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Measuring Temporal Distance Focus from Tweets and Investigating its Association with Psycho-demographic Attributes

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Abstract—Temporal distance (TD) is a type of psychological distance which shows how an individual construes past and future. It is not explored with empirical research as to how an individual's *focus* on temporal distance (near-past, far-past, near-future and far-future) can be measured from human-written text and further used for studying human tendencies. Traditionally, focus on a Temporal Distance is studied by self-report measurements. In this article, we present a study on human focus on a temporal distance from their Twitter posts (English tweets). We first identify the tweet-level temporal focus by deep neural classifiers which make use of linguistic knowledge for classification. The model classifies each tweet into one of *near-past*, *far-past*, *near-future* or *far-future*. Classified tweets are then grouped by users to obtain the user-level temporal focus. Finally, we correlate the user's focus on temporal distance (*near-past, far-past, near-future, and far-future*) with his/her demographic (age, gender, education, and relationship status) and psychological attributes (intelligence, optimism, joy, sadness, disgust, anger, surprise, and fear). Our empirical analysis reveals that users' *near-past* focus is more positively correlated to their age. We also observe that users' *near-future* focus is correlated to joy while users' focus on *far-past* is associated with negative emotions like sadness, disgust, anger, and fear.

Index Terms—temporal distance focus, classification, tweets, psycho-demographic attributes, tweet-level semantics.

1 Introduction

The emergence of digital media has provided many aspects of social and psychological research with a huge amount of data availability. Past research predicts age, gender, psychological well being, emotion recognition, depression study, etc. from the human-written texts [1], [2], [3], [4], [5], [6]. Temporal focus has also found to have influenced from human demographics and emotions. In the psychological literature, the past focus has been related to age, sadness [7], [8] while the future focus has been related to education, optimism, joy [9], [10], [11]. However, more fine-grained aspects of temporal focus like near or far distance focus have not been established. For instance, whether the relationship between people's age and past focus is more about near past distance or far past distance is not studied empirically in literature.

In psychology, episodic memory and foresight refer to the human capacity to mentally reconstruct personal events from the past and envisage possible scenarios in the future, respectively. These human abilities are well documented in the Construal Level Theory (CLT) literature. The CLT says that more-distant events would be construed in more abstract level and simple terms than the near distant events [12]. CLT has been useful for predicting self-control, risk perception, negotiation style, temporal discounting, behavioral intentions, decision making, etc. [13]. TD, in particular, can provide a gateway for understanding the corollary of TD on social communication, medical treatment, interpersonal relationships, risk management, human perceptions, attitudes, beliefs, etc. This kind of research thus can be beneficial for various social and psychological phenomenon where social media data can be a medium for studying human attributes.

Temporal distance (TD) shows how an individual interprets past and future where the present or current state in self is taken as a reference point [14], [15]. TD is a subjective experience which shows something to be close or far from the self, and present. It varies person to person and individuals construe TD uniquely [15]. This signifies that a person may perceive a future event to be far from the present but another person may perceive it to be quite nearer. The same also holds for past events. In a generalized scenario (i.e. for a large number of people) the actual passing of time is constant across individuals and contexts [16]. Thus, it will be beneficial if we can measure people's focus on a particular TD and investigate how that affects their behaviors. In order to achieve this goal, we need to define the *near distant* and the *far distant* events. *For this current study, we follow the definition of near distance and far distance as mentioned in a recent study* [17]. The study says that the *near future* events are those events which will occur within the next few days or weeks while the *far future* events are those events which will happen in the coming year(s). We follow the same definition in the past direction and define that near past events are those events which happened in the last few days or weeks and far past events are those events which happened one year ago or before that. We fit these definitions in the context of Twitter events.

In this work, we present a large scale study which finds people's focus on a particular temporal distance using the

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language they use in Twitter (English tweets). We represent people's temporal focus in terms of their relative emphasis that they put on different temporal categories. This relative emphasis on a particular temporal category is also known as the temporal orientation (past, present and future) [18]. Here, we incorporate the concept of TD and measure focus on TD. For example, the sentence "*We hope that our next generation will be the beneficiary of AI.*" has a focus on *far future* whereas the sentence "*I still remember my childhood.*" has a focus on *far past*. We extract these kinds of language-use from tweets and finally measure the *near* and *far distance* focus of the Twitter users and correlate those with their different demographic and psychological factors.

