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Mental Health Disorders on Netflix: Analyzing Stereotypes Across 13 Countries Using the Stereotype Content Model and Machine Learning

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Guided by Fiske's Stereotype Content Model (SCM), this study investigates the portrayal of mental health disorders in Netflix movies and series from 13 production countries, spanning from 2001 to 2023. Two methodological innovations were utilized: First, a codebook aligned with the *International Classification of Diseases (ICD)* was employed to code mental health disorders on Netflix. Second, the analysis was based on the full transcripts of Netflix movies and series, applying Nicolas et al.'s Stereotype Content Model Dictionary to automatically detect the dimensions of "warmth" (the degree of friendliness or likeability) and "competence" (the degree of capability or efficacy). Combining unsupervised hierarchical clustering and supervised K-nearest neighbor (K-NN) classification revealed that the warmth stereotype dimension tends to vary along a spectrum, whereas competence tends to be categorized in a more binary "high-or-low" manner. Moreover, cultural individualism had no impact on cluster assignments. These findings support Netflix's efforts to reduce stigma in the portrayal of mental health.

Public Policy Relevance Statement

Netflix content offers culturally nuanced portrayals of mental health disorders, reducing stigma and stereotypes across global narratives. The findings support Netflix's efforts to combat stigma and emphasize the value of realistic and respectful mental health representations in media. Netflix has a unique opportunity to build on this positive trend, solidifying its role as a platform for meaningful and accurate mental health representation.

Keywords: Stereotype Content Model, mental health, Netflix, cross-cultural comparison, content analysis

Movies, series, and TV programs are key sources of information about mental health disorders, often perpetuating stereotypes, including aggression and dangerousness (e.g., Bathina et al., 2021; Riles et al., 2021), low treatment-seeking (Bathina et al., 2021), risky health behaviors (e.g., drinking, smoking; Riles et al., 2021), engagement in concealment (Smith et al., 2019), and sensationalism (Smith et al., 2019). The Stereotype Content Model (SCM; Fiske et al., 2002) suggests individuals with mental disorders are perceived as low in both warmth and competence (e.g., Boysen et al., 2023), though cultural differences exist (Sadler et al., 2012; Sönmez & Karaoğlu, 2023). Research primarily focuses on U.S. content, overlooking global portrayals—although Netflix offers cultural content, it still lacks adequate representation of cognitive and physical disabilities. Despite Netflix's Inclusion Strategy (Smith et al., 2023), previous studies often rely on small sample sizes, manual content analysis, and lack an in-depth application of the SCM (e.g., Donohue & Swords, 2024; Higueras-Ruiz & Pérez-Rufí, 2025; Peña & Sarrionandia, 2023), underscoring the need for comprehensive cross-cultural studies.

This study assesses mental health disorder stereotype patterns in Netflix movies and series through a cross-cultural, quantitative content analysis. Using descriptive Netflix data, we manually coded mental health disorders based on the *International Classification of Diseases and Related Health Problems* (10th ed.; *ICD-10*) and analyzed show transcripts with the Linguistic

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Katharina Angermayr served as lead role for conceptualization, investigation, methodology, writing–original draft, and contributed equally for formal analysis and writing–review and editing. Sebastian Scherr served as lead role for supervision, contributed equally for formal analysis and writing–review and editing, and served in a supporting role for conceptualization.

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Inquiry and Word Count (LIWC) and the Stereotype Content Dictionary (Nicolas et al., 2021). We applied unsupervised hierarchical clustering and supervised K-nearest neighbor (K-NN) classification to assess stereotypes across different shows and production countries.

Portrayal of Mental Health Disorders on Netflix

Fictional media has long perpetuated stereotypical depictions of characters with mental disorders (e.g., Bathina et al., 2021; Riles et al., 2021; Smith et al., 2019). Although Netflix presents the perception of diversity, however, it remains unclear if streaming services offer truly diverse stories or merely excel in marketing (Khoo, 2023). Netflix's Inclusion Strategy has examined representation across several inclusion categories, including gender, race/ethnicity, LGBTQ+, and disability—highlighting that only 4.2% of main characters are portrayed as disabled, and of these, just 23.3% with mental disorders. This representation is biased, predominantly featuring White, male characters with physical disabilities (Smith et al., 2023). Although research on Netflix focuses on specific series like *13 Reasons Why* (e.g., Wang et al., 2023), there is a gap in broader analyses. Limited research states that mental health portrayals on Netflix are as unrealistic as those in traditional media (Peña & Sarrionandia, 2023), including children's programs (Donohue & Swords, 2024). In addition, Netflix's content varies culturally, revealing national biases, not just Western ones (Lotz, 2021). To address this gap, the present study examines demographic (i.e., age, gender, sexuality) and contextual inclusion attributes (i.e., medication use, crime involvement, risky health behavior, psychotherapy engagement, employment) that may shape the cultural portrayal of mental health disorders on Netflix. We ask:

> *Research Question 1 (RQ1):* What are the demographic and contextual attributes of characters with a mental disorder as portrayed in Netflix movies and series across cultures?

