. Given that celebrity endorsements often leverage personality traits to forge connections with consumers, aligning celebrity brand personalities with consumer preferences through the Big Five framework could yield significant insights into brand loyalty and consumer behavior (Chaudhuri & Holbrook, 2001; Maehle & Shneor, 2010).

Furthermore, studies on coherent mapping between Aaker's dimensions and the Big Five traits, provide a solid foundation for developing a more comprehensive method for human brand personality detection, correlating sincerity with agreeableness, excitement with extraversion, and competence with conscientiousness (Arora et al., 2021; Lin, 2010; Mulyanegara et al., 2009; Udomkit & Mathews, 2015). As suggested by Dikčius et al., various dimensions of human personality, represented by the Big Five model, can be mapped to brand personality dimensions, offering a framework through which brands can enhance consumer connection and loyalty (Dikcius et al., 2013).

This model seamlessly combines the psychological depth of the Big Five with the market-oriented insights of brand personality framework, offering a comprehensive approach that enhances the accuracy and applicability of personality assessments in celebrity branding. By incorporating this model, the analysis of human brand personality benefits from both the empirical robustness of the Big Five and the strategic insights of Aaker's framework, ensuring a thorough and effective evaluation of celebrity brands in the context of consumer interaction and market dynamics. This dual approach not only enriches the theoretical underpinnings but also bolsters practical applications in branding and marketing.

2.2. Technological Advancements in Personality Assessment

The integration of deep learning and Natural Language Processing (NLP) technologies into personality assessment has ushered in a new era of enhanced accuracy and depth for understanding personality traits. These technologies are able to process and analyze vast amounts of unstructured text data from social media and other digital platforms, providing opportunities to identify intricate patterns and nuances related to human personality, which addresses some limitations of traditional assessment methods. These technologies excel at processing large datasets of unstructured text frequently found on digital platforms, where human brands often interact.

Research by Sikström et al. (2024) emphasizes how NLP methods can facilitate more objective personality assessments by analyzing everyday language and communication styles, thereby reducing the impact of cognitive biases often present in self-report measures. NLP methodologies are particularly influential in identifying emotional content and sentiment within textual data. Researchers like Markon et al. (2005), have articulated methods for analyzing emotional undertones in communications, which can be crucial for developing models that assess personality traits and emotional states. This capability is critical for creating accurate models based on a variety of textual inputs ranging from casual social media interactions to more formal communications.

The lexical hypothesis, first articulated by Galton (1950), serves as a foundational principle for these advancements, positing that language usage can reflect significant personality traits. Yoon et al. (2024) indicates that natural language can be effectively analyzed to quantify personality traits from linguistic statistics derived from daily interactions. This concept aligns with findings from Azkhosh et al., (2020), which discuss how machine learning approaches can enhance personality assessment. By analyzing this rich data, deep learning and NLP models can identify complex patterns and nuances in data, significantly reduce the impact of human biases and cognitive fallacies, which are essential for accurately deciphering the intricate personality aspects that traditional models might overlook (Bleidorn & Hopwood, 2019; F. Hu & Trivedi, 2020; "Machine Learning Approach to Personality Assessment and Its Application to Personnel Selection," 2021).

Machine learning algorithms have been increasingly utilized in personality assessment, enabling automated data extraction, cross-validation, and predictive modeling, enhancing both the process and its outcomes. Recent studies have demonstrated the effectiveness of deep learning-based methods in extracting personality traits by minimizing the need for manual feature engineering and the adoption of linguistic (Abdurahman et al., 2024; Azzahra et al., 2024; Devlin et al., 2018; Leonardi et al., 2020).

NLP methods have proven instrumental in extracting emotional content, sentiment, and personality traits from textual data, including social media posts (Islam et al., 2024). These techniques are critical for successful personality trait prediction models, highlighting the importance of linguistic cues for automatic personality recognition in accurately assessing personality traits in conversation and text data (Deb et al., 2021; Mairesse et al., 2007; Miller et al., 2019).

Research leveraging NLP has effectively derived personality profiles from online interactions, demonstrating how linguistic patterns correlate with recognized personality frameworks such as the Big Five traits. Studies have shown that specific linguistic cues in social media posts and digital communications can significantly predict personality traits, aligning well with established models like MBTI Personality dimensions and the Big Five (Golbeck et al., 2011; Khan et al., 2020; Schwartz et al., 2013). Additionally, machine learning algorithms have also been used to predict Big Five personality traits from Arabic tweets, demonstrating the effectiveness of these techniques in analyzing social media textual data (Alsubhi et al., 2023).

The synergy between machine learning and traditional personality scales has enriched my ability to interpret complex datasets. This integration adapts dynamically to the evolving ways people communicate online, ensuring that personality assessments are both accurate and relevant. This dynamic adaptability is essential for maintaining the accuracy and applicability of personality assessments in diverse digital environments (Arora et al., 2021; Tirunillai & Tellis, 2014). Moreover, the application of deep learning facilitates continuous updates and refinements in personality assessment models, allowing them to evolve with the changing patterns of online communication. The ongoing adaptation of these models is supported by further research that applies text mining techniques to reveal brand associations and their evolutions in user-generated content, enhancing my understanding of how brands and individual personalities are perceived and interacted with online (Paschen et al., 2017; Ranfagni et al., 2021).

In summary, the combination of deep learning and NLP not only improves the accuracy and efficiency of personality detection methods but also ensures that these techniques are adaptable to the rapidly changing landscape of digital communication. As these technologies continue to evolve, they promise to further enhance my understanding of personality dynamics, offering more personalized and precise analytics for both research and practical applications in various fields.

This review underscores the transformative role of advanced computational techniques in personality psychology, setting the stage for future innovations that could redefine how I understand and interact with digital personas.

3. Methodology

This study builds a supervised NLP approach for measuring human-brand personality, leveraging the Big Five and brand-personality models and validating it on text corpora. The pipeline employs deep learning techniques by combining closed-vocabulary features with open-vocabulary embeddings, trains per-trait classifiers, and evaluates with five-fold cross-validation, using macro-F1 accuracy as the main metric. Utilizing two distinct datasets, "Essays I", and "MyPersonality" for training and validation, this research rigorously applies machine learning algorithms to distill and measure these traits from extensive unstructured text.

3.1. Data Sources

My methodology incorporates a comprehensive analysis of the Aaker and Big-Five personality traits through textual data from two datasets: "Essays I," and "MyPersonality":

Essays I Dataset, compiled by Pennebaker and King (1999), includes 2,468 anonymous essays annotated with the authors' self-reported Big-Five traits. These essays provide rich, qualitative data for linguistic analysis, essential for developing models that map textual features to Big-Five personality traits. Quantitatively, the corpus comprises around 1.66 million words (total tokens = 1,658,317), with a mean of 672 words per essay (median 648), and a vocabulary of 30,043 unique tokens.

MyPersonality Dataset, compiled by Stillwell and Kosinski (2012), features user responses from a Facebook application's personality questionnaire. It bridges self-reported personality traits with natural language use on social media, offering insights into how personality is projected online. At corpus scale, the sample contains 9,917 posts and around 148,673 words in total (mean 15 words per post; median 11), with 15,529 unique tokens.

3.2. Data Integration and Advanced Preprocessing

The methodology begins with standardizing text across datasets and merge features needed for model training. I employed comprehensive text preprocessing, using both basic and advanced techniques to refine and enrich the text data. Key steps include:

3.2.1. Data Augmentation

Model performance in NLP depends heavily on the quantity and diversity of training data. Because many corpora used in personality-trait analysis lack linguistic variety, I applied meaning-preserving data augmentation to increase textual richness while preserving the semantic integrity of the original text (Feng et al., 2021; Gokhale et al., 2022; Kapusta et al., 2024; Wang et al., 2024). Among common approaches, back-translation and random word insertion/deletion can generate variation but often introduce subtle semantic drift or unnatural phrasing. In contrast, I adopted synonym replacement as a more controlled method.

My implementation substitutes selected words with contextually appropriate synonyms drawn from the WordNet lexical database. To prevent semantic distortion, I cap the number of substitutions per sentence and exclude sensitive tokens (e.g., proper nouns and domain-specific terms). For example, the sentence "She is a happy and friendly person," could be augmented to the new "She is a joyful and sociable person." The augmented version and original one carries the same meaning but lexically they are different.

This controlled modification process expands lexical variety without altering the underlying sentiment or trait-relevant information. Practically, when the corpus contained repetitive wording (e.g., frequent use of "happy"), synonym replacement broadened the distribution into variants ("joyful," "cheerful," "delighted"), yielding a richer dataset that improves model robustness and generalization without sacrificing accuracy or relevance.

3.2.2. Data Balancing

Class imbalance arises when certain classes are represented disproportionately, biasing models toward majority labels and degrading performance for minority classes (Haibo He & Garcia, 2009). In personality-trait text analysis, such skew can compromise predictive reliability. For example, in my datasets, Extraversion appears more frequently than Introversion, introducing a systematic imbalance in training.

Multiple strategies exist to mitigate this issue. Oversampling (e.g., duplicating minority samples or SMOTE) can increase minority representation but risks overfitting and adding artificial noise. Class weighting adjusts the loss to penalize minority-class errors more strongly but may underperform when textual diversity is low. Undersampling reduces majority-class size to restore balance but can cause information loss if applied indiscriminately.

I therefore adopt a selective undersampling strategy that prioritizes removal of the shortest, least informative texts from overrepresented classes, reducing redundancy while preserving data richness. Because traits can co-occur in a multi-label setting, undersampling is applied under multi-label constraints: at each step I monitor the full trait distribution and limit unintended shifts in non-target traits. For illustration, if the dataset contained 10,000 Extraversion-labeled samples but only 2,000 with Openness, selective undersampling trims the majority class by removing the shortest Extraversion texts, improving balance while maintaining sufficient variety for robust training.

This length-aware, constraint-guided undersampling mitigates imbalance while preserving text quality, yielding a fairer distribution across traits, and improving model generalization and reliability on all five dimensions.

3.2.3. Data Cleaning

Textual data is inherently messy, often containing inconsistencies, noise, and variations that can hinder effective analysis. The goal of data cleaning is to preprocess text in such a manner that facilitates better insights and model performance. Data cleaning includes comprehensive text cleaning performed to ensure the quality and consistency of the data. This phase includes tokenization; normalization; stop-word removal; lemmatization; named entity recognition (NER); and part-of-speech (POS) tagging.

Tokenization is the initial step in text cleaning, which involves breaking down text into smaller units, commonly referred to as tokens. Tokens can be individual words, phrases, or sentences, depending on the granularity required for subsequent analysis (Manning et al., 2008).

Normalization refers to the conversion of textual data into a standard format to facilitate uniformity across the dataset. This typically involves converting all text to lowercase and removing punctuation and special characters to ensure uniformity (Sproat et al., 2001).

Stop-words are commonly occurring words in a language that often do not contribute significant semantic meaning to the overall content (e.g., "the," "is," "and"). By eliminating stop-words, the meaningfulness of the remaining tokens can be amplified, thereby focusing analysis on more relevant terms (Biber & Quirk, 2012).

Lemmatization is a linguistic process that reduces words to their base or root form considering the context of a word, ensuring that variations are converted to a meaningful base form (e.g., "ran" becomes "run") (Harris, 1954; Plisson et al., 2004) to standardize variations and improve the consistency of the text data.

Named Entity Recognition (NER) is a specialized technique that identifies and categorizes key entities (e.g., names, locations, organizations) within the text to enhance the understanding of context and relevance (Nadeau & Sekine, 2007).

As finally Part-of-Speech tagging which assigns labels to words based on their grammatical roles in a sentence (e.g., noun, verb, adjective) to provide deeper linguistic insights and improve the analysis of sentence structure and meaning (Manning & Schütze, 1999).

3.3. Data Splitting and Embedding

All machine learning pipelines begin with data partitioning; I create train, validation, and test splits that reflect true class distributions. I then derive compact text representations using complementary embedding strategies that capture both contextual meaning and interpretable linguistic cues. These preparations set the stage for the modeling and evaluation steps that follow.

3.3.1. Data Partitioning

Effective model development in NLP depends on partitions that reflect the true class distribution of the population. I therefore used stratified sampling to construct training, validation, and test sets whose label proportions mirror the full corpus, improving robustness and out-of-sample generalization (Kohavi, 1995; H. Liu & Motoda, 2007). For multi-label settings, I applied iterative stratification to preserve per-label and label-co-occurrence frequencies, and I fixed random seeds and enforced group-wise splits to prevent leakage when multiple texts originated from the same source.

3.3.2. Embedding and Feature Extraction Techniques

The complexity of human language necessitates the use of advanced techniques for converting textual data into formats suitable for machine learning algorithms. Among these techniques, BERT (Bidirectional Encoder Representations from Transformers) Embeddings and LIWC (Linguistic Inquiry and Word Count) Feature Extraction have gained prominence.

As the final step of data preparation, I derive model-ready text representations using BERT embeddings and LIWC features. BERT provides dense, context-aware vectors, while LIWC maps words to psychologically grounded categories. Integrating these open- and closed-vocabulary signals yields a compact, comprehensive representation for downstream modeling.

BERT, developed by Devlin et al. (2019), employs the transformer architecture to produce dense vector representations (embeddings) of words that capture their contextual semantics. Unlike traditional methods such as Word2Vec or GloVe that generate static embeddings, BERT achieves dynamic representations by considering the surrounding words in each context. This facility allows BERT to disambiguate meanings based on context and to understand complex relationships and structures present in text.

BERT Embeddings was used in my model to generate dense vector representations that capture the semantic properties of words, thereby facilitating sophisticated analyses of text, such as my classification task.

In parallel, I employed LIWC (Linguistic Inquiry and Word Count) Feature Extraction as a valuable tool for feature extraction that categorizes words into predefined linguistic categories. Originally developed by Pennebaker et al. (2015), LIWC provides insightful psychological, biological, and grammatical analyses by quantifying various linguistic components. This method offers a lens into the emotional and cognitive aspects of communication, thus allowing us to explore psychological states or traits reflected in language.

LIWC's linguistic categories, such as affect, cognition, and social processes, can help unveil the underlying psychological constructs associated with textual data, facilitating analyses relevant to mental health, relationships, and social behavior (Tausczik & Pennebaker, 2010). By integrating LIWC features into my textual analysis framework, I enhanced the understanding of psychological dimensions embedded within language use.

This integrative approach helps my final model to overcome the limitations inherent in either technique when employed independently. While BERT excels in understanding context and generating nuanced representations, LIWC provides structured psychological categories that can complement the depth of BERT embeddings. Consequently, this synthesis has the potential to facilitate more nuanced and accurate interpretations of text data (Biggiogera et al., 2021; Eyrikaya & Dağ, 2025, p. 2025; Maharjan et al., 2025; Tavabi et al., 2021).

By integration of BERT embeddings with LIWC feature extraction I created a robust methodology that takes advantage of both open-vocabulary and closed-vocabulary approaches. This dual strategy not only allows us for a deep linguistic understanding through contextual embeddings but also incorporates psychological insights rendered through LIWC's rigid categorical framework. By uniting these methodologies, my final model could benefit from a comprehensive analysis that yield richer semantic and psychosocial insights.

3.4. Model Selection and Training

For each personality trait, I trained a set of supervised classifiers using the feature representations described earlier (LIWC-style features and BERT embeddings). my goal was to balance accuracy, interpretability, and robustness across heterogeneous signal types, so I evaluated a diverse family of models under a common protocol (five-fold CV; within trait macro-F1 primary, across trait macro-F1 supplementary).

First, I started with fitting base learners, including logistic regression, support vector machines (SVM), random forests, gradient boosting machines (GBM), XGBoost, and multilayer perceptrons (MLP). This diverse set of algorithms was chosen to ensure both accuracy and versatility in predictive modeling.

Logistic regression, widely used for binary classification, was included for its simplicity and interpretability (Cheever & Weiss, 2009). SVMs were employed given their strong generalization performance across classification and regression tasks (Steinwart & Christmann, 2008). Decision trees and random forests provided interpretable yet robust ensemble-based classifiers, with the latter improving predictive accuracy by aggregating multiple trees (Breiman, 2001; Song & Lu, 2015). GBM and XGBoost, both sequential ensemble methods, were used for their capacity to iteratively correct errors and achieve state-of-the-art performance in structured data tasks (AlDahoul et al., 2023; Meharie et al., 2022). Finally, MLPs, as a class of neural networks, were utilized for their ability to capture complex, nonlinear patterns through backpropagation and optimization (Gardner & Dorling, 1998; Murtagh, 1991).

I then estimated a stacking ensemble that combines GBM and XGBoost as base models, with a logistic-regression meta-learner to aggregate their predictions. This leverages complementary inductive biases and typically improves stability and accuracy over any single model. Hyperparameters used library defaults with light cross-validation checks; a full grid search is planned but not included in the current code.

3.4.1. Hyperparameter Tuning

Hyperparameter tuning is a critical aspect of optimizing machine learning models, and in this study, I utilized Grid Search, which systematically explores a pre-defined grid of hyperparameter values to identify the optimal settings for each algorithm. This method ensured that my models achieved peak performance (Bergstra & Bengio, 2012; Kohavi, 1995).

3.4.2. Ensemble Learning

To enhance the accuracy and stability of my predictive models, I implemented ensemble learning techniques, specifically focusing on a stacking classifier. This approach advanced aggregates predictions from multiple base models using logistic regression as the final estimator to synthesize the outputs, typically delivering more accurate outcomes than any individual model (Sagi & Rokach, 2018). By aggregating diverse predictive signals, the stacking classifier enhances overall accuracy and provides a robust solution by leveraging the unique strengths of each base model.

3.4.3. Cross-Validation

To ensure the robustness of my predictive models, I adopted k-fold cross-validation as a method for validating model performance. Dividing the dataset into 'k' partitions allows each segment to be used as a test set while utilizing the remaining segments for training, thereby enabling every sample to contribute to both training and validation phases. I opted for five-fold cross-validation to achieve an optimal balance between comprehensiveness and computational efficiency (Browne, 2000). This technique is instrumental in mitigating bias and variance in performance estimates, thereby fostering the development of reliable models.

3.5. Choosing Model Evaluation Metric

In selecting an evaluation metric, I compared precision, recall, and F1-score for classifying the Big Five traits. Precision is preferable when false positives are costly, whereas recall is critical when missing true positives has higher consequences. The F1-score, the harmonic mean of precision and recall, provides a single measure that balances both and is particularly appropriate for personality assessments that require balancing misses and false alarms.

Because error costs are symmetric in my setting, but class frequencies can be imbalanced, I designate macro-F1 as the primary metric. Macro-F1 computes an F1 score per class (within each trait) and then averages equally across classes, ensuring that no majority class dominates the score. I also report across the five traits macro-F1 as a complementary summary. All metrics are reported under five-fold cross-validation, which helps balance bias and variance and mitigates the effects of uneven class distributions (Chung, 2017; Finkelstein et al., 2021; Ishizaka et al., 2024; Maitín et al., 2020; Pendyala & Kim, 2024) (Pendyala & Kim, 2024; Finkelstein et al., 2021; Ishizaka et al., 2023; Maitín et al., 2020; Chung, 2017).

3.6. Summary

To recap, in this research, three complementary technological layers are employed: Natural Language Processing (NLP), Deep Learning (DL), and Machine Learning (ML).

NLP (Section 1.3.2) provides the foundation by converting raw text into analyzable input through cleaning, normalization, tokenization, lemmatization, stop-word removal, and the extraction of linguistically and psychologically grounded features (e.g., affective, cognitive, and social markers). These steps standardize inputs for downstream modeling.

Building on this, DL (Section 1.3.3) provides context-aware representations via neural architectures (e.g., BERT). These embeddings capture semantic dependencies and nuances beyond surface lexical counts (for example, mapping idiomatic phrases such as "I am over the moon" to heightened positive affect) thereby enriching the representational space for trait inference.

Finally, ML (Section 1.3.4) serves as the primary predictive layer. Supervised algorithms learn statistical associations between these representations (closed-vocabulary LIWC features and open-vocabulary DL embeddings) and established psychological constructs (Big Five), turning subjective inference into scalable, data-driven prediction.

In sum, NLP delivers preprocessing and feature extraction, DL contributes advanced contextual representations, and ML performs prediction. Together, these layers form an integrated framework for automated personality trait extraction from natural language.

This structured and methodical approach culminated in an insightful and empirically grounded interpretation of personality traits as expressed through language. The integration of diverse datasets and rigorous preprocessing, combined with advanced text analysis and sophisticated machine learning techniques, ensures a comprehensive and robust analysis of personality traits from text. The subsequent results will highlight the effectiveness of my models in interpreting personality traits and demonstrate the practical implications of my research in personality trait analysis. Below you can find the end-to-end pipeline for my proposed framework for human brand personality inference from text.

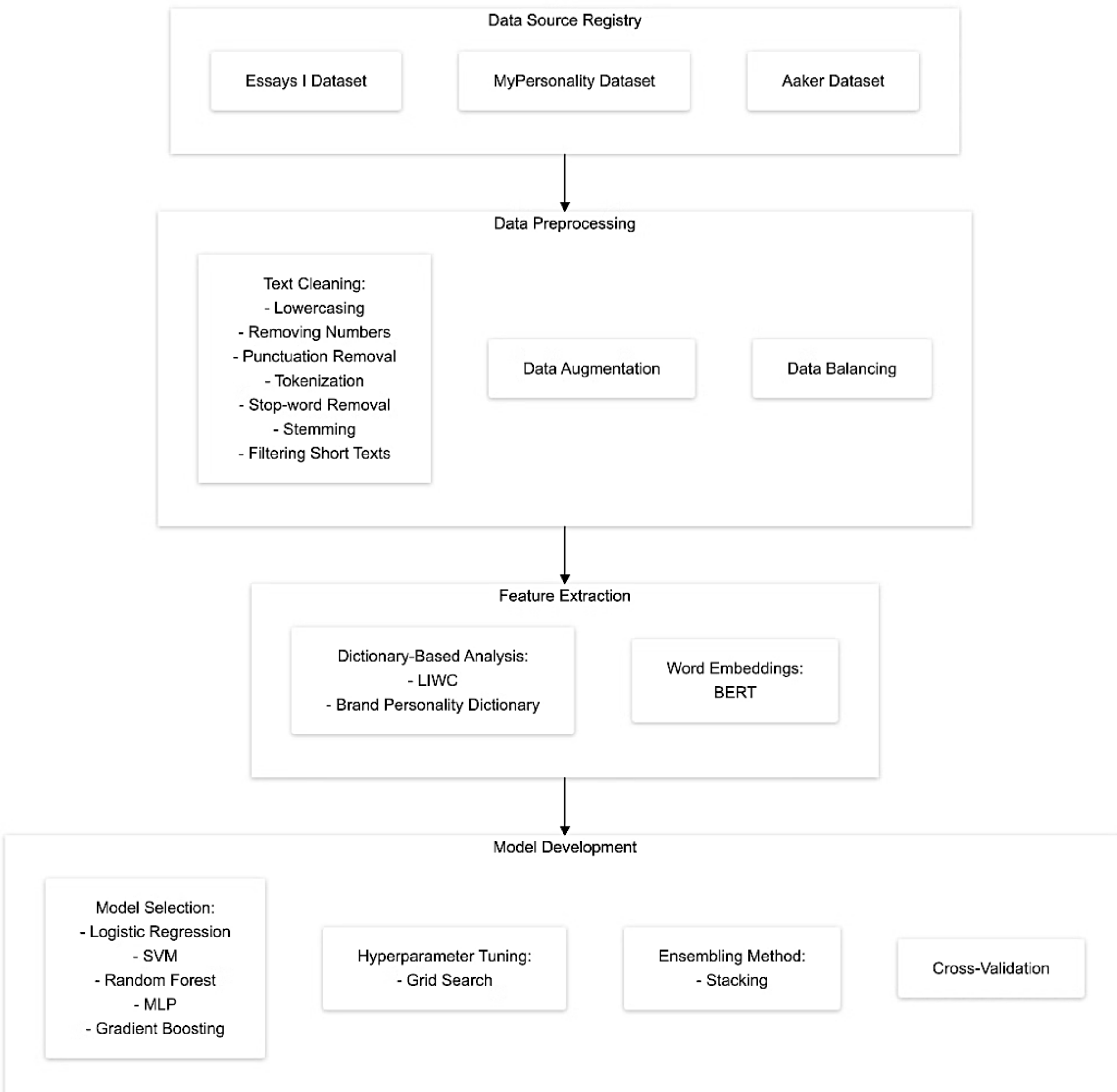

Figure 1. End-to-end pipeline for text-based personality modeling

4. Results

This section compares seven classifiers on human-brand text across the Big Five traits (cEXT, cNEU, cCON, cOPN, cAGR). I report macro-F1 averaged over five-fold cross-validation as the primary metric in the main text; supporting diagnostics (precision, recall, support, micro-F1, and accuracy) appear in the Appendix for transparency. Because prior studies also report trait-wise results, I summarize those for qualitative comparison.