We first develop a hashtag-based method to create the training set for the tweet classification. We also create a manually annotated test set for the validation of the trained model. Our classification method follows a hierarchical framework where we first classify tweets into one of the *past*, *future* or *other* categories. Then, the *past* and *future* tweets are classified into either of *near* or *far* category. *As only past and future come under the definition of TD, the present focus is not considered for analysis*. In our study, we consider present class into *other* category as described in the *Methodology* section. Our classification model uses a self-attention based Bi-directional Long Short Term Memory network and three linguistic features for classification. We apply the built classifier on a user-level tweet dataset [19] of 5,191 users of the UK which contains ≈10 million tweets. We then group the tweet-level focus over users to get the user-level temporal focus. Finally, we find the association between the users' focus on a temporal distance and their different demographic and psychological attributes.

For this current study, we consider age, gender, education, and relationship status as users' demographic attributes and intelligence, optimism, and Ekman's [20] six basic emotions (joy, anger, sadness, disgust, fear, and surprise) as psychological attributes. We use these basic emotion categories as these are the most extensively used in the existing literature of emotion analysis, and the relation between the users' temporal focus on a TD and basic emotions has not been investigated with large scale empirical experiments. As emotion detection is not our main goal, we use the user-level attributes developed by Preoţiuc-Pietro et al. [19].

In summary, we state the main contributions of the article as follows:
a) We present an approach to measure Twitter users' TD focus by automatically classifying their tweets into different temporal categories and then aggregating over users to get user-level measurements. b) We propose a hashtag-based approach to collect data for preparing the training set for our classification model which required no manual annotations. c) We have manually annotated a gold standard test for validation of our classification model, d) Finally, we investigate the relationship between the users' TD focus and their age, gender, education, relationship status, intelligence, optimism, and six basic emotion.

The rest of the article is structured as follows. We report a brief overview of the related background literature in Section 2. We demonstrate the methodology in Section 3 and describe the datasets used for our experiment in Section 4. In Section 5, we present the results of temporal distance focus classification results along with the necessary analysis. In Section 6, we investigate the association between user-level TD focus and different user-level attributes in terms of correlation study. Section 7 highlights limitations of our study. Finally, we conclude in Section 8 with the future scope of research.

2 Related Background

In psychological literature, Temporal Distance (TD) has been measured in both the directions (*past* and *future*). However, measure based on the *future* dimension dominates the *past* dimension based measure in prior works [16], [17], [21], [22]. A series of studies by Liberman et. al [23] shows that in the far future, the negative and positive experiences, are likely to be more prototypical, more extreme and less variable. The authors also reported that dealing with more distant future experiences efficiently is expected to be less variable.

An individual's focus on a particular TD can affect their physical, psychological and social phenomena. For example, Dargembeau et al. [21] have claimed that people who envision the emotional events in the *far future*, their anterior part of the ventromedial prefrontal cortex (a part of the human brain) becomes more active while for the *near future*, the caudate nucleus (another part of the human brain) becomes more active. Past studies have found that people's judgment and decision making about an event varies depending upon whether the events will happen in either *near* or *far* temporal distance [14], [15]. Milkman et al. [22] have shown that discrimination against women and minorities is an outcome of the decisions about the *far future* events. Another research shows that people are optimistic about their distant future lives, and they believe that these will be rosy despite their current problems [24].

Previous works manifest that far distance temporal focus brings attention to one's core and thus defines one's characteristics, whereas a near distance temporal focus switches one's attention to situational circumstances that are according to one's true nature [25]. Studies conducted by Nussbaum et. al [26] and Pronin et. al [27] show that people who think about far distant actions, they have a tendency to ignore situational causes of behavior. Those people are also inclined to consider far distant actions as characteristics of the related attitude and personality. Agerström et al. [28] examined whether the weight individuals put on morality concerns is increased by temporal distance. Zhao et al. [29] revealed that other people's recommendations shift one's preferences about distant-future consumption than for near-future consumption. Day et al. [30] assessed the effects of temporal distance on perceived similarity.