The Stereotype Content Model

The SCM (Fiske et al., 2002) analyzes stereotypes using two dimensions: warmth and competence. Warmth reflects perceived intentions or friendliness, whereas competence relates to goal-achieving abilities, such as intelligence or skill (Cuddy et al., 2009). Combining these dimensions creates a 2 × 2 matrix: low warmth and competence result in contemptuous stereotypes, high warmth and competence in admiration, high competence but low warmth in envy, and high warmth with low competence in paternalism (Fiske et al., 2002). Recent SCMs have refined subcategories of warmth and competence or proposed distinct additional dimensions (Abele et al., 2016; Koch et al., 2016; Nicolas et al., 2021). To ensure theoretical coherence for our study, we mapped relevant constructs identified in the literature (Nicolas et al., 2021) onto warmth (sociability, morality, health, religion, beliefs-other, ordinariness, beauty) and competence (ability, agency, status, work, politics). This allocation reflects their conceptual alignment: warmth-related categories involve interpersonal closeness, inclusion, and moral judgment, whereas competence-related categories concern efficacy, agency, and status (Abele et al., 2016; Koch et al., 2016; Nicolas et al., 2021).

Differentiating Stereotypes Across Mental Disorders and Cultures

Individuals with mental disorders are often viewed as low in warmth and competence (Boysen et al., 2023; Sadler et al., 2012), though perceptions vary by disorder and culture. For example, psychotic disorders are rated low in both dimensions, whereas neurocognitive disorders are seen as warm but incompetent (Sadler et al., 2012). Cultural differences also shape these views: For instance, both German and U.S. participants perceive individuals with depression as moderately warm and competent (Allstadt Torras et al., 2023; Sadler et al., 2012). In contrast, Turkish participants see them as warmer but less competent (Sönmez & Karaoğlu, 2023). Given cultural variation in warmth and competence, and limited SCM use in Netflix research, we ask:

> *Research Question 2 (RQ2):* How will portrayals of mental disorders in Netflix movies and series vary along the dimensions of "warmth" and "competence"?

The SCM explains variations in stereotypes by focusing on cultural context, with the "individualism-collectivism" paradigm (Papadopoulos et al., 2013) being central. Although critiques exist (Berry et al., 2011), recent research supports its relevance (Fatehi et al., 2020). Cuddy et al. (2009) and Fiske and Durante (2016) found that collectivistic cultures tend to show more ambivalence in perceptions of warmth and competence, which may contribute to the stigmatization of mental disorders. In contrast, individualistic cultures—by valuing autonomy, openness, and personal differences—are more likely to foster empathetic portrayals that emphasize complexity and competence. Considering country-specific attitudes toward mental illness and the cultural background of Netflix decision-makers influencing narrative choices (Haddad, 2019), we hypothesize:

> *Hypothesis 1 (H1):* Netflix movies and series produced in individualistic countries will attribute higher warmth and higher competence in their depiction of mental health disorders than Netflix movies and series produced in a collectivistic production country.

Given the overlap between SCM dimensions and mental illness stigma (Sadler et al., 2012), we analyzed indicators of mental health stigma in a cross-cultural context. Stereotypes of laziness, weakness, and irrationality contribute to discrimination in education and employment (WHO, 2022). They are also often portrayed as violent or dangerous (Zhang & Firdaus, 2024), aligning with their low warmth rating in the SCM (Sadler et al., 2012), and are associated with risky health behaviors (Riles et al., 2021). Such behaviors are deemed inappropriate in collectivist cultures, prompting avoidance of facilities like psychotherapy that signal group membership (Yu et al., 2021). Instead, individuals in collectivistic cultures may prefer medication over psychotherapy to manage symptoms discreetly and avoid the stigma associated with seeking mental health treatment, thereby maintaining an appearance of normalcy (Tse & Ng, 2014). Collectivistic values protect against inappropriate behavior, but people with mental disorders may be excluded from this protection if their actions deviate from social norms. This behavior may be seen as a cry for help due to lack of social support (Kam, 2011). Conversely, individualistic cultures prioritize personal recovery, often interpreting it through a biomedical lens that emphasizes individual treatment and symptom management over holistic approaches (Tse & Ng, 2014). To explore Netflix's cultural variations, we hypothesize:

> *Hypothesis 2 (H2):* Characters with a mental disorder as portrayed in Netflix movies and series from collectivistic production countries are more likely to take medication (*H2a*), to commit a crime (*H2b*), to show risky health behaviors (*H2c*), to not undergo psychotherapy (*H2d*), and to not pursue a job (*H2e*) than in individualistic production countries.

Linguistic Indicators of Mental Health Stereotypes

Linguistic indicators can reveal mental states and reduce mental illness stigma (Ślebioda, 2020). Although some progress has been made (e.g., Decter-Frain & Frimer, 2016; Pietraszkiewicz et al., 2019), reliable text-based measures of warmth and competence remain limited (Fiske et al., 2021). The Stereotype Content Dictionary (Nicolas et al., 2021), covering over 80% of stereotypes, addresses this gap, offering a reliable tool for identifying stereotypes despite limitations in dictionary analysis.

