Myers-Briggs Type Indicator and the Big Five Model - How Our Personality Affects Language Use

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***Abstract*—Recently there has been an increasing interest in personality computing, a research field that mainly concerns itself with problems of personality perception, synthesis and recognition. In order to provide personality measure for these tasks, two models have been most commonly applied: the Myers-Briggs Type Indicator (MBTI) and the Big Five model (BF). Since some early scientific works have been critical of MBTI, the Big Five model has historically been more favoured by the scientific community. However, in recent years there has been an increasing number of researchers examining the possible application of MBTI in personality computing. Although the correlation between the set of measures offered by these two models has been proven to exist, works that directly compare the two, especially from the aspect of language usage, have been scarce. In this paper we examine the linguistic similarities between individuals labelled with MBTI types and Big Five dimensions by conducting an analysis using Linguistic Inquiry and Word Count (LIWC). Our study has further substantiated previous linguistic qualities of the Big Five model, while providing a novel insight into how MBTI types influence language use. Additionally, the results of our research have indicated existence of language use patterns shared by these two models. To the best of our knowledge, this is the first time a comparison of effects the two personality models have on language usage has been made.**

***Index Terms*—Personality Computing, Five Factor Model, Big Five, MBTI, LIWC**

I. INTRODUCTION

Differences in motives and behaviours on an individual level between people have been a source of scientific inquiry since at least the ancient times [1]. Answering this question, personality psychology has pointed to the existence of personality – a construct aimed at explaining the patterns of thought, feeling and behaviour that are characteristic to an individual, and as such represent an integral part in how we present ourselves and interact with others. Later, developments in computer science began to facilitate the use of personality in order to give new insights into how people communicate, leading to the development of the personality computing research field.

Located at the intersection of computer science and personality [2], this research field has sought to identify and examine personality relevant information from the ways in which people express themselves, such as textual messages or non-verbal communication. In order to label personality differences present in these information sources, the two most commonly adopted sets of measure have been the Myers-Briggs Type Indicator (MBTI) and the Big Five personality model (BF), also known as the Five Factor model (FFM). While the MBTI model has been based on the theoretical works of Carl Gustav Jung [3], the Big Five model stems from the statistical analysis of the English lexicon [4]. It is these differences that caused the two models to be rarely used within the same area, which in turn made the comparison between the two a difficult task.

While the original three categories of **Introversion/Extroversion** (the process through which an individual gains energy), **Sensing/Intuitive** (an individual's way of gaining information) and **Thinking/Feeling** (how an individual makes decisions) come from the theory of Carl Gustav Jung, it is with the introduction of the fourth – **Judging/Perceiving** (the preferred way of interaction with others) by Isabel Briggs-Myers and Katharine Cook Briggs [5] that the MBTI model was finalized. These four categories represent dichotomies, meaning an individual is assigned one of the two possible types from a single category, resulting in one of the 16 possible combinations, e.g. INTJ (**Introverted-iNtuitive-Thinking-Judging**). Due to this nature, the MBTI grew in popularity in commercial areas such as career suggestion [6] and team building processes [7]. However, its nature also received criticism [8], [9], leading to its infrequent adoption in scientific circles.

On the other hand, the Big Five personality model [10] has been described as "the dominant paradigm in personality research, and one of the most influential models in all of psychology" [11], thus seeing extensive use in scientific work that focuses on personality. The name of the model comes from the five continuous dimensions it uses to measure personality. These measures are typically referred to as **Agreeableness** (level of compassion), **Conscientiousness** (how organized an individual is), **Extroversion** (sociability), **Neuroticism** (level of confidence) and **Openness** to experience (curiosity). For example, a person can score 70 percent on the **Agreeableness** measure, showing they are less likely to challenge others' opinion.