Although these kinds of studies exist extensively in the psychological literature, no studies have empirically examined the TD focus at a large-scale. Earlier research on temporal focus concentrated on three dimensions of the temporal focus (past, present, and future) where the correlation with the social media users' temporal focus and their different attributes. In [31], [32], the authors built supervised machine learning-based temporal orientation classifiers using manually annotated data. The authors then report the association between user-level temporal orientation and users' age, gender, Big-five personality factors (conscientiousness, openness, extraversion, neuroticism, and agreeableness), satisfaction with life, etc. Other studies reported in [33], [34] measure user-level temporal orientation by building temporal orientation classifiers. The authors used minimal supervision techniques to create training data and finally measured the correlation between the user-level temporal orientation and their different attributes such as income level, age, relationship, education, etc. In all these studies, the temporal focus is measured based on past, present or future time dimensions. In contrast, we employ the aspects of TD (*near* or *far distance*) from the language used in English tweets by Twitter users and find associations with different user attributes.

3 Methodology

At first, we develop a deep learning-based classifier for determining the message-level focus of the users' tweets. Then we find the users' focus on *near past*, *far past*, *near future* and *far future* by measuring the ratio between tweets in each category and total tweets. Finally, we correlate these orientation measures (near past, far past, near future and far future) with the users' different psychological (intelligence, optimism and six basic emotions) and demographic attributes (age, gender, and education). The overall architecture is shown in Figure 1.

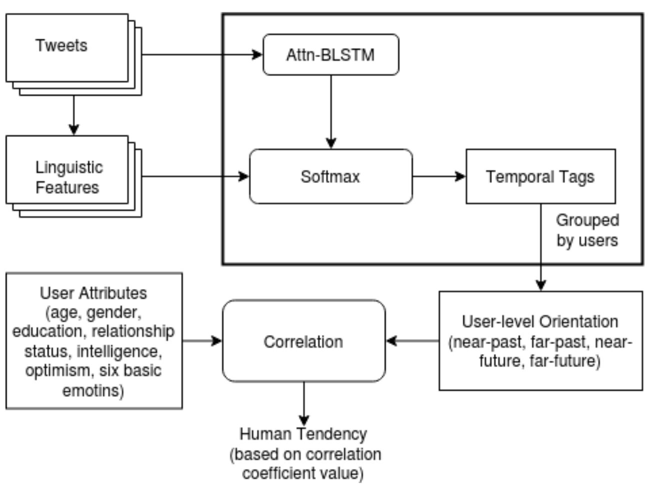

Fig. 1: Overall architecture of the proposed framework.

3.1 Tweet-level Temporal Distance Focus

The temporal classification follows a hierarchical approach that first classifies tweets into *past* vs. *future* vs.*other* category. Finally, the future tweets are classified into either of *near-future* or *far-future* category and the past tweets are classified into *near past* or *far past* category.

Our proposed method uses a Bi-directional Long Short Term Memory (Bi-LSTM) network [35] with self-attention which takes tweet vectors and three linguistic feature vectors as inputs and produces temporal classes as outputs. Only existing temporal keywords and tense of the verb are not enough to capture the temporal focus from a text. For example, the tweet *"can't wait to see you compete at glasgow today."* has temporal focus on future (*near-future*). The existing temporal keyword in the sentence, here *'today'* has a *present* time sense. Here, the tense of the verb is also *present*. LSTMs [36] is found to be good at resolving these kinds of inter-dependencies within the text. Firstly, we represent a tweet by converting its sequence of words into word vectors as w = $(w_1, w_2, w_3, w_4..., w_N)$ where N is the tweet length. These word vectors are given to the input of the Bi-LSTM layer. Finally, the left context ($\overrightarrow{h_t}$) and right context ($\overleftarrow{h_t}$) outputs of Bi-LSTM are concatenated as $m_t = [\overrightarrow{h_t}; \overleftarrow{h_t}]$. Self-attention is used over this concatenated output m_t. The self attention output is given input to a softmax along with other word-level feature vectors.

