Prevention or Promotion? Predicting Author's Regulatory Focus

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Abstract People differ fundamentally in what motivates them to pursue a goal and how they approach it. For instance, some people seek growth and show eagerness, whereas others prefer security and are vigilant. The concept of regulatory focus is employed in psychology, to explain and predict this goal-directed behavior of humans underpinned by two unique motivational systems – the promotion and the prevention system. Traditionally, text analysis methods using closed-vocabularies are employed to assess the distinctive linguistic patterns associated with the two systems. From an NLP perspective, automatically detecting the regulatory focus of individuals from text provides valuable insights into the behavioral inclinations of the author, finding its applications in areas like marketing or health communication. However, the concept never made an impactful debut in computational linguistics research. To bridge this gap we introduce the novel task of regulatory focus classification from text and present two complementary German datasets – (1) experimentally generated event descriptions and (2) manually annotated short social media texts used for evaluating the generalizability of models on real-world data. First, we conduct a correlation analysis to verify if the linguistic footprints of regulatory focus reported in psychology studies are observable and to what extent in our datasets. For automatic classification, we compare closed-vocabulary-based analyses with a state-of-the-art BERT-based text classification model and observe that the latter outperforms lexicon-based approaches on experimental data and is notably better on out-of-domain Twitter data.

1 Introduction

What motivates a person to pursue a goal and what type of strategies they apply to achieve this goal differs from person to person. For instance, some people brush regularly to maintain healthy teeth and gums, while others do the same to avoid cavities; their goal is the same but the motivation is different. The regulatory focus (RF) theory (Higgins, 1997, 1998) from psychology, explains the goal-directed behavior of humans underpinned by two unique motivational systems – *promotion* and *prevention*. Promotion-focused individuals approach a goal by striving for achievements, taking an eager approach, and are interested in maximizing the gains. On the other hand, prevention-focused ones strive for security, are sensitive to losses, avoid negative outcomes, avert risks, and are vigilant. This framework is predominantly used to explain consumer behavior, organizational behavior, message framing, or information processing (Crowe and Higgins, 1997; Aaker and Lee, 2001; Lanaj et al., 2012; Sassenberg et al., 2014, i.a.).

Automatic detection of regulatory focus helps psychology researchers to bypass the need for manual coding or self-reports which are prone to social desirability. Automatic detection would allow for a more objective and standardized measurement of regulatory focus, removing egocentric biases and subjectivity. In the case of downstream applications, like computer-mediated communication, understanding the behavioral inclination of a person allows one to tailor response messages to fit their motivational orientation, facilitating a more persuasive and effective dialogue between the interlocutors. Such tailoring of messages to match the dominant regulatory focus has proven effective in health communication, promoting positive behavior change in areas like exercise (Latimer et al., 2008a), diet (Latimer et al., 2008b), and dental hygiene (Updegraff et al., 2007). It has also been successfully applied in organizational behavior, marketing, leadership, and many other domains of psychology (Sassenberg and Vliek, 2019, p.51-64). With more than 1,500 journal publications and more than 70,000 citations, the concept is prominent in psychology

Statement	Reg. Focus
(A) I woke up early because I did not want to miss the bus and be late for the class	Prevention
(B) I woke up early because I wanted to be on time for my favorite class	Promotion

Table 1: Examples of prevention and promotion-focused statements

and related disciplines[1]. However, this concept has not received any attention in computational linguistics.

Previous studies on the topic of regulatory focus have reported that distinctive linguistic signatures are observed in an individual's text formulation corresponding to their goal attainment strategies (Semin et al., 2005; Vaughn, 2018). Other studies relied on differences in linguistic features to manipulate regulatory focus or persuade people with a specific regulatory focus. Overall, we conclude that promotion and prevention focus resonate with different linguistic patterns. Inspired by these findings and their practical application in communication, we formulate the novel task of regulatory focus classification as an author profiling task.

Consider the two statements in Table 1, both describing a person's motivation *to wake up early*. In Statement (A), the person wants to avoid negative outcomes like *missing the bus* or *being late for the class*, which points to a risk-averting motivation or prevention focus. On the contrary, in Statement (B), the person sounds eager and focuses on the positive outcome of *being on time for the class* which warrants promotion focus. As noted earlier, despite the presence of distinctive stylistic variations and linguistic cues, no attempts to automatically classify texts into promotion or prevention-focus have been reported yet. Also, there are no publicly available datasets annotated with regulatory focus categories.

In the course of our study, we create datasets containing event descriptions and social media data, in German, labeled with regulatory focus notions. We use correlation analysis to investigate the linguistic signatures of regulatory focus and ascertain the validity of our datasets. Further, we conduct text classification experiments to explore the possibility of automatically detecting regulatory focus concepts from text. Our experiments show that a BERT-based classifier outperforms lexicon-based approaches popularly used in psychology and the classifier can generalize from experimental data to Twitter data.

The main contributions of the paper are (1) an introduction to the task of regulatory focus classification, (2) experimental and real-world datasets annotated with RF categories, (3) a correlation analysis to verify to what extent the findings from studies on regulatory focus as observable in the dataset using traditional methods and (4) performance comparison of RF classification using standard measures from psychology vs. state-of-the-art methods from NLP. Our research aims to serve as a starting point for exploring the concept from a computational linguistics perspective and enable future studies. The datasets created as part of this study are freely available for research purposes. They can be accessed together with the corresponding code at https://www.ims.uni-stuttgart.de/data/author-regulatory-focus-detection.

[1] https://www.webofscience.com/wos/woscc/citation-report/aac080af-4516-427f-bf6f-ae9e89494de9-57fbd01c

2 Background

2.1 Regulatory focus

The regulatory focus theory (RFT) posits that all goal-directed behavior of humans is regulated by two distinct motivational systems, *promotion* and *prevention* (Higgins, 1997, 1998). Promotion-focused individuals are motivated by their growth and development needs, try to attain their *ideal* selves by eagerly approaching a goal and are sensitive to positive outcomes. On the contrary, prevention-focused individuals are motivated by their security needs, try to attain their *ought* selves by vigilantly approaching a goal and are sensitive to negative outcomes (Brockner and Higgins, 2001). RFT has been employed in domains like organizational psychology (Crowe and Higgins, 1997; Lanaj et al., 2012), consumer psychology (Aaker and Lee, 2001; Higgins, 2002) and health communication (Keller, 2006; Kees et al., 2010) to explain phenomena like decision making (Crowe and Higgins, 1997; Higgins, 2002; Sassenberg et al., 2014), social relations (Righetti et al., 2011) and information processing (Aaker and Lee, 2001).

Regulatory focus varies interindividually and situationally. Hence, each individual has a chronic regulatory focus (similar to differences in personality factors). In addition, events can induce a situational regulatory focus. Darkness and strange noises will for instance induce a situational prevention focus. Researchers often employ priming experiments in which they vary (the recall of) events to situationally induce promotion or prevention focus in individuals (Higgins et al., 2001; Hamstra et al., 2014), which is also the main data collection method used in this study. Such approach for text corpus annotation and collection has been shown to work in the NLP context, for instance in emotion classification (Troiano et al., 2019, 2023).

Semin et al. (2005) investigated how an individual's motivation affects the use of language and reported distinctive linguistic signatures of individuals corresponding to their goal attainment strategies or regulatory focus. They observed that promotion-focused individuals

	Promotion	Prevention
Success	Positive activating emotions *enthusiasm, happiness, hope, pride, cheerfulness*	Positive non-activating emotions *contentment, relief, relaxation, calmness*
Failure	Negative non-activating emotions *disappointment, sadness, dejection, depression*	Negative activating emotions *anxiety, fear, anger, shame, hate*

Table 2: A mapping of emotions related to a regulatory focus category and outcome of a particular situation (success/failure) (drawn following Brockner and Higgins, 2001).

convey intentions and goals in abstract terms characterized by interpretive action verbs (e.g., hurts), state verbs (e.g., hate), and adjectives. On the contrary, individuals with a prevention focus tend to use more concrete terms like descriptive action verbs (e.g., walk, throw). Further in promotion focus, individuals tend to view their goals as hopes and aspirations, while in prevention focus, they tend to view their goals as duties and obligations (Higgins, 1997, 1998). Vaughn (2018) notes differences in language use when describing hopes (focus on positive outcomes) as compared to duties (focus on social relationships). Conley and Higgins (2018) used lexical analysis of essays as an RF measure.

In consumer psychology, the influence of regulatory focus orientation on the persuasiveness of messages has been investigated with reference to "message framing" or the linguistic presentation of information (Aaker and Lee, 2001; Cesario et al., 2013, i.a.). The persuasiveness of a message is enhanced when it is framed to fit the regulatory focus inclination of the recipient or reader (Higgins, 2000). In this study, we focus on the imprints of regulatory focus left behind by the author of a text.

Regulatory focus is a psychological variable that varies inter-individually like a personality trait and varies situationally like emotions, which makes it a manipulable attribute (Higgins et al., 2001; Hamstra et al., 2014). While personality and emotion have been investigated in author profiling studies (Stamatatos et al., 2015; Rangel and Rosso, 2016a, i.a.,), regulatory focus has not received any attention there.

Authorship profiling, an application of text analysis relevant for this study, involves assessing the properties of the author like age, gender, personality, and emotion from their linguistic signatures in text (Goswami et al., 2009; Argamon et al., 2003; Nowson and Oberlander, 2006; Pennebaker et al., 2003; Gill et al., 2008; Rangel and Rosso, 2016b). While some of these properties are stable, such as gender and age, others, such as emotion, vary based on the author's current situation or state of mind. Regulatory focus is a psychological variable that varies inter-individually like a personality trait and varies situationally like emotions (e.g., anxiety Gaudry et al. (1975)), which makes it a manipulable attribute (Higgins et al., 2001; Hamstra et al., 2014). While personality and emotion have been investigated in author profiling studies (Stamatatos et al., 2015; Rangel and Rosso, 2016a, i.a.,), regulatory focus has not received any attention there.