Despite the differences between the two models, researchers have found a correlation between the measures present in the MBTI model and some measures of the Big Five model [9], [12]. Big Five's **Extroversion**, **Openness**, **Agreeableness** and **Conscientiousness** dimensions were specifically found to be correlated to the **Introvert/Extrovert**, **Sensing/Intuition**, **Thinking/Feeling** and **Judging/Perceiving** types respectively, while no statistically significant correlation was observed for the **Neuroticism** dimension. With high labelling costs and privacy issues in creating personality labelled data [13] being cited as one of the obstacles present in personality computing, the correlation between the two models as well as the noted easier access to MBTI labels [14] can possibly benefit any research involving the Big Five model. However, the relationship between the two models was never examined past the mentioned correlations.

In this paper we set out to provide further insight into the relationship between the MBTI and Big Five model by conducting analysis into the language use on the social media platform Reddit. We utilize Linguistic Inquiry and Word Count (LIWC) [15] software, a tool commonly used in language analysis, to better understand how individuals labelled with different personalities express themselves and what the differences between the personality measures belonging to the two models are. To our knowledge, this is the first time an in-depth analysis has been conducted on the language usage of individuals labelled with MBTI types, as well as the first time a direct comparison has been made between the MBTI and Big Five models from the perspective of language use.

The rest of this paper is structured in the following way. The next section discusses some of the related work performed in the area of personality computing. Section III presents and discusses the results of our work. Finally, Section IV provides the conclusion to this paper and insight into future work.

II. Related Work

A. Personality Computing and Personality Labelled Data

Often cited as one of the first works in personality computing, the work of Pennebaker and King [16] examined the connection between language and personality using essays written by 838 students as a data source. Other early works that followed also relied on smaller datasets from either essays [17] [18], emails [19] or blogs [20]. However, with some of the early models capability to predict behavioural and thinking patterns [21], as well as different aspects of life, such as occupational choice or even political ideology [22], it soon became apparent that any work that seeks to analyze, understand, predict or even replicate human behaviour can greatly benefit from personality computing approaches [1].

Furthermore, the increase in online communication caused by the popularity of social media opened the possibility of looking into how individuals labelled with different personality traits interact in online environments. In 2015, the first large scale dataset with personality labels appeared under the name "MyPersonality" dataset [23]. It contained labels for the Big Five personality measures of more than 7.5 million Facebook users, which were collected through an online survey. However, due to privacy concerns the dataset has since been made publicly unavailable, leaving only a small portion of the data available for research use [24]. Therefore, researchers had to return to smaller sources of data for their work, but the interest in social media platforms as a potential data source did not stop. Nowadays, a large part of work involving personality is done on data that comes from various social media platforms, such as Facebook [25], Twitter [26]–[28], Reddit [13] and in some cases chat applications like Telegram [29]. Wiegmann, Stein and Potthast [30] provide an overview of author profiling corpora in their work, with some of the listed sources of data being publicly unavailable.

B. Comparison Between Personality Models

Despite social media services increasing the amount of available data, the high cost of labelling and privacy concerns were still an issue for works that set out to create a publicly available corpora containing personality labels. Additionally, early criticism towards the MBTI model has caused it to be neglected by the scientific community, until the work of Plank and Hovy [31] restored the interest in the model. It is due to these issues that most of the research was constrained only to the Big Five personality model, making the comparison with MBTI a difficult task.

To our knowledge, the first dataset to contain labels for both the MBTI and Big Five personality models, as well as for another personality model known as Enneagram, is the PANDORA dataset, which is the result of work done by Gjurković, Karan, Vukojević, Bošnjak and Šnajder [32]. The PANDORA dataset is the direct extension of their previous work which utilized tags present on Reddit posts (the so-called 'flairs') in order to create a large scale dataset containing MBTI labels [13]. As such, the PANDORA dataset consists of $17,640,062$ comments coming from $10,288$ users labelled with either the MBTI or Big Five personality measures. Among these users, only 393 have both the MBTI and Big Five labels present. Additionally, the dataset contains various other demographic information such as gender and age.