For overall framework, we use *categorical cross-entropy* loss function and *Root Mean Square Propagation (rmsprop)* optimizer. We set batch size as 128 and train the model for 500 *number of epochs*. We also used *dropout rate* of 0.5. We select all the parameters using the grid search method based on 10-fold cross-validation accuracy.

All the input words to the Bi-LSTM as well as the words selected for features are vectorized using the pre-trained GloVe vectors [37] of 200 dimensions which were trained on 2 billion tweets.

3.1.1 Word-level Features

We use the following three word-level linguistic features and concatenate with the attention outputs. A non-linear layer is used over this concatenated output vector and finally, the output of the non-linear layer is passed through a Softmax function for class prediction. The linguistic features are as follows:

3.1.1.1 **Temporal Keyword (TK)**: The list of temporal keywords present in a tweet is used as a feature. The temporal keywords are captured using an existing temporal knowledge-base, TempoWordNet [38]. TempoWordNet is an extension of English WordNet where each WordNet synset is associated with its intrinsic temporal dimensions. In particular, each WordNet synset is automatically tagged in either of the past, present, future or atemporal (no time sense) category by machine learning-based approach.

3.1.1.2 **Verb Part-of-speech (Verb)**: The words in a tweet having verb as PoS tags are used as features. The verbs are detected using the CMU tweet-tagger [39].

3.1.1.3 **Expanded words (EW)**: We expand the temporal keywords and the words with verb PoS tag in a tweet using a query expansion technique. We obtain the word embedding representation of the target word from GloVe embedding [37]. We then compute the cosine similarities between the target word vector and all the other GloVe vectors and retrieve the top-3 similar vectors. The words associated with these similar vectors are finally chosen. For example, for the word *join*, expanded words are *joining, visit, check*.

Our intuition behind using these linguistic features is explained by the following examples: i). The sentence, *"Please deliver better product next time."* has *'future'* temporal dimension. It is determined by the presence of temporal keyword *'next time'* and not by the tense information of the verb *'deliver'*. We considered the temporal keywords which are present in the TempoWordNet. The word "time" does not explicitly refer to past, present or future. However, the word "next" has an underlying future temporal orientation which

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can be found from the TempoWordNet. ii). The sentence, *"Just because of the rain our plan worked."* has a temporal focus on *'past'* which we can know by the tense of the verb *'worked'*. Here, the future-related temporal keyword *'plan'* is not helpful. Thus, we see that both the verb and temporal keywords help but not in the same way. iii). The expanded feature EW is used for two reasons: a) the words present in the TempoWordNet are more formal but tweets are informal. b) the expansions add additional information during the training process.

We also investigated another feature called Time Expression. The time expressions are measured by the difference of the resolved date, time of expressions from the tweet and the date when the tweet was created. We measured this using the state-of-the-art HeidelTime tagger.[1] Let us consider the following example, the tweet "*some of the reasons you should reach out on gis day November this year.*". If the tweet is created on *'October this year'* then by resolving 'November this year', we can derive that the tweet is an instance of *'near-future'*. But, we could find useful time expressions for only approximately 10% of the test tweets, and hence we excluded this for further experiments.

3.2 User-level Temporal Distance Focus

We measure the user-level TD orientation/focus by aggregating a user's tweets per temporal category using the following equation:

$$orientation_d(user) = \frac{|tweets_d(user)|}{|tweets_{total}(user)|} \quad (1)$$

where $d \in \{$ *near past, far past, near future, far future*$\}$. Here, we find the proportion of each temporal category with respect to the total tweets ($tweets_{total}(user)$) to obtain the user-level temporal focus.

3.3 Predictive Model

We measure how users' focus on *near past, far past, near future* and *far future* are correlated with their different psychological and demographic attributes. We use linear regression [40] as the predictive model. The relationship is measured using the *Pearson's correlation coefficient r* which measure the linear association between users' TD focus and different attribute.

4 Data Sets

We use English tweets for creating the *training set*, *test set* and *user-level test set*. The *training set* contains 36,000 tweets with the tags generated by a hashtag-based method. The *test set* contains 700 tweets which are manually annotated. The *user-level test set* contains ≈10 million tweets of 5,191 Twitter users with known user attributes (age, gender, education, emotions, etc.).

