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ARTICLE

Digital footprints of personality: Large-scale analysis reveals quantitative links between MBTI traits and emotional expression on Reddit

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ABSTRACT

The intersection of personality psychology and computational social science offers unprecedented opportunities to understand human behaviour at scale. However, the precise link between stable personality traits and an individual's online emotional expression remains unquantified across large, naturalistic datasets, with research often bifurcating between complex, "black-box" predictive models and small-scale qualitative studies. Here, we bridge this divide by applying a computationally efficient, lexicon-based framework to a massive dataset of 2,005 Reddit users who publicly self-declared their Myers-Briggs Type Indicator (MBTI) personality type. We analysed the aggregated emotional content of their comment histories, controlling for user activity. We find robust, statistically significant associations between personality dimensions and distinct emotional footprints. The Thinking (T) versus Feeling (F) dimension emerged as the most potent predictor of average sentiment polarity, with 'Thinking' types exhibiting significantly lower average sentiment polarity (β=-0.061, p<1.5e-19). We also find that 'Thinking' types display significantly lower emotional volatility, measured by the standard deviation of their sentiment scores (β=-0.008, p=0.038). Contrary to our initial pro-social hypothesis, Extroversion (E) was not significantly linked to specific'joy'or 'trust' frequencies in the full model, but did correspond to a small but significant increase in overall positive polarity (β=0.016, p=0.032). Furthermore, the Judging (J) dimension unexpectedly emerged as a strong, positive predictor of both overall sentiment (β=0.023, p<0.001) and 'joy' expression (β=0.079, p=0.003). These findings demonstrate that foundational personality traits leave distinct, quantifiable imprints in digital language and that trait-based emotional expression is a multi-dimensional phenomenon where decision-making (T/F) and planning (J/P) traits can be as, or more, influential than social (I/E) traits.

Keywords: MBTI personality traits; Online emotional expression; Digital footprints; Text analysis; Lexicon-based framework.

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INTRODUCTION

The digital platforms of the twenty-first century have become vast, unstructured archives of human cognition and social interaction (Stella et al., 2023). Billions of individuals now use social media to express thoughts, beliefs, and emotions, providing an unprecedented ecological dataset for the social and computational sciences (Musk & K., 2023). Understanding the fundamental drivers of this online behaviour is a central challenge. A classic question in psychology, predating the digital age, is the extent to which stable, internal personality traits govern external behaviour and expression (S et al., 2022b; B et al., 2019). The convergence of these two domains—personality psychology and digital social data—presents a unique opportunity to test foundational psychological theories at a scale previously thought impossible (Schwartz et al., 2013).

The field of Natural Language Processing (NLP) applied to mental health, personality, and emotion is growing rapidly (Musk & K., 2023; S et al., 2022a; B et al., 2019; C et al., 2021). Early research largely focused on coarse sentiment analysis (positive vs. negative), but the field has increasingly shifted towards finer-grained emotion detection (e.g., joy, anger, sadness) to capture a more nuanced view of user expression (H et al., 2021; A et al., 2023). Concurrently, a dominant trend in computational personality research has been prediction: using complex machine learning (ML) and deep learning (DL) models to infer personality traits (typically the Big Five) from a user's text (A et al., 2021; M et al., 2020; N et al., 2021; I et al., 2022; G et al., 2023). Recent studies demonstrate that modern Large Language Models (LLMs) can infer personality from social media posts with moderate, above-chance accuracy (V et al., 2024; H et al., 2023). However, this predictive arms race towards model complexity is often detrimental to interpretability, computational expense, and scalability. These "black-box" models, while powerful, often obscure the specific linguistic mechanisms linking personality and expression (S et al., 2022b; G et al., 2023). Furthermore, their performance against traditional, feature-based methods is not always superior, especially when considering computational trade-offs (V et al., 2024).