2.2 Emotionality and regulatory focus

The relationship between emotionality and regulatory focus has been explored in a few studies (Higgins et al., 1997; Brockner and Higgins, 2001). Emotions arise from an interaction between a person and a situation. While valence and arousal dimensions help to understand the experienced emotions, regulatory focus aids to explain why an emotion is experienced in a given situation. The nature and magnitude of an emotional reaction when a person succeeds or fails in their attempt to achieve a goal is influenced by their regulatory focus orientation. When a desired end-state (success) is achieved, promotion-focused individuals experience positive activating emotions like cheerfulness and happiness, while prevention-focused individuals experience positive non-activating emotions like relaxation and calm. Similarly, negative non-activating emotions like sadness are related to promotions focus, and negative activating emotions like anger, hate, and fear are linked to prevention focus when an undesired end-state (failure) is encountered. Table 2 shows an approximate mapping of different emotions with respect to regulatory focus and situational outcome (Brockner and Higgins, 2001).

In the current study, we collect data by manipulating situational regulatory focus and present the task of regulatory focus classification from the text. Also, the annotators wield the knowledge of the relationship between emotions and regulatory focus to facilitate better annotation of real-world Twitter data.

3 Data collection

We create three different datasets as part of this study – two containing self-reported event descriptions (EDD-1 and EDD-2) and one manually annotated Twitter dataset (TwD). The event description datasets are created by regulatory focus manipulation experiments and contain self-reported event descriptions provided by participants who were experimentally primed for one of the regu-

Focus	Instructions
Promotion	... a situation in which you felt you made progress towards (*being successful in your life / achieving a goal that is important to you*). ... a situation in which, compared to others, you felt like you were not making any progress towards (*being successful in your life / achieving something*). ... a situation in which you wanted to attain something that was very important to you personally, and in which you were able to do as well as you ideally would like.
Prevention	... a situation in which being careful enough avoided from getting into trouble. ... a situation in which lack of caution caused you to get into trouble. ... a situation in which you behaved in a way that no one could have found fault with.

Table 3: Instructions used to prime promotion or prevention focus. All instructions started with *Please describe..* The text in italics shows the minor difference in the formulation in the datasets given as (EDD-1/EDD-2).

latory focus conditions. The Twitter dataset contains manually annotated tweets. While the event description datasets, generated using well-established psychological experiments, contain high-quality annotations, they are not naturally produced text. The Twitter dataset, on the other hand, contains real-world data, nevertheless might not be on par with the experimental data in terms of the quality of annotations, given the risk of noise introduced by annotators. However, evaluating the efficiency of models, exposed only to experimental data, on real-world data helps to assess the extent to which such models can be employed in practical applications.

3.1 Self-reported event descriptions

We create two self-reported event description datasets (to which we refer as EDD-1 and EDD-2) using a standard experiment employed in psychology to manipulate regulatory focus (Higgins et al., 2001; Hamstra et al., 2014, i.a.). Participants are asked to recount an event from their past based on a given regulatory focus condition. The instructions are formulated in a way to prime participants to temporarily re-experience a situation in which they held a promotion or a prevention focus. For each condition, three different situations are presented where they succeeded or failed. For example, in the promotion success condition, they are asked, *"Please describe an experience in which you felt you were making progress toward being successful in your life"*, which points to a situation, where they were eagerly seeking a positive end state (being successful) and managed to achieve it. To induce a prevention focus they are for instance asked, *"Please describe an experience where a lack of caution caused you to get into trouble"*. In this situation, they are primed to recount an event in which they did not exercise caution which resulted in a negative outcome. See Table 3 for an overview of instructions (Appendix A&B shows complete instructions in German).

EDD-1 and EDD-2 are in German and differ only on a few accounts. EDD-1 is a consolidation of data from seven independent studies, both published and unpublished (Sassenrath et al., 2014; Hamstra et al., 2014; Sassenberg et al., 2015). The original purpose of these studies was not to collect data for NLP modeling; instead, for psychology research that required the manipulation of regulatory focus.[2] The majority of the participants were university students and the number of participants per study ranged between 28 to 172. Every participant contributed to three questions related to one of the regulatory focus conditions. The questions were presented in an open-ended format, so the length and quality of the texts vary substantially. The length of responses ranges from 4 to 308 tokens[3] with a mean response length of 38.3 (*median* = 33).

The data collection experiment for the second event description dataset (EDD-2), following the same procedure as EDD-1, is conducted on a crowd-sourcing platform (Clickworker[4]), with the participation restriction as "*working at least 50% of a full employment*" to include a broader demographic. The questionnaire is formulated in terms of goal achievement in a work context. Similar to the previous experiment, we collect three responses per participant corresponding to either promotion or prevention. Participants are mandated to write a minimum of 150 characters for each open-ended question. The questionnaire was completed by 455 participants. The length of responses ranges from 5 to 748 tokens[3] with a mean response length of 51.3 (*median* = 41). Table 4 shows examples from EDD-1.

3.2 Annotated tweets

When an individual actively participates in a social media activity, such as posting on Twitter, the action is driven by underlying motivational factors. We build upon this assumption to create a Twitter data dataset (TwD), a social media dataset to investigate the real-world occurrences of the regulatory focus concepts. In order to eliminate noisy content from Twitter and prioritize instances that are more likely to reflect motivational inclinations, we gather a subset of tweets that convey

[2] We received the data through personal communication and agreed with the original authors to make the data available upon acceptance of this paper.

[3] We use https://www.nltk.org/api/nltk.tokenize.html#nltk.tokenize.word_tokenize

[4] https://www.clickworker.com/

Dataset	RF	Example (German)	Translation (English)
EDD-1	Prom.	(1) Fast immer dann, wenn Durchhaltevermögen über einen längeren Zeitraum gefragt war. (2) Als ich zwei Monate lang nichts tat außer saufen und chillen. (3) Ich konnte am Wochenende zum See fahren, weil ich nicht ganz so viele Klausuren haben wie andere.	(1) Almost always when perseverance was required over a longer period of time. (2) When I didn't do anything for two months except drink and chill. (3) I could go to the lake on weekends, because I did not have quite as many exams as others.
	Prev.	(1) Beim Skifahren habe ich nicht genügend aufgepasst und bin beinahe in einen Baum gefahren. (2) Wir kletterten verbotenerweise als Jugendliche auf ein Dach einer Hütte und wurden erwischt. (3) Zu viel Alkohol auf einer Party hat dazu geführt, dass ich leichtsinnig mein Handy verloren habe.	(1) I didn't pay enough attention when skiing and almost crashed into a tree. (2) As adolescents, we illegally climbed onto the roof of a hut and were caught. (3) Too much alcohol at a party made me recklessly lose my phone.
TwD	Prom.	Wir sind so stolz und erleichtert – unsere Präsentation in Offenburg war ein Erfolg! Danke an alle für die Unterstützung!	We are so proud and relieved – our presentation in Offenburg was a success! Thanks everyone for the support!
	Prev.	Ich hasse es, dass ich nichts aus meinem Leben mache und nur vergammel. Und meine Ernährung ist auch grauenhaft.	I hate that I don't do anything with my life and just rot. And my diet is terrible too.

Table 4: Examples from EDD-1 and TwD with their translations to English.

subjective emotional experiences. We ensure this by selecting tweets that starts with a first-person pronoun ("Ich" or "Wir") and at least one emotion word (See Appendix C.1 for the list of emotion words). The messages to be annotated are sub-sampled from the period 2016 to 2019. Further, they are required to contain less than 20 % hashtag tokens, no images, no URLs, and not the word "corona". We sampled 1,500 instances to be annotated.

Annotating tweets with regulatory focus categories is quite challenging for non-expert annotators. Preparatory to the actual annotation, training sessions are conducted to make sure the concepts are understood well. We update the annotation guidelines accordingly (see Appendix C) to support the quality of the annotation. We instructed the annotators to label each instance with one of the four labels – (1) *prevention*, (2) *promotion*, (3) *neither promotion nor prevention* or (4) *not sure*. The instances labeled as *neither promotion nor prevention* or *not sure* were disregarded to retain only the most confident instances.[5] From the 1,500 annotated tweets, we retained instances in which both annotators agreed on the two labels *promotion* (Cohen's κ=.42) or *prevention* (κ=.39), which amounts to 923 (61.5%) tweet instances. Table 4 shows some examples.

To understand the characteristics and differences between the datasets we look into some descriptive statistics on the distribution of labels and tokens in the collected datasets as shown in Table 5. The label distribution is relatively balanced in the event description datasets which can be attributed to the collection procedure. However, in the Twitter dataset, the imbalance is prominent as the data is representative of real-world occurrences wherein out of the filtered 923 annotated tweets around 70% are labeled as promotion. Regarding the text length, we note that the TwD dataset containing only tweets maintains a minimum word count of 11 words, while the event description datasets contain very long as well as very short texts. So, in the real-world scenario that we are considering in this study, the texts are relatively short and prevention scenarios are scarce compared to promotion.

	Label stats			Token stats		
Dataset	Prom.	Prev.	Tot.	Max	Min	Median
EDD-1	776	799	1575	309	4	33.0
EDD-2	678	582	1260	746	5	41.0
TwD	655	268	923	61	11	22.0

Table 5: Descriptive statistics of labels and tokens distribution in the collected datasets.

4 Linguistic correlation analysis

As discussed in Section 2, previous research has reported that authors' regulatory focus orientation leaves distinctive markers in their language use. Semin et al. (2005) studied abstractness or concreteness of words used, while Brockner and Higgins (2001) looked into expressed emotionality and Vaughn (2018) investigated

[5] In Appendix F we include a discussion on the occurrence of *neutral* instances in real-world data and address regulatory focus classification as a tertiary classification task.

the differences in the description of hopes vs. duties. Conley and Higgins (2018) used lexical analysis of essays as a measure to regulatory focus.