1. http://heideltime.ifi.uni-heidelberg.de/heideltime/

4.1 Training Set

We develop our training set for tweet classification using a hashtag-based method which does not require any manual annotation. The main issue here is to recognize the candidate hashtags which are representative of *past*, *future* and *other (neither past nor future)* categories. We consider the trending topics (i.e. hashtags) from the *trends24.in* website for the hashtag identification. In this website, hour-wise trending hashtags are reported. From these hashtags, we manually select those hashtags which signify any temporal (past, future or other) events. To increase hashtag variations in our data collection, we drop those hashtags which do not change much for many days. The final set of manually selected hashtags are used as query keywords for searching tweets daily. We collect tweets from Twitter using the Twitter streaming API. Data collection duration was September 2017 to July 2018.[2]

We follow four hypotheses for collecting the tweets:

1) If a hashtag is associated with an event which has occurred in the last few days or weeks then people will mostly write near past tweets,
2) If a hashtag is associated with an event which had occurred a year ago or even earlier then people will mostly write *far past* tweets,
3) If a hashtag is associated with an event which will happen within the next few days or next few weeks then people will write mostly about *near future*,
4) If a hashtag is associated with an event which will occur within a year time or later then we can say that people will mostly write about *far future*.

Challenges: Data collection was challenging because the trends of Twitter events are as such that the trending topics are mostly concerned about the present and future events. The motivation of choosing the hashtags which were trending (and not any random one) was that these would give more generalized views about the event. The collection of past tweets (especially the far-past) was more challenging as in the context of twitter events trending topics are less about the past. To generate more data for the past dimension, we select some trending hashtags which were trending in the past. Apart from these, the tweets are also noisy and people use various ways to represent different temporal frames through tweets. So, it is important to remove the irrelevant tweets from the dataset. From our observation, we found that tweets that do not contain a verb are the most irrelevant ones. So, we filter out the tweets having no verbs. We use CMU tweet-tagger [39] to determine the existence of a verb in the tweet.

Finally, we select 36,000 tweets for the training set. The distribution of the training set is as follows: 12,000 *past* (6,000 *near*, 6,000 *far*), 12,000 *future* (6,000 *near*, 6,000 *far*) and 12,000 other (neither past nor future). Few tweets with associated trending topics are shown in Table 1.

4.2 Test Set

We evaluate the classifiers' performance on a manually created test set. Samples for the test set are collected randomly from the user-level test set (c.f. Section 4.3). As our

2. A full list of hashtags used can be found here: https://drive.google.com/open?id=1ePfScybMyQMi9xKCchaGhOQwK2INdDXJ

TABLE 1: Few example tweets with tags and associated hashtags.

Tweet Category	Hashtags	Example Tweet
Near Past	#Russia2018	last week i was strolling around a palace.
Far Past	#Election2016	He was the one who discretely taped the conversation but the audio did n't surface.
Near Future	#MayDay	there is some flying to be found this week.
Far Future	#CaptainMarvel	awesome movie, awaiting for to arrive in next year.

classification model finally predicts TD focus of user-level data, the test set tweets are collected from these user-level tweets to have a proper assessment. It also ensures that the test set is composed of by tweets of different users than the ones employed in the training set. Three annotators were employed for the annotation task. The annotators were given the occurring time of the events along with the tweet creation time. We summarize annotation guidelines as follows:

1) Annotate a tweet as *near past* if it explicitly or implicitly refers to an event which has occurred in the last 4 weeks with respect to the tweet creation time.
2) Annotate a tweet as *far past* if it explicitly or implicitly refers to an event which had occurred a year ago or earlier with respect to the tweet creation time.
3) Annotate a tweet as *near future* if it explicitly or implicitly refers to an event which will occur within the next 4 weeks with respect to the tweet creation time.
4) Annotate a tweet as *far future* if it explicitly or implicitly refers to an event which will occur within a year or later with respect to the tweet creation time.
5) Annotate a tweet as *other* if the tweet is not related to the past or future.