4.1 Analysis of Big Five Personality Traits

Across traits, the Stacking classifier is consistently best on macro-F1 and exhibits low cross-trait variability (SD ≈ 0.57). The Voting classifier is the strongest non-stacking baseline. For Extraversion, stacking attains 73.56 macro-F1, an 8.00-point gain over the best non-stacking alternative (Voting, 65.56). For Neuroticism, stacking reaches 73.35 versus Voting's 67.09 (+6.25). For Conscientiousness, stacking posts 74.13 versus 67.25 (+6.88). For Openness, stacking records 74.35 versus 68.71 (+5.64). For Agreeableness, stacking delivers 72.76 versus 70.00 (+2.76).

Averaged across traits, mean macro-F1 is 73.63 for stacking, 67.72 for Voting, 62.52 for Random Forest, 62.18 for MLP, 61.39 for SVM, 61.20 for Gradient Boosting, and 58.70 for Logistic Regression. Alternative baselines remain in the Appendix for robustness, ablations, and sensitivity checks. Table 1 reports trait-wise macro-F1 by model (five-fold CV) for the Big Five.

Estimation results

Model	cEXT	cNEU	cCON	cOPN	cAGR	Across Traits (Macro-F1)
Logistic Regression	58.12	59.39	62.20	57.59	56.18	58.70
SVM	61.61	62.21	60.73	63.33	59.05	61.39
Random Forest	59.87	65.18	64.51	62.05	60.99	62.52
Gradient Boosting	61.57	61.29	61.34	62.86	58.94	61.20
MLP	60.49	64.89	62.72	62.15	60.62	62.18

Voting Classifier	65.56	67.09	67.25	68.71	70.00	67.72
Stacking Classifier	73.56	73.35	74.13	74.35	72.76	73.63

All values are macro-F1, %.

Table 1. Trait-wise macro-F1 (five-fold CV) and across-traits macro-F1

4.2. Comparative Analysis with Previous Studies

In evaluating the effectiveness of my machine learning models for personality analysis, it is crucial to compare my results with existing studies to contextualize my advancements in predictive accuracy. To contextualize my model performance, I compare trait-wise macro-F1 to representative text-based models. Because datasets, labels, and splits differ, these serve as qualitative context, not protocol-matched benchmarks. Relative to published text-based personality models, my macro-F1 scores are directionally higher. Table 2 presents the cross-paper macro-F1 comparison, and Figure 1 plots trait-wise macro-F1 across studies.

Estimation results

Paper \ Trait	EXT	NEU	CON	OPN	AGR	AVG per Paper
Majumder et al., 2017	55.14	56.53	55.19	59.79	56.74	56.68
Rahman et al., 2019	39.40	40.46	37.19	41.40	41.88	40.07
Kazemimi et al., 2020	56.06	55.68	55.46	55.96	56.03	55.84
Mehta et al., 2020	57.61	60.11	56.08	56.46	58.09	57.67
Tinwala & Ramiyar, 2021	60.32	61.18	60.62	58.85	60.16	60.23
My Model	73.60	73.30	74.10	74.40	72.80	73.64

Table 2. Cross-paper Average model performance comparison for the Big Five

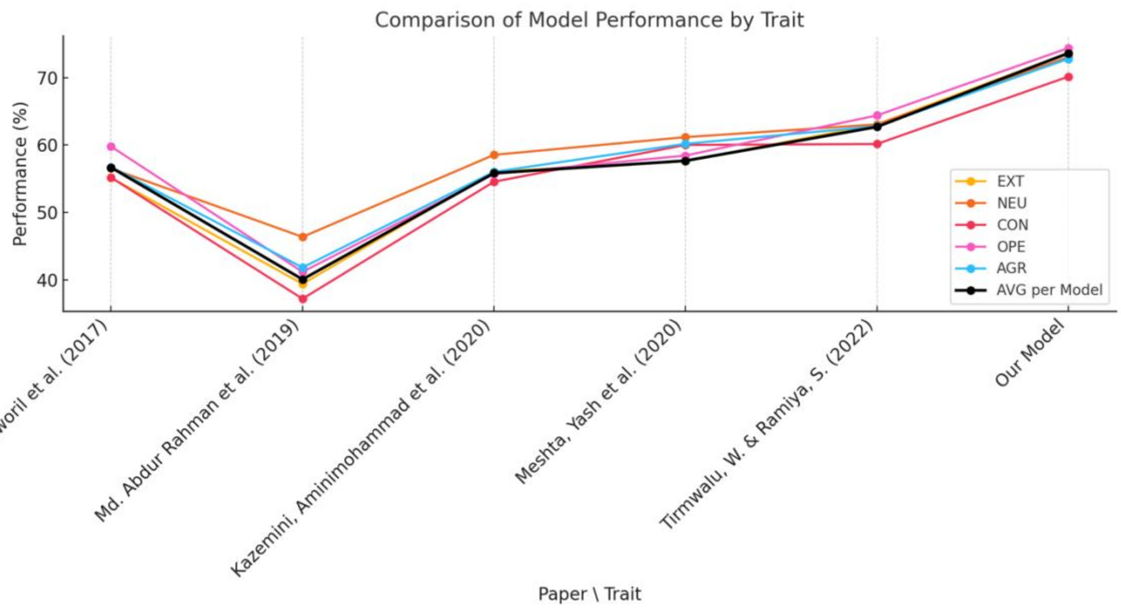

Figure 2. Trait-wise performance across prior studies and this study

The results of my model demonstrate noteworthy advancements over previous studies in the field of personality trait prediction. Relative to Tinwala & Rauniyar (2021), the improvements are 73.03% vs 60.52% for Extraversion (+12.51 pp), 73.41% vs 61.11% for Neuroticism (+12.30 pp), 74.40% vs 60.62% for Conscientiousness (+13.78 pp), 72.88% vs 58.46% for Openness (+14.42 pp), and 73.62% vs 60.16% for Agreeableness (+13.46 pp), averaging +13.29 percentage points across traits. Again, these are directional because protocols differ.

When comparing overall performance across traits, my model achieved an average accuracy of 73.46%, a clear improvement over the range of 56% to 61% observed in earlier research. These findings highlight the effectiveness of my approach, underscoring the advancements in accuracy and practical applicability that my methodology brings to the field. Through enhanced modeling techniques, my work represents a step forward in achieving reliable personality trait predictions for real-world applications.

5. Discussion

Beyond raw scores, the question is what the estimates mean for research and practice on human brands. The text-based measure yields reliable macro-F1 across all five traits, with the largest gains for Openness and Conscientiousness. Because macro-F1 weights classes equally within each trait, it matches my symmetric error-cost assumption and prevents majority classes or traits from dominating headline results. The low cross-trait variability for the top model (Stacking; SD ≈ 0.57) suggests stability suitable for downstream use.

Two patterns in my results point to a complementary-signal view: (i) models using contextual embeddings outperform those relying only on shallow lexical categories, and (ii) the largest gains occur for Openness and Conscientiousness, traits with context-rich linguistic cues. This is consistent with prior findings that transformers capture idioms and long-range dependencies, whereas LIWC supplies interpretable affect, social, and cognitive categories. (Devlin et al., 2018; Sagi & Rokach, 2018; Tausczik & Pennebaker, 2010). The meta-learner in stacking exploits this complementarity, down-weighting regions where base models disagree and emphasizing areas of consensus. This mechanism is consistent with the observed +5–8 pp gains over the strongest non-stacking baseline on four traits (and around +3 pp on Agreeableness).

Trait-level differences are informative. The strongest improvements appear for Openness and Conscientiousness, traits that exhibit clearer linguistic correlates (e.g., variety/novelty expressions; planning/organization markers) that contextual models can represent well. However, the result indicate that the model performance is still lower for Agreeableness whose linguistic signals are diffuse or culturally contingent, consistent with its more diffuse, politeness- and culture-dependent language signals; pragmatic markers (hedging, mitigation, stance-taking) may be more sensitive to platform norms, topic mix, and register than to stable persona.

Compared with aforementioned text-based models, my trait-wise macro-F1 levels are directionally higher. However, as mentioned before, because datasets, labels, and split protocols differ, I treat cross-paper comparisons as contextual rather than protocol-matched. Substantively, the pattern reinforces two points in the literature: (i) naturally occurring language encodes usable trait cues, and (ii) combining contextual embeddings (Bert) with interpretable lexicons (LIWC) improves recovery of those cues relative to single-signal approaches.

Considering the big picture, the findings imply that if text encodes stable trait cues, celebrity brand positioning and audience response can be studied with a level of granularity previously limited by measurement cost (Grunenberg et al., 2023; Kim et al., 2017). The personality prediction model enables: (i) screening of candidate endorsers or cast members, (ii) monitoring of persona drift over time, and (iii) diagnosing persona-context fit before campaign or release. This interpretation links the measurement advance here (Chapter 1) to the market-response tests later. In my thesis, this substantive implication is evaluated later in Chapter 2 in movie industry setting.

6. Contribution to Knowledge

This study advances human-brand research by introducing a scalable, text-based measure that integrates foundational personality theory with modern NLP to infer Big Five traits from naturally occurring language. Grounded in established psychology and implemented with contemporary models, the approach converts public text into trait estimates validated using macro-F1 under five-fold cross-validation. The result is a lower-cost, lower-latency assessment of person-level traits and a replicable infrastructure for analyzing how human-brand personality relates to market contexts, developed in Chapter 2.

6.1. Theoretical Contributions

This study advances personality assessment for human brands by inferring the Big Five (Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism) from public text using modern NLP. This methodological shift bridges personality psychology and consumer behavior by treating linguistic signals as carriers of relatively stable trait cues, enabling scalable, text-based inference at low cost and high pace (Moreno et al., 2021; H. Peters et al., 2024; Youyou et al., 2015).

Conceptually, the work clarifies why the Big Five provide a more appropriate lens for human brands than product-oriented brand-personality scales. Aaker brand-personality scale remains invaluable for organizations and goods, but when applied to people they can blur construct boundaries with brand imagery. Assessing human brands directly on Big Five traits better captures the essence of human brands, yields a theory-consistent representation of person traits, and reduces construct bleed.

Furthermore, using the Big Five to assess human-brand personality yields commensurable measures across studies. Because the Big Five define a human-centric trait space, assessments place entities in a common coordinate system where similarity, distance, and alignment are well defined. This makes congruence (whether between a celebrity and a role; an influencer and audiences; or two collaborators) straightforward to operationalize as comparisons within the same trait space, typically as distances or absolute differences along the five dimensions. This commensurable structure resolves the mismatch that arises when person-level constructs are forced into product-centric descriptors and provides a clearer bridge from personality theory to market-response models.

At the measurement level, the study advances Big Five assessment from text. By combining interpretable lexical features (LIWC) with context-aware embeddings (BERT) and training them with a complementary set of classifiers integrated via stacking, the pipeline captures both pragmatic nuance and psychologically grounded categories within a single estimation framework. The resulting framework improves predictive validity, reported as higher macro-F1 than prior work baselines across all five traits and provides an auditable, refreshable measurement layer that can be extended across domains and over time. In the context of celebrity branding, this constitutes a more precise and reliable operationalization of human-brand personality than existing text-based approaches that rely on a single modeling paradigm.

It is also worth mentioning that the applications of models developed in this chapter can extend well beyond celebrities, human-brands, and following showcases in chapter 2. These models are trained and validated to infer personality traits from any source of big data, which can be used by researchers from various social science fields to interpret personality of social media users, fans, consumers, and online entities for whom textual data are available. With the ever-increasing amount of such data, my model has the potential to contribute to academic research where similar methodological tools are needed.

6.2. Managerial Contributions

For practice, the measure provides transparent, theory- consistent trait profiles that help talent and their teams articulate and steward public personas with clear directional cues grounded in the Big Five. For marketers and strategists, the same profile template support more precise deployment of human brands in co-branding and endorsement decisions, audience targeting, and message framing, as well as early screening for potential misfit before launch.

Because inference is text-based, the system operates at a speed and cadence unattainable with surveys yet remains transparent by reporting macro-F1 as the headline metric (with complementary diagnostics reported in the Appendix). Together, these properties enable decisions tied to engagement, positioning, and purchase intention/behavior without sacrificing interpretability or governance.

Taken together, the theoretical and managerial contributions provide a coherent foundation for studying human-brand personality at scale and for relating trait estimates to contextual performance. The next section outlines the study's limitations and proposes avenues for future work.

7. Limitations and future works

The integration of digital text into personality detection models presents several challenges that may lead to biased or unstable estimates of individual traits. These challenges arise from heterogeneity in cultural context, language use, and data quality. Prior research demonstrates that the digital corpora used to train such models often embed systematic biases that can distort personality predictions (Hashimoto & Oshio, 2024; Thalmayer et al., 2022). Individuals with limited engagement in public discourse may receive "noisy" or unstable trait evaluations, reflecting the unequal representation within training datasets.

Cultural context plays a crucial role in shaping personality signals, as language and topical variations can significantly impact how traits are expressed and interpreted. Lexical cues associated with the Big Five personality traits (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) are sensitive to both linguistic differences and the norms governing their usage across different societal contexts; this variance demands careful consideration of personality assessment methods in diverse cultural settings, underscoring the importance of frameworks that extend beyond Western-centric models (Thalmayer et al., 2022, 2024). As a result, the generalizability of personality inference models across cultural contexts remains constrained, underscoring the need for culturally adaptive or multilingual frameworks.

Moreover, the quality of training data is critical; issues such as class imbalance and measurement errors in ground-truth labels can greatly influence model performance, particularly for traits characterized by ambivalence or complexity in their linguistic expression (Achaa-Amankwaa et al., 2020). Data derived from third-party annotations may be especially vulnerable to inaccuracies, thus highlighting the need for robust validation protocols during model development (Jankowsky et al., 2020). Research indicates that reliance on culturally specific linguistic constructs can undermine the accuracy of personality evaluations due to differential item functioning across varied cultural contexts. Therefore, establishing a universal model for personality detection that transcends cultural boundaries remains an open and critical area of inquiry (Osterholz et al., 2023) due to these multifaceted challenges.

Although this study leverages both long-form essays and short-form social media posts (Mypersonality dataset) to improve coverage and robustness, separate validation using each textual source in isolation is not feasible due to sample size constraints, particularly for the essay corpus, which does not support stable cross-validation on its own. As a result, source-specific performance differences cannot be assessed with precision. More broadly, while the proposed models demonstrate stable performance across traits and low cross-trait variance within the available datasets, their external generalizability is necessarily bounded by the scope of the training corpora. Accordingly, the findings support internal robustness rather than universal applicability. Future research could address these limitations by assembling larger, balanced datasets across distinct communication genres, languages, and cultural contexts, enabling explicit cross-source validation and stronger claims about generalizability.

Relatedly, while the proposed model demonstrates strong predictive performance relative to prior text-based approaches, the present study does not include an independent construct-validation exercise for the inferred personality traits. Cross-validated macro-F1 provides evidence of predictive validity against labeled datasets, but it does not directly assess alignment between model-based trait estimates and human judgments in applied contexts. Future work could incorporate targeted validation using independent human raters (e.g., trained coders or PhD student evaluators) who assess a subset of profiles based on curated textual materials, with raters blinded to model predictions. Such exercises would strengthen construct validity and further enhance interpretability.

In this context, human raters are not treated as definitive ground truth, but as an interpretive benchmark that complements text-based inference. Their role is to assess construct alignment and face validity rather than to replace scalable algorithmic measurement, particularly in applied settings where human judgment itself is subject to variability and bias.

Looking forward, future iterations of the model could benefit from incorporating multimodal data, including video and audio inputs, to capture a wider range of expressive traits, thus enhancing model accuracy. Additionally, improving datasets to encompass more culturally diverse populations could amplify the global applicability of these models, facilitating a nuanced understanding of personality across cultural landscapes. Continuous refinement through real-time feedback mechanisms would also support necessary adaptations with new data, thereby augmenting the relevance and precision of personality evaluations.

In conclusion, addressing the complexities of personality detection in a culturally sensitive manner is crucial for advancing psychological understanding. As research increasingly illuminates the interplay among language, culture, and personality, the development of reliable, generalizable models that effectively traverse cultural boundaries must be a priority. Consequently, careful interpretation of confidence intervals, sensitivity checks, and adherence to established evaluation protocols are vital to ensuring the external validity of personality detection systems.

8. Roadmap to Chapter 2

I now move from the research question's importance to application. With the measurement layer established, Chapter 2 tests whether personality fit predicts market outcomes. The payoff is a tighter bridge from trait theory to box-office behavior; I cross it in Chapter 2. I proceed empirics-first: baseline effects on box-office performance, heterogeneity by genre, moderation by artistic recognition, and persistence from opening weekend to domestic totals, estimated with prespecified controls and clustered standard errors.

Chapter 2: Application of the Developed Measure to Movie Stars

1. Introduction

This chapter explores the application of my personality measure, developed using deep learning techniques, to analyze the personas that movie stars (human brands) project to the public. I apply the model I developed in the previous chapter to a real-world problem where brand perceptions and measurable outcomes meet at scale: cinema. Below, I explain why film is a strong fit for this investigation.

The decision to focus on cinema, rather than other entertainment sectors like music or social media, is driven by three practical features. First, wide reach: theatrical releases are marketed to broad, heterogeneous audiences across countries and age groups. At a global level, cinemas sold roughly 4.8 billion tickets in 2024 (around €28 billion box office; European Audiovisual Observatory, Cannes 2025), underscoring population-scale exposure. Second, standardized outcome measures: box-office metrics (e.g., opening weekend and total domestic grosses) are consistently recorded and comparable across titles and time. Third, rich public language: press kits, interviews, screenplays when available, promotional appearances, and social posts create abundant text that enables trait inference for both stars and (when needed) characters.

Cinema serves as a potent platform where branding strategies can influence consumer perceptions and behaviors, reflecting broader market trends and audience dynamics (Wyatt, 1994). The industry's economic scale reinforces this relevance: the global box office reached about \$33.9B in 2023 and around \$30B in 2024, underscoring a large, measurable marketplace for studying brand effects (Motion Picture Association, 2023, 2023).

The sector's economic and cultural salience makes film a practical testbed for assessing the interplay between personal branding and market success and for linking personality-based constructs to audience connection and purchasing behavior. Furthermore, a unique feature of film is its dual layer of personality: stars act as human brands with enduring personas (Lunardo et al., 2015; Thomson, 2006), while on-screen characters carry role-specific personalities, providing an excellent context to examine human-brand personality and its effects. Additionally, cinema is particularly important for personal branding: stars build and maintain recognizable personas over time, and films both leverage and sometimes subvert those personas to shape expectations and attention.

Much prior research on box-office performance emphasizes factors such as budget, franchise, release timing, competition, and reviews, rather than the perspective of the human brand (Carrillat et al., 2018). Even when movie stars are considered, the focus is often on star power or presence (Hofmann et al., 2017). The literature rarely treats human brands as measurable inputs, and almost never at the level of star-role personality fit. This chapter not only demonstrates the application of my measure, but also addresses that gap by quantifying persona-role alignment (and misalignment) and relating it to market outcomes in the movie industry.

There are plenty of well-documented moments where studios and directors debated whether to align with a star's established persona (persona congruence) or deliberately depart from it (persona incongruence). For Steve Carell in Foxcatcher (2014), Bennett Miller's against-persona choice drew curiosity and skepticism until audiences saw the performance. Miller said he cast Carell despite his comedic image so an unexpected face would make du Pont's menace more unsettling; until then, Carell was known for warm, comic roles; 'mushy centers,' as Miller put it. Likewise, when Heath Ledger was cast as the Joker in The Dark Knight (2008), skepticism extended beyond fans; co-writer Jonathan Nolan later said, “no one got it; the studio didn’t get it.”

Directors aren’t the only ones dealing with persona challenges, actors face the same calculus. A familiar on-screen persona is career insurance: it reassures studios and marketers and reduces audience uncertainty. As a result, some stars actively protect a consistent image even if they’re criticized for repetition or admit frustration with the limits. For example, Jennifer Aniston is often linked to wry, relatable leads and has spoken about struggling to shed her *Friends* persona (Rachel), a classic typecasting bind. These cases spotlight a recurring dilemma for casting decision-makers: exploit a bankable persona, or gamble on an off-type stretch with uncertain payoffs.

Casting is a high-stakes decision under uncertainty. Misalignment can prompt audience skepticism or, when credible, generate breakthrough attention. As noted above, while studios recognize this practical problem, but scholarly work that analyzes movies from a human-brand perspective, and measures persona-role fit at scale, remains scarce and stakeholders, lack scalable, credible ways to quantify persona-role fit pre-release. I address this gap by deriving star and character personality estimates from public language (star interviews; scripts when available) using my personality measure and translating them into pre-release congruence metrics. I then link these metrics to box-office outcome using linear regression models. With these congruence measures in hand, I proceed to my first research question:

Research Question 1. *Does star-character personality congruence relate to box-office?*

This baseline test is central, but congruence does not operate in isolation, its apparent effect can be amplified, muted, or reinterpreted by context. Audiences don’t approach films as blank slates. Prior work shows that pre-release demand is shaped by expectations and cues, and that those priors are not uniform. Two structural elements (genre conventions and credibility signals) guide how audiences read persona-role information.

In film markets, genre functions much like product category: it helps audiences form inferences before experience, just as consumers use categories to set expectations and interpret new offerings. Category theory in consumer research argues that stored category representations shape how people process information and evaluate fit. Furthermore, related schema-congruity work suggests that the degree of match or mismatch with a category prototype steers attention and judgments.

Within film studies, genre is the field's native categorization system. It encodes expectations through a blend of recurrent semantic elements (iconography, situations) and syntactic relations (narrative structures), and it operates by repetition and difference; enough familiarity to cue the schema, enough novelty to sustain interest. In practice, genre shapes audience expectation for tone, pacing, and character tendencies, tightening or loosening what "feels right" before anyone has seen the film. Filmmakers can conform to these norms or strategically subvert them, thereby shaping reception in predictable ways. This leads directly to my second question:

Research Question 2. *How do genre conventions shape the relationship between star-character persona congruence and box-office performance?*

Beyond genre, pre-viewing expectations are also shaped by credibility signals tied to performers. In markets for experience goods like film, audiences rely on observable cues to infer quality. Actor recognition functions as such a cue, raising expectations and framing how a casting choice is interpreted. Actors' prior nominations or wins in major cinema recognitions, including Oscars, Golden Globes (film) and festival honors (e.g., Cannes, Venice, Berlin), can shift attention and recalibrate priors about what a performer can credibly do.