To investigate these linguistic features, they use the psychological categories defined in dictionary-based methods like *Linguistic Inquiry and Word Count* (LIWC, Pennebaker et al., 2015). Our analysis aims at confirming that these findings on the linguistic intricacies of regulatory focus are observable in our datasets as well. This serves on one side as a replication study of previous work and on the other side as a preliminary study for developing automatic RFT classifiers based on these lexical resources. We consider the datasets EDD-1, EDD-2, and TwD for this analysis.

4.1 Method

A commonly used dictionary-based method employed to analyze text samples automatically is to count words corresponding to psychologically relevant categories, which is also referred to as the word-count approach (Stone and Hunt, 1963; Gottschalk and Gleser, 1979; Berry et al., 1997, i.a.). We use this closed-vocabulary approach to understand the relationship between a set of predefined psychological categories and regulatory focus. To our knowledge, there are no publicly available dictionaries that encapsulate different psychological concepts, let alone in German. For this reason, we resort to two commercially available text analysis systems with support for German, namely LIWC(Pennebaker et al., 2015) and *100W*[6](Spitzer, 2019).

LIWC is one of the most popularly used tools in psychology for automated text analysis. It relies on exact matches with words, word stems, and selected emoticons. 100W employs various NLP disambiguation techniques on top of the lexicons. For instance, it disambiguates word senses named entity recognition and word embeddings to count only specific senses of a word. Both tools do not provide access to their raw dictionaries but return the relative frequency of terms in each category per text.

We use the measure of *point-biserial correlation* (Glass and Hopkins, 1996) to explain the correlation between the regulatory focus label of instances (a discrete value) and the relative frequency of any given psychological variable (a continuous value). If n is the total number of instances in the dataset, then the point-biserial correlation ρ_{pb} is calculated as

$$\rho_{\text{pb}} = \frac{\mu_{\text{prev}} - \mu_{\text{prom}}}{\sigma_n} \sqrt{\frac{n_{\text{prev}} n_{\text{prom}}}{n(n-1)}}, \tag{1}$$

where μ_{prom} and μ_{prev} are the mean values of the continuous variable for promotion and prevention labeled instances respectively, σ_n the standard deviation of the continuous variable, and n_{prom} and n_{prev} the frequencies of the promotion and prevention labels, respectively, within the dataset. The point-biserial correlation coefficient ranges from -1 to $+1$ indicating perfect negative and perfect positive correlation, respectively. A high positive correlation coefficient suggests that the relative frequency of the psychological variable tends to be higher when the instance label is prevention. Conversely, a high negative correlation coefficient indicates that the relative frequency of the variable is higher when the label is promotion. The magnitude and sign of the correlation coefficient provide insights into the strength and direction of the relationship between the regulatory focus label and the psychological variable.

To account for the potential issue of multiple comparisons and control the family-wise error rate, we apply Bonferroni correction (Bonferroni, 1936), a method to adjust the significance level when conducting multiple statistical tests simultaneously. It divides the desired overall significance level (α) by the number of comparisons to derive the adjusted significance level for each individual test. In our study, since we perform multiple point-biserial correlation tests between the regulatory focus label and various psychological variables, we divide the α level by the number of correlations to obtain the adjusted α level.

4.2 Experimental setup

We use the German version of the LIWC 2015 dictionary (DE-LIWC2015) and the 100W API to analyze all instances in our datasets, to obtain the relative frequencies corresponding to each of the included psychological categories. For the analysis, we take into account 80 LIWC categories and all 49 categories from 100W[7]. To calculate the point-biserial correlation, we use the implementation from scipy.[8] For Bonferroni correction, we set the desired overall significance level (α) to 0.05 and the adjusted significance level is calculated by dividing it by the number of psychological categories in each lexicon. We also calculate 95% confidence intervals for each point biserial correlation coefficient, considering the adjusted alpha level and the degrees of freedom.[9]

4.3 Results

We look into those categories which show a high correlation with promotion and prevention focus labels and compare the observed trends of different psychological categories in our datasets with previously reported relationships between these concepts and the regulatory focus orientation of the author. We report the point

[6] https://www.100worte.de/en/science

[7] See Appendix D for the complete list of categories.

[8] https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.pointbiserialr.html

[9] We use the percent point function (t.ppf) from scipy.stats

	LIWC						100W					
	EDD-1		EDD-2		TwD		EDD-1		EDD-2		TwD	
categories	corr.	CI	corr.	CI	corr.	CI	corr.	CI	corr.	CI	corr.	CI
achievement	−.38*	[−.47, −.29]	−.36*	[−.46, −.26]	−.11	[−.24, .03]	−.18*	[−.28, −.08]	−.30*	[−.41, −.19]	−.04	[−.17, .09]
adjective	−.19*	[−.29, −.08]	−.21*	[−.32, −.10]	−.12	[−.26, .01]	−.11*	[−.22, −.01]	−.09	[−.21, .02]	.04	[−.09, .18]
affect	−.17*	[−.27, −.07]	−.17*	[−.28, −.06]	−.08	[−.21, .05]	—	—	—	—	—	—
affiliation	.12*	[.02, .22]	.02	[−.10, .13]	−.03	[−.16, .11]	.05	[−.06, .15]	−.07	[−.19, .04]	.03	[−.10, .16]
anger	.10	[−.01, .20]	.03	[−.08, .15]	.62*	[.54, .70]	.15*	[.04, .25]	.08	[−.04, .19]	.60*	[.51, .68]
anxiety	.08	[−.03, .18]	.06	[−.05, .18]	.12	[−.01, .25]	.20*	[.10, .30]	.20*	[.09, .32]	.10	[−.04, .23]
article	−.11*	[−.21, −.00]	.07	[−.05, .19]	−.04	[−.18, .09]	−.11*	[−.21, −.00]	.05	[−.06, .17]	−.01	[−.14, .13]
auxverb	.14*	[.04, .25]	.10	[−.02, .21]	−.22*	[−.34, −.09]	.08	[−.02, .19]	.04	[−.08, .15]	−.23*	[−.35, −.10]
clout	.11*	[.00, .21]	.11	[.00, .23]	−.17*	[−.30, −.04]	—	—	—	—	—	—
compare	−.16*	[−.26, −.06]	−.18*	[−.30, −.07]	.04	[−.09, .18]	—	—	—	—	—	—
differ	−.04	[−.15, .06]	−.13*	[−.24, −.02]	.17*	[.04, .30]	—	—	—	—	—	—
discrep	.06	[−.05, .16]	.02	[−.09, .14]	.10	[−.03, .23]	.18*	[.08, .28]	.14*	[.02, .25]	.00	[−.13, .14]
drives	−.14*	[−.24, −.04]	−.22*	[−.33, −.10]	−.11	[−.24, .02]	—	—	—	—	—	—
feel	−.13*	[−.24, −.03]	−.19*	[−.30, −.08]	.01	[−.13, .14]	—	—	—	—	—	—
feminine	.11*	[.00, .21]	.01	[−.11, .12]	.07	[−.06, .20]	.16*	[.06, .26]	.08	[−.04, .20]	−.10	[−.23, .03]
focuspresent	.11*	[.01, .21]	−.04	[−.15, .08]	−.22*	[−.34, −.09]	—	—	—	—	—	—
i	−.07	[−.18, .03]	−.07	[−.18, .05]	.14*	[.01, .27]	−.07	[−.18, .03]	−.06	[−.18, .05]	.17*	[.04, .30]
insight	−.15*	[−.25, −.05]	−.14*	[−.26, −.03]	−.03	[−.16, .10]	—	—	—	—	—	—
negemo	.09	[−.01, .20]	.12*	[.00, .23]	.36*	[.25, .48]	.19*	[.09, .29]	.11	[−.01, .22]	.35*	[.23, .47]
negpower	—	—	—	—	—	—	.16*	[.05, .26]	.18*	[.07, .29]	.08	[−.05, .22]
posachieve	—	—	—	—	—	—	−.27*	[−.36, −.17]	−.33*	[−.43, −.22]	−.02	[−.16, .11]
posemo	−.26*	[−.36, −.16]	−.26*	[−.37, −.16]	−.39*	[−.51, −.28]	−.01	[−.12, .10]	−.09	[−.20, .03]	−.26*	[−.38, −.13]
reward	−.30*	[−.40, −.21]	−.37*	[−.47, −.27]	−.11	[−.24, .02]	−.26*	[−.36, −.16]	−.38*	[−.48, −.28]	−.07	[−.20, .06]
risk	.25*	[.15, .35]	.27*	[.16, .38]	.01	[−.13, .14]	.25*	[.15, .35]	.29*	[.18, .40]	.08	[−.06, .21]
sadness	.01	[−.10, .11]	.01	[−.11, .12]	−.23*	[−.36, −.11]	.01	[−.10, .11]	−.02	[−.14, .10]	−.23*	[−.36, −.10]
social	.14*	[.04, .25]	.06	[−.06, .18]	.03	[−.10, .17]	—	—	—	—	—	—
sv	—	—	—	—	—	—	−.04	[−.15, .06]	−.06	[−.18, .06]	.39*	[.27, .50]
tone	−.27*	[−.36, −.17]	−.26*	[−.37, −.15]	−.47*	[−.57, −.37]	—	—	—	—	—	—
we	.16*	[.06, .26]	.06	[−.06, .18]	−.05	[−.18, .08]	.16*	[.06, .26]	.06	[−.06, .18]	−.04	[−.17, .10]
work	−.40*	[−.49, −.31]	−.29*	[−.39, −.18]	.00	[−.13, .14]	—	—	—	—	—	—

Table 6: Point-biserial correlation between regulatory focus labels (prevention–promotion) and relative frequencies for the categories in LIWC and 100W discussed in Section 4.3. *n* takes the value of 1575, 1260 and 923 for EDD-1, EDD-2 and TwD respectively. The correlations considered significant (p-value < 0.05) are marked with a * symbol.

biserial correlation coefficient, and the lower bound and upper bound of the 95% confidence interval, of the categories for which the correlation was statistically significant after Bonferroni correction. Table 6 shows the point-biserial correlation between the regulatory focus labels and the relative frequencies of categories in LIWC and 100W, mentioned in the following discussion. In order to ensure meaningful and reliable conclusions, we exclude categories that appear in only one of the lexicons and exhibit statistically significant correlations in only one of the datasets. This decision was based on the understanding that drawing substantial conclusions from such observations would be challenging and could potentially lead to unreliable findings.