Method

Sample

We used *criterion-based*, *purposeful sampling* to select Netflix shows focused on mental health, given the limited scope of such content (Smith et al., 2023). The sampling took place between June 5 and June 11, 2023, with the following inclusion criteria: (a) the movie or series had to be accessible via Netflix in the author's country at the time of sampling, (b) it had to feature at least one character with a mental disorder, (c) it had to include English subtitles, and (d) it had to be released between 2000 and May 2023. The search strategy consisted of several steps: (a) potential movies and series were systematically screened using the Netflix search engine based on a pregenerated keyword list (for the list see https://osf.io/7ske4/files/7q8fb), (b) if all criteria were met, the country of production was coded, and (c) the process was repeated based on the keywords specifically filtered for each coded country. If the format was a series, we analyzed either the first episode mentioning relevant keywords or the first episode of the first season. This approach captures the foundational context and cultural references, as the initial episode often sets the tone, introduces key characters, and establishes themes (Idiz et al., 2024), while also simplifying analysis and focusing on early audience engagement and perception shaping.

The final sample consisted of a total of $N = 130$ Netflix movies and series episodes (13 countries, with 10 Netflix productions each). Cultural categorization was based on the show's production country. It is important to acknowledge that international collaborations in Netflix productions can blend cultural perspectives for global audiences. However, despite the common research practice (Götz et al., 2008; Götz et al., 2018), there have been critical voices about using production countries as culture proxies (e.g., Taras et al., 2016). However, research also indicates that the locality of Netflix content still plays a significant role in authentic cultural representation through local talent, locations, and traditions (Idiz et al., 2024). All selected Netflix movies and series are listed in our OSF (https://osf.io/7ske4/files/n6m9v).

Coding and Intracoder Reliability

All codebook categories were coded and recoded by a single coder, with a 12-day interval between sessions. Although intracoder reliability is not ideal, this approach was chosen for economic and practical reasons. Methodological literature acknowledges that intracoder reliability reflects consistency over time caused by fatigue or inattention (e.g., Lamprianou, 2023). Krippendorff (2012) emphasizes that reliability depends on the consistent application of coding rules. Research has shown that clearly defined coding schemes can yield acceptable intracoder reliability (e.g., Jacinto et al., 2016; Moore et al., 2019). In addition, a substantial portion of the data (i.e., warmth and competence scores) was generated automatically, minimizing subjective bias. Following these guidelines, we assessed intracoder reliability by recoding a random 10% subsample ($n = 13$) after a 12-day interval, using SPSS to calculate Krippendorff's alpha (see Hayes & Krippendorff, 2007). All intracoder reliabilities are available in our OSF (https://osf.io/7ske4/files/cj24h).

Krippendorff's alpha ranges from 0 (no reliability) to 1.00 (perfect reliability), with values of $1.00 \geq \alpha \geq .80$ considered good and $.80 > \alpha \geq .67$ acceptable (Krippendorff, 2012, p. 241). The average intracoder reliability for content categories was $\alpha = .75$. Reliability issues arose with the character's age ($\alpha = .63$) and sexuality ($\alpha = .72$), leading to simplification of the age category into "young" and "old." The sexuality category remained in the analysis as it was within the acceptable range, whereas all other categories had perfect reliability ($\alpha = 1.00$).

The codebook, based on project theory and research, is available on our OSF page (https://osf.io/7ske4/files/8xgtp). For manual coding, the unit of analysis was the first-mentioned character with a mental disorder per movie/show, coded in detail using our codebook. Predefined keywords in the codebook guided transcript searches. Due to format limits, manual coding relied on context and supplemental data from Netflix descriptions and film databases.

Formal Categories

We coded the original title (open text), English title (open text), original language (open text), year of release (open text), format (0 = *movie*, 1 = *series*), episode (season number, episode number), length (in HH:MM:SS), and country/region of production and Netflix genres (e.g., 1 = *Children and Family*, 2 = *Comedies*).

Individualism Index

Each country was scored between 1 and 120 using Hofstede's (1980) Individualism Index via Hofstede Insights (2022); higher scores indicate more individualism. Hofstede was chosen for its simplicity, intuitive structure, and widespread use as a generalizable cultural framework across nations (e.g., Sum et al., 2024).

Mental Disorder

Mental disorders were coded using *ICD-10* classification (e.g., 1 = *depression,* 2 = *anxiety disorder*), including only diagnoses listed in the ICD-10 Chapter V(F) 9th edition (World Health

Organization, 2019). Disorders must be explicitly named in the title, Netflix descriptions, transcript, or databases. If not named, symptoms must align with the *ICD-10*. General issues were coded as 22 = mental disorders without further specification (F99).

Demography

We coded the gender (0 = *male*, 1 = *female*, 2 = *diverse*), the age (0 = *young*, 1 = *old*), and sexuality (1 = *heterosexual*, 2 = *homosexual*, 3 = *other*).

Contextual Factors

We coded if the character received medical treatment (0 = *no*, 1 = *yes*), was associated with committing a crime (0 = *no*, 1 = *yes*), expressed risky health behaviors (0 = *no*, 1 = *yes*), was in therapy (0 = *no,* 1 = *yes*) and whether the character was depicted as having a job (0 = *no*, 1 = *yes*).