As reported by its authors, the correlations between Big Five and MBTI measures present in the PANDORA dataset seem to be largely in agreement with those reported in works that examined the statistical relationship between the two [9], [12]. This has led us to believe that the PANDORA dataset represents a good starting point for further examining the relationship between these two personality models. For reference, we include the correlation measures reported by the authors of the PANDORA dataset in Table I, while Table II contains the correlations reported by McCrae and Costa, who first analyzed the statistical relationship between the two models.

TABLE I
CORRELATION BETWEEN BIG FIVE DIMENSIONS AND MBTI TYPES AS REPORTED FOR THE PANDORA DATASET BY ITS AUTHORS

Big Five Traits	**MBTI Traits**			
	Introverted	***Intuitive***	***Thinking***	***Perceiving***
Openness	-0.062	**0.434**	-0.27	**0.132**
Conscientiousness	-0.062	-0.027	**0.138**	**-0.575**
Extroversion	**-0.748**	-0.042	-0.043	**0.145**
Agreeableness	-0.055	0.030	**-0.554**	0.055
Neuroticism	**0.157**	0.065	**-0.341**	0.031

Significant correlation ($p < 0.05$) is represented in bold font

TABLE II
CORRELATION BETWEEN BIG FIVE DIMENSIONS AND MBTI TYPES AS REPORTED BY COSTA AND MCCRAE

Big Five Traits	**MBTI Traits**			
	Introverted	***Intuitive***	***Thinking***	***Perceiving***
Openness	0.03	0.72	-0.02	0.30
Conscientiousness	0.08	**-0.15**	**0.15**	-0.49
Extroversion	-0.74	0.10	-0.19	**0.15**
Agreeableness	-0.03	0.04	-0.44	-0.06
Neuroticism	0.16	-0.06	-0.06	0.11

Significant correlation ($p < 0.05$) is represented in bold font

In their work, the authors of the PANDORA dataset attempted leveraging MBTI and Enneagram labels in order to predict Big Five personality measures. Although this work utilizes the relationship between two models, it does not provide an analytical insight into the possible linguistic nature of the correlation. One other work that compared the two models is that of Celli and Lepri [14] which reported promising results in personality prediction of MBTI measures, despite later works suggesting prediction of MBTI personality to be a more challenging task [33]. However, to the best of our knowledge, no previous work has set out to provide an answer to how language usage differs between individuals labelled with these two personality models.

C. Linguistic Analysis

Work conducted on the task of speaker identification from dialogue data [34] has shown that language models like BERT [35] are capable of detecting subtle differences in how interlocutors with different personality traits express themselves through text. However, due to the black box nature of BERT, no direct tie to personality traits has been made. In order to examine the way in which personality shapes language usage, we used Language Inquiry and Word Count (LIWC) [15].

Ever since its inception in the mid 90's, LIWC has been one of the most popular tools for language analysis. It has been applied to a wide variety of topics, such as research into political affiliation [36], depression [37] and sarcasm detection [38]. Apart from these research areas, many different works relied on LIWC for personality analysis as well as personality prediction [18], [27], [39].

While LIWC has been leveraged for personality prediction in the past, the works that link LIWC features to features of the personality models have been small in number, and only examine such a relationship for the Big Five model [40]. To the best of our knowledge, the relationship between linguistic features offered by LIWC and personality types of the MBTI model have not been examined before. Furthermore, the direct comparison between the results of such analysis and the one conducted on the Big Five model has not been attempted in the past.

III. ANALYSIS AND RESULTS

For our experimental setting, we replicate the approach taken by Holtgraves in their work that previously examined the relationship between LIWC features and the features of the Big Five model [40]. This allows us to compare our results with the ones they reported, in addition to uncovering the relationship between the LIWC features, user's gender and personality traits on the social media platform Reddit.

We split the data into groups of users labeled either with MBTI personality traits or Big Five dimensions. This results in total a of $8,691$ users and $15,597,237$ comments labeled with MBTI types, while the group with Big Five dimensions amounted for $1,175$ users and $3,006,566$ comments in total. We followed this by grouping each user's comments together, allowing for the LIWC analysis to be conducted on an individual level as well as on the level of personality model.