Risk and reward: LIWC and 100W approximate the prevention and promotion concepts with their categories *risk* and *reward* respectively (Meier et al., 2019; Spitzer, 2019). In the event description datasets, the *risk* category of LIWC significantly correlated with prevention (.25 for EDD-1, .27 for EDD-2) and *reward* category with promotion (.30 for EDD-1, .37 for EDD-2) categories. For 100W, the values are slightly lower yet significant for *risk* (.25 for EDD-1, .29 for EDD-2) and *reward* (.26 for EDD-1, .38 for EDD-2). In the Twitter dataset, they show only a very weak correlation to the same categories, but also statistically significant. We conclude that the *risk* and *reward* categories represent an approximation of the regulatory focus concepts in EDD-1/2.

Emotionality: In promotion focus, individuals experience positive-activating emotions like cheerfulness and happiness on successfully achieving the desired goal. While in prevention focus they experience positive non-activating emotions like relaxation and relief. Similarly, on failing to attain the desired goal, in promotion focus, people experience negative non-activating emotions like sadness. At the same time, in prevention focus they experience negative activating emotions like anger and hate (Higgins, 1997; Brockner and Higgins, 2001).

LIWC and 100W represent affective states in the categories *positive emotion*, *negative emotion*, *tone*, *anxiety*, *anger*, and *sadness*. They do not include categories corresponding to all different magnitudes of emotional activation (e.g., calmness, fear, hope), which proves to be a drawback of these lexicon-based methods in capturing the characteristics of regulatory focus.

We make following observation to be aligned with previous studies. In both 100W and LIWC, *anger*, a negative activating emotion, correlates with prevention focus (.6 and .62 resp.) and *sadness*, a negative non-activating emotion, correlates with promotion focus (.23) in the Twitter data. In 100W, the *anxiety* category is positively correlated to prevention in the event description datasets (.2 for EDD-1/2). The *tone* category in LIWC, representing overall the positive tone of a text, highly correlates with promotion focus in all datasets (.27 for EDD-1, .26 for EDD-2 and .47 for TwD). The Twitter dataset reflects findings on emotionality more reliably than the event description datasets.

Abstractness vs. concreteness: Semin et al. (2005) argued that markers of abstractness and concreteness in language are associated with the promotion and prevention focus, respectively. They attributed state verbs (e.g., *love*, *hate*), interpretive action verbs (i.e., *hurt*, *console*) and adjectives to abstractness and descriptive action verbs (e.g., *walk*, *throw*) to the concreteness of language. The category *adjective* in both LIWC and 100W shows a significant correlation to promotion focus in event description datasets (.19 for EDD-1, .2 for EDD-2, and .11 for EDD-1), reinforcing the claim made in Semin et al. (2005). The mentioned verb classes are, however, not included as psychological categories in LIWC. In 100W only *descriptive action verbs* and *state verbs* are defined, but they do not show any consistent pattern across datasets. We conclude that not all aspects of language abstraction are represented.

Hopes and duties: Goals are viewed as duties and obligations in prevention focus, and as hopes and aspirations in promotion focus. Vaughn (2018) observed that people talk more about positive outcomes when describing hopes which are reflected in the categories *positive emotion*, *reward*, and *achievement*. While describing duties the focus is on maintaining social relationships which is represented in the categories *social processes* and *affiliation*.

Corroborating with these findings, a significant correlation with the promotion label is observed for the LIWC categories *positive emotion* (.26 for EDD-1, .26 for EDD-2), *reward* (.30 for EDD-1, .37 for EDD-2) and *achievement* (.38 for EDD-1, .36 for EDD-2) for event description datasets. For Twitter data and 100W lexicon, significant correlation patterns are not observed. The *social processes* and *affiliation* categories do not show any consistent pattern across lexicons or datasets.

We construe that some, but not all linguistic markers from studies on regulatory focus are discernible in our datasets. Existing dictionary-based methods have the drawback that they capture emotionality only in terms of a few psychological categories (e.g., anger, sadness, anxiety) and do not include activating and non-activating emotions discussed in Section 2.2. Additionally, there are significantly correlated categories not being invested in previous studies (*drives*, *feel*).

5 Classification experiments

The linguistic correlation analysis sheds some light on the strengths and limitations of traditional automated text analyses. We go one step further to assess how well we can automatically predict the regulatory focus of the author from the text. To this end, we explore open and closed vocabulary text classification methods.

5.1 Methods

5.1.1 Closed vocabulary approach

We use the LIWC and the 100W analyses used earlier as candidates for the closed vocabulary approach. We consider all psychological categories defined in both tools and as noted earlier, these tools do not provide access to the raw dictionaries, instead, return the relative frequency of terms in each category per text. We use these relative frequency values and reweight them with logistic regression on the training data.

5.1.2 Open vocabulary approach

We use two machine-learning-based approaches. The first is a tf-idf-bag-of-words logistic regression classifier with unigrams and bigrams. The second is BERT-based (Devlin et al., 2019), a bidirectional transformer-based language model pre-trained with masked token prediction and next-sentence prediction objectives. We use the `deepset/GBERT-large`[10] (Chan et al., 2020) model which is trained on a large dataset sourced from Common Crawl, German Wikipedia, legal data, movie subtitles, parliament speeches, and books. We fine-tune BERT on our regulatory focus-annotated data for a sequence classification task.

5.2 Experimental setup

We conduct our classification experiments on the three regulatory focus labeled datasets. We conduct 10-fold cross-validation on the event description datasets EDD-1, EDD-2, and EDD-1+2, and identify the best event

[10] https://huggingface.co/deepset/gbert-large

description dataset suited for the task. We then evaluate all our models trained on the best dataset on the out-of-domain TwD dataset.

For the LIWC and 100W experiments, we weight their output with logistic regression models from *sklearn*[11] with default parameters. The details of each model are as follows:

LR_LIWC: We use the German version of the LIWC 2015 dictionary (DE-LIWC2015). The output file from the software contains relative frequencies of words from all psychological categories per document. We use these relative frequency values as features.

LR_100W: The API from 100W accepts a text document to be analyzed and returns a JSON response containing relative frequencies of all psychological categories. We use these relative frequency values as features.

LR_TFIDF: We use the `TfidfVectorizer` from `sklearn`[12] to vectorize the documents and use NLTK[13] to remove the German stopwords.

GBERT: We use the pre-trained German BERT model `deepset/GBERT-large` with 24-layer, 1024-hidden, 16-heads and 335M parameters. For fine-tuning, we use the `BertForSequenceClassification`[14] implementation from Hugging Face (Wolf et al., 2020). During fine-tuning, we set the number of epochs to 8, the learning rate to 10^{-5}, and the batch size to 16. Additionally, to prevent over-fitting, we monitor the validation loss and stop training if it does not improve for 5 steps. For other hyper-parameters, we used the default values from the implementation.[15].

We split the datasets into training, validation, and test sets by allocating 80% for training, 10% for validation, and 10% for testing. We perform 10-fold cross-validation and in each fold, we assess the performance of the model trained on 80% of the data, on two separate test datasets: the 10% reserved as the test set and the annotated Twitter data. The validation split of data was utilized only for GBERT fine-tuning.

5.3 Results

Table 7 shows the performance of comparison between all models and a random baseline, of 10-fold cross-validation on EDD-1, EDD-2, and EDD-1+2 datasets. Table 7 also presents the results of the models trained on the best dataset evaluated in the TwD dataset.

We see that the performance of both closed vocabulary-based approaches LR_100W and LR_LIWC are almost similar on all of the event description dataset settings. The LR_TFIDF model on the other hand outperforms closed-vocabulary models by a good margin on all event description datasets (average accuracy of 0.86 on EDD-1, 0.81 on EDD-2 and 0.87 on EDD-1+2). Also, as hypothesized, the GBERT model outperforms all other models in the majority of the experiments, with an average accuracy above 0.91 when trained on any of the event description datasets.

Evaluations on the event description datasets show that models perform better when trained on a combination of both event description datasets, possibly because it adds more diversity to the topics and helps the models to learn better generalizations. So we conclude EDD-1+2 to be the best dataset and use it as training data to test generalizations on out-of-domain datasets.

For LR_100W and LR_LIWC, despite their reasonably good performance on event description datasets, the accuracy on the out-of-domain TwD dataset is in most cases only slightly better than the random baseline and sometimes worse. Additionally, the number of instances labeled as prevention (268/923) is quite low compared to the promotion label. The closed-vocabulary approaches have a high recall compared to other methods, with 100W giving the best recall for prevention. Overall, LR_LIWC performs better than LR_100W on the out-of-domain dataset.

The LR_TFIDF model outperforms LR_100W and LR_LIWC on TwD datasets with an accuracy of 0.58. This observation supports the argument that there are possibly more lexical features that capture the regulatory focus concepts, however, cannot essentially be represented as dictionaries of words.

Finally, the GBERT model outperforms all other models when trained on the EDD-1+2 dataset.[16]

5.4 Error analysis

We conduct an error analysis in order to get a comprehensive understanding of the best model's (GBERT+EDD-1+2) behaviour and its generalization capability to real-world Twitter instances. The analysis involved comparing the representations generated by the pre-trained language model before and after fine-tuning for the regulatory focus classification task. Additionally, we manually examine instances misclassified by the model to identify common error patterns.