Linguistic Analysis

The unit of analysis of the linguistic analysis was the entire transcript. Because linguistically motivated film analysis effectively reflects narrative inferences (Tseng & Bateman, 2012), we employed the LIWC-22 dictionary for initial linguistic analysis and the Stereotype Content Dictionary (Nicolas et al., 2021) to empirically investigate warmth and competence. We opted to analyze entire transcripts from downloaded subtitles, as exemplified by Alenzi and Badruddin (2019) and Yu et al. (2023), for several reasons: First, character-focused approaches may lead to fragmented interpretations by overlooking cohesive narrative structures and broader thematic contexts (Tseng, 2013). Aggregating data at the transcript level enhances narrative clarity and ensures that conclusions reflect characters and dynamics with substantial impact. Second, transcripts were extracted directly from Netflix via a browser developer tool, using unmodified subtitle files focused solely on spoken dialogue. Due to inconsistent formatting, automated speaker attribution was not possible, making character-level linguistic analysis unfeasible (Labatut & Bost, 2020). We therefore analyzed the transcripts as cohesive wholes to preserve narrative coherence. Despite formatting issues, it is important to note that Netflix maintains high standards for subtitle accuracy and quality (Netflix, 2023). Using LIWC stop words, we focused on spoken dialogue to capture narrative coherence.

Although manual coding focused on the first-mentioned character, transcript-level linguistic analysis captured broader narrative patterns. This dual approach ensured thematic coherence (Tseng, 2013) and was necessary due to inconsistent formatting, which hindered character-level attribution—though it may include unrelated content and dilute character-specific insights.

Summary Dimensions

We included total word count, words per sentence, words with more than six letters, dictionary word count, analyticity, authenticity, clout, and emotional tone.

Warmth

To code "warmth," we included seven categories: sociability, morality, health, beliefs, religion, ordinariness, and beauty. For each category, we captured both the frequency of relevant words and their direction (positive or negative). The direction was used to generate the *warmth* index (M = .236, SD = 0.17), calculated by averaging all individual subdimensions.

Competence

To code *competence*, we examined five categories: ability, agency, status, work, and politics. As with warmth, we recorded the frequency and direction for each category. The direction was then used to generate the *competence* index (M = .818, SD = 0.17).

This study's research questions, hypothesis, and analyses were not preregistered.

Results

Descriptive Findings

The sample consists of 80 Netflix movies and 50 series from 13 countries (N = 130 with n = 10 per country) released between 2001 and May 2023. Additional analyses for this project can be found at https://osf.io/7ske4/files/34jpt.

Mental Health Disorders

A total of 22 mental illnesses classified in the *ICD-10* were identified. The most common were "depression" (n = 22), followed by "response to severe stress and adjustment disorders" (n = 19) and "mental and behavioral disorders caused by psychotropic substances" (n = 15).

Demographic and Contextual Factors (RQ1)

Among the 130 characters, a majority were male, comprising 58% (n = 76) of the sample, whereas 41.5% (n = 54) were female. The age distribution showed that 88.5% (n = 115) of characters were coded as old, with the remaining 11.5% (n = 15) categorized as young. In terms of sexual orientation, 69.2% (n = 90) of the characters were heterosexual, 3.8% (n = 5) were homosexual, 1.5% (n = 2) were categorized as "other," and 25.4% (n = 33) could not be defined (Table 1).

Most of the characters, 53.1% (n = 69), had a job, whereas 46.9% (n = 61) were unemployed. Regarding therapy attendance, 73.8% (n = 96) of the characters did not attend therapy, whereas 26.2% (n = 34) did. In terms of medical treatment, 77.7% (n = 101) did not receive any, whereas 22.3% (n = 29) did. Risky health behavior, such as alcohol, drug use, and/or smoking, was exhibited by 53.8% (n = 70) of the characters, whereas the remaining 46.2% (n = 60) did not engage in such behavior. Regarding criminal behavior, 65.4% (n = 85) of the characters did not commit a crime, whereas 34.6% (n = 45) did.

The Portrayal of Mental Disorders on Netflix (*RQ2*, *H1*)

Our second research question asked if the portrayal of mental disorder on Netflix will vary along the lines of "warmth" and "competence." We used a clustering technique (Shapcott, 2024) with 12 categories to capture "warmth" (consisting of seven categories) and "competence" (comprising five categories). We first