A. Group containing Big Five labels

Out of the $1,175$ users labeled with Big Five dimensions present in the PANDORA dataset, we first extracted a group of 599 users that also reported their gender. This gave us a subset of 232 female and 367 male users. For comparison purposes, in Table III we report the correlations between the three Big Five dimensions (**Agreeableness**, **Extroversion** and **Neuroticism**) and most of the LIWC dimensions for which statistically significant correlations were reported in the previous work, with some notable exceptions.

In order to better capture the nature of human language in texting, Holtgraves introduced certain categories by expanding the LIWC dictionary, such as slang, acronyms and words that have their g's at the end dropped (e.g. goin'). We have decided to skip this step, as the frequency of such terms in the PANDORA dataset has led us to conclude that there is no need for a separate category. Additionally, we selected two more LIWC dimensions we found to be interesting for analysis, which are usage of *inclusive* and usage of *exclusive* language. The results presented in Table III as well as the results for other categories are discussed later in this chapter.

Our analysis has pointed to several LIWC features positively correlating with the **Extroversion** dimension. Namely, the results have suggested that people with a higher value for this Big Five dimension tend to use more words ($r = 0.066$), as well as more personal pronouns when they comment

TABLE III
CORRELATION BETWEEN BIG FIVE PERSONALITY TRAITS AND LIWC CATEGORIES

LIWC	**Agreeableness**			**Extroversion**			**Neuroticism**		
Dimensions	Overall	Female	Male	Overall	Female	Male	Overall	Female	Male
Word count	0.02	0.051^{**}	0.004	0.066^{**}	0.137^{**}	0.019	-0.009	-0.015	-0.001
Personal pronouns	0.091^{**}	0.109^{**}	0.029	0.062^{**}	0.177^{***}	-0.034	-0.033^{**}	-0.039	-0.088^{**}
1st person singl.	0.054^{**}	0.052^{**}	0.005	-0.002	0.083^{**}	-0.09^{**}	0.063^{**}	0.013	0.061^{**}
Impers. pronouns	0.077^{**}	0.093^{**}	0.067^{**}	-0.102^{**}	-0.102^{**}	-0.104^{**}	0.029^{**}	0.085^{**}	-0.003
Positive emotions	0.177^{***}	0.265^{***}	0.114^{**}	0.073^{**}	0.09^{**}	0.056^{**}	-0.005	0.047^{**}	-0.048^{**}
Negative emotions	-0.096^{**}	-0.023	-0.127^{**}	-0.003	0.047^{**}	-0.024	0.011	0.031	0.005
Anxiety	0.056^{**}	0.055^{**}	0.024	0.043^{**}	0.163^{**}	-0.048^{**}	0.095^{**}	0.067^{**}	0.09^{**}
Anger	-0.193^{***}	-0.143^{**}	-0.202^{***}	0.039^{**}	0.016	0.066^{**}	-0.067^{**}	-0.057^{**}	-0.054^{**}
Swearing	-0.123^{***}	-0.075^{**}	-0.131^{**}	0.019	0.007	0.034	-0.057^{**}	-0.042	-0.052^{**}
Sex	-0.043^{**}	0.009	-0.116^{**}	0.054^{**}	0.041	0.054^{**}	-0.002	0.026	-0.047^{**}
Function Words	0.124^{***}	0.146^{**}	0.091^{**}	-0.014	0.015	-0.043^{**}	-0.063^{**}	-0.026	-0.104^{**}
Prepositions	0.109^{***}	0.054^{**}	0.135^{***}	0.035^{**}	0.051^{**}	0.023	-0.073^{**}	-0.094^{**}	-0.067^{**}
Death	-0.083^{**}	-0.108^{**}	-0.047^{**}	-0.047^{**}	-0.121^{**}	0.027	0.011	0.04	-0.001
Health	-0.007	-0.027	-0.012	0.03^{**}	0.058^{**}	0.004	0.01	-0.026	0.019
Inclusive	0.107^{***}	0.145^{**}	0.053^{**}	0.13^{***}	0.095^{**}	0.142^{***}	-0.089^{**}	-0.11^{**}	-0.109^{**}
Exclusive	0.07^{**}	0.065^{**}	0.064^{**}	-0.122^{***}	-0.088^{**}	-0.148^{***}	-0.082^{**}	-0.057^{**}	-0.106^{**}