Representation comparison: To understand how fine-tuning for the task affects representations generated by the model, we employ a t-SNE visualization which reduces the high-dimensional representations

[11] https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html

[12] https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfVectorizer.html

[13] nltk.corpus.stopwords.words('german')

[14] https://huggingface.co/transformers/model_doc/bert.html

[15] See Appendix E for more information on fine-tuning.

[16] To ensure a fair comparison, we conducted experiments using non-linear models, such as SVM, Random Forest, and Gradient Boosting. However, logistic regression was observed to produce more stable results across LIWC, 100W, and tf-idf features and across datasets. See Appendix F for comparison of these results.

		Cross validated on corresponding dataset						
		Promotion			Prevention			
Train Dataset	Model	P	R	F_1	P	R	F_1	Acc
EDD-1	random	.49 ± .06	.50 ± .06	.49 ± .05	.51 ± .07	.50 ± .06	.50 ± .06	.50 ± .04
	LR_LIWC	.78 ± .03	.76 ± .05	.77 ± .03	.77 ± .05	.79 ± .05	.78 ± .04	.77 ± .02
	LR_100W	.77 ± .06	.76 ± .04	.76 ± .03	.77 ± .05	.77 ± .06	.77 ± .03	.77 ± .03
	LR_TFIDF	.89 ± .02	.83 ± .04	.85 ± .02	.84 ± .05	.89 ± .02	.86 ± .03	.86 ± .02
	GBERT	**.91 ± .05**	**.93 ± .03**	**.92 ± .03**	**.94 ± .03**	**.91 ± .05**	**.92 ± .03**	**.92 ± .03**
EDD-2	random	.53 ± .06	.48 ± .06	.50 ± .05	.45 ± .07	.49 ± .07	.47 ± .06	.49 ± .05
	LR_LIWC	.77 ± .04	.77 ± .05	.77 ± .04	.73 ± .07	.73 ± .05	.73 ± .05	.75 ± .04
	LR_100W	.78 ± .03	.77 ± .06	.77 ± .03	.73 ± .07	.74 ± .06	.74 ± .05	.76 ± .04
	LR_TFIDF	.77 ± .05	.94 ± .03	.84 ± .03	.90 ± .06	.67 ± .07	.77 ± .06	.81 ± .04
	GBERT	**.90 ± .04**	**.94 ± .05**	**.92 ± .03**	**.93 ± .05**	**.87 ± .05**	**.90 ± .02**	**.91 ± .02**
EDD-1+2	random	.52 ± .04	.50 ± .05	.51 ± .04	.50 ± .04	.52 ± .03	.51 ± .03	.51 ± .03
	LR_LIWC	.78 ± .02	.77 ± .03	.77 ± .02	.76 ± .03	.78 ± .02	.77 ± .02	.77 ± .01
	LR_100W	.78 ± .04	.77 ± .03	.77 ± .04	.76 ± .03	.77 ± .04	.76 ± .03	.77 ± .03
	LR_TFIDF	.86 ± .02	.88 ± .03	.87 ± .02	.88 ± .03	.85 ± .02	.86 ± .02	.87 ± .02
	GBERT	**.94 ± .02**	**.91 ± .04**	**.93 ± .02**	**.92 ± .04**	**.94 ± .03**	**.93 ± .01**	**.93 ± .02**
EDD-1+2	Best Model (trained on EDD-1+2) tested on TwD							
	random	.71 ± .02	.50 ± .02	.58 ± .02	.29 ± .02	.50 ± .03	.37 ± .02	.50 ± .02
	LR_LIWC	.79 ± .01	.46 ± .04	.58 ± .03	.34 ± .01	.70 ± .03	.46 ± .01	.53 ± .02
	LR_100W	.76 ± .03	.33 ± .03	.46 ± .03	.31 ± .01	**.75 ± .04**	.44 ± .02	.45 ± .01
	LR_TFIDF	.77 ± .02	.57 ± .05	.66 ± .04	.37 ± .03	.59 ± .02	.45 ± .02	.58 ± .04
	GBERT	**.82 ± .04**	**.61 ± .10**	**.70 ± .05**	**.41 ± .03**	.66 ± .14	**.50 ± .05**	**.63 ± .04**

Table 7: Cross-validation results (summarized as mean ± standard deviation) for all models trained on different event description datasets

Example (German)	Translation (English)	Gold Label
1. Ich hasse mein Leben langsam, ich hab einfach kein Glück... Ich finde keine Arbeit und werde deswegen angemeckert	1. I'm starting to hate my life, I just don't have any luck.... I can't find a job and I get bitched at for it	prevention
2. Ich hasse den "Sommer" ... Ich kann da nie einschlafen, weil es zu warm ist ._.	2. I hate the "summer" ... I can never fall asleep there because it's too warm ._.	prevention
3. Ich habe Angst.Angst dich zu verlieren oder Angst wie ich damit klar kommen werde wenn du nicht mehr da bist.	3. I am afraid of losing you or afraid of how I will cope when you are gone.	prevention
4. Ich hoffe nur Sie lesen nicht allzu viele von den Kommentaren hier unter Ihrem Beitrag! So viel Hass und Hetze würde ich selbst mit Ihrem Gehalt nicht lange durchstehen! Bleiben Sie stark für eine tolerante, weltoffene Gesellschaft.	4. I just hope you don't read too many of the comments here under your post! I wouldn't last long with that much hate and agitation even on your salary! Stay strong for a tolerant, open-minded society.	promotion
5. Ich bin so froh das Chingy nichts passiert ist. Ich wäre wortwörtlich fast vor Sorge gestorben.Zum Glück ist es nochmal "gut" ausgegangen..	5. I am so glad that nothing happened to Chingy. I would have literally almost died of worry.fortunately it is once again "well" ended.	promotion
6. Die leute waren traurig und wütend.Ich bin froh dass sie friedlich geblieben sind nach diesem Tag.	6. People were sad and angry. I'm glad they stayed peaceful after that day.	promotion

Table 8: Instances from TwD dataset misclassified by the GBERT+EDD-1+2 model.

into a two-dimensional space (van der Maaten and Hinton, 2008). Figure 1 shows this visualization on the test splits generated using the `deepset/gbert-large` model, before and after fine-tuning.

We see distinct clusters after fine-tuning. However, in the TwD data it lacks clear separability compared to the event description dataset. This questions the extent of the model's ability to generalize to real-world instances and emphasizes the need to investigate and understand the types of errors made by the model.

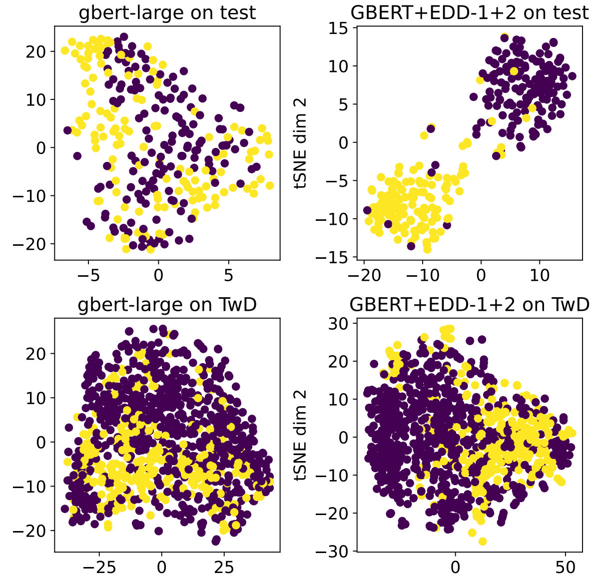

Figure 1: t-SNE visualization of representations generated by the pre-trained `deepset/gbert-large` model before (*left*) and after fine-tuning (*right*) on event-description data for regulatory focus classification.

Common error patterns: We extend the error analysis by manually going through misclassified instances to understand the pattern and characteristics of the model's most frequent errors. We take into account the tweets that have been classified incorrectly in every fold in the 10-fold cross-validation setting, . Table 8 shows examples corresponding to the two main types of errors discussed in this section.

We observe that the emotion *hate* is completely absent in the event description dataset, despite being one of the most frequently occurring emotions in the Twitter data, accounting for about 25% of the instances in the annotated data. The emotion *hate* is a negative activating emotion often associated with a prevention motive. Interestingly, when examining misclassified instances related to prevention, we find that 87% of them contain the emotion word *hate* (Examples 1, 2). However, due to the absence of this emotion word in the training data, the model was unable to capture this particular nuance accurately. Other false negatives in the promotion class also point to the fact that the model fails to capture the relationship between emotions and regulatory focus category accurately (Example 3).

In misclassified instances of promotion, a common error arises when the text mentions a negative event and is followed by an expression of optimism or anticipation for something positive (Examples 4, 5, 6). This occurrence refers to the emotion of *hope*, which is associated with promotion. Many incorrectly classified promotion tweets exhibit this pattern. These instances express elements of both promotion and prevention, hence the model encounters challenges in accurately classifying them.

6 Conclusion

In this study, we bring attention to regulatory focus, a construct used in psychology to explain the goal-oriented behavior of humans. To encourage NLP research into this topic, we introduce the novel task of regulatory focus classification (*promotion* vs. *prevention*) and datasets of experimental and real-world data annotated with the concept. Our correlation analysis with lexicons uncovers corroborating evidence from previous research and also highlights some limitations of dictionary-based approaches. Further, we apply automatic text classification methods for regulatory focus detection. The results show that a language-model-based classifier outperforms models which rely on lexical-level features. Our best model identifies the regulatory focus inclination of a person from text with high accuracy and can be considered a strong baseline for future research. Further, by evaluating the best model on manually annotated Twitter data, we confirm the generalization capability of the model on unseen domains. We achieve good results by disregarding the preconceived relationship between an *a priori* list of words and psychological categories. Instead, relying only on the language model's capability to learn them shows the best performance on the task. Nevertheless, a model that can combine these two aspects would be worth investigating further.