We measure the annotator's agreement by the multi-rater kappa agreement [41]. We found a kappa value of 0.83 among the annotators. We finally select the class based on the majority voting. Finally, 700 tweets are selected as the test set. The distribution of the test tweets is as follows: *Past-219* (near: 127, far- 92); *Future-202* (near: 111, far: 91), and *other- 279*. We show wordcloud visualization for each class in Figure 2 where words with bigger font represents more dominant words associated with that particular temporal class.

4.3 User-level Test Set

We use the learned tweet classification model to predict TD focus of user-level tweets. The user-level tweets are of UK population of 5,191 users and contain ≈10 million tweets mapped to their *user-level attribute values* which are developed by Preoţiuc-Pietro et al. [19]. In particular, we use *age*, *gender*, *education*, *relationship status* as demographic attributes and intelligence, optimism and six basic emotions (*joy*, *sadness*, *disgust*, *anger*, *surprise* and *fear*) as psychological attributes for this current study. Users' demographic attributes (age, gender, education, and relationship status) were automatically inferred via regression using lexical features (annotated via crowdsourcing) of users' published text. Intelligence and optimism were predicted based on users' written text using regression. Six basic emotions were predicted from users' texts and then aggregated all emotions over users by calculating the proportion of every emotion for each user. We consider those users who have written at least 100 messages.

TABLE 2: Comparative results among Proposed method and Baseline1 for past vs future vs other. Baseline1: Method proposed by Park et al. [32]. Proposed Method: Classification using self attention over Bi-LSTM, with features Temporal keywords, Expanded words of temporal keywords and verbs. Results are shown by triplet of precision, recall and F-measure (p, r, f).

	Methods	
Temporal Focus	**Baseline 1**	**Proposed Method**
Accuracy	54.46	**69.10**
Past (p, r, f)	(60.22, 57.56, 58.86)	(**68.90, 82.35, 75.02**)
Future (p, r, f)	(58.47, 55.24, 56.81)	(**63.54, 59.20, 61.29**)
Other (p, r, f)	(52.32, 53.67, 52.99)	(**57.81, 57.22, 57.51**)

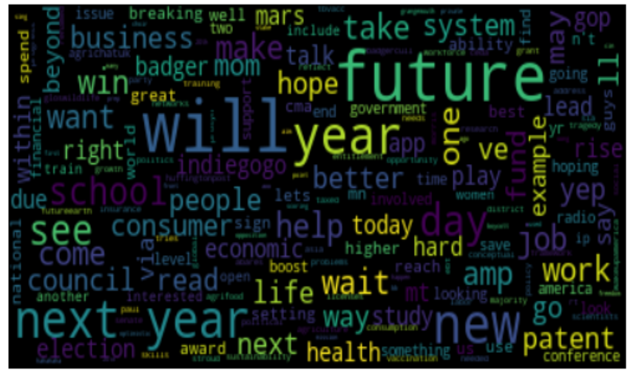
TABLE 3: Comparative results among Proposed method and Baseline 2 for Near past vs far past. Baseline 2: Classification using SVM with all feature combination. Proposed Method: Classification using self attention over Bi-LSTM, with features Temporal keywords, Expanded words of temporal keywords and verbs. Results are shown by triplet of precision, recall and F-measure (p, r, f).

	Methods	
Temporal Focus	**Baseline 2**	**Proposed Method**
Accuracy	62.10	**69.44**
Near Past	(72.91, 55.11, 62.78)	(**76.35, 68.54, 72.23**)
Far Past	(53.65, 71.73, 61.39)	(**61.95, 70.69, 66.03**)

TABLE 4: Comparative results among Proposed method and Baseline 2 for Near future vs far future. Baseline 2: Classification using SVM with all feature combination. Proposed Method: Classification using self attention over Bi-LSTM, with features Temporal keywords, Expanded words of temporal keywords and verbs. Results are shown by triplet of precision, recall and F-measure (p, r, f).