* when $p < 0.1$, ** when $p < 0.05$, *** when $p < 0.01$

($r = 0.062$). This trend has been especially apparent in users labelled with the female gender ($r = 0.137$ and $r = 0.177$, respectively). These results are in agreement with those previously reported by Holtgraves, as they have also observed a similar trend. Additionally, positive correlation has been observed with words that are often associated with the topic of *sex* ($r = 0.054$), a trend that was also present in the results of previous research. However, while previous work has pointed to the existence of a negative correlation with words relating to *anxiety* and *anger*, our analysis has indicated that users with higher **Extroversion** measure are more prone to using such words ($r = 0.043$ and $r = 0.039$, respectively).

For the **Neuroticism** dimension, we observed that people with higher values tended to avoid words associated with *anger* ($r = -0.067$) and less *swear* words ($r = -0.057$), while also avoiding the usage of both *inclusive* ($r = -0.089$) and *exclusive* ($r = -0.082$) language. In addition to these, we observe that users with higher **Neuroticism** are less likely to use words tied to *positive emotions* ($r = -0.047$ for female and $r = -0.048$ for male gender). While the work of Holtgraves has reported the opposite to be the case, in their analysis they have pointed out that a negative correlation between the two dimensions was expected.

Finally, in our analysis, **Agreeableness** has shown a negative correlation with the usage of *swear* ($r = -0.123$) words as well as words relating to *negative emotions* ($r = -0.096$). This was previously noted to be expected by Holtgraves in their paper. We further observed the **Agreeableness** dimension correlating with the usage of *impersonal pronouns* ($r = 0.077$) and *positive emotions* ($r = 0.177$), while words relating to *death* have been negatively correlated ($r = -0.083$). Additionally, users with high agreeableness are more likely to use both *inclusive* ($r = 0.107$) and *exclusive* ($r = 0.07$) language.

Previous work has not reported a significant correlation for **Conscientiousness** and **Openness** when compared to LIWC dimensions; however, our analysis has indicated that the usage of *personal pronouns* seems to be negatively correlated with high **Openness**. Additionally, female Reddit users that score highly on the **Conscientiousness** dimension are more likely to use *inclusive* language, while no significant correlation was observed in users that listed their gender as male.

B. Group containing MBTI labels

For the MBTI analysis we focused on the subset of $2,695$ users that reported their gender ($1,184$ female and $1,511$ male). So as to directly compare the results to those achieved when using Big Five personality traits, we selected the same set of LIWC categories used in the previous subsection. In Table IV we report the results for **Introvert**, **iNtuitive** and **Feeling** types, while the results for the **Perceiving** type are reported in Table V. In addition to the LIWC dimensions analyzed in the previous subsection, we included reports on the correlations with *working*, *achievement* and *leisure* dimensions for the **Perceiving** type, as some authors have previously reported existence of correlation between them [41].

Due to MBTI types being dichotomies, we have reported correlations only for a single value (e.g. for **Introvert** not for **Extrovert**). The results for the other type value can be obtained by multiplying the correlation reported by -1.

Following the results presented in the previous subsection, one might expect the **Introvert** type to show a negative correlation with LIWC dimensions such as *positive emotions*, *word count* and *personal pronouns*, but no significant correlation was observed for these three dimensions. However, our analysis has shown that the language of users labelled with the **Introvert** type is negatively correlated with words that relate to topics like *sex* ($r = -0.041$), as well as with words that are associated with *anger* ($r = -0.058$) and *swear* words ($r = -0.073$). Additionally, users labelled with this type seem to use more *impersonal pronouns* ($r = 0.055$), while there has been no significant correlation in the usage of *personal pronouns*.