We also acknowledge that tweets might be too short or sometimes too vague in terms of context for the model to make a reliable prediction. As RFT is a concept in between stable traits and variable states, consolidating multiple texts from the same author could be one possible way to produce a more accurate prediction on the author's regulatory focus.

Regulatory focus detection can find practical applications in general computer-mediated communication and human-computer interaction, where automatically identifying the needs, motivations, traits, etc., of the collocutor, ensures more efficient communication. For instance, a message that addresses the needs and motivation of the collocutor could be more persuasive or be received more positively. In future research, we would like to investigate paraphrasing of a given text to fit the regulatory focus of the counterpart and to what degree it influences the persuasiveness of a text.

7 Limitations

In this study we consider regulatory focus as a binary classification problem as supported by the framework of regulatory focus theory. While it was deemed appropriate for the current study, it may not be adequate for the real-world applications like Twitter. This is because there could be *neutral* instances which do not reflect the motivational orientation of the author owing to the limited context. Even though we heuristically subset tweets expressing emotional experience, by reducing it to a binary classification task, our classifier could potentially be misrepresenting the regulatory focus landscape in real-world scenarios. Additionally, a truly neutral motivational orientation is not well supported in the current theoretical framework.

In order to ensure practical applicability, future work could explore establishing predetermined conditions or criteria for selecting potential texts that can be used to identify the regulatory focus of authors. By defining specific guidelines or requirements for text inclusion, a focused analysis can be conducted on the relevant texts that provide valuable insights into individuals' regulatory focus orientations.

8 Ethical considerations

The regulatory focus manipulation experiment collects personal experiences from participants which can be classified as sensitive data. However, the study was conducted online and we do not store any personally identifiable information of the participants, to ensure that the original author cannot be traced back from the data. Before the start of the regulatory focus manipulation experiment, informed consent was read and explicitly acknowledged by the participants. Instructions to the participants detailed the purpose and procedure of the study, the remuneration, and data handling (see Appendix B for full instructions). Participation in the study was voluntary and participants were compensated as agreed, after completing the task. They were also informed that they could quit the experiment at any point or revoke the consent before submission.

We acknowledge that a system which can predict the regulatory focus accurately can not only be used to promote positive behavior change in areas like health care. It can also raise serious ethical concerns. Automated assessment of psychological constructs from text can potentially be employed to profile people based on their regulatory focus orientation, manipulate or persuade them in targeted marketing, political campaigns, or other persuasive endeavors. Also, employing inaccurate systems in downstream applications may result in unintended consequences as the system can make incorrect assessment about the behavioral inclinations of the person.

If automatic detection of regulatory focus is implemented in any application, the end-users should be explicitly notified that the system assumes knowledge of an individual's personality and behavioral patterns, and might entail biases. To prevent any kind of misuse, it is crucial to establish ethical guidelines and ensure transparency in the usage and obtain informed consent from the users. Responsible use, strict data governance, and clear communication about the limitations and potential risks of the system are essential to safeguard individuals' rights.

The study we presented in this paper is a novel attempt to automatically label regulatory focus which could be lacking in many aspects. We acknowledge that the bias contained in the data and the chosen method may inadvertently perpetuated or amplified. We do not advocate the use of our methods in any fully automated downstream applications.

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A EDD-1 data creation

A.1 Experiment questionnaire

Bedingung 1: In diesem letzten Teil möchten wir Sie bitten, sich an einige persönliche Erlebnisse aus Ihrer Vergangenheit zu erinnern. Dabei kann es sich beispielsweise um Erfahrungen handeln, die Sie im Laufe Ihrer Schulzeit bzw. Ihres Studiums oder in Ihrem Privatleben gemacht haben. Bitte beschreiben Sie in einigen Sätzen drei verschiedene Erlebnisse Ihrer Vergangenheit:

1. Bitte beschreiben Sie ein Erlebnis, bei dem Sie das Gefühl hatten, Sie machen Fortschritte dahingehend, in Ihrem Leben erfolgreich zu sein.

2. Bitte beschreiben Sie ein Erlebnis, bei dem Sie das Gefühl hatten, Sie machen keine Fortschritte dahingehend, in Ihrem Leben erfolgreich zu sein.

3. Bitte beschreiben Sie ein Erlebnis, bei dem Sie im Vergleich zu anderen Personen dazu fähig waren, das zu bekommen, was Sie wollen.

Bedingung 2: In diesem letzten Teil möchten wir Sie bitten, sich an einige persönliche Erlebnisse aus Ihrer Vergangenheit zu erinnern. Dabei kann es sich beispielsweise um Erfahrungen handeln, die Sie im Laufe Ihrer Schulzeit bzw. Ihres Studiums oder in Ihrem Privatleben gemacht haben. Bitte beschreiben Sie in einigen Sätzen drei verschiedene Erlebnisse Ihrer Vergangenheit:

1. Bitte beschreiben Sie ein Erlebnis, bei dem eine ausreichende Vorsicht Sie davor bewahrt hat, in Schwierigkeiten zu geraten.

2. Bitte beschreiben Sie ein Erlebnis, bei dem eine mangelnde Vorsicht dazu geführt hat, dass Sie in Schwierigkeiten geraten sind.

3. Bitte beschreiben Sie sowie ein Erlebnis, bei dem Sie sich so verhalten haben, dass niemand etwas daran hätte aussetzen können.

A.2 Experiment questionnaire (translation)

Condition 1: In this last part, we would like you to recall some personal experiences from your past. These can be, for example, experiences you had during your school years or studies or in your private life. Please describe in a few sentences three different experiences from your past:

1. Please describe an experience where you felt you were making progress toward being successful in your life.

2. Please describe an experience in which you felt you were not making progress toward being successful in your life.

3. Please describe an experience where you were able to get what you want compared to other people.

Condition 2: In this last part, we would like you to recall some personal experiences from your past. These can be, for example, experiences you had during your school or university years or in your private life. Please describe in few sentences three different experiences from your past:

1. Please describe an experience in which being sufficiently careful kept you from getting into trouble.

2. Please describe an experience where a lack of caution caused you to get into trouble.

3. Please describe an experience in which you behaved in a way that no one could have found fault with.

B EDD-2 data creation

B.1 Introduction

Liebe Untersuchungsteilnehmerin, lieber Untersuchungsteilnehmer, vielen Dank für die Bereitschaft, an der Studie teilzunehmen! Bitte lesen Sie sich die folgenden Informationen sorgfältig durch und entscheiden dann über Teilnahme oder Nichtteilnahme an dieser Studie.

Inhalt: In dieser Studie untersuchen wir, wie unterschiedliche Zielverfolgungsstrategien zusammenhängen. Dazu werden wir Sie bitten, offene Fragen zu Situationen aus der Vergangenheit zu beantworten, in denen Sie (un)erfolgreich Ziele verfolgt haben. Danach folgen einige Fragen zu Ihrem Verhalten am Arbeitsplatz und zu der Verfolgung von Leistungszielen.

Studienablauf und Bezahlung Insgesamt dauert die Studie in etwa 8-10 Minuten. Alle Teilnehmenden erhalten dafür eine Entlohnung von 1.50 €. Die Studie sollte zusammenhängend am Computer, Laptop oder Tablet (nicht auf dem Handy) bearbeitet werden. Voraussetzung für Ihre Teilnahme ist, dass Sie mindestens 18 Jahre alt sind und fließend Deutsch sprechen.

Vertraulichkeit und Handhabung der Daten Alle personenbezogenen Daten werden streng vertraulich behandelt und nur für Forschungszwecke verwendet. Durch Ihre Bestätigung unten erlauben Sie uns, Ihre Antworten für wissenschaftlichen Zwecken auszuwerten und in vollständig anonymisierter Form anderen Wissenschaftlern öffentlich zur Verfügung zu stellen. Am Ende der Umfrage haben Sie nochmals die Möglichkeit, diese Einwilligung zu widerrufen. Danach ist ein Rückzung der Daten nicht mehr möglich, da die Daten anonym gespeichert werden und wir nicht in der Lage sind, Ihre Daten zu identifizieren. Sollten Sie Fragen bezüglich Ihrer Daten oder Datenspeicherung haben, können Sie unsere Datenschutzbeauftragten kontaktieren: XXXX

- Ich bin mindestens 18 Jahre alt und habe die Informationen gelesen und verstanden. Ich erkläre mich damit einverstanden, an der Studie teilzunehmen.
- Ich möchte nicht an der Studie teilnehmen.

B.2 Experiment questionnaire

In diesem ersten Teil möchten wir Sie bitten, sich an einige persönliche Erlebnisse aus Ihrer Vergangenheit zu erinnern. Wir interessieren uns für Erfahrungen, die Sie gemacht haben, während Sie ein Ziel verfolgt haben - beispielsweise während der Arbeit oder im privaten Kontext. Bitte beschreiben Sie in einigen Sätzen drei verschiedene Erlebnisse Ihrer Vergangenheit (jeweils mindestens 150 Zeichen):

1. Bitte beschreiben Sie ein Erlebnis, bei dem Sie das Gefühl hatten, Sie machen Fortschritte dahingehend, in Bezug auf ein Ihnen wichtiges Ziel erfolgreich zu sein.
2. Bitte beschreiben Sie ein Erlebnis, bei dem Sie das Gefühl hatten, Sie machen keine Fortschritte dahingehend, etwas zu erreichen.
3. Bitte beschreiben Sie ein Erlebnis, bei dem Sie im Vergleich zu anderen Personen dazu fähig waren, das zu bekommen, was Sie wollten.

In diesem ersten Teil möchten wir Sie bitten, sich an einige persönliche Erlebnisse aus Ihrer Vergangenheit zu erinnern. Wir interessieren uns für Erfahrungen, die Sie gemacht haben, als Sie ein Ziel verfolgt haben - beispielsweise während der Arbeit oder im privaten Kontext. Bitte beschreiben Sie in einigen Sätzen drei verschiedene Erlebnisse Ihrer Vergangenheit (jeweils mindestens 150 Zeichen):

1. Bitte beschreiben Sie ein Erlebnis, bei dem ausreichende Vorsicht Sie davor bewahrt hat, in Schwierigkeiten zu geraten.
2. Bitte beschreiben Sie ein Erlebnis, bei dem eine mangelnde Vorsicht dazu geführt hat, dass Sie in Schwierigkeiten geraten sind.
3. Bitte beschreiben Sie ein Erlebnis, bei dem Sie sich so verhalten haben, dass niemand etwas daran hätte aussetzen können.