Therefore, alongside genre conventions, artistic recognition serves as a second structural lens for audience pre-viewing judgment, shaping how persona-role information is read before audiences gain experience with the film. This motivates my third research question:

Research Question 3. *How does pre-release actor recognition (awards/nominations in acting categories) shape the relationship between star-character persona congruence and box-office performance?*

Early and later box-office dynamics are not driven by the same forces. Pre-release demand is largely heuristic driven, built on cues such as trailers, genre, franchise status, and star signals to shape opening-weekend box office results. As audiences gain experience, outcomes increasingly reflect social learning via word-of-mouth and audience reviews. Empirical studies demonstrate that review sentiment determine post-opening revenue trajectories.

Taken together, this logic implies that opening weekend captures priors organized, whereas cumulative performance absorbs experience-based learning. Guided by this distinction, I estimate separate outcome models on single dataset for two horizons: opening weekend (OW) and total domestic (TD) box office; to assess whether expectation-driven signals persist, strengthen, or attenuate as experience and WOM accumulate. This framing motivates my final question:

Research Question 4. *How does the effect of persona congruence evolve over time, from opening weekend through the full domestic run?*

Building on my focus on the interplay between stars' on-screen and off-screen personas across settings, I ask whether and when (if at all) alignment helps (e.g., by enhancing clarity and credibility) and when incongruence may be advantageous (e.g., by offering novelty, surprise, or repositioning).

The idea is supported by prior work on authenticity and perceived fit. Studies link perceived authenticity to trust, likability, and marketability (Finkelstein et al., 2021; Fritz et al., 2017) and suggest that alignment between a celebrity's persona and the messages or roles they adopt can shape audience response (Guèvremont & Grohmann, 2018; Rindova & Kotha, 2001; Thompson et al., 2006). In film, such alignment has implications for casting, creative development, and marketing: it can reduce the risk of misfit and help target communication more effectively. At the same time, adjacent literatures suggests that deviations from established persona norms, when presented effectively, can capture audience attention and signal versatility, or facilitate repositioning when credible (Haywood et al., 2025).

This incongruence can yield mixed consequences, indicating a nuanced landscape where both congruent and incongruent portrayals can produce varied audience reactions depending on contextual factors (Ou et al., 2024; Parmar & Mann, 2021). Accordingly, effects can be mixed, and in both directions, so the existing evidence does not offer consistent guidance to studios or to actors. Building on both perspectives, I treat persona congruence and persona incongruence as viable pathways whose consequences depend on context and try to solve the puzzle by deriving the conditions for each impact can be rewarding in practice.

For casting directors and producers, evidence on this interplay can inform role-talent decisions and performance expectations, potentially reducing miscasting risk and downstream costs, and improving audience relatability where appropriate. Movie stars can use these insights to evaluate roles that either resonate with or intentionally stretch their established persona, strengthening their personal brand or strategically refreshing it; such clarity also supports co-branding opportunities that harmonize with (or purposefully reframe) their public image (Luffarelli et al., 2019).

From a marketing perspective, showcasing the practical applications of the new measure provides actionable guidance for positioning human brands, emphasizing personality relatability where it matters and novelty where it pays off. I thus anticipate more nuanced branding strategies that can improve market performance and audience satisfaction.

Guided by the foregoing discussion, I proceed with an empirics-first design: rather than starting from formal propositions, I first characterize the data, estimate baseline associations, and specify two theory-motivated moderators (genre conventions and artistic recognition); later, I formalize these insights into propositions with stated boundary conditions.

I establish a baseline by estimating whether the star-character personality similarity relates to box-office results after accounting for common film determinants (budget, sequel/franchise status, seasonality, etc.). Next, I examine whether this relationship changes across genres, where audience expectations are tighter or looser. I then ask whether artistic recognition reframes how audiences read persona-role information. I also estimate a combined model with both moderators to see whether genre expectations and recognition signals operate additively or jointly. Finally, I study how early expectations carry through over time by contrasting opening weekend with total domestic box office, tracing whether initial cues persist or fade.

In this study, star personality reflects a public persona inferred from off-screen language such as interviews, media coverage, and other public textual materials, while character personality is inferred from linguistic cues embedded in scripts and narrative summaries. Audience perceptions are not directly observed; instead, they are theorized as schema-based inferences formed from these pre-release cues. Accordingly, the analysis models inputs into audience expectations rather than post-viewing perceptions, allowing persona–role congruence to be interpreted as an expectation-setting signal prior to consumption.

I do not find a single "fit always wins" rule. Across specifications, relationships are context-dependent, not uniform. In genres with tighter conventions, both congruence and credible off-type choices can matter; in others, neither shows reliable associations, suggesting story/production factors dominate. Recognition reframes alignment and off-type choices and generally grant more latitude to off-type choices as credible stretches. Signals are strongest at first weeks and typically attenuate over time. Overall effects are modest and heterogeneous, so pooled averages can mask subgroup patterns (aggregation bias), motivating my moderator analyses and separate opening weekend vs. domestic box-office models.

The next section reviews the theoretical foundations like human brands, authenticity/fit, schema-based expectations, and signaling that motivate these steps and inform my hypotheses.

2. Literature Review

To organize the literature for my purposes, this section proceeds in four steps. First, I situate movie stars within human-brand and character-development research and synthesize evidence on their market impact. Second, I narrow to personality congruence, distinguishing actor-persona, character, and narrative alignment and clarifying how fit (and misfit) can shape response. Third, I frame genre and artistic recognition as expectation lenses that guide how audiences read persona-role congruence before viewing and update those beliefs afterward. Finally, I summarize established non-human drivers of box office to delineate scope conditions and controls. Together, this structure motivates my focus on persona-role congruence as a demand-side signal that complements, not replaces, operational factors.

2.1. Movie Stars as Human Brands, Character Development and Their Market Impact

Building on Chapter 1's framing of celebrities as human brands and the study's focus on persona-role congruence, this section situates movie stars within branding theory and synthesizes evidence on their market impact. Prior research shows that strategically leveraging star visibility can enhance recognition and shape attitudes toward embedded brands and the films themselves (M. Yang & Roskos-Ewoldsen, 2007). Extending this logic to demand formation, Luo et al. (2010) argue that a star's brand can influence film demand and that strategic selection and timing of releases can optimize a celebrity's brand equity, thereby maximizing box-office success. Because star branding is culturally and temporally situated, maintaining relevance requires aligning a celebrity's persona with prevailing norms and market cues (Lunardo et al., 2015).

Applying brand personality language to human brands, however, requires care. Human brands embody person traits that do not map one-to-one onto product or corporate imagery. Treating stars as human brands and focusing on their personal traits, while using traditional brand-image frameworks only as support, helps preserve the integrity and appeal of celebrities as brands and sustains both their marketability and the films they endorse). Complementary perspectives from social identity theory and brand anthropomorphism further explain why audiences connect with stars: personifying brands with human-like traits increases relatability and can strengthen consumer–brand relationships (Carlson & Donavan, 2013).

Empirically, star power is economically salient but context dependent. How well actors resonate with audiences, together with director reputation, cast experience, and cast diversity, can drive revenue and shape demand (Antipov & Pokryshevskaya, 2017; Lash & Zhao, 2016; Treme, 2010). Established actors can meaningfully improve a film's prospects; replacing an average star with a top-tier star has been estimated to yield approximately $16.6 million in additional revenue (R. A. Nelson & Glotfelty, 2012). Reputation and familiarity create an initial draw (Elberse, 2007), and likability can elevate perceived quality and satisfaction, contributing to early box-office momentum (Moon et al., 2010).

Star effects also operate through off-screen dynamics. Publicity shocks, from visibility surges to reputational crises, can shift expectations at the margin and subtly affect performance (Elberse & Eliashberg, 2003). Likewise, societal attitudes and behaviors associated with actors (e.g., smoking, or racial views) can shape audience perceptions and, in turn, box-office outcomes (Aumer et al., 2017; Fong & Wyer, 2012; Kasdovasilis et al., 2019). Importantly, while star-studded casts can raise willingness to view and enhance marketability, they do not guarantee success; outcomes remain closely tied to storytelling quality, performances, directing, and overall production values (Hofmann et al., 2017; Simonton, 2009).

Extending this view, audience response and market performance depend not only on who the star is but also on how the character is written and portrayed, and how these elements align. Renowned actors can offer an initial edge and enhance audience engagement, yet their structural placement within the industry and the quality of their collaborative network remain critical to long-term outcomes (Cattani & Ferriani, 2008). In particular, as audiences increasingly favor multi-dimensional, relatable characters, star casting should not eclipse the essential quality of character development. Character personalities thus become a central lever that links star power and story quality, strengthening emotional investment among viewers(Hofmann et al., 2017; Huang et al., 2024).

Empirical work reinforces this interdependence between persona, character, and demand. Initial viewership is often influenced by the popularity of stars, but effectiveness is notably contingent on the strength of the characters they portray (Moon et al., 2010). Historical cases further illustrate how a star's real-life persona can shape narrative choices and deepen audience resonance. For instance, Bruce Lee's influence extended beyond martial arts iconography to directorial and narrative decisions that challenged gender roles and cultural expectations, demonstrating the feedback loop between star identity and character portrayal (Pellerin, 2019; Shimizu, 2020).

Psychological depth similarly matters characters with varied, complex traits engage viewers at deeper cognitive and affective levels, as seen in analyses of franchises such as Star Wars (Hall & Friedman, 2015). These dynamics translate economically. Meta-analytic evidence indicates that both star brand equity and the psychological nuances of character portrayals shape box-office outcomes; audiences' emotional connection to the star-character nexus can amplify financial performance (Carrillat et al., 2018, 2018).

Taken together, the prior subsections point to a simple progression: star brands help attract attention and shape early expectations, while character depth and psychological nuance sustain engagement and evaluations (e.g., Elberse, 2007; Hall & Friedman, 2015; Moon et al., 2010). Audiences also routinely map what they know about an actor onto the roles they inhabit; linking off-screen persona to on-screen portrayal (Moon et al., 2010; Pellerin, 2019). This makes the interplay between a star's perceived persona and the character's portrayal a natural next step: not a new construct, but the junction where previously discussed mechanisms meet on the screen.

2.2. Personality Congruence in the Film Industry

One way to see this interplay is under the broader congruence umbrella; that is, as a family of alignments among actor persona, character presentation, and narrative cues that can organize engagement, emotion, and market response. Importantly, the extensive congruence literature has focused largely on audience self-congruence (alignment between viewers' self-concepts and brand/character signals) rather than actor-character alignment (Malär et al., 2011; Saputra et al., 2020). Within this lens, films that cultivate emotional fit between content and audience feelings tend to elicit stronger engagement; many film clips elicit fair-to-moderate convergence with viewers' emotions, implying that affective alignment can bolster attention and involvement (Scheibe et al., 2023).

Audience processing plays a role as well. Individuals who can moderately infer protagonists' emotions exhibit stronger emotional responses, highlighting the value of congruent emotional storytelling for sustaining interest (Katzorreck & Kunzmann, 2018). Related insights from consumer psychology and branding help explain why these alignments influence behavior. Self-congruence (i.e., the match between audience self-concepts and character or film signals; Ekinci & Riley, 2003 positively affects satisfaction and, by extension, repeat viewership and loyalty (Saputra et al., 2020). In parallel, effective celebrity endorsements and brand placements that align the celebrity's brand personality with film themes can enhance marketing effectiveness and box-office returns (Lin, 2010; Mulyanegara et al., 2009).

Congruence can also shape narrative strategies for different audiences: in children's media, coherence between thematic content and presentation supports comprehension and longer-term discussion of cinematic narratives (Djonov & Tseng, 2025). Taken together, these findings portray congruence as a multidimensional construct (emotional, personality-based, and identity-based) that links star branding, character design, and narrative form to audience perceptions, satisfaction, and commercial performance.

In sum, prior work establishes that movie stars function as human brands that shape attitudes, demand, and early outcomes, while character depth and psychological nuance enhance engagement; and congruence across persona, character, and narrative strengthens emotional response and can boost market performance. In other words, seizing audience interest and achieving cinematic success depend on the melding of a star's personal characteristics with compelling, coherent character personas and emotionally congruent storytelling.

However, the literature leaves open the question of when these effects are amplified or muted, specifically whether the fit between a star's off-screen persona and on-screen character (persona-role congruence) conditions star impact. It also lacks an established, transparent methodology for quantifying these inherently qualitative traits at scale. Accordingly, understanding persona-role congruence in audience perceptions and box-office outcomes requires an all-inclusive view that integrates human-brand theory, character design, and narrative alignment (Carrillat et al., 2018; Hall & Friedman, 2015; Malär et al., 2011; Moon et al., 2010; Scheibe et al., 2023).

Taken together, the literature positions persona-role congruence as a psychologically grounded, demand-side signal that complements, rather than replaces, established non-human drivers of box office. In the analyses that follow, I treat those operational and contextual attributes (e.g., genre, budget, distribution intensity/timing, runtime, sequel status) as scope conditions and controls. Conditional on these factors, I test whether congruence provides incremental explanatory power at the box-office, and whether its effects systematically vary by genre and artistic recognition, two moderators that shape expectations and credibility ex ante.

2.3. Factors Influencing Box Office Success

Before modeling persona-role congruence, I summarize non-human factors that the literature shows predict box office. These variables capture supply-side resources and exposure, category context, franchise position, runtime, and information. Laying out these drivers clarifies where congruence can add value: as a distinct, demand-side match at casting that should complement, rather than substitute for, these established predictors, with heterogeneity by genre and artistic recognition.

A film's box office performance emerges from a layered set of influences that extend beyond the intrinsic qualities of the movie themselves. Prior research documents the importance of operational and contextual attributes to shape revenue potential. Genre emerges as a foundational aspect, with action, sci-fi, and fantasy typically outperform categories such as comedy and drama, reflecting inherent market preferences (Chiu et al., 2019).

In addition to genre, other critical attributes play significant roles in driving box office success. Studies consistently point to attributes such as production budget, distribution planning, release timing, and even awards signals as salient correlates of commercial success (Elliott & Simmons, 2008; Kwak & Zhang, 2011; S. Lee & Choeh, 2020).

The production budget is often a key determinant, where higher expenditures typically correlate with better box office returns. Films backed by substantial budgets not only benefit from enhanced production quality but also afford more aggressive marketing strategies and broader distribution networks, both of which are essential for maximizing visibility and audience reach (Hao, 2023; Pangarker & Smit, 2013). Furthermore, the timing of a film's release is crucial; strategic placement during peak seasons or aligned with significant cultural events can significantly enhance a movie's financial performance (Eliashberg et al., 2007; Pangarker & Smit, 2013).

Film awards, particularly prestigious ones like the Academy Awards, serve as important indicators of quality that can enhance a film's perceived value and marketability. Research indicates that winning or being nominated for these awards can lead to significant increases in box office revenues. Estimates suggest that an Academy Award nomination can add approximately $4.8 million to a film's total earnings, while a win could contribute around $12 million (R. Nelson, 2001; Pangarker & Smit, 2013). Certain awards are more effective signals than others, with awards bestowed by peers in the industry or consumer-based juries having a pronounced impact on audience behavior and box office performance (Gemser et al., 2008).

The total runtime of a film also plays an important role in its box office success. Research suggests that runtime can affect viewer engagement; shorter films are often seen as more accessible, possibly leading to higher viewer turnout. In contrast, longer films may be associated with more complex storytelling, appealing to niche audiences while potentially limiting broader commercial appeal (Simonton, 2002, 2007). Therefore, an optimal runtime strategically aligns with genre expectations and audience tendencies, impacting overall box office performance.

Another significant aspect is whether the movie is a sequel. Research consistently shows that sequels tend to outperform original films at the box office due to pre-established fan bases and recognition. The familiarity associated with sequels can lower the perceived risk for audiences, encouraging more individuals to attend theaters (Chang & Ki, 2005). This trend highlights the strategic advantage that major studios capitalize on when investing in franchise films, as sequels benefit not only from brand loyalty but also from prior audience experiences that can lead to heightened anticipation and stronger opening revenues (Gaenssle et al., 2018; Ryu, 2020).

Marketing strategies are also pivotal in shaping box office outcomes. These strategies encompass a range of factors, including advertising intensity, critical reviews, and audience engagement through online WOM (Basuroy et al., 2003; Chintagunta et al., 2010; Eliashberg & Shugan, 1997; J. Lee & Hwang, 2021; S. Lee & Choeh, 2020). These elements, combined with strategic use of technological advancements and a deep understanding of audience preferences and cultural nuances, are essential for film companies aiming to maximize their box office potential (Duan et al., 2008; Leem et al., 2023).

Prior research documents the importance of information dynamics: online word-of-mouth and consumer reviews exert measurable effects on demand (Y.-H. Hu et al., 2018). Empirical studies consistently show that positive reviews and prior viewer sentiment can materially shape box-office trajectories, underscoring critical reception’s dual role as both an influencer and a predictor of financial success (Y. Liu, 2006).

Cultural considerations further complicate the landscape of film success. Films that resonate with local cultural contexts or align well with prevailing social norms tend to perform better in foreign markets. The concept of cultural discount, introduced by Hoskins & Mirus, (1988), illustrates how the acceptance of films can vary significantly across different cultures, underscoring the importance of cultural relevance in global marketing strategies (Basuroy et al., 2003; F. L. F. Lee, 2006, 2009).

Taken together, the non-human drivers explained above account for much of the variance in revenue. Yet two additional factors (genre, and artistic recognition) do more than merely impacting the box-office: they also act as expectation lenses (filters through which audiences see the film) that can shape how audiences read my key independent variable, perceived persona-role congruence.

Unlike controls such as budget or screen count which alter exposure and resources, these factors work like lenses that prime the audience’s interpretation of “fit.” Genre frames the kind of story audiences think they are about to see (Altman, 2012; Neale, 2005), and artistic recognition frames what they believe an actor can credibly deliver (Rossman et al., 2010; Zuckerman et al., 2003); in short, audiences arrive with a sense of what a film should be and what certain performers can do . Because these lenses color what “fit” looks like before viewing, the next section examines genre (as a schema/category) and recognition (as a credibility/status cue) not merely as revenue correlates, but as expectation templates that guide how audiences interpret the alignment between a star’s persona and a role.

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2.4. Audience Expectations as Lenses for reading congruence

In exploring the dynamics of audience expectations in film, it is essential to recognize that genre plays a critical role in influencing how viewers decode and react to cinematic experiences. Genre serves as a predefined framework through which audiences form expectations about a film's narrative, themes, and stylistic choices. This categorization system is not merely arbitrary; it encodes expectations through recurrent semantic elements such as iconography and narrative structures, effectively guiding audience perceptions before they even engage with the film itself (Barthel-Bouchier, 2012; Friedland, 2016). The concept of "repetition and difference," as articulated by Steve Neale, underscores the balance between familiar genre markers that cue viewer schemas and the innovative deviations that sustain engagement (Neale, 2005).

Research has demonstrated that genre influences audience expectations significantly. For instance, when a film’s genre aligns with prior genre conventions, audiences tend to respond more positively, reinforcing the notion that genre acts similarly to product categories in consumer markets (Hung & Guan, 2020). Moreover, the film industry's reliance on genre classifications enables filmmakers to predict audience reactions, often influencing marketing strategies and box office performance (Barthel-Bouchier, 2012). This relationship between genre and expectation is compounded by the principles of schema theory, which propose that pre-existing mental frameworks guide how new information, such as a film, is interpreted (Ghosh & Gilboa, 2014; Rumelhart, 2017; Van Kesteren et al., 2012). Branigan (2013), applies schema theory to realise how viewers interpret films based on expectations shaped by narrative/genre structures and character construction.

Furthermore, differences in genre characteristics dictate what specific cues an audience might look for in a film's narrative. For instance, action films typically prioritize pace and adrenaline-inducing sequences, aligning with viewer preferences for excitement and urgency (Nowack, 2025), while dramas might focus more on character development and emotional resonance. The interplay between genre expectations and audience engagement can also diverge based on individual differences such as personality traits, suggesting varied audience experiences even within the same genre. Research indicates that individuals with different personality types may gravitate towards distinct genres, affecting their engagement and enjoyment levels (J. Yang, 2023).

Building on prior movie industry's studies, this review uses eight widely acknowledged genres: comedy, drama, action, horror, thriller, documentary, musical, and adventure (Altman, 1999; Neale, 2005). Across these genres, prior work explains how conventions shape audience engagement and platform programming: comedy relies on relatable humor and evolving teen-comedy patterns (Krutnik & Neale, 2006; Montaño, 2021); drama emphasizes character, emotion, and social themes (Plantinga, 2009); action foregrounds physical spectacle and sometimes "mythic" violence, often paired with adventure to heighten engagement and commercial appeal (Tasker, 2004, 2012); horror evokes fear and suspense, appealing to sensation-seeking viewers and adapting to cultural anxieties (Carroll, 2003; Clasen et al., 2020); thrillers sustain tension at the intersection of horror and drama while mirroring societal fears (Rubin, 1999); documentaries aim to inform through truth-claims that enable cultural critique and attract audiences seeking both education and entertainment (Nichols, 1991, 2017); musicals integrate song, dance, and narrative with modern reimagining that maintain broad appeal (Bruckner, 2015; Feuer, 1993); and adventure centers on quest and exploration, frequently interwoven with action (Azizah et al., 2022; Carroll, 2003; Clasen et al., 2020).

In markets characterized by experience goods like films, audiences depend on observable indicators, such as an actor's prior accolades and recognition, to gauge the potential quality of a film before viewing it. Recognition from prestigious platforms, including the Oscars, Golden Globes, and prominent film festivals, serves as a critical cue that informs audience expectations and assessments of an actor's capability, which in turn can significantly shift pre-existing notions about the performance quality within a given film (Dodds & Holbrook, 1988; F. L. F. Lee, 2009; R. Nelson, 2001). Prior studies indicate that skilled actors, specifically those with substantial experience and accolades, are perceived as more capable of elevating the quality of a film (Gemser et al., 2008; Simonton, 2007).

For example, Zhu and Wu (2021) posit that audiences exhibit a higher willingness to engage with films featuring accomplished actors compared to those with less recognized performers, particularly within genres that demand a strong artistic presence, such as patriotic films. This is further supported by findings from Aadland et al. (2020), which highlight how an actor's high-status can enhance audience expectations and attention based on their perceived competence. Additionally, Reschke et al. outline a two-stage cognitive process where audiences first categorize performers based on known expectations before evaluating the distinctions among those categorized, offering insight into how award recognitions influence audience perceptions (Reschke et al., 2018).

Artistic recognition does not merely provide a background; it actively shapes the lens through which audiences interpret performances. For instance, actors who have received significant accolades may recalibrate viewer expectations, creating anticipatory biases that favor their performances. This notion aligns closely with the findings presented by Slavich and Castellucci (2016), who assert that certifications like awards offer useful comparisons in creative industries, influencing public perception and expectations. The high status associated with these awards can inherently lead to a belief in a performer's enhanced competence prior to experiencing their work, as noted by Goldstein and Filipe (2018), who discuss the impact of audience perceptions shaped by actors' prior achievements. Empirical studies show that performers' status and award recognition act as credibility signals that attract attention, raise pre-release demand, and shape audience expectations (Nalabandian & Ireland, 2019; Veenstra et al., 2020). Thus, the structural significance of artistic recognition emerges as a potent mechanism in shaping pre-viewing judgments and broader audience expectations for cinematic experiences.

Empirically, such pre-release heuristics, like genre classification and star salience, have their clearest footprint in opening-weekend outcomes, where category fit and prominence jointly anchor expectations and reduce search costs (Giannetti et al., 2024; Hung & Guan, 2020; Patil et al., 2022). Once viewing begins, those priors are updated through social learning: audience experience accumulates in reviews and WOM, and these public signals recalibrate beliefs about quality and match, thereby steering longer-run revenue trajectories (Chen et al., 2016; Chiu et al., 2019; Nagamma et al., 2015). In practical terms, early demand is expectation-led meaning what viewers infer "at the gate" from genre templates and recognition-based credibility can set the initial path, whereas subsequent performance becomes increasingly experience-led, governed by lived performance and the collective feedback loop of critics and peers (Chiu et al., 2019; Giannetti et al., 2024).