When it comes to the **iNtuitive** type, as it has shown to be highly correlated with the **Openness** dimension [9], no

TABLE IV
CORRELATION BETWEEN MBTI'S **INTROVERT**, **INTUITIVE** AND **FEELING** TYPES AND LIWC CATEGORIES

LIWC Dimensions	**Introvert** Overall	Female	Male	**iNtuitive** Overall	Female	Male	**Feeling** Overall	Female	Male
Word count	0.0	-0.008	0.005	-0.016^{**}	-0.044^{**}	-0.009	-0.11^{***}	-0.08^{***}	-0.119^{***}
Personal pronouns	0.002	0.017	-0.016	-0.078^{***}	-0.06^{**}	-0.028^{**}	0.214^{***}	0.196^{***}	0.187^{***}
1st person singl.	0.037^{**}	0.046^{**}	0.031^{**}	-0.075^{***}	-0.054^{**}	-0.032^{**}	0.209^{***}	0.171^{***}	0.197^{***}
Impers. pronouns	0.055^{***}	0.071^{**}	0.044^{**}	0.035^{**}	0.071^{**}	0.013	0.112^{***}	0.091^{***}	0.122^{***}
Positive emotions	0.006	-0.001	0.009	0.044^{**}	0.075^{***}	0.048^{**}	0.267^{***}	0.22^{***}	0.282^{***}
Negative emotions	-0.038^{**}	0.011	-0.058^{**}	0.007	0.008	0.006	-0.017^{**}	0.001	-0.023^{**}
Anxiety	0.037^{**}	0.036^{**}	0.038^{**}	0.004	0.035^{**}	0.042^{**}	0.193^{***}	0.145^{***}	0.192^{***}
Anger	-0.058^{***}	-0.036^{**}	-0.071^{***}	0.006	-0.015	-0.001	-0.067^{***}	-0.086^{***}	-0.06^{**}
Swearing	-0.073^{***}	-0.062^{**}	-0.079^{***}	-0.019^{**}	-0.03^{**}	-0.04^{**}	-0.114^{***}	-0.086^{***}	-0.109^{***}
Sex	-0.041^{**}	-0.049^{**}	-0.047^{**}	0.007	0.02^{**}	0.009	-0.005	0.069^{**}	-0.023^{**}
Function Words	0.037^{**}	0.048^{**}	0.032^{**}	-0.019^{**}	0.005	0.007	0.125^{***}	0.079^{***}	0.117^{***}
Prepositions	0.02^{**}	0.009	0.027^{**}	0.046^{**}	0.072^{**}	0.036^{**}	0.03^{**}	-0.025^{**}	0.057^{**}
Death	0.031^{**}	0.048^{**}	0.026^{**}	0.025^{**}	0.013	-0.003	-0.072^{***}	-0.039^{**}	-0.056^{**}
Health	0.033^{**}	0.038^{**}	0.028^{**}	0.014^{**}	0.043^{**}	0.039^{**}	0.03^{**}	0.013	-0.012
Inclusive	-0.01	0.002	-0.025^{**}	-0.008	0.004	0.037^{**}	0.138^{***}	0.112^{***}	0.114^{***}
Exclusive	0.026^{**}	0.009	0.036^{**}	-0.035^{**}	-0.051^{**}	0.005	0.03^{**}	-0.026^{**}	0.045^{**}