Table 1
Descriptive Results of Total Sample

Characteristics	Full sample		U.S.		GBR		ITA		SCAND		FRA		GER		ESP		IND		TUR		KOR		IDN		EGY		AUS	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%
Format																												
Movie	80	61.5	5	50	3	30	5	50	9	90	8	80	7	70	7	70	8	80	6	60	1	10	8	80	9	90	4	40
Series	50	38.5	5	50	7	70	5	50	1	10	2	20	3	30	3	30	2	20	4	40	9	90	2	20	1	10	6	60
Mental disorder																												
Depression	22	16.9	1	10	1	10	4	40	5	50	2	20	0	0	2	20	1	10	1	10	1	10	1	10	1	10	2	20
Anxiety disorder	8	6.2	1	10	0	0	2	20	1	10	0	0	0	0	0	0	0	0	2	20	0	0	1	10	0	0	1	10
Phobic disorder	3	2.3	0	0.0	0	0	1	10	0	0	0	0	0	0	0	0	0	0	0	0	1	10	0	0	0	0	1	10
Bipolar disorder	2	1.5	1	10	0	0	0	0	0	0	0	0	0	0	1	10	0	0	0	0	0	0	0	0	0	0	0	0
Manic disorder	1	0.8	1	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Schizophrenia, schizotypal and delusional disorder	10	7.7	1	10	0	0	0	0	0	0	2	20	1	10	1	10	1	10	1	10	1	10	1	10	1	10	0	0
Response to severe stress and adjustment disorders	19	14.6	0	0.0	4	40	2	20	0	0	1	10	1	10	1	10	3	30	3	30	2	20	1	10	0	0	1	10
Eating disorder	2	1.5	1	10	0	0	1	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Personality and behavioral disorder	6	4.6	2	20	1	10	0	0	2	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	10
Obsessive compulsive disorder	4	3.1	0	0	0	0	0	0	0	0	0	0	1	10	0	0	1	10	1	10	1	10	0	0	0	0	0	0
Dissociative disorders	8	6.2	1	10	1	10	0	0	0	0	1	10	0	0	1	10	1	10	0	0	0	0	1	10	2	20	0	0
Alzheimer's disease	5	3.8	0	0	1	10	0	0	0	0	0	0	1	10	2	20	0	0	0	0	1	10	0	0	0	0	0	0
Mental and behavioral disorders caused by psychotropic substances	15	11.5	0	0	0	0	0	0	0	0	3	30	4	40	1	10	1	10	0	0	2	20	1	10	2	20	1	10
Profound developmental disorders	2	1.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	10	0	0	0	0	1	10
Intellectual disability	1	0.8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	10	0	0	0	0	0	0	0	0
Suicidal ideation	4	3.1	1	10	1	10	0	0	1	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	10	0	0
Developmental disabilities	1	0.8	0	0	1	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Disorders of social functioning with onset in childhood and adolescence	1	0.8	0	0	0	0	0	0	0		0	0	1	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Neurodevelopmental disorders	2	1.5	0	0	0	0	0	0	0	0	0	0	1	10	0	0	0	0	0	0	0	0	1	10	0	0	0	0
Other neurotic disorders	1	0.8	0	0	0	0	0	0	0	0	0	0	0	0	1	10	0	0	0	0	0	0	0	0	0	0	0	0
Sexual preference disorders	1	0.8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	10	0	0	0	0	0	0	0	0	0	0
Mental disorders without further specification	12	9.2	0	0	0	0	0	0	1	10	1	10	0	0	0	0	1	10	1	10	0	0	3	30	3	30	2	20
Gender																												
Male	76	58.5	5	50	6	60	3	30	7	70	4	40	7	70	6	60	6	60	7	70	7	70	6	60	8	80	4	40
Female	54	41.5	5	50	4	40	7	70	3	30	6	60	3	30	4	40	4	40	3	30	3	30	4	40	2	20	6	60
Age																												
Young	15	11.5	3	30	1	10	1	10	1	10	1	10	3	30	2	20	1	10	0	0	0	0	1	10	0	0	1	10
Old	115	88.5	7	70	9	90	9	90	9	90	9	90	7	70	8	80	9	90	10	100	10	100	9	90	10	100	9	90
Sexuality																												
Heterosexual	90	69.2	6	60	8	80	5	50	9	90	5	50	7	70	6	60	7	70	7	70	6	60	8	80	8	80	8	80
Homosexual	5	3.8	0	0	0	0	3	30	1	10	0	0	1	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Other	2	1.5	1	10	0	0	0	0	0	0	0	0	0	0	1	10	0	0	0	0	0	0	0	0	0	0	0	0
Undefined	33	25.4	3	30	2	20	2	20	0	0	5	50	2	20	3	30	3	30	3	30	4	40	2	20	2	20	2	20
Job																												
No	61	46.9	3	30	1	10	9	90	5	50	4	40	6	60	7	70	5	50	4	40	0	0	7	70	4	40	6	60
Yes	69	53.1	7	70	9	90	1	10	5	50	6	60	4	40	3	30	5	50	6	60	10	100	3	30	6	60	4	40

Table 1 (*continued*)

Characteristics	Full sample		U.S.		GBR		ITA		SCAND		FRA		GER		ESP		IND		TUR		KOR		IDN		EGY		AUS	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%
Therapy																												
No	96	73.8	6	60	6	60	8	80	7	70	8	80	7	70	6	60	7	70	8	80	7	70	9	90	9	90	8	80
Yes	34	26.2	4	40	4	40	2	20	3	30	2	20	3	30	4	40	3	30	2	20	3	30	1	10	1	10	2	20
Medical treatment																												
No	101	77.7	8	90	10	10	8	80	7	70	9	90	10	100	7	70	5	50	7	70	7	70	10	100	7	70	6	60
Yes	29	22.3	2	20	0	0	2	20	3	30	1	10	0	0	3	30	5	50	3	30	3	30	0	0	3	30	4	40
Crime																												
No	85	65.4	6	60	3	30	8	80	5	50	7	70	6	60	2	20	8	80	10	100	8	80	8	80	7	70	7	70
Yes	45	34.6	4	40	7	70	2	20	5	50	3	30	4	40	8	80	2	20	0	0	2	20	2	20	3	30	3	30
Risky health behavior																												
No	60	46.2	7	70	6	60	7	70	6	60	3	30	4	40	4	40	5	50	3	30	6	60	5	50	3	30	2	20
Yes	70	53.8	3	30	4	40	3	30	4	40	7	70	6	60	6	60	5	50	7	70	4	40	5	50	7	70	8	80