Put differently, the expectation lenses supplied by genre and artistic recognition loom largest before viewing, when audiences, confronting the uncertainty of an experience good, lean on category and status cues to form priors and make go/no-go decisions. Therefore, the distinction between immediate and ongoing audience responses helps to articulate how perceived persona-role congruence is read by audience through genre conventions and audience familiarity lenses and how that reading might evolve over the release cycle.

Taken together, the literature suggests a simple narrative: audiences approach films with expectation lenses; notably genre (which pre-frames story and role schemas) and artistic recognition (which pre-frames performer credibility). These lenses help explain how viewers initially read perceived persona–role congruence and why the same casting can be received differently across contexts. Differentiating immediate from ongoing responses may help clarify the extent to which that initial reading is filtered through genre conventions and familiarity, and how such filtering evolves across the release cycle. Section 3 (Methods) details how I operationalize these ideas (persona and character personality traits from text; genre categories; recognition coding), assemble the data, and estimate models that include the standard non-human controls summarized above.

3. Data & Measures

This section describes the data, construction of personality and congruence measures, and the estimation setup that underpins the empirics-first model sequence reported in section 2.5 (Results). I infer Big Five traits for stars from interview text and for characters from script dialogue, construct trait-match indicators and a summed match count (0–5) and relate these congruence measures to two outcomes; opening-weekend and domestic box office, while conditioning on prespecified controls and fixed effects. The observational unit is the star-role pair within a film, which allows within-title comparison across different characters associated with the same movie.

3.1. Data

My Empirical analysis integrates four datasets to measure personality congruence between stars and characters and relate it to film performance. The unit of analysis is the star-role pair within a film, enabling within-movie comparisons across different characters while controlling for film-level heterogeneity.

The first dataset, *MediaSum*, contains approximately 464,000 media interview transcripts from outlets such as NPR and CNN. I use these interviews to infer actors' Big Five personality traits based on their linguistic patterns in public-facing promotional contexts. In total, the MediaSum subset used here covers 1283 distinct movie stars.

The second dataset comprises *Movie Scripts* sourced from public repositories and licensed collections, providing character-level dialogue that I use to infer the personality profiles of fictional characters across genres and studios. The script corpus includes 2,142 feature-film scripts.

The third dataset, *Acting Credit* (cast-mapping), links films to credited performers and canonical character names (including billing order/lead status). This mapping is the backbone join between interviews and scripts: it resolves actor identities, connects actors to their specific roles in the film, and standardizes character names across sources. These three datasets provide the inputs to infer star and character personalities and to compute star-character congruence. The cast-mapping covers roughly 11,000 films.

Finally, the *Movie Summary* dataset contains movie-level metadata, including box-office outcomes, genre, production budgets, distributor, release timing, and other film-level attributes which are used as dependent variables and covariates. The dataset file contains 23,877 titles and spans films released from 1902 to 2018. Together, these sources allow me to build a unified dataset that maps textual signals to Big Five traits for both stars and characters and links these measures to film outcomes.

3.2. Integration of interviews, scripts, and summaries

I integrate the four sources in three sequential steps: normalize identifiers, link actors to roles, and assemble star-role observations with film-level outcomes.

For interviews (MediaSum), I standardize speaker identities across shows and dates. Because names vary in format (titles, commas, hyphenated surnames), I apply regex-based parsing and normalization to extract canonical name strings and remove descriptors (e.g., “John Doe, Actor”). A random sample is audited to refine patterns and reduce false positives. Multiple interviews per person are then concatenated into a single actor-level interview text.

For scripts, each file is parsed line by line into character-dialogue pairs. I normalize character strings (case-folding, punctuation stripping, alias resolution) and concatenate all utterances by film and character while preserving order markers. The output is an explicit mapping from each film, and character name to that character’s aggregated dialogue, i.e., a per-film, per-character text that represents the character’s full speech in that film.

I then link off-screen and on-screen personas at the role level by cross-referencing films using the *Acting Credit* file. For each film i and each credited lead actor j, I create a star-role record that pairs the actor's aggregated interview text (encompassing off-screen persona) with the matched character's aggregated dialogue (encompassing on-screen persona). Each record contains both actor's and the matched character's text, which I later use to compute star-character personality congruence.

Lastly, I merge the star-role records with the *Movie Summary* dataset by film to append dependent variables and covariates: opening-weekend and domestic box office, genre, distributor, release timing, production budget, and other controls. I retain only titles with complete coverage across interviews, cast mapping, scripts, and summaries. A random audit checks samples of actor-character matches and name normalizations; regex rules and alias lists are refined iteratively as needed. After enforcing completeness across sources, the integrated panel retains 1,673 films and 45,144 star-role observations for analysis.

Below figures compares distributions before and after dataset integration. The post-integration sample shows a far fewer characters per movie (around 2 principal roles) (Figure 3); opening-weekend revenues cluster at higher values (fewer zeros/very low values) (Figure 4); the production window narrows to 1942–2018 (Figure 5); and average theater counts rise (Figure 6). These shifts are consistent with prioritizing films featuring recognized stars and aligning with the movie-star interview dataset.

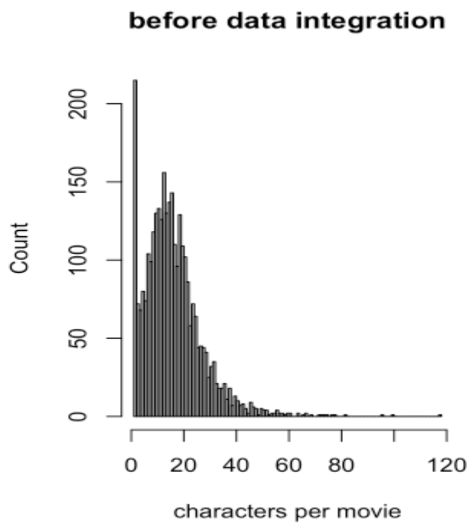

Figure 3. Histogram comparison for character per movie before and after dataset integration

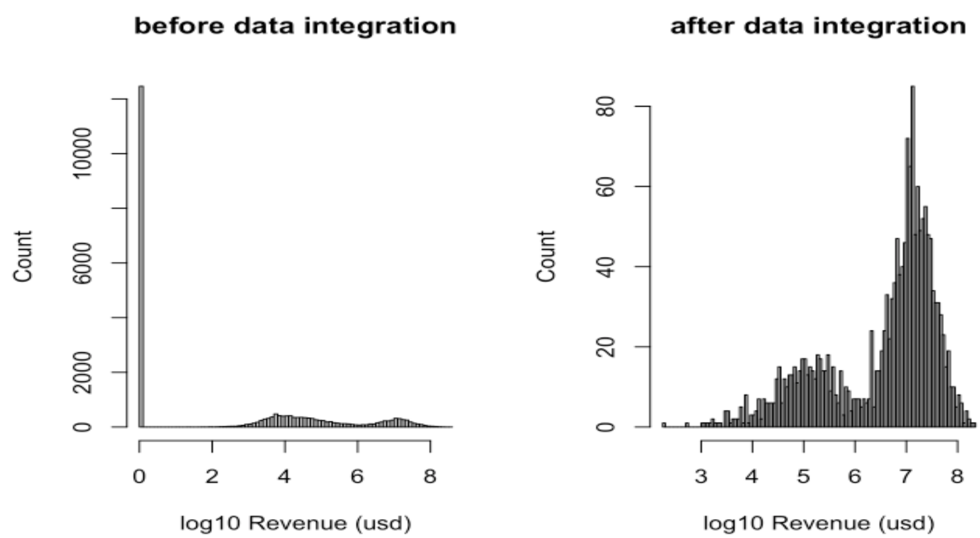

Figure 4. Histogram comparison of opening weekend revenue before and after dataset integration

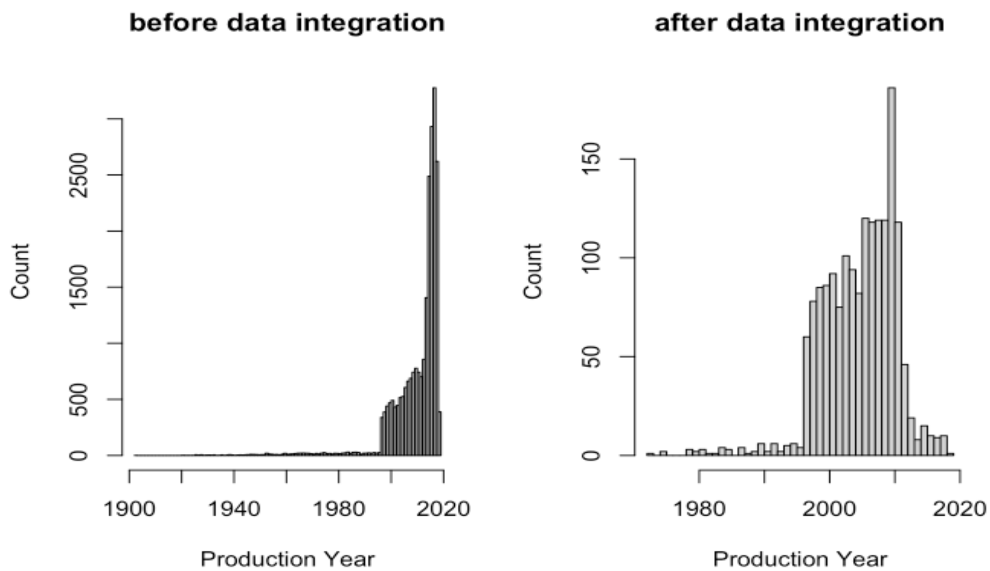

Figure 5. Histogram comparison of Production Year before and after dataset integration

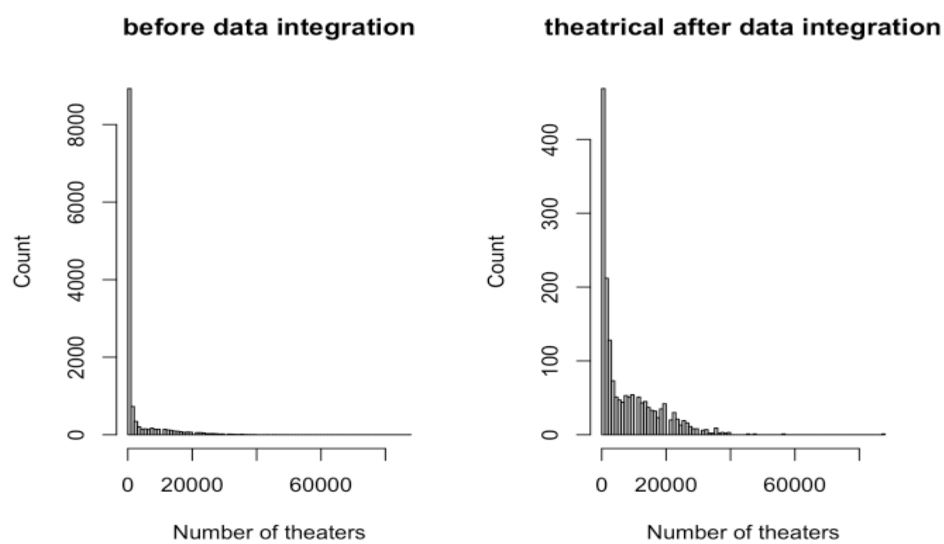

Figure 6. Histogram comparison of total theatres before and after dataset integration

3.3. Personality Traits Estimation

For each film *i* and character *j* (mapped to its credited actor via the People dataset), I infer two Big Five profiles assessed using my intergraded personality measure:

- Actor's Personality (off-screen) is derived from aggregated interview transcripts, reflecting stars key five personality traits ($\boldsymbol{Z_{ij}}^{\boldsymbol{star}}$: $AGR_{ij}{}^{star}$, $CON_{ij}{}^{star}$, $EXT_{ij}{}^{star}$, $NEU_{ij}{}^{star}$, $OPN_{ij}{}^{star}$).
- Character's Personality (on-screen) traits exhibited by the character in the movie, extracted from aggregated script dialogue ($\boldsymbol{Z_{ij}}^{\boldsymbol{char}}$: $AGR_{ij}{}^{char}$, $CON_{ij}{}^{char}$, $EXT_{ij}{}^{char}$, $NEU_{ij}{}^{char}$, $OPN_{ij}{}^{char}$).

The process involves feeding the movie scripts and interviews textual data to brand personality framework to systematically extract key personality traits, providing a structured personality profile for each subject. Using these paired star and character profiles for each pair of (*i*,*j*), I can now proceed to congruence calculation.

3.4. Measuring Congruence

The Personality Congruence variable quantifies the similarity between the actor's and character's personalities. While alternative measures (like absolute/summed differences, Euclidean distance, cosine similarity, Pearson correlation) are available, with my binary coded personality traits (0/1), all these measures will convey same information and lead to equivalent inferences. Accordingly, I use the simplest, most interpretable approach: absolute differences.

Therefore, I operationalize trait-level congruence as exact matches between the star's and character's Big Five values.

For Trait $\in$ {AGR, CON, EXT, NEU, OPN}

$$\text{Trait}_{ij} = 1 \text{ if } \{ \text{Trait}_{ij}{}^{star} = \text{Trait}_{ij}{}^{char} \}, \text{ else } 0.$$

Each indicator equals 1 when the star's trait matches the character's trait and 0 otherwise. These five trait-match indicators (AGR, CON, EXT, NEU, OPN) will be used to assess the impact of trait-level congruence in the trait-level specified models. In addition, to see whether the holistic-match impact might differ, I will define the overall congruence as summed match count (SC) across the five traits as the aggregate index:

$$SC_{ij} = AGR_{ij} + CON_{ij} + EXT_{ij} + NEU_{ij} + OPN_{ij} \in \{0, \ldots, 5\}.$$

This summed congruence measure will be used as second IV in a separate aggregated model. Higher values mean closer fit; lower values mean greater mismatch. In all regressions, a positive coefficient on AGR, …, OPN or on congruence indicates that greater congruence is associated with higher box-office performance and similarly negative coefficient is associated with lower box-office.

In every specification, I retain the congruence KPIs (the five trait-match indicators: AGR, CON, EXT, NEU, OPN) in the trait-level models and the summed match count (SC) in the aggregate models. These data are essential for my next step, model specification, in which I feed my personality and congruence data into a regression model to analyze their impact on box office performance.

2.3.5. Variables, construction, and estimation choices

Now, I assemble a model-ready star-role dataset: for each film *i* and focal star/character *j*, the same film-level outcome is assigned to multiple observations, one each pair. my model variables fall into four groups: (i) outcomes (opening-weekend and domestic box office), (ii) personality and congruence KPIs measures (star Big Five mains; character Big Five are used to construct congruence; trait level congruence and the summed match index), (iii) moderators (genre; artistic recognition coded per actor-film), and (iv) controls and covariates (production budget, sequel status, running time, theatrical engagements, distributor, etc.). Table 3 lists all variables carried into §2.4.

Variable	Description
movie name	Name of the movie
character name	Name of the character in the movie
actor name	Name of the actor or actress portraying the character
production_year	Year the movie was released
running_time	Total runtime of the movie. in minutes
sequel	Indicator if the movie is a sequel. 1 is Yes, 0 is No
distributor	Company that distributed the movie
opening_weekend_revenue	Revenue generated during the opening weekend. in dollars
opening_weekend_theaters	Total number of theaters the movie was screened in during the opening weekend
theatrical_engagements	Total number of theaters the movie was screened in during its entire theatrical run
genre	Primary genre(s) of the movie
production_budget	Total budget allocated for production (in dollars)
release_month	Month the movie was released
release_season	Season the movie was released
domestic_box_office	Total domestic box office earnings (in dollars)
Artistic Recognition	Indicator of artistic recognition on major film awards (e.g., Oscar, Golden Globe, Cannes) based on whether the actor was recognized at the time of movie production
Openness_star	Openness trait score of the movie star
Conscientiousness_star	Conscientiousness trait score of the movie star
Extraversion_star	Extraversion trait score of the movie star
Agreeableness_star	Agreeableness trait score of the movie star
Neuroticism_star	Neuroticism trait score of the movie star
Openness_char	Openness trait score of the character
Conscientiousness_char	Conscientiousness trait score of the character
Extraversion_char	Extraversion trait score of the character
Agreeableness_char	Agreeableness trait score of the character
Neuroticism_char	Neuroticism trait score of the character
AGR	Congruence indicator for Agreeableness (1 = Congruent, 0 = Not Congruent)
CON	Congruence indicator for Conscientiousness (1 = Congruent, 0 = Not Congruent)
EXT	Congruence indicator for Extraversion (1 = Congruent, 0 = Not Congruent)
NEU	Congruence indicator for Neuroticism (1 = Congruent, 0 = Not Congruent)

OPN	Congruence indicator for Openness (1 = Congruent, 0 = Not Congruent)
congruence	Overall Congruence measuring count of matched personality trait between character and actor. Ranges from 0 (lowest) to 5 (highest) congruence.

Table 3. Description of variables

4. Methodology

This section develops the models I will estimate in the Results section. I follow an empirics-first sequence that moves from a pooled association to structured heterogeneity: (i) a baseline model with congruence only; (ii) Genre × Congruence; (iii) Artistic Recognition × Congruence; and (iv) a combined specification with both moderators.

Each step is estimated in two parallel forms, a trait-level model using the five trait-match indicators (AGR, CON, EXT, NEU, OPN) and a summed model using the 0–5 match count (*SC*), and on two outcomes: opening-weekend (OW) and total domestic (TD) box office. This design permits a direct comparison of short-run and longer-run associations.

4.1. Model Estimation Framework

To keep all design choices in one place before I present the equations, I briefly review the variables I use and show how they feed into my linear regression model sequence. As noted, I estimate at the star-role pair within a film; the same film-level outcome is assigned to each pair.

Prior film research routinely analyzes these outcomes separately because opening weekend typically concentrates the peak of box-office demand and strongly shapes eventual totals; as audience novelty wanes over time, above and beyond quality decay, preferences and revenues naturally erode (Ho et al., 2017). Likewise, I estimate each specification on two outcomes that capture distinct horizons: opening-weekend revenue (short run) and total domestic box office (longer run). Domestic box office reflects total U.S. theatrical receipts and excludes international revenues and ancillary income (e.g., merchandise, home video) (Sharda & Delen, 2006). Opening-weekend revenue is the domestic gross earned over the film's first Fri–Sun frame as reported in the summaries metadata. Using both outcomes provide a temporal contrast between immediate expectations and cumulative market response. Y_{ij} will represent outcome for star-role pair *j* in film *i* (opening-weekend or domestic box office).

Personality enters as the star's Big Five mains plus congruence (either five trait-match indicators; AGR, CON, EXT, NEU, OPN, or the summed index, SC). I omit character level Big five traits from main effect because congruence is built from star and character traits; including all three would double-count information, inflate collinearity, and make the "fit" term hard to interpret. Keeping star mains Big five traits let the congruence coefficient be read as the incremental return to match, conditional on baseline persona. Let Z_{ij}^{star} (AGR_{ij}^{star}, CON_{ij}^{star}, EXT_{ij}^{star}, NEU_{ij}^{star}, OPN_{ij}^{star}) denote the star's Big Five personality traits. $\mathbf{T}_{ij}$ (AGR_{ij}, CON_{ij}, EXT_{ij}, NEU_{ij}, OPN_{ij}) represent five trait-match indicators (1 = match, 0 = mismatch), and $SC_{ij} \in \{0, \ldots, 5\}$ represent summed congruence.

To isolate the association between personality congruence and revenue, I include a concise set of pre-releases, film-level controls selected ex ante: sequel/franchise status (indicator = 1 if the title is part of an established franchise at release), running time (minutes), and distribution breadth/intensity. These variables proxy audience familiarity and risk, show-scheduling and narrative scope, and market availability, respectively, providing a standard baseline against which to evaluate personality congruence.

The distribution measure is DV-specific: for domestic box office models I use theatrical engagements (cumulative availability over the run); for opening-weekend models I use opening-weekend screens, which capture initial availability. I never include both together to avoid release-scale collinearity. These variables proxy audience familiarity and risk, narrative scope and scheduling, and market availability. I deliberately exclude post-release reception variables (e.g., review polarity, WOM metrics, marketing spends) from all main models to avoid conditioning on outcomes. In my models X_i represent controls (production budget, sequel, running time, plus opening-weekend screens when Y is opening-weekend; theatrical engagements when Y is domestic).

To absorb remaining between-movie heterogeneity while preserving within-title variation, I include fixed effects for production year, release month, and distributor, and I cluster standard errors at the movie level. I do not include movie itself in the fixed effects because the outcome is constant within a title and would eliminate the within-movie, between-character variation of interest. In R, I implement these models with 'feols' function (fixed-effects OLS estimation) of 'fixest' package. Interpretation of interactions relies on marginal effects and simple slopes reported in results. Descriptive statistics for outcomes and controls appear in Table 4. FE_i represent fixed effects for production year, release month, distributor and standard errors are clustered at movie level.

Feature	Type	Mean	Min	Max	Std. Dev
production_year	int64	2003.47	1944	2018	9.17
running_time	int64	105.08	0	196	39.89
sequel	bool	0.04	0	1	0.20
opening_weekend_revenue	int64	18235910	0	207438700	21752840
opening_weekend_theaters	int64	1960	0	4349	1327
theatrical_engagements	int64	15441	0	56286	10678
production_budget	int64	49227580	0	425000000	48757230
domestic_box_office	int64	84213560	0	760507600	90025520
release_date	date	2004-03-25	1945-02-16	2019-05-31	3408

Table 4. Descriptive statistics

I estimate linear models at the star-role level with film-level outcomes assigned to each pair. Because the dependent variable is constant within a film, coefficients are identified from cross-film differences in cast composition and context, i.e., whether films whose casts display higher star–role personality congruence (and its interactions) have higher revenues, conditional on controls and fixed effects. Genre interactions identify how the congruence slope differs across primary genres; recognition interactions identify how the slope differs between recognized and unrecognized stars.

Stars and producers may select roles that match the star's persona. If such selection correlates with unobserved determinants of revenue (e.g., script quality or marketing intensity not fully captured), my OLS slopes on congruence should be read as conditional associations rather than causal effects. I mitigate concerns with film-level controls and fixed effects for year, month, and distributor, and by clustering at the movie level. As robustness, I (i) add star fixed effects to absorb time-invariant star quality, (ii) control for sequels/franchises, (iii) use two-way clustering by film and star, (iv) and (v) use alternative functional forms (levels vs. logs). Because revenue is right-skewed, I also re-estimate all specifications using log revenue (ln(1+Y)) as a robustness check. For interpretability and comparability of marginal effects, I report level-specification results in the main text; the corresponding log-specification tables appear in Appendix A and show qualitatively consistent patterns. I interpret results accordingly.

My estimands are partial correlations under the following conditions: (i) after conditioning on distributor, calendar timing, budget, sequel status, running time, and distribution breadth, there are no omitted pre-release factors jointly correlated with both congruence and revenue; (ii) I avoid conditioning on post-release outcomes (e.g., reviews, WOM) by excluding them from main models; (iii) measurement error in personality inputs is approximately classical, tending to attenuate slopes; (iv) within-film dependence is handled by clustering standard errors at the movie level.

My modeling choices follow standard practice in empirical box-office and marketing analytics (e.g., Basuroy et al., 2003; De Vany & Walls, 1999; Einav, 2007; Elberse, 2007; Ravid, 1999) and fixed-effects OLS implementation in fixest (R). Full citations appear in the References section. The next subsections implement my empirical model, moving from a baseline to specifications that add Genre and Artistic Recognition moderators and both. Each uses the same controls, fixed effects, and clustering, and each is estimated in trait-level and summed-congruence forms on both outcomes

4.2. Baseline (no moderators)

The baseline asks a simple question: holding constant calendar and distribution conditions and basic exposure controls, is better star-role personality fit associated with higher box office? These baselines provide reference slopes; given pooled effects can be small, they primarily set the stage for moderated models. Each baseline is estimated twice: once with opening-weekend and once with domestic box office.