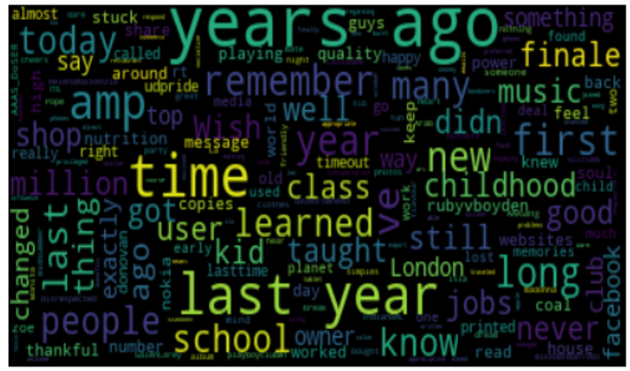
	Methods	
Temporal Focus	**Baseline 2**	**Proposed Method**
Accuracy	64.35	**67.82**
Near Future	(69.69, 62.16, 65.71)	(**70.02, 72.49, 71.23**)
Far Future	(59.22, 67.03, 62.88)	(**64.94, 62.14, 63.51**)

(a) **Word cloud visualization of near-future test set.**



(b) **Word cloud visualization of far-future test set.**

(c) **Word cloud visualization of near-past test set.**



(d) **Word cloud visualization of far-past test set.**

Fig. 2: **Word cloud visualization of the manually annotated test set.**

TABLE 5: Feature ablation Study for the Proposed Method (past vs future vs other). Results are shown by triplet of precision, recall and F-measure (p, r, f). Here, A-BLSTM: Self attention over Bi-LSTM, TK: Temporal keywords, EW: Expanded words of temporal keywords and verbs.

Features	Past	Future	Other
A-BLSTM	(69.04, 69.04, 69.04)	(62.04, 56.83, 59.32)	(56.93, 56.93, 56.93)
A-BLSTM+TK	(63.75, 88.25, 74.03)	(60.56, 46.04, 52.31)	(64.89, 30.20, 41.21)
A-BLSTM+Verb	(68.19, 68.68, 68.44)	(60.37, 53.71, 56.85)	(56.00, 55.44, 55.72)
A-BLSTM+EW	(64.30, 73.17, 68.44)	(61.23, 57.20, 59.15)	(58.63, 41.66, 48.70)
A-BLSTM+ TK+Verb+EW	**(68.90, 82.35, 75.02)**	**(63.54, 59.20, 61.29)**	**(57.81, 57.22, 57.51)**
w/o TK	(66.67, 69.51, 68.06)	(60.59, 56.10, 58.25)	(57.11, 42.35, 48.63)
w/o Verb	(69.39, 69.39, 69.39)	(59.67, 50.00, 54.40)	(57.42, 57.42, 57.42)
w/o EW	(66.02, 73.31, 69.47)	(60.94, 61.11, 61.02)	(56.14, 47.52, 51.47)

TABLE 6: Feature ablation Study for the Proposed Method (Near past vs far past). Results are shown by triplet of precision, recall and F-measure (p, r, f). Here, A-BLSTM: Self attention over Bi-LSTM, TK: Temporal keywords, EW: Expanded words of temporal keywords and verbs.

Features	Past tweets	
	Near Past	Far Past
A-BLSTM	(73.49, 64.81, 68.88)	(58.23, 67.73, 62.62)
A-BLSTM+TK	(75.66, 65.07, 69.97)	(59.59, 71.11, 64.84)
A-BLSTM+Verb	(75.05, 63.76, 68.94)	(58.57, 70.73, 64.08)
A-BLSTM+EW	(72.78, 61.11, 66.44)	(56.05, 68.45, 61.63)
A-BLSTM+ TK+Verb+EW	**(76.35, 68.54, 72.23)**	**(61.95, 70.69, 66.03)**
w/o TK	(75.14, 62.24, 68.09)	(57.86, 71.58, 64.00)
w/o Verb	(72.65, 63.40, 67.71)	(57.03, 67.06, 61.64)
w/o EW	(75.08, 61.60, 67.68)	(57.52, 71.78, 63.86)

TABLE 7: Feature ablation Study for the Proposed Method (Near future vs far future). Results are shown by triplet of precision, recall and F-measure (p, r, f). Here, A-BLSTM: Self attention over Bi-LSTM, TK: Temporal keywords, EW: Expanded words of temporal keywords and verbs.