Note. The table presents the descriptive characteristics broken down by each of the 13 countries (with each country $N = 10$ cases). The total sample consisted of $N = 130$ cases. The percentages listed for each country refer to the values within that country. U.S. = United States; GBR = Great Britain; ITA = Italy; SCAND = Scandinavia; FRA = France; GER = Germany; ESP = Spain; IND = India; TUR = Turkey; KOR = South Korea; IDN = Indonesia; EGY = Egypt; AUS = Australia.

performed a hierarchical cluster analysis in JASP using different distance measures (Euclidean distance and Pearson distance) and different algorithms, namely Ward's method (minimizes within cluster variance; sum of errors) and Ward's D2 method (sum of squared errors). We considered R^2, Akaike information criterion (AIC), and Bayesian information criterion (BIC) as model fit indicators, and Dunn's index (Dunn, 1974) to evaluate the clustering performance to determine the optimum number of clusters (k). For $k = 4$ *Dunn's index* with .132 shows the highest value of all methods used. For AIC/BIC values, the four-cluster solution shows the lowest values, which is also the solution with the highest R^2. Conceptually in line with the SCM (see Fiske et al., 2002), and for empirical reasons, we went with the four-cluster solution (see Table 2).

Based on hierarchical clustering with Euclidean distance and the Ward method, a K-NN classification was performed. The K-NN algorithm (Wu, 2012) is computationally efficient for data sets of varying sizes. The optimal k value was determined using fivefold cross-validation, with $k = 4$ showing the best results with a validation accuracy of .894, a test accuracy of .962 and an average accuracy of .981. The false positive rate for $k = 4$ was .011, indicating accurate classification. The four-cluster solution was deemed most reliable.

Subsequently, to analyze differences in the four clusters, we conducted an analysis of variance using composite scores for competence and warmth, with the grouping variable being the identified four-cluster solution (Figure 1). Paired contrasts revealed that Cluster 3 ($M_{\text{Cluster 3}} = 1.0$, $SE = 0.03$) scored higher on "competence" compared with the other three clusters ($M_{\text{Cluster 1}} = 0.81$, $SE = 0.02$; $M_{\text{Cluster 2}} = 0.72$, $SE = 0.03$; $M_{\text{Cluster 4}} = 0.77$, $SE = 0.03$), $F(3, 126) = 19.07$, $p < .001$, $\eta^2 = .312$. Notably, the "warmth" dimension exhibited larger mean differences across the four clusters ($M_{\text{Cluster 1}} = 0.26$, $SE = 0.02$; $M_{\text{Cluster 2}} = 0.17$, $SE = 0.02$; $M_{\text{Cluster 3}} = 0.45$, $SE = 0.03$; $M_{\text{Cluster 4}} = 0.03$, $SE = 0.03$), $F(3, 126) = 45.40$, $p < .001$, $\eta^2 = .519$.

To address *RQ2*, the portrayal of mental disorder in Netflix movies and series varies primarily along the "warmth" dimension, whereas "competence" tends to be more binary.

H1 proposed that Netflix productions from individualistic countries portray mental disorders with more warmth and competence than collectivistic ones. However, no significant difference was found for competence, $F(13, 116) = 0.700$, $p = .760$. Although warmth showed more variance, the difference was also not significant, $F(13, 116) = 1.578$, $p = .101$. We reject *H1*.

As an additional exploratory analysis, we observed significant differences between the production country and the number of clusters, $\chi^2(36) = 58.8$, $p = .010$, $V = .388$. For detailed findings, please refer to our supplementary materials found at https://osf.io/7ske4/files/6de85. Most cases were categorized into Cluster 3 (competent and warm//"The capable"), with 58 films and series. However, India had eight cases in Cluster 4 (incompetent and cold//"The detached") and one in Cluster 3, whereas Egypt had five cases in Cluster 2 (incompetent and moderately cold//"The disengaged") and two in Cluster 3. Both India and Egypt have low Individualism Index scores. Australia, with a higher individualism index, showed five cases in Cluster 1 (incompetent and moderately warm//"The sociable") and only three in Cluster 3.