A distinct methodological gap thus exists: a lack of large-scale, confirmatory studies that use computationally efficient, interpretable, and transparent methods to validate the linguistic correlates of personality. We are not interested in predicting personality; we leverage a large, self-labeled dataset to explain its linguistic consequences. This study fills this gap by reversing the typical research question. Instead of asking "Can we predict personality from text?", we ask, "Does a known personality trait manifest in text in a predictable way?". We use a computationally efficient, lexicon-based framework (VADER and NRC), which remains robust, highly interpretable, and validated for analysing social media text (S et al., 2022b; C et al., 2019).

Based on our theoretical framework integrating MBTI theory with the Emotion as Social Information (EASI) model (C et al., 2019), we formulated specific hypotheses: (1) Extroversion (E) would correlate with higher mean sentiment (H1a) and elevated frequencies of pro-social emotions like 'joy' (H1b) and 'trust' (H1c) (L et al., 2017; S et al., 2022a); (2) Feeling (F) types would exhibit higher average sentiment, greater affective word expression (H2a), and higher frequencies of interpersonally-focused negative emotions like 'sadness' (H2c) compared to Thinking (T) types; (3) the Thinking (T) dimension would be associated with lower variance in sentiment polarity, indicating greater emotional stability (H3a).

Related Works

The study of human psychology through digital traces is a rapidly expanding field at the intersection of computational linguistics, artificial intelligence, and social science. Social media platforms provide unparalleled resources for analysing mental health (Musk & K., 2023; C et al., 2021), behaviour (W et al., 2021), and personality (B et al., 2019; S et al., 2022a). Research has evolved from broad sentiment analysis to granular emotion detection (H et al., 2021; A et al., 2023) and complex cognitive phenomena (Stella et al., 2023).

A primary focus has been predicting personality traits from user-generated text, with applications in marketing, team-building, and personalized recommendations (B et al., 2019; S et al., 2022a). Early approaches relied on traditional machine learning pipelines with engineered features like TF-IDF (A et al., 2021), emotion lexicons (N et al., 2021), and psycholinguistic dictionaries (S et al., 2022b), using models like SVM, Naive Bayes, or Random Forests (N et al., 2021; C et al., 2021) valued for interpretability and efficiency.

Recent trends shift to deep learning, with hybrid models (e.g., CNN-LSTM) for MBTI classification (M et al., 2020) and Bi-LSTMs for extroversion prediction (A et al., 2021). Pre-trained transformers (e.g., BERT, RoBERTa) and LLMs (e.g., GPT) show strong performance, even in zero-shot settings (H et al., 2023; V et al., 2024). However, these models suffer from an “interpretability gap,” obscuring the reasons behind predictions (G et al., 2023; S et al., 2022b), a critical limitation for scientific inquiry focused on explanation. Recent work addresses this by linking LLM embeddings to linguistic markers (V et al., 2024; S et al., 2022b).

A parallel research stream examines emotional expression on social media, including tools (e.g., text, emoticons) (F et al., 2020) and influencing factors like personality. For example, extroversion predicts positive social media posts (L et al., 2017), and the EASI model explains emotional cues as persuasive signals (C et al., 2019).

Our study bridges these fields by using a transparent, lexicon-based methodology for large-scale confirmatory analysis. We validate linguistic manifestations of personality in emotion, responding to calls for psychometrically valid and explainable models (V et al., 2024; S et al., 2022b).

METHODS

Literature Review Methodology

To situate our study, we conducted a systematic literature review of articles published between January 2017 and December 2023 in Google Scholar, PubMed, and ACM Digital Library. Search queries combined keywords from personality (e.g., ’personality’, ’MBTI’, ’Big Five’), platform (’social media’, ’Reddit’, ’Twitter’), and method (’NLP’, ’text analysis’, ’machine learning’, ’LLM’, ’emotion’), yielding 92 potential articles. Manual screening for relevance to personality prediction or linguistic correlates of personality resulted in 22 core papers. This review identified a gap between high-compute predictive models (e.g., LLMs, DL) (A et al., 2021; M et al., 2020; V et al., 2024; H et al., 2023; I et al., 2022) and small-scale explanatory models (L et al., 2017; S et al., 2022b). Our study addresses this gap with a low-compute, explanatory model applied to a large dataset.