Trait-level version:

$$Y_{ij} = \alpha + \beta\, T_{ij} + \delta\, Z_{ij}^{\text{star}} + \gamma\, X_i + \text{FE}_i + \varepsilon_{ij}. \quad (1)$$

Where α is the baseline revenue in the reference context (genre = "other," unrecognized star), β is the vector of returns to trait-level "fit" (elements β_k); if congruence is beneficial, I expect $\beta_k > 0$. δ captures associations with the star's baseline persona, γ captures associations with film-level controls, FE_i *are fixed effects for year, month, and distributor, and* ε_{ij} is the error term (SEs clustered by movie).

Summed-congruence version:

$$Y_{ij} = \alpha + \beta_C\, SC_{ij} + \delta\, Z_{ij}^{\text{star}} + \gamma\, X_i + \text{FE}_i + \varepsilon_{ij}. \quad (2)$$

Where β_C is the return to the summed congruence index $SC_{ij} \in \{0, \dots, 5\}$; if fit helps, ($\beta_C > 0$). Other symbols are as in (1).

4.3. Genre × Congruence

As previously stated, for audiences, movie genre functions like a product category: it bundles narrative conventions, pacing, affect, and risk into recognizable formats. If genre reframes what "fits," then a pooled average may obscure real differences. For example, the value of an extraverted-match may be stronger in comedy, while a neuroticism-match might matter more in horror. I therefore allow the return to congruence to vary with genre, while also letting genre dummies absorb level differences in typical revenues across categories.

Genre is a categorical variable coded from the primary listed genre in the summaries metadata. Drawing on prior work, I focus on eight genres defined by distinct narrative conventions and cultural implications: comedy, drama, action, horror, thriller, documentary, musical, and adventure, and collapse all remaining labels into "other," which serve as the omitted (reference) category. Genre enters the models as main effects and interacts with the congruence KPIs (trait-level matches and the summed index).

Let G*i* denote the set of genre dummy indicators for film *i* corresponding to the eight focal genres (each dummy equals 1 if the film's primary genre is g, 0 otherwise), with "other" omitted as the reference. Interaction coefficients are interpreted relative to "other" for both outcomes; they show how the congruence slope in each genre differs from the slope in the reference group.

Trait-level version:

$$Y_{ij} = \alpha + \beta\, T_{ij} + \phi\, G_i + \theta\big(T_{ij} \times G_i\big) + \delta\, Z_{ij}^{\text{star}} + \gamma\, \boldsymbol{X_i} + \text{FE}_i + \varepsilon_{ij}. \qquad (3)$$

Where $\phi\, G_i$ captures genre level shifts relative to "other" (elements ϕ_G sign not restricted); $\theta\big(T_{ij} \times G_i\big)$ captures genre-specific differences in the return to trait-level fit (elements θ_{kg}). The simple slope for trait *k* in genre *g* is β_k+θ_{kg}; a positive θ_{kg}>0 means fit on trait *k* pays more in genre *g* than in "other." Remaining terms are as in (1).

Summed-congruence version:

$$Y_{ij} = \alpha + \beta_C\, SC_{ij} + \phi_C\, G_i + \theta_C\big(SC_{ij} \times G_i\big) + \delta\, Z_{ij}^{\text{star}} + \gamma\, \boldsymbol{X_i} + \text{FE}_i + \varepsilon_{ij}. \qquad (4)$$

Where $\phi_C\, G_i$ are genre level shifts in the summed model; $\theta_C\big(SC_{ij} \times G_i\big)$ are genre-specific differences in the return to summed congruence. The simple slope of SC_{ij} in genre *g* is β_C+θ_g; θ_g>0 means fit pays more in genre *g* than in "other."

Notation note: Genre is one primary label per film, but in estimation I represent it as a set of dummies. Thus, $\phi\, G_i$ (or $\phi_C G_i$) is shorthand for $\sum_{g \in \mathcal{G}} \phi_g\, 1\{\text{Genre}_i = g\}$ (with $\mathcal{G}$ = the eight focal genres; "other" omitted). Similarly, $\theta(T_{ij} \times G_i)$ or $\theta_C(SC_{ij} \times G_i)$ denotes the full set of interactions between the congruence KPIs and each genre dummy.

4.4. Artistic Recognition × Congruence

Having allowed the return to congruence to differ by genre, I now ask whether status cues also shift that return. If status shapes persuasion or credibility, the payoff to congruence might differ when a star is recognized, either because recognition reinforces expectations or because it draws attention to persona-role consistency. Therefore, I test whether the payoff to actor-character 'fit' changes when the actor already has artistic recognition (major nominations/wins earned before the film), consistent with the idea that recognized stars are more salient or credible. I therefore moderate congruence by recognition.

Let R_{ij} equal 1 if the actor tied to role *j* in film *i* had a major industry nomination/win prior to release, 0 otherwise (post-release awards do not backfill earlier films). I include the recognition main effect and in interaction with the congruence KPIs ($T_{ij} \times R_{ij}$ or $SC_{ij} \times R_{ij}$). I report simple slopes of congruence by recognition status for both outcomes.

Trait-level version:

$$Y_{ij} = \alpha + \beta\, T_{ij} + \psi\, R_{ij} + \lambda(T_{ij} \times R_{ij}) + \delta\, Z_{ij}^{\text{star}} + \gamma\, X_i + \text{FE}_i + \varepsilon_{ij}. \qquad (5)$$

Where ψ is the level shift associated with recognition (sign not restricted); $\lambda(T_{ij} \times R_{ij})$ are recognition-specific differences in returns to trait-level fit (elements λ_k). The simple slope for trait *k* when recognized is $\beta_k+\lambda_k$; $\lambda_k > 0$ indicates amplification of fit under recognition.

Summed-congruence version:

$$Y_{ij} = \alpha + \beta_C\, SC_{ij} + \psi_C\, R_{ij} + \lambda_C(SC_{ij} \times R_{ij}) + \delta\, Z_{ij}^{\text{star}} + \gamma\, X_i + \text{FE}_\text{i} + \varepsilon_{ij}. \qquad (6)$$

Where ψ_C is the recognition level shift in the summed model; λ_C is the difference in the slope on SC_{ij} when recognized. The simple slope under recognition is β_C+λ_C; λ_C>0 again indicates amplification.

The following subsection combines both moderators (Genre × Congruence and Recognition × Congruence) to assess whether their effects are additive or overlapping.

4.5. Combined moderation

Finally, I test both mechanisms jointly: does the recognition-conditional pattern persist once I account for genre structure, and vice versa? This guards against spurious moderation driven by omitted context. So, I estimate a model that includes both moderators simultaneously to assess whether genre-conditional patterns persist once I account for status, and whether recognition effects are robust to genre structure. Consistent with my empirics-first plan, I keep the design to two-way interactions (no three-way terms), preserving interpretability and statistical power.

Trait-level version:

$$Y_{ij} = \alpha + \beta\, T_{ij} + \phi\, G_i + \psi\, R_{ij} + \theta\left(T_{ij} \times G_i\right) + \lambda\left(T_{ij} \times R_{ij}\right) + \delta\, Z_{ij}^{\text{star}} + \gamma\, X_i + \text{FE}_i + \varepsilon_{ij}. \quad (7)$$

Where ϕ and ψ are main-effect level shifts for genre and recognition; θ and λ are differences in the return to fit by genre and recognition, respectively. The simple slope for trait *k* in genre *g* at recognition status *r* ∈ {0, 1} is β_k+θ_{kg}+$r\lambda_k$. No three-way terms are included by design.

Summed-congruence version:

$$Y_{ij} = \alpha + \beta_C\, SC_{ij} + \phi_C\, G_i + \psi_C\, R_{ij} + \theta_C\left(SC_{ij} \times G_i\right) + \lambda_C\left(SC_{ij} \times R_{ij}\right) + \delta\, Z_{ij}^{\text{star}} + \gamma\, \text{X}_i + \text{FE}_i + \varepsilon_{ij}. \quad (8)$$

Where ϕ_C and ψ_C are level shifts; θ_C and λ_C are differences in the slope on SC_{ij} by genre and recognition. The simple slope of SC_{ij} in genre *g* at recognition *r* is β_C+θ_g+ $r\lambda_C$. Signs are not restricted ex ante, though $\beta, \beta_C > 0$ are expected if better fit raises revenue. With the specification finalized, I now report estimates for the baseline and moderated models on both outcomes.

5. Results

This section reports model-based evidence in the empirics-first order: baseline ⇒ Genre × Congruence ⇒ Recognition × Congruence ⇒ combined moderation. I keep all effects in levels (USD); log–DV replications and the full coefficient grids are relegated to the Appendix. Each subsection embeds a table with just the terms needed in the main text; all other coefficients (including the star main effects and the complete interaction matrices) appear in Appendix.

5.1. Baseline Model Result

I begin with the baseline association between personality congruence and revenue at the star-role level, estimated separately for Opening Weekend and Domestic box office. In both the trait-level specification (five match indicators) and the summed index, personality congruence does not predict revenue on average.

In the trait-level baseline (five match indicators), none of AGR/CON/EXT/NEU/OPN is significant for Domestic or Opening Weekend (Table 5). In the holistic baseline (summed 0–5 matches), the holistic congruence index is likewise non-significant for both Domestic and Opening Weekend (Table 6).

Controls behave as expected in every column: Sequel status is strongly positive ($44.16M*** Domestic; $21.89M*** Opening), and distribution breadth loads positively and significantly (e.g., each additional opening screen adds about $4,571 on average; each unit of theatrical engagements adds $3,840), and longer films show small/marginal positive associations.

This is informative. Pooled means mask structure and personal matching does not impact in the aggregate, despite widespread industry beliefs. This is consistent with match-up/human brand logic that fit is contextual; audiences don't reward "fit" in the abstract, but under specific genre conventions and status cues (recognition). I therefore turn to heterogeneity in the next steps to test where congruence does matter in my empirical set-up.

Estimation results (Model 1)

	Domestic box office	Opening weekend revenue
Agreeableness	-247,836.4 (572,738.6)	-200,576.2 (189,486.7)
Conscientiousness	59,330.1 (557,847.5)	95,586.6 (178,834.9)
Extroversion	595,166.0 (489,282.9)	191,338.7 (148,384.1)
Neuroticism	230,214.3 (683,808.7)	270,686.1 (242,292.6)
Openness	-1,023,071.7. (575,088.9)	-267,501.3 (175,900.0)
sequel	44,163,387.6*** (12,627,625.6)	21,889,444.8*** (4,282,365.2)
Running time	91,955.5. (47,109.7)	47,907.3** (16,737.5)
Theatrical engagements	3,839.5*** (472.4)	
Opening weekend theaters		4,571.0*** (820.0)
Fixed-Effects: ----------------------	------------------------------------	----------------------------------
Production Year	Yes	Yes
Release Month	Yes	Yes
distributor	Yes	Yes
S.E.: Clustered by	\`moviename\`	\`moviename\`
Observations	45,143	45,143
R2	0.5709	0.50381
Within R2	0.22242	0.21376

Notes: ** p < 0.01, * p < 0.05, + p < 0.1

Table 5. Baseline Model Results (trait level congruence)

Estimation results (Model 2)		
	Domestic box office	Opening weekend revenue
HCongruence	-26,788.7 (245,595.8)	33,619.1 (79,614.4)
sequel	44,207,880.1*** (12,631,996.7)	21,901,790.8*** (4,284,168.4)
running time	92,128.5. (47,108.2)	47,969.6** (16,733.8)
theatrical engagements	3,840.2*** (472.5)	
opening weekend theaters		4,572.5*** (820.0)
Fixed-Effects: -----------------------	-------------------------------------	-----------------------------------
Production Year	Yes	Yes
Release Month	Yes	Yes
distributor	Yes	Yes
S.E.: Clustered by	\`moviename\`	\`moviename\`
Observations	45,143	45,143
R2	0.57083	0.50371
Within R2	0.304	0.20726

Notes: ** p < 0.01, * p < 0.05, + p < 0.1

Table 6. Baseline Model Results (holistic congruence)

5.2. Genre-Moderated Model Result

Interacting congruence with genre indicators yields several theory-consistent patterns in Opening Weekend, when fit should work as a fast, expectation-based heuristic, with fewer, weaker echoes in Domestic. Below I highlight the results, tying each claim to Table 7 and 8.

Comedy. Comedies penalize conscientious matches at the gate and weakly reward extraversion matches. In Opening Weekend levels (Table 7), CON × Comedy = −\$578,034 (p<.05). Extraversion has a marginal positive lift of \$605,484 (p<.10; same model). Holistically, Comedy shows a small positive bump: SC × Comedy = \$331,966 (Table 8). These boosts do not carry into Domestic in a statistically reliable way, consistent with genre conventions that prize spontaneity and high-energy timing, audiences reward "outward energy" and disfavor over-structured personas on the first weekend; once WOM and reviews arrive, the advantage dissipates.

Adventure. Adventure rewards extraversion congruence at the gate and dislikes openness-to-experience matches. For Opening Weekend (Table 7), EXT × Adventure = \$2,245,843 ($p<.10$) and OPN × Adventure = −\$2,014,163 ($p<.05$). Holistic fit is non-significant (SC × Adventure = \$41,876; ns; Table 8). One plausible explanation for this counter intuitive negative sign of openness congruence effect in adventure could be attributed to in this emotion rich exploratory genre people would be overwhelmed with extra openness so they are looking for balanced vibe. In other words, for this high-stakes, quest-driven stories, audiences appear to prefer straightforward, as audience expectations favor clarity and can-do personas over experimental or novelty-oriented matches.

Action. A notable domestic box office indicator in action genre is a penalty for openness: OPN × Action = −\$6,288,867 ($p<.10$) (Table 7). This aligns with tighter action templates that favor archetypal leads over exploratory persona–role sameness. Holistic congruence is effectively null (SC × Action = −\$520,550; ns; Table 8). Tightly coded action templates reward conventional heroic cues; "novel" persona-role sameness (high openness) reads off-type and suppresses first-weekend demand. The incongruity of high openness likely detracts from audience identification with the hero, leading to reduced initial interest and ticket sales.

Horror. For the Horror genre, minimal impact from personality congruence on box office performance is noted, with non-significant results during Opening Weekend (SC × Horror =

−\$664,274; ns). However, a slight penalty in the domestic box office where holistic congruence was marginally negative (SC × Horror = −\$3,210,341, p<.10; Table 8) indicates that audience expectations for horror narratives lean towards shock and unpredictability, limiting positive word-of-mouth effects from similar character traits.

Drama showcases a complex interaction among genres, often overlapping with various others. The results indicate no significant impact from either holistic or trait-level congruence on box office performance (Table 7 & Table 8), which reflects the intricacy and potential ambiguity in audience reception associated with dramatic narratives, where mixed elements from various genres complicate clear audience expectations.

Furthermore, genres such as Thriller, Musical, and Documentary yielded insignificant results, indicating the need for further scrutiny due to potential dataset limitations in capturing subtle impacts from the small number of films studied. The overarching theme suggests that while genre significantly shapes audience expectations, the clarity of character traits aligned with these conventions ultimately influences box office outcomes more pronouncedly during the Opening Weekend.

Estimation results (Model 3)

	Domestic box office	Opening weekend revenue
Agreeableness	0.0004 (308.4)	-0.0007 (220.8)
Conscientiousness	-0.0026 (180.6)	0.0011 (140.3)
Extroversion	-0.0013 (209.7)	0.0011 (148.4)
Neuroticism	0.0003 (109.3)	0.0004 (89.98)
Openness	0.0023 (112.3)	-5.05e-5 (64.89)
sequel	35,512,732.2** (12,055,278.4)	19,106,508.1*** (3,852,876.1)
running time	63,149.6 (42,394.4)	34,704.8** (13,384.3)
theatrical engagements	3,576.4*** (471.0)	
opening weekend theaters		4,155.3*** (838.7)

Conscientiousness x Comedy	-963,746.8 (978,521.2)	-573,709.5* (268,322.9)
Extroversion x Adventure	7,337,650.0. (4,003,693.1)	2,237,486.4. (1,250,604.9)
Extroversion x Comedy	956,288.3 (961,758.2)	605,353.4. (327,852.7)
Extroversion x Thriller	3,765,026.0. (2,222,796.5)	615,038.4 (463,332.0)
Neuroticism x Comedy	1,886,638.6 (1,692,696.1)	985,090.9. (563,732.6)
Openness x Action	-5,679,642.1. (3,299,749.0)	-1,709,537.6 (1,370,861.2)
Openness x Adventure	-4,232,637.8 (3,979,415.2)	-2,097,148.0* (1,002,706.8)
Fixed-Effects: --------------	-------------------------------------	-----------------------------------
Production Year	Yes	Yes
Release Month	Yes	Yes
distributor	Yes	Yes
S.E.: Clustered by	\`moviename\`	\`moviename\`
Observations	45,143	45,143
R2	0.5709	0.50381
Within R2	0.22242	0.21376

Notes: ** p < 0.01, * p < 0.05, + p < 0.1

Table 7. Genre Moderated Model Results (trait level congruence)

Estimation results (Model 4)

	Domestic box office	Opening weekend revenue
HCongruence	-0.0003 (8.677)	-0.0002 (3.901)
sequel	35,667,372.6** (12,112,836.8)	19,169,545.4*** (3,885,982.0)
running time	63,449.8 (42,508.0)	34,629.7* (13,449.6)
theatrical engagements	3,586.5*** (477.0)	
opening weekend theaters		4,168.5*** (849.1)
HCongruence x Action	-2,955,682.7. (1,705,896.8)	-369,988.6 (672,994.3)
HCongruence x Adventure	83,423.5 (2,067,629.1)	-13,590.9 (537,177.2)
HCongruence x Comedy	708,958.2 (605,150.0)	330,740.9. (177,626.0)
HCongruence x Documentary	-238,289.0 (787,718.7)	-421,107.1 (461,382.1)
HCongruence x Drama	78,176.9 (577,254.8)	-121,913.7 (181,240.0)
HCongruence x Horror	-3,190,449.8. (1,737,681.5)	-648,140.9 (683,340.9)
HCongruence x Musical	218,896.3 (1,914,456.9)	-633,532.4 (477,050.0)
HCongruence x Thriller	-131,318.9 (1,018,091.3)	-49,216.0 (250,607.5)

Fixed-Effects: --------------	------------------------------------- -	------------------------------------
Production Year Release Month distributor	Yes Yes Yes	Yes Yes Yes
S.E.: Clustered by	\`moviename\`	\`moviename\`
Observations	45,143	45,143
R2	0.59391	0.54511
Within R2	0.34143	0.2734

Notes: ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

Table 8. Genre Moderated Model Results (holistic congruence)

5.3. Artistic Recognition-Moderated Model Result

Recognition (major nomination/win before release) operates as a status/quality signal for "human brands," and can systematically reshape the return to fit. They shift audience priors from "can this actor carry the role?" to "what new range will they show?" which could reduce the premium on safe, type-congruent casting and reward craft cues instead of sameness. I therefore interact congruence with Artistic Recognition (indicator = 1 if the actor had a major nomination/win before the film's release) and the result data match that logic.

Results demonstrate that recognition discounts perfect sameness. The summed fit × recognition term is negative for both Domestic (SC × Recognition = −$1,746,187 (p<.05)) and Opening weekend (−$523,547* **(**p<.05) box-office (Table 10). Thus, a "perfectly sameness" overall match is worth less when audiences believe the actor can stretch, consistent with prestige conferring latitude rather than rewarding sameness. This suggests that audiences tend to reward actors who display versatility, indicating that recognition not only affirms their talent but also grants them leeway in their portrayals.

Exploring trait-specific interactions (Table 9) reveals that prestige can reverse the financial incentives associated with character traits. In Domestic results, OPN × recognition is positive ($3,608,219* (p<.05)), NEU × recognition is negative (−$7,668,267, p<.01). Craft-aligned openness becomes a positive revenue lever for prestige actors over the run, while anxious-anxious mirroring becomes a negative. There is also a marginal Domestic lift for CON × Recognition ($3,571,988, *p<.10*), consistent with disciplined preparation complementing prestige over the run. These patterns imply that traits associated with craft, such as openness and conscientiousness, become more advantageous when linked to recognized actors, while more conventional or safe portrayals may dissuade audience investment, highlighting a broader trend where actors with prestigious accolades are expected to stretch beyond typecasting.

Findings regarding extraversion during the opening weekend provide further insights. A negative relationship with recognition (EXT × Recognition = −$1,873,907, p<.05; Table 9) indicates that typical extroverted portrayals may not add significant value when audiences already regard the actor as competent in carrying their role. This suggests that audiences are less likely to respond favorably to actors confined by their established personas when they expect a competent performance.

Estimation results (Model 5)

	Domestic box office	Opening weekend revenue
Agreeableness	911,640.9 (1,469,917.9)	79,452.4 (505,738.5)
Conscientiousness	-1,109,374.6 (924,516.9)	-196,610.6 (294,069.1)
Extroversion	1,655,885.3 (1,167,483.8)	899,999.0* (453,438.8)
Neuroticism	3,140,850.5** (1,213,039.3)	697,680.3. (379,894.4)
Openness	-2,187,557.7* (979,858.7)	-531,118.4. (299,510.0)
artistic recognition	2,591,242.5 (3,790,163.4)	853,016.1 (1,417,103.4)
sequel	44,119,013.1*** (12,533,282.5)	21,884,757.6*** (4,244,766.7)
running time	91,509.3. (47,119.7)	47,860.0** (16,789.3)
theatrical engagements	3,840.9*** (472.5)	
opening weekend theaters		4,569.5*** (823.9)
Agreeableness x artistic recognition	-3,010,896.6 (2,782,598.5)	-748,080.2 (982,333.2)

Conscientiousness x artistic recognition	3,571,987.9. (2,007,539.1)	874,955.2 (745,030.9)
Extroversion x artistic recognition	-3,001,407.7 (2,845,262.8)	-1,873,906.6 (1,199,543.5)
Neuroticism x artistic recognition	-7,668,266.5** (2,508,790.6)	-1,184,815.1 (796,998.9)
Openness x artistic recognition	3,608,219.3* (1,729,528.6)	740,876.6 (560,121.7)
Fixed-Effects: --------------	-------------------------------------	-----------------------------------
Production Year	Yes	Yes
Release Month	Yes	Yes
distributor	Yes	Yes
S.E.: Clustered by	\`moviename\`	\`moviename\`
Observations	45,143	45,143
R2	0.57185	0.50454
Within R2	0.30566	0.2086

Notes: ** p < 0.01, * p < 0.05, + p < 0.1

Table 9. Artistic Recognition Moderated Model Results (trait level congruence)

Estimation results (Model 6)		
	Domestic box office	Opening weekend revenue
HCongruence	627,858.2 (435,047.5)	228,363.0. (126,447.9)
artistic recognition	3,938,845.1 (3,700,936.5)	927,170.3 (1,323,843.1)
sequel	44,166,681.4*** (12,585,453.8)	21,877,191.9*** (4,253,401.2)
running time	92,096.2. (47,153.6)	47,918.7** (16,750.5)
theatrical engagements	3,839.3*** (473.1)	
opening weekend theaters		4,572.6*** (821.3)
HCongruence x artistic recognition	-1,746,186.5* (881,412.4)	-523,547.4* (252,612.5)
Fixed-Effects: --------------	-------------------------------------	-----------------------------------
Production Year	Yes	Yes
Release Month	Yes	Yes
distributor	Yes	Yes
S.E.: Clustered by	\`moviename\`	\`moviename\`
Observations	45,143	45,143
R2	0.57098	0.50391
Within R2	0.30425	0.20758

Notes: ** p < 0.01, * p < 0.05, + p < 0.1

Table 10. Artistic Recognition Moderated Model Results (holistic congruence)

5.4. Combined-Moderation result

As I already described above, for both genre and recognition mediated models there were some significant impacts under certain scenario they can have positive or negative impact of box office sort term or long-term result. This leads us to the next question whether interplay of these two variables can create any insight or prove my result robustness.