A post hoc power analysis using G*Power assessed our sample's statistical power with an alpha of .05, a sample size of 130, and four groups (incompetent/moderately warm, incompetent/

Table 2
Clustering Performance Evaluation

	Distance	Clustering method	Cluster solution	R^2	AIC	BIC	Dunn's index	Cluster	WSS 1	WSS 2	WSS 3	WSS 4	BSS
Hierarchical	Euclidean	Ward's	**4**	**.239**	**1,078.00**	**1,215.64**	**.132**		434.14	369.48	105.5	72.89	**308**
		Ward's D2	4	.239	1,078.00	1,215.64	.132		434.14	369.48	105.5	72.89	308
	Pearson	Ward's	2	.115	1,190.11	1,258.93	.124		744.04	369.48	–	–	176.49
		Ward's D2	2	.115	1,190.11	1,258.93	.124		744.04	369.48	–	–	176.49

	Number of clusters	Validation accuracy	Test accuracy	Average accuracy	Average false positive rate
K-NN classification	2	0.942	0.846	0.846	0.400
	3	0.923	0.923	0.949	0.080
	4	**0.894**	**0.962**	**0.981**	**0.011**
	5	0.846	0.731	0.892	0.100

Note. Clustering performance (i.e., determining the optimal number of clusters) was evaluated combining a hierarchical cluster analysis and a K-NN classification. K-NN classification is based on a hierarchical clustering with Euclidian distance and the Ward method using a fixed number of clusters for cluster determination. Predictions were saved and used as the starting point for the K-NN classification. Bold values indicate optimal cluster solutions based on model fit and classification performance across methods. The K-NN classification used 80% of the data for training and validation and 20% of the data for testing. A fivefold cross-validation was used that splits the sample randomly into five groups and uses one of the groups for testing and the other four groups for training. The process is repeated until each group has been used for testing. AIC = Akaike information criterion; BIC = Bayesian information criterion; WSS = within-cluster sum of squares; K-NN = K-nearest neighbor.

moderately cold, incompetent/cold, competent/warm). With an estimated effect size of f = .30 (based on prior research, e.g., Cuddy et al., 2009), the analysis showed over 80% power (b = .817), indicating sufficient power to detect meaningful effects.

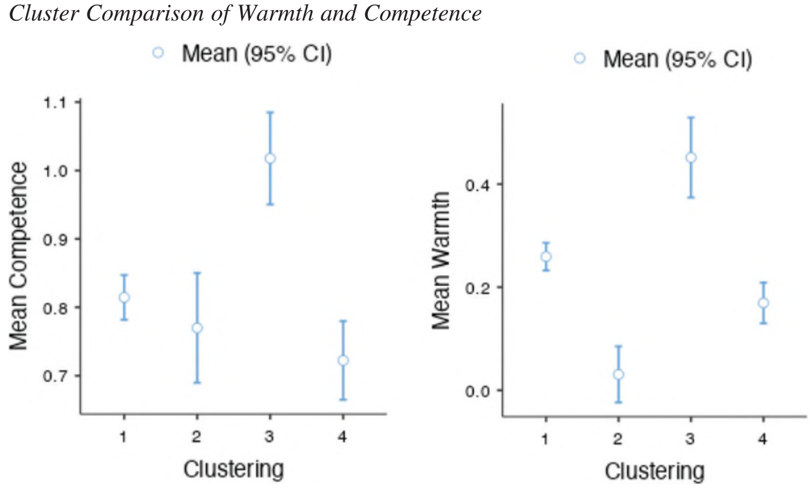
The Portrayal of Mental Disorder on Netflix (*H2*)

H2 postulated that characters with mental disorders differ across production countries. Spearman rank correlations between the individualism/collectivism index and various contextual factors related to mental health stigma, while controlling for production country, revealed no significant correlations for medication (*H2a*; r = –.028, p = .755), risky health behaviors (*H2c*; r = –.071, p = .425), psychotherapy (*H2d*; r = .102, p = .246), or job pursuit (*H2e*; r = –.026, p = .769). In other words, country-level individualism/collectivism was not linked to stigmatizing portrayals of mental health in Netflix content. However, committing a crime (*H2b*; r = .185, p = .036) showed a significant positive correlation with individualism. Contrary to *H3b*, the results imply that higher individualism index values are associated with higher crime ranks.

Post Hoc Analysis

Given differences in the narrative structure between Netflix movies and series (Katerynych et al., 2023), a post hoc analysis separated both formats. For each format, we examined whether demographic and contextual characteristics of characters with mental

Figure 1
Cluster Comparison of Warmth and Competence



Note. The figure shows the comparison of warmth and competence means about groups. CI = confidence interval. See the online article for the color version of this figure.