Data Collection and Preprocessing

The dataset was derived from the public Pushshift Reddit comment corpus. Data collection followed two stages: (1) Targeted scanning of personality-focused subreddits (e.g., r/mbti, r/infp, r/intj) identified 5,044 users with self-declared 4-letter MBTI types in their user “flair”; (2) Retrieval of complete comment histories for this cohort, excluding comments from personality subreddits to avoid topical bias. A minimum activity filter (≥20 valid comments) ensured statistical reliability, resulting in a final sample of 2,005 users. Binary dummy variables were created for each MBTI dimension (e.g., ’Is Extrovert’ = 1 for E-types, 0 for I-types).

RESULTS

Data Description and Distributions

The final sample of 2,005 users was skewed towards Introversion (’isExtrovert’ mean = 0.237), Thinking types (’isThinking’ mean = 0.637), and Intuitive types (’isSensing’ mean = 0.109), characteristic of online personality communities. User-level average sentiment polarity ('avgSentimentPolarity') was approximately normal (Mean = 0.170, Std. Dev. = 0.146). User activity ('commentCount') followed a long-tail power law (median = 56, mean = 113.15), justifying the 'commentCountScaled' control variable. Full descriptive statistics are presented in Table 1.

Table 1. Descriptive Statistics for Key Analytical Variables (N=2,005)

Variable Class	Variable	Mean	Std. Dev.	Min	25%	50% (Median)	75%	Max
Personality Dims.	isExtrovert	0.237	0.426	0.000	0.000	0.000	0.000	1.000
(Binary)	isSensing	0.109	0.311	0.000	0.000	0.000	0.000	1.000
	isThinking	0.637	0.481	0.000	0.000	1.000	1.000	1.000
	isJudging	0.386	0.487	0.000	0.000	0.000	1.000	1.000
Sentiment Metrics	avgSentimentPolarity	0.170	0.146	-0.263	0.067	0.148	0.256	0.768
	stdSentimentPolarity	0.476	0.080	0.211	0.420	0.474	0.527	0.761
Emotion Metrics	freqJoy	0.711	0.572	0.000	0.362	0.576	0.879	9.250
(NRC Freq.)	freqSadness	0.564	0.430	0.000	0.277	0.444	0.690	12.292
	freqAnger	0.520	0.886	0.000	0.258	0.411	0.650	7.292
	freqTrust	1.059	0.469	0.000	0.533	0.829	1.308	5.865
Control Variable	commentCount	113.15	521.40	20.000	32.000	56.000	112.00	22707.00

Note: Emotion metrics are mean frequencies derived from the NRC lexicon. Statistics are rounded to 3 decimal places.

Baseline Comparative Analysis

Welch's t-tests of 'avgSentimentPolarity' revealed a highly significant difference for the T/F dimension ($p<8.2e-18$), with Feelers (F) (Mean = 0.237, N=727) exhibiting higher average sentiment than Thinkers (T) (Mean = 0.132, N=1278), supporting H2a. The I/E dimension showed a non-significant trend ($p=0.057$), with Extroverts (E) (Mean = 0.179) slightly more positive than Introverts (I) (Mean = 0.166). ANOVA comparing 'freqSadness' across four MBTI types (INFP, INTJ, ESTP, ESFJ) was non-significant ($F(3,149)=0.94$, $p=0.418$), highlighting the need for multivariate regression Multivariate Regression and Ablation Analysis

Correlation analysis and OLS regression models isolated the independent effect of each personality dimension . The ablation study predicting 'avgSentimentPolarity' showed the 'isThinking' coefficient remained stable (-0.060 to -0.061) as predictors and controls were added, demonstrating robustness. The full mode had the highest explanatory power (Adj. $R^2=0.045$).