Treating films as genre-typed products and allowing status (artistic recognition) to reweight expectations yields a coherent picture: a small set of genre-specific matches matter at the gate, a few persist domestically, and prestige reliably discounts safe sameness while rewarding craft-aligned traits. Several interpretable trait-by-genre and status patterns remain when both moderators are included in the model (Table 11):

Comedy penalizes conscientious matches at the gate: CON × Comedy = −$813,503 ($p<.05$). Adventure rewards extraversion matches: EXT × Adventure = +$3,113,057 ($p<.05$). This is a large, economically meaningful lift consistent with high-energy leads drawing first-weekend turnout in adventure fare. Drama rewards neuroticism matches at the gate: NEU × Drama = +$1,284,828 ($p<.05$), suggesting that visible anxiety/emotional volatility reads as authentic in dramatic roles early on. Action continues to penalize openness matches: OPN × Action = −$7,210,581 ($p<.05$), consistent with audiences preferring archetypal, not exploratory, action leads at the gate.

At the holistic level (Table 12), Comedy shows a marginal positive return to total fit at the gate (SC × Comedy = +$264,272, $p<.10$), while status penalizes perfect sameness (SC × Recognition = −$414,357, $p<.10$). Together, these say: in crowd-pleasing genres the “overall fit” heuristic helps on Friday–Sunday, but for recognized actors, audiences discount safety. Fewer interactions survive into the longer run, but two robust signals remain when both moderators are included (Table 8, Model 4&8):

Status continues to reweight the return to fit: Holistically, the status penalty for sameness persists on Domestic: SC × Recognition = −\$1,789,583 ($p<.108$). There is also a positive domestic tilt for total fit in Comedy (SC × Comedy = +\$1,261,020, $p<.10$), indicating that light genres can sustain some fit benefits past opening when laughs align with known personas.

Even with genre in the equation, recognition keeps the same profile (Table 11):

OPN × Recognition = +\$3,624,693 ($p<.05$) and CON × Recognition = +\$3,237,184 ($p<.10$) on Domestic, remarking craft-aligned matches pay for prestige actors over the run. NEU × Recognition = −\$8,033,654 ($p<.01$) on Domestic, aligned with anxious mirroring depresses legs for prestige actors. At the gate, the EXT × Recognition penalty observed in the recognition-only model diminishes once genre is added (−\$1,286,220, ns), suggesting that much of the opening-weekend extraversion story is genre-channeled (e.g., Comedy/Adventure) rather than purely status-driven.

Overall, the combined model shows complementarity between genre expectations and status signals. Genres prescribe what "fit" should look like (e.g., spontaneity in Comedy, vigor in Adventure; caution with openness in Action), while recognition shifts how much audiences value fit vs. stretch. Genre-conditioned fit is front-loaded, strongest at the gate when expectations dominate, while status-conditioned reshaping survives into Domestic, where audiences and critics weigh craft and range. This is exactly the timing pattern I expect if persona-role fit acts as a quick cue that gives way to learning, while prestige alters what "good fit" even means.

All coefficients cited above are from Table 8 (trait-level combined: Models 4/20; holistic combined: Model 32). Full interaction grids, and log-version results are in Appendix.

Estimation results (Model 7)		
	Domestic box office	Opening weekend revenue
Agreeableness	0.0006 (307.0)	-0.0005 (132.8)
Conscientiousness	-0.0020 (179.0)	0.0009 (89.89)
Extroversion	-0.0013 (208.7)	0.0009 (90.11)
Neuroticism	0.0003 (108.6)	0.0002 (51.78)
Openness	0.0015 (110.9)	-6.94e-5 (59.51)
artistic recognition	726,416.8 (3,463,371.4)	-341,834.6 (1,094,266.7)
sequel	35,363,946.4** (11,945,837.6)	16,739,349.1*** (3,742,037.2)
running time	61,961.3 (42,337.5)	22,172.4. (11,856.7)
theatrical engagements	3,577.5*** (470.9)	
opening weekend theaters		4,781.7*** (149.9)
Conscientiousness x Comedy	-1,819,975.9 (1,242,189.3)	-817,363.1* (330,403.6)
Extroversion x Adventure	8,102,826.9. (4,314,087.8)	3,107,612.2* (1,403,076.6)
Extroversion x Documentary	3,812,988.7. (2,207,243.8)	1,386,946.1. (756,765.3)
Extroversion x Thriller	4,855,380.4. (2,625,052.9)	1,248,835.6. (715,748.4)
Neuroticism x Comedy	4,293,556.3* (1,875,294.1)	1,070,092.1* (499,773.0)
Neuroticism x Documentary	5,261,300.8* (2,131,352.9)	1,282,667.6* (650,225.0)
Neuroticism x Drama	5,132,718.1* (2,028,329.7)	1,284,237.3* (627,478.7)
Openness x Action	-6,604,184.5. (3,395,873.9)	-2,510,765.6* (1,192,074.6)
Openness x Adventure	-5,609,861.3 (4,047,830.9)	-1,986,557.0. (1,028,618.8)
Openness x Drama	-2,266,955.4. (1,218,559.6)	-579,403.9. (342,347.0)
Agreeableness x artistic recognition	-2,213,284.8 (2,887,380.5)	-107,218.7 (956,948.9)
Conscientiousness x artistic recognition	3,301,227.9. (1,847,508.6)	996,833.6. (601,066.2)
Extroversion x artistic recognition	-3,004,115.4 (2,550,954.2)	-1,318,550.4 (876,636.3)
Neuroticism x artistic recognition	-8,113,942.8** (2,497,115.2)	-1,974,494.6** (764,365.1)
Openness x artistic recognition	3,613,746.6* (1,650,322.3)	970,450.1* (450,575.1)
Fixed-Effects: --------------	-------------------------------------	-----------------------------------
Production Year	Yes	Yes
Release Month	Yes	Yes
distributor	Yes	Yes
S.E.: Clustered by	\`moviename\`	\`moviename\`

Observations	45,143	45,143
R2	0.5709	0.50381
Within R2	0.22242	0.21376

Notes: ** p < 0.01, * p < 0.05, + p < 0.1

Table 11. Combined Moderated Model Results (trait level congruence)

Estimation results (Model 8)		
	Domestic box office	Opening weekend revenue
HCongruence	-0.0002 (8.662)	-0.0001 (3.186)
artistic recognition	2,252,195.0 (3,440,193.4)	-69,876.9 (1,072,593.8)
sequel	35,512,235.2** (12,042,187.5)	16,773,690.6*** (3,786,798.3)
running time	62,685.0 (42,475.9)	22,249.1. (11,895.3)
theatrical engagements	3,584.4*** (477.3)	784.0*** (152.3)
HCongruence x Action	-2,161,769.2 (1,727,580.9)	-136,052.5 (582,075.9)
HCongruence x Adventure	732,300.7 (2,106,003.0)	579,920.7 (627,898.6)
HCongruence x Comedy	1,261,274.3. (692,175.6)	261,342.9. (148,520.6)
HCongruence x Documentary	1,147,872.3 (1,077,202.6)	94,442.1 (425,212.7)
HCongruence x Drama	939,000.5 (686,509.8)	96,640.9 (203,101.4)
HCongruence x Horror	-2,754,191.1 (1,780,861.2)	-715,338.5 (609,031.8)
HCongruence x Musical	496,434.9 (1,954,673.3)	-610,894.2 (733,034.4)
HCongruence x Thriller	476,033.8 (1,111,109.7)	53,265.1 (293,388.6)
HCongruence xartistic recognition	-1,797,698.8* (873,429.8)	-413,791.3. (245,187.4)
Fixed-Effects: --------------	-------------------------------------	-----------------------------------
Production Year	Yes	Yes
Release Month	Yes	Yes
distributor	Yes	Yes
S.E.: Clustered by	\`moviename\`	\`moviename\`
Observations	45,143	45,143
R2	0.59421	0.57048
Within R2	0.34191	0.31391

Notes: ** p < 0.01, * p < 0.05, + p < 0.1

Table 12. Combined Moderated Model Results (holistic congruence)

6. Discussion

This section interprets the empirical patterns reported in §2.5 and links them to established work on human brands, persuasion, and market response, particularly the stream that argues effects are context-dependent and time-varying (Osinga et al., 2010; M. Yang & Roskos-Ewoldsen, 2007). Taken together, my results show that personality congruence does not pay on average (baseline) but does in specific narrative contexts (genre) and under status cues (artistic recognition), with stronger effects at the gate (Opening Weekend) than over the full run (Domestic). These findings reconcile industry beliefs about "casting fit" with the mixed results in the literature: fit matters, but not uniformly; it emerges when audience schemas and priors make it diagnostic.

6.1. Reconciling pooled nulls with conditional effects

The baseline models in §2.5.1 yield no reliable main effect of either trait-level matches or the holistic congruence index on revenue (Table 5). This informs, rather than contradicts, theory. Considering that audiences view a star-role pairing through genre-specific expectations and status priors, then pooling across all genre and movie stars would dilute the effects. Methodologically, the nulls also help discipline the narrative: they justify shifting from "does fit matter?" to "when does fit matter?", which is consistent with persuasion accounts in which schema congruity moderates processing ease and response (M. Yang & Roskos-Ewoldsen, 2007) and with marketing response models that emphasize heterogeneous effects across contexts and over time (Osinga et al., 2010). This aligns with previous research indicating that interpretations of audience reception can vary significantly and may not always confirm long-held industry beliefs about character fit driving success (C. Peters & Christian Schrøder, 2018; Schrøder, 2019).

The pattern of results is consistent with schema–congruity theory, which predicts that audience responses depend not simply on whether a cue is congruent or incongruent, but on how that cue is interpreted relative to existing expectations. In this setting, persona–role congruence functions as an early heuristic that audiences use to organize expectations prior to viewing, rather than as a uniformly valued attribute. The absence of a pooled main effect therefore does not imply irrelevance; instead, it reflects aggregation across contexts in which congruence is rewarded, penalized, or largely ignored. Genre conventions and artistic recognition operate as schema-defining lenses that shape how congruence information is read, clarifying why effects emerge conditionally rather than universally.

6.2. Genre as an expectation architecture

Once I treat movies as genre-typed products, congruence begins to move markets in expected directions (§2.5.2; Table 6). In Comedy, conscientiousness matches are penalized at the gate (CON×Comedy = −\$578k, $p<.05$), while extraversion matches are rewarded (EXT×Comedy = +\$605k, $p<.10$). This can be interpreted as comedy prizes spontaneity, looseness, and high-energy timing, and not over-structured, meticulous personas (Rifkin et al., 2023). At the holistic level, Comedy shows a small positive bump on Opening Weekend (C×Comedy = +\$332k, $p<.10$), an effect that dissipates in Domestic, consistent with an early, heuristic use of fit that is later washed out by reviews and word-of-mouth (Elberse, 2007; Y. Liu, 2006).

In Adventure, extraversion congruence lifts the gate (EXT×Adventure = +\$2.25M, $p<.10$), whereas openness congruence hurts (OPN×Adventure = −\$2.01M, $p<.05$). Quest narratives reward a can-do, outward-facing persona and are less compatible with novelty-seeking/quirky cues tightly mirrored between star and role.

In Action, I observe a robust penalty for openness (e.g., OPN×Action = −\$6.29M, $p<.10$, Domestic), indicating that highly exploratory, off-template sameness dampens performance in tightly coded action franchises.

And in Horror, holistic sameness reduces domestic box office (C×Horror = −\$3.21M, $p<.10$, Domestic), consistent with the idea that one-note, anxiety-mirrored pairings generate early scares but fade as conversations shift to story and craft (Clasen et al., 2020).

This echo industry practice: the sustained use of high-energy comedians in Comedy (e.g., Jim Carrey in *Ace Ventura*), can-do leads in Adventure (e.g., Harrison Ford in *Indiana Jones*), and archetypal heroes in Action (e.g., Keanu Reeves in *John Wick*) that emphasize how specific genres establish normative expectations for character traits that resonate with audiences (Pisarek & Zabielska-Mendyk, 2022).

By contrast, Horror's negative holistic effect on Domestic fits the genre's history of travel hinging on narrative innovation rather than persona sameness (e.g., Sigourney Weaver's composed resilience in Alien vs. purely anxious mirroring) (Witherington & deCruz-Dixon, 2025). Drama, interestingly, shows no significant congruence effects, consistent with genre conventions that value emotional range and depth more than mere alignment (Kuhn & Westwell, 2012; Tan, 2013).

Congruence is thus rewarded when it aligns with these expectations and punished when it clashes, demonstrating that these genre-conditioned effects are especially pronounced during Opening Weekend when audience judgments rely heavily on immediate impressions (Hsu et al., 2009; Zuckerman et al., 2003).

6.3. Status as latitude to stretch

Artistic recognition (major nomination/win before release) reshapes the return to fit (§2.5.3; Table 7). Holistically, perfect sameness is discounted for recognized actors (C×Recognition = −$0.52M, p<.05, Opening; −$1.75M, p<.05, Domestic), suggesting that prestige is itself a quality/latitude signal: audiences expect range, not safety. At the trait level, openness pays for prestige actors (OPN×Recognition = +$3.61M, p<.05, Domestic), conscientiousness shows a marginal positive tilt (+$3.57M, p<.10), while neuroticism is penalized (−$7.67M, p<.01). For the gate, extraversion is discounted when the actor is already recognized (EXT×Recognition = −$1.87M, p<.05, Opening), a finding that weakens once genre is controlled (Table 8), implying that part of the "loud persona" story is genre-channeled (Comedy/Adventure) rather than purely status-driven.

Substantively, these patterns fit a "stretch over sameness" logic for human brands: audiences come to expect highly valued actors to demonstrate versatility, which diminishes the importance of perfect persona-role alignment (Cattani et al., 2014, 2017; Ganz, 2024).

Recognized actors are perceived as capable of exploring a range of roles, and traits like openness and conscientiousness gain more favorable evaluations while on-the-nose anxiety or over-broadcasted charisma are penalized (Rossman et al., 2010).

Real-world cases map cleanly: repeated, range-driven reinvention by Meryl Streep illustrates the openness premium, while meticulous preparation associated with Daniel Day-Lewis resonates with my conscientiousness tilt. Conversely, highly flamboyant, on-brand turns by already famous actors can underwhelm at the gate (e.g., when audiences perceive showiness over craft).

6.4. Putting the pieces together: genre × status and timing

The combined models (§2.5.4; Table 8) show that genre and status complement one another. Genre prescribes what kind of fit counts (e.g., spontaneity in Comedy, vigor in Adventure, caution with openness in Action), while status reweights how much audiences value fit vs. stretch. At the gate, I see genre-conditioned fit: CON×Comedy = −\$0.81M ($p<.05$) and EXT×Adventure = +\$3.11M ($p<.05$). Over the run, I see status-conditioned reshaping: OPN×Recognition = +\$3.62M ($p<.05$), NEU×Recognition = −\$8.03M ($p<.01$), and a holistic sameness penalty (C×Recognition = −\$1.79M, $p<.10$). In short, fit acts as a fast cue when expectations dominate; prestige alters what "good fit" even means once reviews and word-of-mouth set in (Osinga et al., 2010).

7. Contribution to Knowledge

This study contributes to both academic theory and industry practice by clarifying *when, where,* and *why* personality congruence between movie stars and their roles matters. my findings reveal that the effects of actor/character congruence on movie box office are neither uniform nor automatic but are highly context-dependent and emerge under specific narrative and status conditions and vary over time. The implication of this complex interplay is thus discussed in two subsections, discussing the theoretical contributions such as how this study extends existing frameworks, as well as managerial implications, highlighting actionable insights for studios and movie stars regarding casting, positioning, and marketing strategies across different genres and recognition levels.

7.1. Theoretical Contributions

This study contributes to research on human brands and audience expectations by reframing persona–role congruence as a context-dependent signal rather than a universally beneficial attribute. Drawing on schema–congruity theory, the findings demonstrate that congruence operates as an expectation-organizing heuristic whose meaning depends on genre conventions and credibility cues such as artistic recognition. By identifying when congruence matters, and when deviation is tolerated or even advantageous, this work clarifies boundary conditions that have been largely overlooked in prior research, which has tended to treat fit as uniformly desirable.

The exploration of how dynamics influence the box office success of films is an emerging area of research that intersects human branding theory and character alignment. The existing literature mainly emphasizes non-human drivers such as budget, release timing, distribution, and word of mouth and even when human brands are considered, tends to examine their off-screen characteristics in isolation, overlooking the correlation between these traits and the roles they portray onscreen. This oversight is significant, as it may impact the effectiveness of models that aim to predict movie success, which frequently fail to account for the congruence, or lack thereof, between an actor's personal attributes and their character's traits.

Previous studies have often overlooked the methodology needed to effectively quantify personality traits. This research employs machine learning techniques to extract personality attributes from various sources, including actors' interviews and screenplay analyses. This advanced approach facilitates a dual-level investigation into both overall persona alignment and specific trait congruences, such as extraversion and openness. This study is positioned uniquely within the match-up and human brand literature, shifting the conversation from a generalized comprehension of fit to a more detailed understanding of its implications.

Insights into the context-dependent nature of audience perception reveal that congruence effects can be nuanced. Findings indicate that genre significantly moderates audience evaluations of fit, for example extraversion congruence positively influences audience response in comedic and adventure films, while openness congruence may detract from performance in action genres. Artistic recognition complicates these dynamics, serving as a signal that transforms audience expectations. This highlights the shifting nature of perceived congruence, where an actor's past achievements can reframe how audiences evaluate their potential in new roles, allowing for a more nuanced understanding of success that encompasses both heuristic evaluations and long-term reputation effects in the film industry.

Additionally, the study elucidates the intricate relationship between short-term audience reactions and long-term market performances. When audiences have limited information about a film, congruence (or incongruence) serves as a salient cue for judgment and affects revenues at time of movie release; over time, as more information arrives (e.g., word of mouth and reviews), these signals update and may attenuate or reinforce initial inferences, which is aligned with expectations that immediate audience responses are largely based on perceived fit. Conversely, the influence of artistic recognition appears to be more pronounced over a film's entire commercial lifespan, suggesting that the factors shaping audience engagement evolve during the viewing experience.

Overall, these findings enhance existing frameworks concerning personality congruence by demonstrating that it is not merely a universal advantage but rather that its effects are moderated by contextual variables like genre, audience anticipation, and temporal dynamics. This framework integrates elements of human brand research with a broader understanding of audience psychology and establishes a foundation for future inquiries into how nuanced actor-character interactions can inform marketing strategies and box office predictions.

By showing that congruence operates as a conditional, schema-mediated signal rather than a uniform predictor, this study reconciles mixed prior findings on fit and authenticity in human-brand research.

7.2. Managerial Implications

The strategic implications of my findings regarding actor-character personality congruence extend beyond the academic realm, providing studios and stars with practical insights into casting, positioning, and promotional strategies. Evidence suggests that the impact of congruence varies significantly by genre, highlighting the necessity for studios to adopt a context-specific approach rather than applying a uniform strategy across all types of films. For instance, in genres like Comedy and Adventure, aligning actors whose personalities reflect high-energy and extraverted characteristics can enhance audience appeal and bolster opening weekend box office performance.

Conversely, in Action films, where clarity and formulaic expectations are paramount, studios should be cautious about casting actors who possess overly open or exploratory personas, as such choices may detract from the straightforwardness that audiences typically anticipate from the genre. In the horror genre, research indicates that an exact match between an actor's persona and their role may be counterproductive. Instead, studios should aim to cultivate narrative novelty and emotional depth, which can sustain audience interest post-release and promote long-term engagement with the film, although more comprehensive studies on this specific aspect may be needed.

Artistic recognition plays a critical role in this equation, particularly for established movie stars. Audiences tend to have elevated expectations from recognized stars, where their performances are assessed considering their previous works. Findings indicate that these audiences are more likely to reward stars for versatility and creative departures that align with traits such as openness and conscientiousness. In contrast, performances that exhibit excessive neuroticism or exaggerated displays of extraversion can lead to negative responses. Thus, it would be prudent for studios and talent managers to market projects featuring prestigious stars by emphasizing themes of range and artistic reinvention rather than relying on the familiar trope of sameness.

The contrast between short-term and long-term models illustrates an essential consideration for decision-makers in the film industry. Congruence can serve as a valuable heuristic tool for attracting audiences in the initial opening weeks, but for projects aiming at long-term success and prestige, there should be an investment in diversifying persona-role combinations. This strategic pivot may enhance not only the film's credibility but also its critical reception and sustainable box office performance over time.

The implications also extend to actors themselves: celebrities seeking to build strong human brands should make role choices with care. Well-recognized stars can judiciously experiment, with credible signals and framing, to showcase range, while emerging stars may benefit from first consolidating a clear, congruent persona within suitable genres and then introducing selective, well-scaffolded stretches. By integrating insights about genre preferences, character traits, and the significance of artistic recognition, studios and filmmakers can better balance short-term market impacts against long-term brand development, ultimately leading to more informed and effective casting and marketing strategies.

8. Limitations and future work

The observational design of this research carries inherent limitations, particularly with respect to potential confounders such as selection bias in casting decisions and the unobserved intensity of marketing efforts. Although the models employ film-level fixed effects to account for factors such as release timing and distributor affiliations, the correlation of actor recognition with unobserved elements, including production budgets, script quality, or studio support, remains a relevant concern. To address these complexities, future research could adopt several methodological extensions to enrich the insights generated by the present framework.

For instance, incorporating more granular pre-release marketing indicators would allow for a clearer separation of personality-based effects from promotional intensity in shaping audience demand and box-office outcomes. Similarly, leveraging natural experiments—such as unexpected casting changes, last-minute role substitutions, or exogenous variation in the timing of award recognition—could enable more credible causal inference by isolating variation in persona-role alignment that is plausibly orthogonal to film quality.

Another important limitation concerns the functional form of persona–role congruence. In this study, congruence is operationalized as a binary indicator, which precludes the examination of nonlinear or asymmetric effects. As a result, the analysis cannot test whether moderate incongruence may outperform either strict congruence or extreme mismatch—an implication suggested by schema congruity theory and related expectation-based accounts. Future research could address this limitation by modeling congruence as a continuous distance measure in personality trait space, enabling direct tests of curvilinear or threshold-based effects and offering a more nuanced understanding of when incongruence enhances, rather than undermines, audience response.

Another important limitation concerns the functional form of persona–role congruence. In this study, congruence is operationalized as a binary indicator, which precludes the examination of nonlinear or asymmetric effects, such as inverted-U patterns implied by schema–

congruity theory. As a result, the analysis cannot test whether moderate incongruence may outperform either strict congruence or extreme mismatch; an implication suggested by schema congruity theory and related expectation-based accounts. Future research could address this limitation by modeling congruence as a continuous distance measure in personality trait space, enabling direct tests of curvilinear or threshold-based effects and offering a more nuanced understanding of when incongruence enhances, rather than undermines, audience response.

Another avenue for future research lies in the examination of nonlinear and asymmetric effects, particularly in scenarios where a discrepancy between actor and character traits might surprisingly benefit a film's performance. This could enhance understanding of the conditions under which audience expectations may shift, leading to a re-evaluation of traditional frameworks that prioritize congruence.

Furthermore, extending the analysis beyond the Big Five personality traits to incorporate constructs related to motivation and agency could be particularly valuable, especially as these elements may resonate differently across genres. The exploration of actor characteristics in relation to various contextual factors is crucial; for instance, recognizing how different genres elicit distinct audience expectations can refine the strategic implications for casting and marketing. Understanding that genres differ in their reception of congruence versus incongruence unlocks a nuanced narrative about audience preferences and expectations, potentially leading to differentiated strategies for both filmmakers and actors alike.