illness varied systematically (*RQ1*), and whether certain contextual factors predict different ratings of warmth and competence (*H2*). No clear demographic or contextual patterns emerged, and the previously significant crime effect (*H2*) was not stable in both formats. Cluster analysis showed four clusters for movies (as in the total sample) and two for series. For movies, Cluster 4 ($M_{\text{Cluster 4}} = 1.13$, $SE = 0.30$) scored higher on competence compared with the other three clusters ($M_{\text{Cluster 1}} = 0.91$, $SE = 0.02$; $M_{\text{Cluster 2}} = 0.74$, $SE = 0.03$; $M_{\text{Cluster 3}} = 0.74$, $SE = 0.02$), $F(3, 4.76) = 9.01$, $p = .021$, $\eta^2 = .85$. For warmth, Cluster 4 ($M_{\text{Cluster 4}} = 0.81$, $SE = 0.12$) also scored higher compared with the other clusters ($M_{\text{Cluster 1}} = 0.27$, $SE = 0.02$; $M_{\text{Cluster 2}} = .27$, $SE = 0.02$; $M_{\text{Cluster 3}} = 0.10$, $SE = 0.02$), $F(3, 4.87) = 18.23$, $p = .004$, $\eta^2 = .87$. For series, Cluster 1 ($M_{\text{Cluster 1}} = 1.03$, $SE = 0.02$) scored higher on competence than Cluster 2 ($M_{\text{Cluster 2}} = 0.80$, $SE = 0.05$), $F(1, 11) = 17.6$, $p = .001$, $\eta^2 = .62$. Likewise, for warmth, Cluster 1 ($M_{\text{Cluster 1}} = 0.49$, $SE = 0.03$) scored higher than Cluster 2 ($M_{\text{Cluster 2}} = 0.21$, $SE = 0.02$), $F(1, 12.1) = 40.6$, $p < .001$, $\eta^2 = .77$. This suggests that movies offer more character variation, whereas series follow more fixed patterns. However, these findings are exploratory, as the sample sizes for both formats fall below commonly recommended thresholds for robust cluster analysis (e.g., Dalmaijer et al., 2022) and lack sufficient power (movies: $b = .579$; series: $b = .547$). Full results are available on our OSF (https://osf.io/7ske4/files/osfstorage).

Discussion

This study examined the portrayal of mental health disorders in Netflix movies and series from 13 countries, spanning from 2001 to May 2023. A quantitative content analysis of full transcripts was conducted using the Stereotype Content Dictionary (Nicolas et al., 2021) to assess the dimensions of warmth and competence. Depression appeared most frequently, which may reflect its narrative accessibility and emotional familiarity (Peña & Sarrionandia, 2023; Riles et al., 2021). This focus reinforces established storytelling patterns, particularly in the drama genre, and may shape public perceptions of mental illness.

The K-NN cluster analysis revealed that Netflix portrayals of mental disorders vary more in terms of warmth, whereas competence tends to be more binary. This supports the SCM (Fiske et al., 2002), which suggests that competence judgments are linked to perceived status and are therefore less flexible, whereas warmth is more context-sensitive. The results also imply that creators may subtly modulate warmth to fit character narratives, whereas competence remains relatively rigid—potentially shaping viewers' perceptions of individuals' functional abilities.

Our analysis found only subtle cross-cultural differences in how mental health was portrayed across Netflix productions. First, individualistic countries depicted more character warmth than collectivistic countries. This aligns with research suggesting that individualistic cultures, which emphasize autonomy and openness, tend to show lower mental health stigma (Fiske & Durante, 2016; Yu et al., 2021), whereas collectivistic cultures may avoid open portrayals to preserve social harmony (Papadopoulos et al., 2013). No significant differences were found in terms of competence. These results suggest that warmth is culturally sensitive, whereas competence appears globally stable—both warrant further study. Second, chi-square tests showed most shows were rated high in both warmth and competence, regardless of production country. Third, no link between collectivism and portrayals of crime emerged, defying expectations. Both findings challenge persistent media stereotypes about mental illness (e.g., Bathina et al., 2021; Boysen et al., 2023), particularly in non-Western contexts. They also suggest that global streaming platforms increasingly favor universal, de-stigmatized portrayals over culturally specific tropes.

No production country explicitly portrayed mental illness in a stereotypical or stigmatized manner. As Netflix continues to target global audiences (Khoo, 2023), cultural tailoring may be declining. This shift could explain the absence of significant cultural differences, as content is designed to appeal to a broad, international viewership.

Limitations

This study has several limitations. First, interrater reliability was not assessed due to resource constraints. Second, the Netflix focus may explain limited cultural differences; future research should include other platforms and regions for broader insights. Moreover, as Netflix increasingly produces content for global audiences, cultural adaptation may be less prominent, potentially limiting observable cultural differences. Next, analyzing a single episode may miss character development. Future research should use full audio transcripts and detailed dialogue analysis to capture interactions more comprehensively. Furthermore, although we use production country as a cultural proxy, international coproductions may blur cultural distinctions. As movies and series were analyzed within one sample, post hoc subsample analyses were likely underpowered; future studies should explore both formats separately using larger data sets. Relying on linguistic analysis (Nicolas et al., 2021) and English transcripts poses challenges like dialect variation (Kučera & Mehl, 2022). Averaging dictionary scores may bias results. Future research should assess effects on viewer stereotyping and stigma.

Conclusion

Understanding mental illness portrayals on Netflix is crucial given its commitment to inclusion. Our study highlights opportunities to update older scripts while recognizing Netflix's nuanced storytelling, which minimizes stereotypes and stigma across global content. Realistic portrayals of mental illness can educate audiences, support mental health professionals, and encourage help-seeking (Zhang & Firdaus, 2024). Netflix has a unique opportunity to lead in creating content that fulfills these roles. Incorporating linguistic analysis early in scriptwriting or production could further enhance this positive trend, strengthening its role as a platform for meaningful and accurate mental health representation.

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