DISCUSSION

Our large-scale analysis provides quantitative evidence that MBTI personality dimensions correspond to distinct emotional footprints in online language. The dominant role of the T/F dimension confirms its status as a primary driver of sentiment polarity and emotional stability. Thinkers exhibited lower average sentiment and volatility, empirically validating the "logically stable" T-type archetype. This aligns with MBTI theory, as Feelers prioritize harmony and values while Thinkers emphasize logic.

Extroversion's effects were nuanced: a small positive impact on overall sentiment but no link to specific pro-social emotions. This refines prior work (L et al., 2017) by showing bivariate links may not hold when controlling other personality factors, suggesting Extroversion's linguistic marker is generalized positivity.

The unexpected positive role of the J dimension—predicting higher sentiment, joy, and trust—offers a new research avenue. J-types' preference for structure may manifest as more positive, trusting emotional expression, warranting further investigation.

Limitations include self-declared MBTI labels (not clinical diagnoses), self-selection bias, potential NRC lexicon limitations (capturing expressiveness over discrete emotions), and non-representative

Reddit user base. Cross-sectional design limits causal inference. Future work should replicate findings across platforms (Schwartz et al., 2013) and cultures (N et al., 2021), integrating lexicon-based features with LLM embeddings in a confirmatory framework.

In conclusion, our findings demonstrate that personality traits leave quantifiable imprints in digital language, with decision-making (T/F) and planning (J/P) traits as influential as social (I/E) traits. This advances understanding of personality-expression links in naturalistic digital environments.

DATA AVAILABILITY STATEMENT

The aggregated, anonymized user-level sentiment and emotion feature data, and code to reproduce analyses, are deposited in the Zenodo repository:

Repository Name: Digital footprints of personality: Emotional expression and MBTI traits on Reddit (Aggregated Dataset and Code)

Persistent Identifier (DOI): https://doi.org/10.5281/zenodo.17538772

Access Link: https://zenodo.org/records/17538772

Raw comment content from Reddit cannot be shared publicly due to user agreements. Researchers may obtain raw data via the Reddit API (https://www.reddit.com/dev/api/) or Pushshift dataset, complying with terms of service.

REFERENCES

[1] The author declares no conflicts of interest regarding the design, execution, data analysis, and writing of this study.

[2] A, A., et al. (2023). Deep emotion recognition in textual conversations: a survey. Artificial Intelligence Review, 56:11333–11406.

[3] A, B., et al. (2021). Ai knows you: Deep learning model for prediction of extroversion personality trait. IEEE Access, 9:118464–118475.

[4] B, R., et al. (2019). Personality prediction with social behavior by analyzing social media data – a survey. International Journal of Advanced Computer Science and Applications, 10(6):324–332.

[5] C, L., et al. (2019). The persuasive power of emoticons in electronic word-of-mouth communication in social networking. Journal of Business Research, 101:50–65.

[6] C, S., et al. (2021). Big data analytics on social networks for real-time depression detection. Journal of Big Data, 8:111.

[7] H, A. A., et al. (2021). Beyond sentiment analysis: A review of recent trends in text based sentiment analysis and emotion detection. Journal of Big Data, 8:83.

[8] H, L., et al. (2023). Large language models can infer psychological dispositions of social media users. Nature Communications, 14:5678.

[9] I, W. W., et al. (2022). Text based personality prediction from multiple social media data sources using pre-trained language model and model averaging. Journal of Big Data, 9:109.

[10] L, F., et al. (2017). Emotion expression on social networking sites: A study of young persons' use of facebook and twitter in the uk. Journal of Psychological Research and Behaviour Management, 10:247–255.

[11] M, A., et al. (2020). A hybrid deep learning technique for personality trait classification from text. IEEE Access, 8:175960–175971.

[12] Musk, D. R., & K., A. (2023). Mental health analysis in social media posts: A survey. ACM Computing Surveys, 55(1):1–38.

[13] N, A. A., et al. (2021). Big five personality prediction based in indonesian tweets using machine learning methods. PeerJ Computer Science, 7:e521.