In conclusion, this exploration serves to underscore the need for ongoing research into the intricacies of personality alignment within the film industry. By adopting a multifaceted approach that incorporates both quantitative measures and qualitative insights, future studies can reveal deeper understandings of market dynamics, subsequently enrich the academic discourse and provide actionable strategies for industry stakeholders.

9. Conclusion

The findings from the study illuminate the nuanced role of personality congruence in influencing box office outcomes, emphasizing that such congruence is not a universal lever for success. Instead, it is a contextual and time-sensitive instrument that should be strategically applied depending on genre expectations and audience engagement levels. For fast-paced genres like Comedy and Adventure, where clear expectations shape audience responses, leveraging congruence effectively can galvanize early ticket sales and enhance opening weekend performance. Conversely, in the realm of prestige films, audiences seem to favor a range of portrayals and artistic craftsmanship over mere safe sameness, thereby necessitating a different marketing approach that highlights an actor's versatility.

This synthesis integrates my empirical findings with broader literature on persuasion and market response. Previous studies have indicated that while some genres benefit from clear persona-role alignment, others may experience diminished returns from such harmony, calling for a more dynamic understanding of audience expectations. For instance, Iqbal et al. highlight the importance of pre-release factors like marketing efforts in predicting movie success, suggesting that situational contexts could reshape audience anticipation (Giannetti et al., 2024).

Moreover, exploring variations in audience reactions based on genre can enhance strategic decision-making for studios. Research by Chiu et al. (2019) suggests that the impact of online word-of-mouth varies across genres, which can significantly correlate with box office performance. In addition, findings related to the influence of star recognition further augment the argument that established actors can attract audiences by showcasing versatility, which is critical in marketing strategies (Iqbal et al., 2021). Therefore, studios must balance short-term strategies that exploit audience heuristics while simultaneously investing in long-term brand equity that embraces artistic breadth and authenticity.

In conclusion, a deeper understanding of personality congruence in casting reveals its complex relationship with market dynamics, nurturing the potential for nuanced strategies that can enhance both immediate box office performance and sustainable success in the evolving landscape of the film industry.

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Appendices

A. Python codes for personality presiction

1. Code from **augmented.ipynb**: Data Augmentation

```
import nltk
from nltk.corpus import wordnet
import random
import pandas as pd

# Ensure you have the necessary datasets downloaded
nltk.download('averaged_perceptron_tagger')
nltk.download('wordnet')

def get_synonyms(word):
    """Get synonyms of a word."""
    synonyms = set()
    for syn in wordnet.synsets(word):
        for lemma in syn.lemmas():
            synonym = lemma.name().replace("_", " ").replace("-", "
").lower()
            synonym = "".join([char for char in synonym if char.isalpha() or
char == ' '])
            synonyms.add(synonym)
    if word in synonyms:
        synonyms.remove(word)
    return list(synonyms)

def synonym_replacement(sentence, n):
    """Replace n words in the sentence with their synonyms."""
    words = sentence.split()
    random_word_list = list(set([word for word in words if
wordnet.synsets(word)]))
    random.shuffle(random_word_list)
    num_replaced = 0
    for random_word in random_word_list:
        synonyms = get_synonyms(random_word)
```

```
        if len(synonyms) > 0:
            synonym = random.choice(synonyms)
            new_words = []
            for word in words:
                if word == random_word and num_replaced < n:
                    word = synonym
                    num_replaced += 1
                new_words.append(word)
            sentence = ' '.join(new_words)
            if num_replaced == n:
                break
    return sentence

# Load your original data
data_path = '/content/extended_data.csv'
data = pd.read_csv(data_path)

# Apply data augmentation to the TEXT column
data['Augmented_TEXT'] = data['TEXT'].apply(lambda x: synonym_replacement(x, 
1))

# Save the augmented dataset to a new CSV file
output_path = '/content/augmented_data.csv'
data.to_csv(output_path, index=False)
print("Augmented dataset has been saved successfully!")
```

2. Code from **balanced.ipynb:** Balancing the Dataset

```
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split
import pandas as pd
from sklearn.utils import resample

# Load dataset
data = pd.read_csv('/content/augmented_data.csv')

# List of trait names
traits = ['cEXT', 'cNEU', 'cAGR', 'cCON', 'cOPN']
```

```
def balanced_increment(data, trait, other_traits):
    class_0 = data[data[trait] == 0]
    class_1 = data[data[trait] == 1]
    minority_class = class_0 if len(class_0) < len(class_1) else class_1
    majority_class_size = max(len(class_0), len(class_1))
    samples_to_add = majority_class_size - len(minority_class)
    increment_size = min(100, samples_to_add)
    while samples_to_add > 0:
        minority_class_resampled = resample(minority_class, replace=True,
n_samples=increment_size)
        data = pd.concat([data, minority_class_resampled])
        for other_trait in other_traits:
            balance_ratio = data[other_trait].mean()
            if balance_ratio < 0.4 or balance_ratio > 0.6:
                increment_size = max(10, int(increment_size / 2))
        samples_to_add -= increment_size
    return data

# Apply the balancing function to each trait
for trait in traits:
    other_traits = [t for t in traits if t != trait]
    data = balanced_increment(data, trait, other_traits)

# Save the balanced dataset
data.to_csv('/content/balanced_dataset.csv', index=False)
```

3. Code from **model.ipynb**: Training and Evaluating Machine Learning Models

```
import pandas as pd
import numpy as np
from transformers import BertTokenizer, BertModel
import torch
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.ensemble import GradientBoostingClassifier,
RandomForestClassifier, StackingClassifier
from sklearn.linear_model import LogisticRegression
```

```
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
from xgboost import XGBClassifier
from joblib import dump
from sklearn.preprocessing import StandardScaler
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer
import re

# Load LIWC and BPDIC datasets and merge them
df_LIWC = pd.read_csv('/content/LIWC-22 Results - augmented_balanced_dataset
- LIWC Analysis.csv')
df_BPDIC = pd.read_csv('/content/LIWC-22 Results - augmented_balanced_dataset
- BPDIC Analysis.csv')
df = pd.merge(df_LIWC, df_BPDIC, on='TEXT', how='left')

# Drop redundant columns after merging
cols_to_drop = [col for col in df.columns if col.endswith('_drop')]
df.drop(cols_to_drop, axis=1, inplace=True)

# Data Cleaning Steps
df = df.dropna()  # Handle missing values by removing rows with NaNs
df = df.drop_duplicates()  # Remove duplicate rows

# Text Cleaning Function
def clean_text(text):
    text = text.lower()
    text = re.sub(r'\d+', '', text)  # Remove numbers
    text = re.sub(r'[^\w\s]', '', text)  # Remove punctuation
    text = word_tokenize(text)  # Tokenization
    text = [word for word in text if word not in stopwords.words('english')]
# Remove stop words
    stemmer = PorterStemmer()
    text = [stemmer.stem(word) for word in text]  # Stemming
    return ' '.join(text)

# Apply text cleaning to the TEXT column
```

```
df['TEXT'] = df['TEXT'].apply(clean_text)

# Remove rows where TEXT has fewer than 30 words
df = df[df['TEXT'].apply(lambda x: len(x.split()) >= 30)]

# Feature Extraction using BERT
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
model = BertModel.from_pretrained('bert-base-uncased')
texts = df['TEXT'].tolist()

embeddings = []
for text in texts:
    input_ids = torch.unsqueeze(torch.tensor(tokenizer.encode(text,
max_length=512, truncation=True)), 0)
    with torch.no_grad():
        model.eval()
        last_hidden_states = model(input_ids)[0]
    embeddings.append(last_hidden_states[0][0].numpy())

# Combine LIWC Features with BERT Embeddings
X_liwc = df.drop(['TEXT', 'cEXT', 'cNEU', 'cAGR', 'cCON', 'cOPN'],
axis=1).values
X_bert = np.array(embeddings)
combined_features = np.hstack((X_liwc, X_bert))

# Targets (Personality Traits)
target_traits = ['cEXT', 'cNEU', 'cCON', 'cOPN', 'cAGR']
X = combined_features
y = df[target_traits].values

# Split Data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Feature Scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
# Define Models
models = {
    'Logistic Regression': LogisticRegression(max_iter=1000),
    'SVM': SVC(probability=True, random_state=42),
    'Random Forest': RandomForestClassifier(n_estimators=100,
random_state=42),
    'MLP': MLPClassifier(max_iter=500, random_state=42),
    'GBM': GradientBoostingClassifier(n_estimators=100, random_state=42),
    'XGB': XGBClassifier(n_estimators=100, random_state=42)
}

# Add Stacking Classifier
stack = StackingClassifier(
    estimators=[('GBM', models['GBM']), ('XGB', models['XGB'])],
    final_estimator=LogisticRegression()
)
models['Stack'] = stack

# Train and Evaluate Models
for trait_idx, trait in enumerate(target_traits):
    y_train_trait = y_train[:, trait_idx]
    for model_name, model in models.items():
        # Train Model
        model.fit(X_train_scaled, y_train_trait)
        # Cross-Validation
        cv_scores = cross_val_score(model, X_train_scaled, y_train_trait,
cv=5, scoring='accuracy')
        print(f"{model_name} - {trait}: CV Accuracy =
{np.mean(cv_scores):.3f}")
        # Save the Model
        model_filename = f'/content/{trait}_{model_name.replace(" ",
"_")}_model.pkl'
        dump(model, model_filename)
        print(f"Model saved at {model_filename}")
```

B. Personality prediction model results across models

Personality Trait cEXT	'precision'	'recall'	'f1-score'	'accuracy'	'support'
Logistic Regression Classification Report	57.00%	59.23%	58.12%	59.70%	2000
SVM Classification Report	57.57%	67.10%	61.61%	61.03%	2000
Random Forest Classification Report	61.57%	59.15%	59.87%	63.22%	2000
Gradient Boosting Classification Report	59.23%	65.14%	61.57%	61.39%	2000
MLP Classification Report	61.93%	59.78%	60.49%	62.75%	2000
Voting Classifier Report	63.78%	67.74%	65.56%	64.13%	2000
Stacking Classifier Report	72.17%	75.30%	73.56%	74.55%	2000

Personality Trait cNEU	'precision'	'recall'	'f1-score'	'accuracy'	'support'
Logistic Regression Classification Report	63.16%	56.98%	59.39%	59.48%	2000
SVM Classification Report	62.62%	62.60%	62.21%	60.35%	2000
Random Forest Classification Report	64.96%	66.09%	65.18%	63.07%	2000
Gradient Boosting Classification Report	65.23%	58.70%	61.29%	61.39%	2000
MLP Classification Report	66.78%	63.31%	64.89%	63.09%	2000
Voting Classifier Report	69.96%	65.42%	67.09%	65.94%	2000
Stacking Classifier Report	75.23%	71.87%	73.35%	72.54%	2000

Personality Trait cCON	'precision'	'recall'	'f1-score'	'accuracy'	'support'
Logistic Regression Classification Report	58.42%	67.24%	62.20%	61.60%	2000
SVM Classification Report	63.93%	58.09%	60.73%	62.74%	2000
Random Forest Classification Report	64.41%	65.21%	64.51%	63.77%	2000
Gradient Boosting Classification Report	61.48%	61.40%	61.34%	60.76%	2000
MLP Classification Report	66.06%	60.26%	62.72%	62.98%	2000
Voting Classifier Report	69.32%	65.76%	67.25%	63.98%	2000
Stacking Classifier Report	74.41%	73.97%	74.13%	74.07%	2000

Personality Trait cOPN	'precision'	'recall'	'f1-score'	'accuracy'	'support'
Logistic Regression Classification Report	59.15%	56.75%	57.59%	60.41%	2000
SVM Classification Report	62.49%	64.85%	63.33%	62.01%	2000
Random Forest Classification Report	63.91%	60.46%	62.05%	63.04%	2000
Gradient Boosting Classification Report	58.74%	66.94%	62.86%	61.61%	2000
MLP Classification Report	66.08%	58.60%	62.15%	62.82%	2000
Voting Classifier Report	70.29%	67.62%	68.71%	69.95%	2000
Stacking Classifier Report	74.10%	74.63%	74.35%	74.73%	2000

Personality Trait cAGR	'precision'	'recall'	'f1-score'	'accuracy'	'support'
Logistic Regression Classification Report	55.11%	58.32%	56.18%	59.14%	2000
SVM Classification Report	58.39%	60.34%	59.05%	62.18%	2000
Random Forest Classification Report	57.07%	65.56%	60.99%	61.74%	2000
Gradient Boosting Classification Report	57.66%	60.78%	58.94%	61.54%	2000
MLP Classification Report	56.00%	66.58%	60.62%	60.78%	2000
Voting Classifier Report	75.29%	66.14%	70.00%	70.00%	2000
Stacking Classifier Report	70.60%	75.34%	72.76%	74.32%	2000

C. regression result from R

1. Baseline model (no moderators)

a) Trait level congruence:

Estimation results (Model 3)

	Domestic box office	Opening weekend revenue
AGR	0.0004 (308.4)	-0.0007 (220.8)
CON	-0.0026 (180.6)	0.0011 (140.3)
EXT	-0.0013 (209.7)	0.0011 (148.4)
NEU	0.0003 (109.3)	0.0004 (89.98)
OPN	0.0023 (112.3)	-5.05e-5 (64.89)
genreAdventure	-22,428,881.9 (18,736,547.3)	-14,213,621.2* (7,081,158.9)
genreComedy	-49,346,850.5*** (12,208,982.7)	-19,811,953.0*** (5,004,175.3)
genreDocumentary	-55,161,497.4** (19,106,775.8)	-15,474,561.1* (7,518,100.2)
genreDrama	-47,952,088.8*** (11,193,412.7)	-19,393,686.1*** (4,655,641.7)
genreHorror	-47,443,070.6** (14,545,546.9)	-19,959,495.0*** (6,033,296.7)
genreMusical	-28,862,253.6* (12,304,969.9)	-14,630,427.5*** (3,948,309.8)
genreThriller	-39,116,814.3** (12,231,307.8)	-18,785,010.0*** (5,096,651.2)
Openness star	1,053,338.5 (3,000,421.8)	-1,112,214.1 (1,008,987.4)
Conscientiousness star	-2,475,051.1 (3,866,214.4)	-725,010.3 (1,261,103.8)
Extraversion star	-1,016,421.0 (5,460,252.4)	-1,474,940.5 (1,898,728.1)
Agreeableness star	1,926,288.4 (3,004,508.5)	220,796.7 (984,826.0)
Neuroticism star	-1,985,227.3 (3,338,651.9)	-44,913.9 (1,148,632.5)
sequel	35,512,732.2** (12,055,278.4)	19,106,508.1*** (3,852,876.1)

running time	63,149.6 (42,394.4)	34,704.8** (13,384.3)
theatrical engagements	3,576.4*** (471.0)	
opening weekend theaters		4,155.3*** (838.7)
AGRxgenre=Action	-3,487,216.7 (5,840,491.7)	-223,353.4 (2,482,272.0)
AGRxgenre=Adventure	-2,195,560.5 (4,564,208.2)	-531,011.6 (1,200,815.0)
AGRxgenre=Comedy	979,492.5 (1,382,335.7)	492,780.4 (425,857.1)
AGRxgenre=Documentary	-411,813.1 (786,932.2)	-217,819.8 (417,948.2)
AGRxgenre=Drama	151,769.9 (1,611,088.8)	-320,848.3 (523,512.5)
AGRxgenre=Horror	-3,077,276.7 (3,452,964.6)	-1,855,319.0 (1,328,172.6)
AGRxgenre=Musical	9,340,543.3 (8,334,902.6)	1,216,348.7 (2,508,081.3)
AGRxgenre=Thriller	167,885.7 (2,970,571.4)	-1,147,177.8 (793,455.9)
CONxgenre=Action	5,583,872.5 (6,039,599.7)	3,626,472.3 (2,415,128.7)
CONxgenre=Adventure	-1,888,919.1 (3,268,567.4)	-545.7 (871,975.8)
CONxgenre=Comedy	-963,746.8 (978,521.2)	-573,709.5* (268,322.9)
CONxgenre=Documentary	-327,431.2 (1,033,127.6)	-613,355.8 (696,713.3)
CONxgenre=Drama	510,625.6 (927,827.2)	-9,039.9 (286,370.7)
CONxgenre=Horror	-4,305,790.8 (3,564,833.2)	-953,641.7 (1,289,652.8)
CONxgenre=Musical	-7,891,534.8 (8,368,034.0)	-1,205,625.6 (1,470,492.3)
CONxgenre=Thriller	1,582,096.6 (2,024,622.2)	216,288.8 (543,690.6)
EXTxgenre=Action	-9,969,440.3 (6,988,873.3)	-4,358,685.4 (2,803,123.9)
EXTxgenre=Adventure	7,337,650.0. (4,003,693.1)	2,237,486.4. (1,250,604.9)
EXTxgenre=Comedy	956,288.3 (961,758.2)	605,353.4. (327,852.7)
EXTxgenre=Documentary	452,977.6 (514,804.3)	59,758.1 (322,683.5)
EXTxgenre=Drama	-1,084,237.5 (992,356.0)	-249,354.3 (314,940.2)
EXTxgenre=Horror	-1,622,555.2 (2,619,585.7)	616,515.9 (988,633.8)
EXTxgenre=Musical	-4,631,833.9 (5,778,061.3)	-1,140,595.1 (1,760,674.8)
EXTxgenre=Thriller	3,765,026.0. (2,222,796.5)	615,038.4 (463,332.0)
NEUxgenre=Action	-3,142,801.7 (7,046,316.2)	-236,751.5 (2,805,170.5)
NEUxgenre=Adventure	1,033,048.5 (4,243,241.9)	94,784.2 (1,163,850.0)
NEUxgenre=Comedy	1,886,638.6 (1,692,696.1)	985,090.9. (563,732.6)
NEUxgenre=Documentary	-494,822.7 (621,381.7)	-227,514.1 (392,301.3)
NEUxgenre=Drama	1,048,862.3 (1,671,792.7)	83,422.9 (505,787.5)
NEUxgenre=Horror	-4,410,755.8 (3,607,480.3)	-1,205,962.3 (1,477,652.3)

NEUxgenre=Musical	16,572,295.8 (13,202,586.3)	-1,348,967.3 (1,734,818.7)
NEUxgenre=Thriller	-3,795,236.1 (3,326,596.7)	20,456.1 (749,527.5)
OPNxgenre=Action	-5,679,642.1. (3,299,749.0)	-1,709,537.6 (1,370,861.2)
OPNxgenre=Adventure	-4,232,637.8 (3,979,415.2)	-2,097,148.0* (1,002,706.8)
OPNxgenre=Comedy	837,803.5 (832,416.5)	133,144.5 (273,463.9)
OPNxgenre=Documentary	-897,881.7 (3,137,494.1)	-1,701,264.9 (1,790,559.9)
OPNxgenre=Drama	-608,382.6 (817,587.4)	-48,337.0 (250,953.8)
OPNxgenre=Horror	-1,915,540.2 (2,698,210.0)	574,434.0 (941,784.0)
OPNxgenre=Musical	-5,662,664.5 (5,723,000.6)	176,675.4 (854,925.3)
OPNxgenre=Thriller	-2,546,986.4 (2,413,243.3)	52,537.0 (554,394.6)
Fixed-Effects: --------------	-------------------------------------	-----------------------------------
Production Year	Yes	Yes
Release Month	Yes	Yes
distributor	Yes	Yes
S.E.: Clustered by	\`moviename\`	\`moviename\`
Observations	45,143	45,143
R2	0.5709	0.50381
Within R2	0.22242	0.21376

Notes: ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

Table 13. Genre Moderated Model Results (trait level congruence)

b) Summed congruence:

Estimation results (Model 4)		
	Domestic box office	Opening weekend revenue
SC	-0.0003 (8.677)	-0.0002 (3.901)
genreAdventure	-20,575,969.9 (18,303,093.7)	-13,306,970.5. (6,828,008.8)
genreComedy	-48,547,936.3*** (11,660,923.1)	-19,313,034.0*** (4,755,665.1)
genreDocumentary	-53,960,058.4** (18,864,808.1)	-15,110,366.4* (7,314,758.1)
genreDrama	-47,376,898.1*** (10,683,564.1)	-18,820,562.1*** (4,400,686.4)
genreHorror	-46,352,650.2** (14,229,736.5)	-19,156,437.2** (5,896,074.9)
genreMusical	-27,459,893.2* (11,903,781.1)	-13,444,596.3*** (3,908,772.4)
genreThriller	-37,397,836.9** (11,739,750.8)	-18,130,168.4*** (4,836,111.3)

Openness star	702,632.0 (2,986,289.6)	-1,212,803.0 (1,004,528.4)
Conscientiousness star	-2,506,979.6 (3,899,743.8)	-772,272.7 (1,281,658.4)
Extraversion star	-746,593.9 (5,624,269.0)	-1,428,413.0 (1,971,458.2)
Agreeableness star	1,851,316.3 (2,944,171.0)	151,769.1 (946,203.2)
Neuroticism star	-2,143,502.9 (3,243,092.0)	-176,920.8 (1,116,126.2)
sequel	35,667,372.6** (12,112,836.8)	19,169,545.4*** (3,885,982.0)
running time	63,449.8 (42,508.0)	34,629.7* (13,449.6)
theatrical engagements	3,586.5*** (477.0)	
opening weekend theaters		4,168.5*** (849.1)
SCxgenre=Action	-2,955,682.7. (1,705,896.8)	-369,988.6 (672,994.3)
SCxgenre=Adventure	83,423.5 (2,067,629.1)	-13,590.9 (537,177.2)
SCxgenre=Comedy	708,958.2 (605,150.0)	330,740.9. (177,626.0)
SCxgenre=Documentary	-238,289.0 (787,718.7)	-421,107.1 (461,382.1)
SCxgenre=Drama	78,176.9 (577,254.8)	-121,913.7 (181,240.0)
SCxgenre=Horror	-3,190,449.8. (1,737,681.5)	-648,140.9 (683,340.9)
SCxgenre=Musical	218,896.3 (1,914,456.9)	-633,532.4 (477,050.0)
SCxgenre=Thriller	-131,318.9 (1,018,091.3)	-49,216.0 (250,607.5)
Fixed-Effects: --------------	-------------------------------------	-----------------------------------
Production Year	Yes	Yes
Release Month	Yes	Yes
distributor	Yes	Yes
S.E.: Clustered by	\`moviename\`	\`moviename\`
Observations	45,143	45,143
R2	0.59391	0.54511
Within R2	0.34143	0.2734

Notes: ** p < 0.01, * p < 0.05, + p < 0.1

Table 14. Genre Moderated Model Results (holistic congruence)

2. Genre × Congruence model

a) Trait level congruence:

Estimation results (Model 3)		
	Domestic box office	Opening weekend revenue

AGR	0.0004 (308.4)	-0.0007 (220.8)
CON	-0.0026 (180.6)	0.0011 (140.3)
EXT	-0.0013 (209.7)	0.0011 (148.4)
NEU	0.0003 (109.3)	0.0004 (89.98)
OPN	0.0023 (112.3)	-5.05e-5 (64.89)
genreAdventure	-22,428,881.9 (18,736,547.3)	-14,213,621.2* (7,081,158.9)
genreComedy	-49,346,850.5*** (12,208,982.7)	-19,811,953.0*** (5,004,175.3)
genreDocumentary	-55,161,497.4** (19,106,775.8)	-15,474,561.1* (7,518,100.2)
genreDrama	-47,952,088.8*** (11,193,412.7)	-19,393,686.1*** (4,655,641.7)
genreHorror	-47,443,070.6** (14,545,546.9)	-19,959,495.0*** (6,033,296.7)
genreMusical	-28,862,253.6* (12,304,969.9)	-14,630,427.5*** (3,948,309.8)
genreThriller	-39,116,814.3** (12,231,307.8)	-18,785,010.0*** (5,096,651.2)
Openness star	1,053,338.5 (3,000,421.8)	-1,112,214.1 (1,008,987.4)
Conscientiousness star	-2,475,051.1 (3,866,214.4)	-725,010.3 (1,261,103.8)
Extraversion star	-1,016,421.0 (5,460,252.4)	-1,474,940.5 (1,898,728.1)
Agreeableness star	1,926,288.4 (3,004,508.5)	220,796.7 (984,826.0)
Neuroticism star	-1,985,227.3 (3,338,651.9)	-44,913.9 (1,148,632.5)
sequel	35,512,732.2** (12,055,278.4)	19,106,508.1*** (3,852,876.1)
running time	63,149.6 (42,394.4)	34,704.8** (13,384.3)
theatrical engagements	3,576.4*** (471.0)	
opening weekend theaters		4,155.3*** (838.7)
AGRxgenre=Action	-3,487,216.7 (5,840,491.7)	-223,353.4 (2,482,272.0)
AGRxgenre=Adventure	-2,195,560.5 (4,564,208.2)	-531,011.6 (1,200,815.0)
AGRxgenre=Comedy	979,492.5 (1,382,335.7)	492,780.4 (425,857.1)
AGRxgenre=Documentary	-411,813.1 (786,932.2)	-217,819.8 (417,948.2)
AGRxgenre=Drama	151,769.9 (1,611,088.8)	-320,848.3 (523,512.5)
AGRxgenre=Horror	-3,077,276.7 (3,452,964.6)	-1,855,319.0 (1,328,172.6)
AGRxgenre=Musical	9,340,543.3 (8,334,902.6)	1,216,348.7 (2,508,081.3)
AGRxgenre=Thriller	167,885.7 (2,970,571.4)	-1,147,177.8 (793,455.9)
CONxgenre=Action	5,583,872.5 (6,039,599.7)	3,626,472.3 (2,415,128.7)
CONxgenre=Adventure	-1,888,919.1 (3,268,567.4)	-545.7 (871,975.8)
CONxgenre=Comedy	-963,746.8 (978,521.2)	-573,709.5* (268,322.9)
CONxgenre=Documentary	-327,431.2 (1,033,127.6)	-613,355.8 (696,713.3)

CONxgenre=Drama	510,625.6 (927,827.2)	-9,039.9 (286,370.7)
CONxgenre=Horror	-4,305,790.8 (3,564,833.2)	-953,641.7 (1,289,652.8)
CONxgenre=Musical	-7,891,534.8 (8,368,034.0)	-1,205,625.6 (1,470,492.3)
CONxgenre=Thriller	1,582,096.6 (2,024,622.2)	216,288.8 (543,690.6)
EXTxgenre=Action	-9,969,440.3 (6,988,873.3)	-4,358,685.4 (2,803,123.9)
EXTxgenre=Adventure	7,337,650.0. (4,003,693.1)	2,237,486.4. (1,250,604.9)
EXTxgenre=Comedy	956,288.3 (961,758.2)	605,353.4. (327,852.7)
EXTxgenre=Documentary	452,977.6 (514,804.3)	59,758.1 (322,683.5)
EXTxgenre=Drama	-1,084,237.5 (992,356.0)	-249,354.3 (314,940.2)
EXTxgenre=Horror	-1,622,555.2 (2,619,585.7)	616,515.9 (988,633.8)
EXTxgenre=Musical	-4,631,833.9 (5,778,061.3)	-1,140,595.1 (1,760,674.8)
EXTxgenre=Thriller	3,765,026.0. (2,222,796.5)	615,038.4 (463,332.0)
NEUxgenre=Action	-3,142,801.7 (7,046,316.2)	-236,751.5 (2,805,170.5)
NEUxgenre=Adventure	1,033,048.5 (4,243,241.9)	94,784.2 (1,163,850.0)
NEUxgenre=Comedy	1,886,638.6 (1,692,696.1)	985,090.9. (563,732.6)
NEUxgenre=Documentary	-494,822.7 (621,381.7)	-227,514.1 (392,301.3)
NEUxgenre=Drama	1,048,862.3 (1,671,792.7)	83,422.9 (505,787.5)
NEUxgenre=Horror	-4,410,755.8 (3,607,480.3)	-1,205,962.3 (1,477,652.3)
NEUxgenre=Musical	16,572,295.8 (13,202,586.3)	-1,348,967.3 (1,734,818.7)
NEUxgenre=Thriller	-3,795,236.1 (3,326,596.7)	20,456.1 (749,527.5)
OPNxgenre=Action	-5,679,642.1. (3,299,749.0)	-1,709,537.6 (1,370,861.2)
OPNxgenre=Adventure	-4,232,637.8 (3,979,415.2)	-2,097,148.0* (1,002,706.8)
OPNxgenre=Comedy	837,803.5 (832,416.5)	133,144.5 (273,463.9)
OPNxgenre=Documentary	-897,881.7 (3,137,494.1)	-1,701,264.9 (1,790,559.9)
OPNxgenre=Drama	-608,382.6 (817,587.4)	-48,337.0 (250,953.8)
OPNxgenre=Horror	-1,915,540.2 (2,698,210.0)	574,434.0 (941,784.0)
OPNxgenre=Musical	-5,662,664.5 (5,723,000.6)	176,675.4 (854,925.3)
OPNxgenre=Thriller	-2,546,986.4 (2,413,243.3)	52,537.0 (554,394.6)
Fixed-Effects: --------------	-------------------------------------	-----------------------------------
Production Year	Yes	Yes
Release Month	Yes	Yes
distributor	Yes	Yes

S.E.: Clustered by	`moviename`	`moviename`
Observations	45,143	45,143
R2	0.5709	0.50381
Within R2	0.22242	0.21376

Notes: ** p < 0.01, * p < 0.05, + p < 0.1

Table 15. Genre Moderated Model Results (trait level congruence)

b) Summed congruence:

Estimation results (Model 4)

	Domestic box office	Opening weekend revenue
SC	-0.0003 (8.677)	-0.0002 (3.901)
genreAdventure	-20,575,969.9 (18,303,093.7)	-13,306,970.5. (6,828,008.8)
genreComedy	-48,547,936.3*** (11,660,923.1)	-19,313,034.0*** (4,755,665.1)
genreDocumentary	-53,960,058.4** (18,864,808.1)	-15,110,366.4* (7,314,758.1)
genreDrama	-47,376,898.1*** (10,683,564.1)	-18,820,562.1*** (4,400,686.4)
genreHorror	-46,352,650.2** (14,229,736.5)	-19,156,437.2** (5,896,074.9)
genreMusical	-27,459,893.2* (11,903,781.1)	-13,444,596.3*** (3,908,772.4)
genreThriller	-37,397,836.9** (11,739,750.8)	-18,130,168.4*** (4,836,111.3)
Openness star	702,632.0 (2,986,289.6)	-1,212,803.0 (1,004,528.4)
Conscientiousness star	-2,506,979.6 (3,899,743.8)	-772,272.7 (1,281,658.4)
Extraversion star	-746,593.9 (5,624,269.0)	-1,428,413.0 (1,971,458.2)
Agreeableness star	1,851,316.3 (2,944,171.0)	151,769.1 (946,203.2)
Neuroticism star	-2,143,502.9 (3,243,092.0)	-176,920.8 (1,116,126.2)
sequel	35,667,372.6** (12,112,836.8)	19,169,545.4*** (3,885,982.0)
running time	63,449.8 (42,508.0)	34,629.7* (13,449.6)
theatrical engagements	3,586.5*** (477.0)	
opening weekend theaters		4,168.5*** (849.1)
SCxgenre=Action	-2,955,682.7. (1,705,896.8)	-369,988.6 (672,994.3)
SCxgenre=Adventure	83,423.5 (2,067,629.1)	-13,590.9 (537,177.2)
SCxgenre=Comedy	708,958.2 (605,150.0)	330,740.9. (177,626.0)
SCxgenre=Documentary	-238,289.0 (787,718.7)	-421,107.1 (461,382.1)
SCxgenre=Drama	78,176.9 (577,254.8)	-121,913.7 (181,240.0)
SCxgenre=Horror	-3,190,449.8. (1,737,681.5)	-648,140.9 (683,340.9)

SCxgenre=Musical	218,896.3 (1,914,456.9)	-633,532.4 (477,050.0)
SCxgenre=Thriller	-131,318.9 (1,018,091.3)	-49,216.0 (250,607.5)
Fixed-Effects: --------------	-------------------------------------	-----------------------------------
Production Year	Yes	Yes
Release Month	Yes	Yes
distributor	Yes	Yes
S.E.: Clustered by	\`moviename\`	\`moviename\`
Observations	45,143	45,143
R2	0.59391	0.54511
Within R2	0.34143	0.2734

Notes: ** p < 0.01, * p < 0.05, + p < 0.1

Table 16. Genre Moderated Model Results (holistic congruence)

3. Artistic Recognition × Congruence model

a) Trait level congruence:

Estimation results (Model 5)		
	Domestic box office	Opening weekend revenue
AGR	911,640.9 (1,469,917.9)	79,452.4 (505,738.5)
CON	-1,109,374.6 (924,516.9)	-196,610.6 (294,069.1)
EXT	1,655,885.3 (1,167,483.8)	899,999.0* (453,438.8)
NEU	3,140,850.5** (1,213,039.3)	697,680.3. (379,894.4)
OPN	-2,187,557.7* (979,858.7)	-531,118.4. (299,510.0)
artistic recognition	2,591,242.5 (3,790,163.4)	853,016.1 (1,417,103.4)
Openness star	45,088.9 (3,247,237.3)	-1,412,478.9 (1,097,108.8)
Conscientiousness star	-1,934,679.2 (4,006,190.2)	-706,570.8 (1,314,071.1)
Extraversion star	-2,130,727.5 (6,379,907.7)	-2,101,019.5 (2,282,720.3)
Agreeableness star	1,576,011.0 (3,227,738.5)	45,794.7 (1,103,456.4)
Neuroticism star	-2,003,144.5 (3,422,302.8)	-68,397.1 (1,218,297.7)
sequel	44,119,013.1*** (12,533,282.5)	21,884,757.6*** (4,244,766.7)

running time	91,509.3. (47,119.7)	47,860.0** (16,789.3)
theatrical engagements	3,840.9*** (472.5)	
opening weekend theaters		4,569.5*** (823.9)
AGRxartistic recognition	-3,010,896.6 (2,782,598.5)	-748,080.2 (982,333.2)
CONxartistic recognition	3,571,987.9. (2,007,539.1)	874,955.2 (745,030.9)
EXTxartistic recognition	-3,001,407.7 (2,845,262.8)	-1,873,906.6 (1,199,543.5)
NEUxartistic recognition	-7,668,266.5** (2,508,790.6)	-1,184,815.1 (796,998.9)
OPNxartistic recognition	3,608,219.3* (1,729,528.6)	740,876.6 (560,121.7)
Fixed-Effects: --------------	-------------------------------------	-----------------------------------
Production Year	Yes	Yes
Release Month	Yes	Yes
distributor	Yes	Yes
S.E.: Clustered by	\`moviename\`	\`moviename\`
Observations	45,143	45,143
R2	0.57185	0.50454
Within R2	0.30566	0.2086

Notes: ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

Table 17. Artistic Recognition Moderated Model Results (trait level congruence)

b) Summed congruence:

Estimation results (Model 6)		
	Domestic box office	Opening weekend revenue
SC	627,858.2 (435,047.5)	228,363.0. (126,447.9)
artistic recognition	3,938,845.1 (3,700,936.5)	927,170.3 (1,323,843.1)
Openness star	-442,139.4 (3,203,748.7)	-1,564,721.8 (1,078,727.7)
Conscientiousness star	-1,943,519.3 (4,043,686.0)	-722,739.2 (1,331,978.8)
Extraversion star	-2,008,489.1 (6,367,311.3)	-2,015,996.7 (2,272,307.0)
Agreeableness star	1,516,983.7 (3,139,126.0)	-54,273.0 (1,062,896.7)
Neuroticism star	-2,241,208.7 (3,263,105.8)	-202,369.0 (1,160,525.2)
sequel	44,166,681.4*** (12,585,453.8)	21,877,191.9*** (4,253,401.2)
running time	92,096.2. (47,153.6)	47,918.7** (16,750.5)
theatrical engagements	3,839.3*** (473.1)	

opening weekend theaters		4,572.6*** (821.3)
SCxartistic recognition	-1,746,186.5* (881,412.4)	-523,547.4* (252,612.5)
Fixed-Effects: --------------	-------------------------------------	-----------------------------------
Production Year	Yes	Yes
Release Month	Yes	Yes
distributor	Yes	Yes
S.E.: Clustered by	\`moviename\`	\`moviename\`
Observations	45,143	45,143
R2	0.57098	0.50391
Within R2	0.30425	0.20758

Notes: ** p < 0.01, * p < 0.05, + p < 0.1

Table 18. Artistic Recognition Moderated Model Results (holistic congruence)

4. Combined moderation model

a) Trait level congruence:

Estimation results (Model 7)		
	Domestic box office	Opening weekend revenue
AGR	0.0006 (307.0)	-0.0005 (132.8)
CON	-0.0020 (179.0)	0.0009 (89.89)
EXT	-0.0013 (208.7)	0.0009 (90.11)
NEU	0.0003 (108.6)	0.0002 (51.78)
OPN	0.0015 (110.9)	-6.94e-5 (59.51)
genreAdventure	-21,703,683.8 (18,540,892.0)	-12,993,062.8* (6,202,895.7)
genreComedy	-48,841,304.7*** (12,113,649.1)	-18,562,700.3*** (4,182,730.6)
genreDocumentary	-55,180,084.4** (18,633,709.1)	-15,904,963.1* (6,396,961.7)
genreDrama	-47,694,607.3*** (11,077,291.1)	-17,542,168.2*** (3,737,041.8)
genreHorror	-47,067,279.3** (14,415,610.0)	-16,637,665.6*** (4,959,821.6)
genreMusical	-28,073,671.5* (12,088,978.4)	-15,673,042.2*** (4,565,905.2)
genreThriller	-39,010,964.6** (12,090,773.4)	-14,793,083.4*** (3,995,557.3)
artistic recognition	726,416.8 (3,463,371.4)	-341,834.6 (1,094,266.7)
Openness star	892,005.5 (3,062,042.9)	-520,057.5 (915,576.0)

Conscientiousness star	-2,576,117.6 (3,802,192.4)	-893,377.4 (1,264,417.9)
Extraversion star	-708,710.0 (5,650,026.9)	-1,230,279.0 (1,977,356.2)
Agreeableness star	1,877,035.0 (3,033,382.2)	276,623.0 (968,699.6)
Neuroticism star	-1,711,082.5 (3,231,630.2)	313,105.2 (1,052,008.3)
sequel	35,363,946.4** (11,945,837.6)	16,739,349.1*** (3,742,037.2)
running time	61,961.3 (42,337.5)	22,172.4. (11,856.7)
theatrical engagements	3,577.5*** (470.9)	
opening weekend theaters		4,781.7*** (149.9)
AGRxgenre=Action	-2,276,039.1 (5,408,963.2)	49,737.3 (2,025,545.1)
AGRxgenre=Adventure	-1,410,660.7 (4,881,291.2)	-56,952.8 (1,420,868.3)
AGRxgenre=Comedy	1,700,612.4 (1,864,756.1)	195,315.9 (562,887.0)
AGRxgenre=Documentary	781,153.5 (2,691,811.4)	-260,095.1 (889,316.8)
AGRxgenre=Drama	1,167,892.5 (2,531,461.8)	-308,424.9 (848,190.2)
AGRxgenre=Horror	-2,822,263.3 (3,726,005.6)	-1,142,420.7 (1,164,715.0)
AGRxgenre=Musical	8,765,369.4 (8,050,080.8)	2,283,773.6 (2,865,090.2)
AGRxgenre=Thriller	982,201.0 (3,437,608.0)	-709,180.1 (1,140,295.9)
CONxgenre=Action	4,491,149.1 (5,628,185.7)	2,959,360.8 (1,997,915.8)
CONxgenre=Adventure	-2,863,032.4 (3,407,258.0)	-114,826.1 (891,802.4)
CONxgenre=Comedy	-1,819,975.9 (1,242,189.3)	-817,363.1* (330,403.6)
CONxgenre=Documentary	-3,093,420.6 (2,206,890.7)	-1,203,605.4 (783,807.1)
CONxgenre=Drama	-1,104,738.1 (1,402,501.5)	-592,039.9 (463,510.1)
CONxgenre=Horror	-4,930,167.0 (3,749,873.8)	-1,206,626.6 (1,192,544.8)
CONxgenre=Musical	-8,773,954.7 (8,349,064.4)	-415,849.0 (1,486,966.3)
CONxgenre=Thriller	589,887.6 (2,307,803.9)	-467,111.6 (731,342.9)
EXTxgenre=Action	-8,737,852.6 (6,220,844.1)	-3,138,937.0 (2,224,322.3)
EXTxgenre=Adventure	8,102,826.9. (4,314,087.8)	3,107,612.2* (1,403,076.6)
EXTxgenre=Comedy	1,748,190.1 (1,446,375.8)	791,182.0 (492,150.4)
EXTxgenre=Documentary	3,812,988.7. (2,207,243.8)	1,386,946.1. (756,765.3)
EXTxgenre=Drama	428,798.4 (1,925,230.8)	403,129.2 (648,041.0)
EXTxgenre=Horror	-873,611.0 (2,929,805.6)	364,783.3 (1,024,744.6)
EXTxgenre=Musical	-3,782,895.8 (5,605,558.2)	-1,225,640.9 (2,179,347.1)
EXTxgenre=Thriller	4,855,380.4. (2,625,052.9)	1,248,835.6. (715,748.4)
NEUxgenre=Action	419,595.6 (7,093,079.4)	846,411.4 (2,456,136.9)

NEUxgenre=Adventure	4,034,623.2 (4,086,958.9)	1,398,381.9 (1,208,688.2)
NEUxgenre=Comedy	4,293,556.3* (1,875,294.1)	1,070,092.1* (499,773.0)
NEUxgenre=Documentary	5,261,300.8* (2,131,352.9)	1,282,667.6* (650,225.0)
NEUxgenre=Drama	5,132,718.1* (2,028,329.7)	1,284,237.3* (627,478.7)
NEUxgenre=Horror	-1,884,101.4 (3,721,559.4)	-860,101.1 (1,212,128.4)
NEUxgenre=Musical	17,445,018.5 (13,209,077.2)	-4,142,216.8 (3,874,194.6)
NEUxgenre=Thriller	-946,452.4 (3,501,788.5)	397,134.9 (900,774.4)
OPNxgenre=Action	-6,604,184.5. (3,395,873.9)	-2,510,765.6* (1,192,074.6)
OPNxgenre=Adventure	-5,609,861.3 (4,047,830.9)	-1,986,557.0. (1,028,618.8)
OPNxgenre=Comedy	-126,237.7 (988,937.2)	-38,395.0 (269,840.1)
OPNxgenre=Documentary	-3,344,402.3 (3,411,387.9)	-1,600,722.6 (1,420,923.9)
OPNxgenre=Drama	-2,266,955.4. (1,218,559.6)	-579,403.9. (342,347.0)
OPNxgenre=Horror	-2,885,985.3 (2,872,100.3)	-564,076.1 (841,539.6)
OPNxgenre=Musical	-6,076,671.2 (5,840,737.2)	1,178,913.1 (1,071,748.3)
OPNxgenre=Thriller	-3,793,700.5 (2,382,852.9)	-341,436.4 (561,196.6)
AGRxartistic recognition	-2,213,284.8 (2,887,380.5)	-107,218.7 (956,948.9)
CONxartistic recognition	3,301,227.9. (1,847,508.6)	996,833.6. (601,066.2)
EXTxartistic recognition	-3,004,115.4 (2,550,954.2)	-1,318,550.4 (876,636.3)
NEUxartistic recognition	-8,113,942.8** (2,497,115.2)	-1,974,494.6** (764,365.1)
OPNxartistic recognition	3,613,746.6* (1,650,322.3)	970,450.1* (450,575.1)
Fixed-Effects: --------------	-------------------------------------	-----------------------------------
Production Year	Yes	Yes
Release Month	Yes	Yes
distributor	Yes	Yes
S.E.: Clustered by	\`moviename\`	\`moviename\`
Observations	45,143	45,143
R2	0.5709	0.50381
Within R2	0.22242	0.21376

Notes: ** p < 0.01, * p < 0.05, + p < 0.1

Table 19. Combined Moderated Model Results (trait level congruence)

b) Summed congruence:

Estimation results (Model 8)		
	Domestic box office	Opening weekend revenue
SC	-0.0002 (8.662)	-0.0001 (3.186)
genreAdventure	-20,432,895.5 (18,222,295.3)	-12,298,855.2* (6,065,563.0)
genreComedy	-48,334,825.2*** (11,576,750.7)	-18,098,261.6*** (3,968,967.8)
genreDocumentary	-56,162,655.2** (18,608,830.3)	-16,023,702.1* (6,339,978.0)
genreDrama	-47,677,847.8*** (10,605,935.4)	-17,179,963.8*** (3,541,047.6)
genreHorror	-45,858,447.6** (14,165,302.4)	-15,932,120.9** (4,875,921.7)
genreMusical	-27,224,398.8* (11,917,425.8)	-14,079,786.3** (4,764,099.9)
genreThriller	-37,268,352.9** (11,718,162.6)	-14,166,625.3*** (3,830,021.4)
artistic recognition	2,252,195.0 (3,440,193.4)	-69,876.9 (1,072,593.8)
Openness star	408,289.5 (3,048,411.9)	-658,271.7 (905,389.7)
Conscientiousness star	-2,645,348.8 (3,853,523.6)	-940,729.6 (1,287,888.2)
Extraversion star	-572,463.2 (5,732,414.4)	-1,166,824.9 (2,014,537.6)
Agreeableness star	1,799,193.6 (2,969,532.5)	200,747.5 (930,609.3)
Neuroticism star	-1,970,523.9 (3,148,466.8)	182,010.8 (1,018,774.9)
sequel	35,512,235.2** (12,042,187.5)	16,773,690.6*** (3,786,798.3)
running time	62,685.0 (42,475.9)	22,249.1. (11,895.3)
theatrical engagements	3,584.4*** (477.3)	784.0*** (152.3)
SCxgenre=Action	-2,161,769.2 (1,727,580.9)	-136,052.5 (582,075.9)
SCxgenre=Adventure	732,300.7 (2,106,003.0)	579,920.7 (627,898.6)
SCxgenre=Comedy	1,261,274.3. (692,175.6)	261,342.9. (148,520.6)
SCxgenre=Documentary	1,147,872.3 (1,077,202.6)	94,442.1 (425,212.7)
SCxgenre=Drama	939,000.5 (686,509.8)	96,640.9 (203,101.4)
SCxgenre=Horror	-2,754,191.1 (1,780,861.2)	-715,338.5 (609,031.8)
SCxgenre=Musical	496,434.9 (1,954,673.3)	-610,894.2 (733,034.4)
SCxgenre=Thriller	476,033.8 (1,111,109.7)	53,265.1 (293,388.6)
SCxartistic recognition	-1,797,698.8* (873,429.8)	-413,791.3. (245,187.4)
Fixed-Effects: --------------	-------------------------------------	-----------------------------------
Production Year	Yes	Yes
Release Month	Yes	Yes
distributor	Yes	Yes

S.E.: Clustered by	`moviename`	`moviename`
Observations	45,143	45,143
R2	0.59421	0.57048
Within R2	0.34191	0.31391

Notes: ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

Table 20. Combined Moderated Model Results (holistic congruence)