* when $p < 0.1$, ** when $p < 0.05$, *** when $p < 0.01$

TABLE V
CORRELATION BETWEEN MBTI'S **PERCEIVING** TYPE AND LIWC CATEGORIES

LIWC Dimensions	**Perceiving** Overall	Female	Male
Word count	0.017^{**}	0.023^{**}	0.002
Personal pronouns	-0.068^{***}	-0.078^{***}	0.018^{**}
1st person singl.	-0.048^{**}	-0.028^{**}	0.014
Impers. pronouns	0.007	0.022^{**}	0.003
Positive emotions	-0.056^{***}	-0.06^{**}	-0.019^{**}
Negative emotions	0.068^{***}	0.087^{***}	0.066^{**}
Anxiety	-0.06^{***}	-0.034^{**}	-0.016
Anger	0.078^{***}	0.123^{***}	0.066^{**}
Swearing	0.129^{***}	0.105^{***}	0.12^{***}
Sex	0.043^{**}	0.068^{**}	0.05^{**}
Function Words	-0.058^{***}	-0.04^{**}	-0.028^{**}
Prepositions	-0.086^{***}	-0.094^{***}	-0.074^{***}
Death	0.086^{***}	0.113^{***}	0.033^{**}
Health	-0.053^{***}	-0.011	-0.038^{**}
Inclusive	-0.118^{***}	-0.131^{***}	-0.059^{**}
Exclusive	0.047^{**}	0.097^{***}	0.04^{**}
Work	-0.043^{**}	-0.028^{**}	-0.067^{***}
Achievement	-0.056^{***}	-0.118^{***}	-0.057^{**}
Leisure	0.001	0.002	-0.03^{**}

* when $p < 0.1$, ** when $p < 0.05$, *** when $p < 0.01$

significant correlation was expected with any of the linguistic features. However, our analysis has indicated a marginally significant negative correlation concerning the usage of *personal pronouns* ($r = -0.078$), similar to results observed in the previous subsection. Furthermore, users labelled as **iNtuitive** tend to use words that are associated with *positive emotions* ($r = 0.044$) slightly more than chance.

Users labelled with the **Feeling** type have shown a positive correlation with language rich in *personal pronouns* ($r = 0.214$) as well as *impersonal* ones ($r = 0.209$). Additionally, we have observed a negative correlation when it comes to the usage of *swear* words ($r = -0.114$). This is an expected result, as a similar correlation has been observed for the **Agreeableness** Big Five dimension in the previous subsection, with these two personality measures having been shown to correlate in the past [9]. Other dimensions showing a marginally significant correlation with this MBTI type are *inclusive* ($r = 0.138$) and *function words* ($r = 0.125$).

While we have observed a negative correlation with *work* ($r = -0.043$) and *achievement* ($r = -0.056$) related language and the **Perceiving** type, something that was also observed in previous work [41], our analysis has shown no significant correlation with the *leisure* dimension ($r = 0.001$). However it is interesting to note that users labelled with the **Perceiving** type have shown a correlation with several LIWC dimensions such as words relating to *death* ($r = 0.086$), *sex* ($r = 0.043$), *negative emotions* ($r = 0.068$), *swear* words ($r = 0.129$) and *anger* ($r = 0.078$). Additionally, a negative correlation has been observed for the usage of *inclusive* words ($r = -0.118$), words relating to *positive emotions* ($r = -0.056$), *function words* ($r = -0.058$) and *prepositions* ($r = -0.086$). This is interesting to note as the **Conscientiousness**, the Big Five dimension with which the **Perceiving** type has a negative correlation [9], has shown no prevailing pattern relating to language use.

IV. CONCLUSION AND FUTURE WORK

Our study outlines the linguistic features present in the language used on the social media platform Reddit and their correlation to personality measures offered by two distinct personality models – MBTI and the Big Five model. In order to give an accurate comparison to prior work done solely on the Big Five model, we focused on the users that have reported their gender, offering additional insight from this standpoint. Study offers a novel insight into language usage and personality measured by these two models, while also offering a comparison between them.

Study has some potential limitations, as it focuses only on the subset of data involving users that reported their gender. As willingness to report this demographic variable can potentially be influenced by personality, a certain amount of bias was potentially introduced to the study in a desire to compare it to previous work. Despite this, our findings can prove useful in future works involving personality identification, as well as the prediction of Big Five dimensions from the MBTI types, or vice-versa.

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