B.3 Introduction (translation)

Dear participant, thank you for your willingness to participate in the study! Please read the following information carefully and then decide whether to participate or not in this study.

Content: In this study, we will investigate how different goal pursuit strategies are related. For this purpose, we will ask you to answer open-ended questions about situations from the past in which you have (un)successfully pursued goals. This will be followed by some questions about your behavior at work and about the pursuit of performance goals.

Study procedure and payment: In total, the study will take about 8-10 minutes. All participants will receive a payment of 1.50 €. The study should be completed contiguously on a computer, laptop or tablet (not on a cell phone). To participate, you must be at least 18 years old and fluent in German.

Confidentiality and data handling: All personal data will be kept strictly confidential and will only be used for research purposes. By confirming below, you allow us to evaluate your answers for scientific purposes and make them publicly available to other researchers in a completely anonymized form. At the end of the survey, you will again have the opportunity to revoke this consent. After that, it is no longer possible to retrace the data, as the data is stored anonymously and we are not able to identify your data. If you have any questions regarding your data or data storage, you can contact our data protection officers: XXXX

- I am at least 18 years old and have read and understood the information. I agree to participate in the study.
- I do not wish to participate in the study.

B.4 Experiment questionnaire (translation)

Condition 1: In this first part, we would like you to recall some personal experiences from your past. We are interested in experiences you had while pursuing a goal - for example, during work or in a private context. Please describe in a few sentences three different experiences from your past (at least 150 characters each):

1. Please describe an experience in which you felt you were making progress toward being successful in a goal that was important to you.
2. Please describe an experience in which you felt you were not making progress toward achieving something.
3. Please describe an experience where you were able to get what you wanted compared to other people.

Condition 2: In this first part, we would like you to recall some personal experiences from your past. We are interested in experiences you had when pursuing a goal - for example, during work or in a private context. Please describe in a few sentences three different experiences from your past (at least 150 characters each):

1. Please describe an experience where sufficient caution kept you from getting into trouble.
2. Please describe an experience where a lack of caution caused you to get into trouble.
3. Please describe an experience in which you behaved in a way that no one could have found fault with.

C Twitter data creation

C.1 List of emotion words

For detecting emotion words we created a list of words that are represented in Plutchik's emotion wheel (Plutchik, 2001) and two additional items representing shame and pride.

Emotion words: klar, wüt, angewider, betrüb, erstaun, erschrock, bewunder, begeister, froh, bereit, verärger, ablehn, traurig, überrasch, ängst, vertrau, akzeptier, gelass, neugierig, gereiz, gelangweil, nachdenk, verwirr, besorg, stolz, aufmerksam, klar, optimist, verlieb, streitlust, hass, bereund, enttäusch, ehrfürchtig, fügsam, scham

C.2 Annotation Guidelines

C.2.1 Definition & Examples

According to Regulatory focus theory human behavior or thoughts are motivated by a need for achievement (promotion focus) or a need for security (prevention focus). Promotion-focused individuals are motivated by achievement, are more risk seeking and approach tasks eagerly. Prevention focused individuals take a risk-averting approach, are more vigilant and value security. The examples below demonstrate how variation in regulatory focus is captured in formulation of text. In the annotation task that follows only tweets in German are included and for adding diversity, examples cover different domains and not only tweets.

C.2.2 Regulatory Focus and emotion

Prevention and promotion are related to distinct sets of emotions. Emotions triggered in the context of success (i.e., a positive situation) or failure i.e., in a negative situation) can clearly be connected to promotion or prevention focus. Positive activating emotions like cheerfulness and happiness (success situation), and negative non-activating emotions like sad and depressed (failure situation) are indicators of promotions focus. While positive non-activating emotions like relaxed, unstressed, calm, calming down etc.,(success situation) and negative activating emotions like anger, hate, fear etc.,(failure situation) are prevention focus indicators. Below Figure 2 shows the emotions related to a regulatory focus category and outcome of a particular situation (success/failure).

1. **Prevention Focus**

   (a) Die Forschung hat gezeigt, dass Vitamin C vor Krankheiten wie z. B. Erkältungen schützt.
   Explanation : This example emphasises on protection or avoiding sickness, hence it is prevention focus

   (b) Der 100% Grapefruit-Saft sichert den Tagesbedarf an Vitamin C.
   Explanation : This formulation instils a sense of security, hence is prevention focus.

   (c) Habe meine praktische Fahrprüfung bestanden, war doch einfacher als gedacht. Die Straße muss nicht mehr auf mich warten.
   Explanation : The expression "einfacher als gedacht" shows the person was prepared for the difficult task, poining to prevention focus

   (d) Wir konnten uns endlich den Traum vom eigenen Haus erfüllen. Wir sind sooo dankbar! *Explanation : "endlich" refers to a feeling of relief which is a prevention emotion*

   (e) Die Welt fühlt sich manchmal so abweisend an. Früher hatte ich noch ein Gefühl von Sicherheit.

   (f) Können wir drauf vertrauen, dass sich unsere Politiker genug ernsthafte Gedanken gemacht haben über die Risiken des Klimawandels?

   (g) Von Reisen rät doch jeder im Moment ab, richtig so, ist doch viel zu gefährlich!

   (h) Ich bin kein Impfgegner, Impfungen retten Leben, bestes Beispiel Polio oder Tetanus. Aber einen mRNA Impfstoff zu bekommen, der weniger als 6 Monate getestet wurde.... sorry, da kann ich auch Russisch Roulette spielen. Ich hatte Covid übrigens bereits und nix bis auf Husten.

2. **Promotion Focus**

   (a) Forschung hat gezeigt, dass Vitamin C Ihre Gesundheit stärkt.
   Explanation: Compared to the prevention formulation, you can see that this statement emphasises on positive outcome, hence this is promotion focus.

   (b) Unser 100% Grapefruit-Saft hat drei Mal mehr Vitamin C als andere Fruchtsäfte. Richtig gut, oder?
   Explanation: Here the statement focuses on advantage rather than security.

   (c) Die Früchte werden nur zur besten Erntezeit verarbeitet und schmecken daher so gut.
   Explanation: The emphasis here again is on the plus points or advantages, hence promotion focused

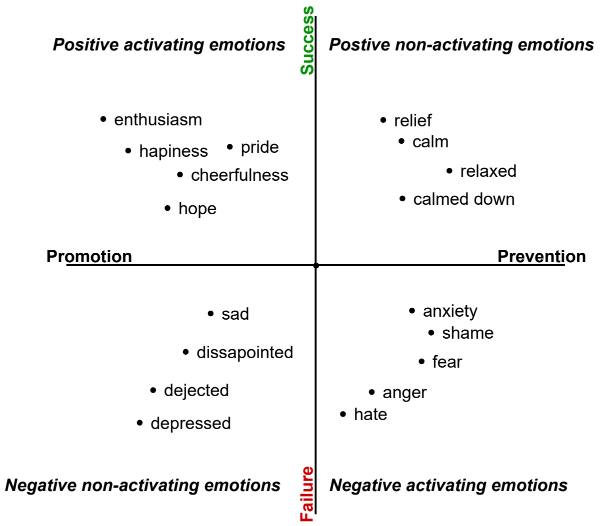

Figure 2: An approximate representation of emotions related to a regulatory focus category and outcome of a particular situation (success/failure) (drawn following Brockner and Higgins, 2001).

(d) Heute nochmal fünf Kilo mehr geschafft. Habe mein Monatsziel fast erreicht, so kann es weitergehen.

(e) Ich bin heute Morgen früh aufgestanden, weil ich zum Beginn meines Psychologie-unterrichts um 8:30 Uhr in der Schule sein wollte, der normalerweise hervorragend ist.

(f) Ich freue mich auf meinen neuen Job bei amnesty. Dort kann ich nicht nur Geld verdienen sondern mich auch für meine Werte einsetzen.

(g) Ich habe mir ein neues Fahrrad gekauft. Ich wusste gar nicht wieviel Spass es machen kann in der Freizeit die nähere Umgebung zu erkunden.

(h) In nur 6 Monaten wurden 50% der Deutschen einmal geimpft. Seid doch mal ehrlich, dass sowas geht hätte vor Corona auch niemand gedacht.

C.2.3 Task Description

Familiarize yourself with the concepts mentioned in the previous section. Note the difference in text formulation for prevention and promotion focus. Ask for more examples, if the concept is not clear. The annotation task requires you to annotate each given tweet with the one of the following labels.

1. *prevention*
2. *promotion*
3. *neither promotion not prevention*
4. *not sure*

Take into consideration the emotion expressed in the context of success or failure. Even though it is more common to see positive emotion in promotion focus text, it is not always the case.

C.2.4 Annotation Environment

The annotation task will be carried out in google sheets. You have to read the text in the column *tweet*, decide which regulatory focus category the tweet belongs and choose a label from the drop-down in the column *label*. If you have any feedback about the instance, please use the *comments* column.

D Psychological categories

For the linguistic correlation analysis we included all 49 categories from the 100W api and 80 categories from DE-LIWC2025. We excluded only those categories referring to punctuations and the categories *fillers*, *other* and *Dic* as they are not relevant in the context of current study. Table 9 shows the categories from both lexicon that where used in this study.

LIWC categories
Analytic (Analytic Thinking), Authentic (Authentic), Clout (Clout), Sixltr (Words > 6 letters), Tone (Emotional tone), WPS (Words/sentence), achiev (Achievement), adj (Common adjectives), adverb (Common Adverbs), affect (Affective processes), affiliation (Affiliation), anger (Anger), anx (Anxiety), article (Articles), assent (Assent), auxverb (Auxiliary verbs), bio (Biological processes), body (Body), cause (Causation), certain (Certainty), cogproc (Cognitive processes), compare (Comparisons), conj (Conjunctions), death (Death), differ (Differentiation), discrep (Discrepancy), drives (Drives), family (Family), feel (Feel), female (Female references), focusfuture (Future focus), focuspast (Past focus), focuspresent (Present focus), friend (Friends), function (Total function words), health (Health), hear (Hear), home (Home), i (1st pers singular), informal (Informal language), ingest (Ingestion), insight (Insight), interrog (Interrogatives), ipron (Impersonal pronouns), leisure (Leisure), male (Male references), money (Money), motion (Motion), negate (Negations), negemo (Negative emotion), netspeak (Netspeak), nonflu (Nonfluencies), percept (Perceptual processes), posemo (Positive emotion), power (Power), ppron (Personal pronouns), prep (Prepositions), pronoun (Total pronouns), quant (Quantifiers), relativ (Relativity), relig (Religion), reward (Reward), risk (Risk), sad (Sadness), see (See), sexual (Sexual), shehe (3rd person singular), social (Social processes), space (Space), swear (Swear words), tentat (Tentative), they (3rd person plural), time (Time), verb (Common verbs), we (1st pers plural), work (Work), you_formal (2nd pers formal), you_plur (2nd person plural), you_sing (2nd person singular), you_total (2nd person)
100W categories
DAV (Descriptive Action Verb), achieve (Achievement), adjective (Adjective), adverb (Adverb), affil (Affiliation), agent (Active voice), anger (Anger), anxiety (Anxiety), article (Article), auxverb (Auxiliary Verb), booster (Intensifiers), conj (Conjunctions), discrep (Discrepancy), feminine (Feminine), future (Future focus), ich (First Person singular), impersonalPronouns (Impersonal Pronouns), masculine (Masculine), money (Money), motion (Motion), negAchieve (Negative Achievement), negAffil (Negative Affiliation), negEmo (Negative Emotion), negPower (Negative Power), negation (Negation), numbers (Numbers), past (Past focus), patient (Passive voice), personalPronouns (Personal Pronouns), posAchieve (Positive Achievement), posAffil (Positive Affiliation), posEmo (Positive Emotion), posPower (Positive Power), power (Power), preposition (Preposition), quant (Quantity), relativ (Absolutness), reward (Reward), risk (Risk), sadness (Sadness), shehe (Third Person plural), space (Space), speak (Speak), strictNegationPrepositions (Strict Negation Prepositions), sv (State Verb), swear (Swear Words), time (Time), we (First Person plural), you (Second Person singular)

Table 9: List of psychological variables and their corresponding categories in both LIWC and 100W lexicons used in the current study

E Training details for GBERT

We fine-tuned the pre-trained German BERT model `deepset/GBERT-large` for the regulatory focus classification task. Figure 3 shows the training and validation loss averaged across folds for each epoch. The number of epochs are varying in some cases because we set an early stopping criteria to stop training if the validation loss does not improve for 5 steps. We use the setting `load_best_model_at_end` to save the model with best performance on the validation set, rather than the model from the last training epoch.

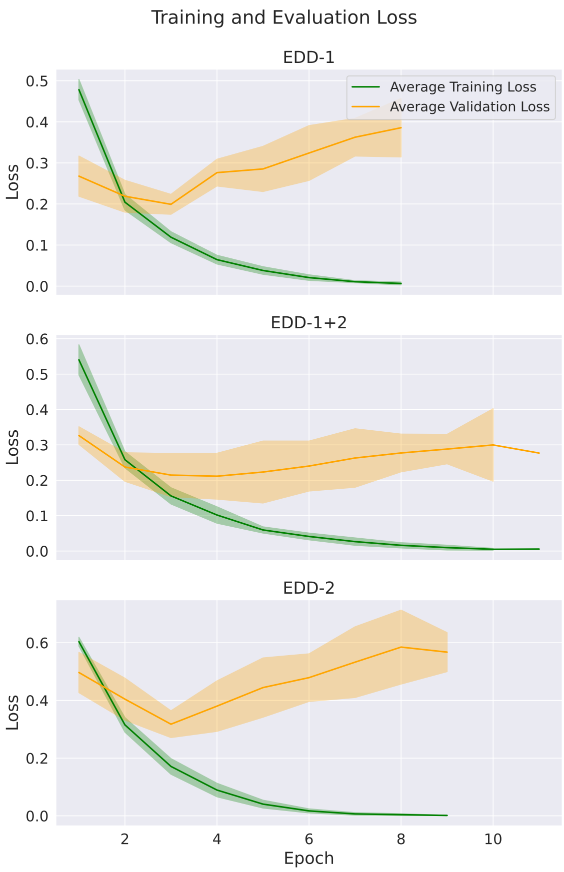

Figure 3: Training and validation loss for each dataset averaged over folds for each epoch.

F Additional experiment results

In closed-vocabulary methods, in addition to the linear models discussed in the paper, we conducted regulatory focus classification using three non-linear models: support vector machines (SVM), random forest, and gradient boosting and the three feature sets: LIWC, 100W, and TF-IDF vectors. We use the default hyper-parameters for the model in the `scikit-learn` python package. The experiments are conducted with the same setup as discussion in Section 5.2 for the linear models. Figure 4 displays the results of 10-fold cross-validation on both the event description dataset and the Twitter dataset for all non-linear models and the logistic regression model. On comparing the results, we observe that the SVM_TFIDF model outperforms other non-linear models. However, the logistic regression model (Logreg_TFIDF) achieves almost similar results and the standard deviation suggests that logistic regression model might be more stable in comparison. Furthermore, the performance of both SVM_TFIDF and Logreg_TFIDF on Twitter data is comparable.

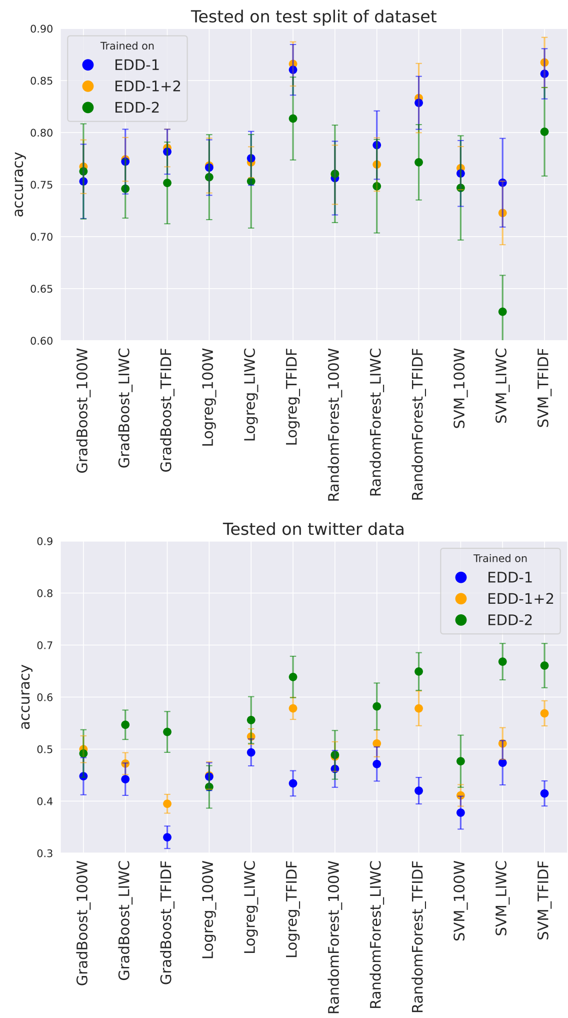

Figure 4

G Binary vs. tertiary classification

Individuals exhibit varying degrees of regulatory focus based on the given situation and context. The notion of a completely neutral regulatory focus, where an individual lacks any inclination towards promotion or prevention, is quite rare. When an individual is engaging in a social media activity like posting in Twitter, they have an active motivational orientation. However, it is possible that it is hard to identify the regulatory focus of the author when there is no sufficient contextual information to make an accurate prediction. This is reflected in the annotation task as well, where the annotators did not choose either of the two labels. As shown in Figure 5, the distribution of labels is skewed with only 3.65% instances labeled as *neutral*.

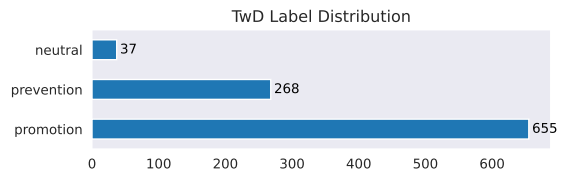

Figure 5: Distribution of labels in Twitter data.

To understand whether the state-of-the-art model used in the study is also able to handle regulatory focus classification as a three class problem, we trained and tested the model using the annotated Twitter data. We fine-tuned the pre-trained German BERT model `deepset/GBERT-large` on the Twitter data with instances labelled as *promotion*, *prevention* and *neutral*. In the *neutral* label we consolidated instances labeled as *neither promotion not prevention* or *not sure* by both annotators. We split each of the datasets into training, validation, and test sets using an 80-10-10 split.

class	**precision**	**recall**	**F_1**
promotion	0.949	0.962	0.955
prevention	0.889	0.896	0.889
neutral	0.400	0.300	0.311

Table 10: Results of GBERT model trained on Twitter data labeled with *promotion*, *prevention* and *neutral* labels

Table 10 shows the results for regulatory focus classification as a 3-class problem. Considering the limited number of instances for the neutral label (3% of the dataset), the model's relatively poor performance on that label is expected. However, it demonstrates good performance on both the promotion and prevention labels. The results could be suggesting that the distinction between promotion-focused and prevention-focused content is more evident and discernible compared to instances exhibiting a neutral regulatory focus.