Features	Future tweets	
	Near Future	Far Future
A-BLSTM	(66.41, 72.40, 69.28)	(62.18, 55.34, 58.56)
A-BLSTM+TK	(68.66, 70.43, 69.53)	(62.76, 60.80, 61.76)
A-BLSTM+Verb	(68.56, 72.63, 70.54)	(66.04, 60.16, 62.96)
A-BLSTM+EW	(68.05, 73.93, 70.87)	(64.46, 57.67, 60.87)
A-BLSTM+ TK+Verb+EW	**(70.02, 72.49, 71.23)**	**(64.94, 62.14, 63.51)**
w/o TK	(66.88, 74.51, 70.49)	(63.88, 55.00, 59.11)
w/o Verb	(69.85, 70.63, 70.23)	(63.68, 62.81, 63.24)
w/o EW	(67.72, 71.17, 69.40)	(62.51, 58.63, 60.51)

5 Evaluation of Temporal Classification

We evaluate our proposed method on the manually annotated test data. For the classification of past vs future vs other, we consider a stable baseline proposed by Park et al. [32]. We refer to this as Baseline-1. Baseline-1 has trained on a forest of extremely randomized trees (ERTs) classifier with features such as n-grams, time expression, PoS tags, tweet-length, and temporal class-specific lexicons. The comparative results are shown in Table 2.

Results of classifying *past* and *future* tweets into near and far categories are shown in Table 3 to Table 4, respectively. As there is no existing work on this type of classification, we define a baseline based on the Support

Vector Machine (SVM) classifier by training it with all the features mentioned in Section 3.1.1. We refer to this as Baseline-2 and show the comparative results in Table 3 and Table 4. We observe from all the results that our proposed method performs better than the baselines. The performance improvement in our proposed method over the baselines are also found to be statistically significant (*T-test*, p <0.001).

Results reported in Table 2 show that our proposed method attains the best performance (accuracy of 69.10%) compared to the Baseline 1 accuracy of 54.46%. We perform feature ablation studies to find which feature combinations are important. The results are shown in Table 5. We observe that the system attains the best performance when all the linguistic features (TK+V+EW) are used with A-BLSTM (Self-attention over Bi-LSTM). Here, for the past class, we obtain precision, recall and f-score of 68.90, 82.35 and 75.02, respectively. For future class, the precision, recall and f-score are 63.54, 59.20, 61.29, respectively. We also see that when we exclude the feature EW (w/o EW in the Table), it provides competitive results (f-score of 67.68 and 63.86 for the past and future, respectively) concerning the only A-BLSTM (f-score of 68.88 and 62.62 for the past and future, respectively). When we exclude either TK or Verb features, then we see a performance drop with respect to the only A-BLSTM. It shows that both TK and verbs are important here.

Results reported in Table 3 show that our proposed method attains the best result (accuracy of 69.44%) compared to the Baseline 2 accuracy of 62.10%. Feature ablation study results for near past vs far past classification are shown in Table 6. Here, we obtain the best result when we use all the features combined (f-score of 72.23 and 66.03 for the near past and far past, respectively).

Results reported in Table 4 show that our proposed method attains the best result (accuracy of 67.82%) compared to the Baseline 2 accuracy of 64.35%. In Table 7, we show feature ablation study for Near-future vs Far-future classification. Here, we also obtain the best result when we use all the features combined (f-score of 71.23 and 63.51 for the near past and far past, respectively).

We also experiment for the five-class classification (near-past vs far-past vs near-future vs far-future vs other), but found inferior performance (accuracy of 30.1%). One of the reasons for this is that the past and future are well separated in terms of patterns. It means that the classifier is good enough to make a clear dividing line between the two classes. The near and far are not well-separated inside the same category (past or future) which means that the separation distance between near and far is thin. Also, there are multiple features possible for future vs past but the features which differentiate near and far are very little. So the learning is problematic in a multi-class scenario which we also observed in terms of accuracy.

The classifier of our proposed method mainly miss-classifies *near-future* tweets into *far-future* category or vice versa where the tweet either has near future connotation or some key words are incorrectly spelled. For example, the tweet *"ok i'm gon study today."* has *near-future* focus. But, it has a *present-oriented* temporal keyword ('today') and the future oriented word ('gon') is not correctly spelled. The *near-past* tweets are miss-classified into *far-past* category or vice versa where both verb and temporal keyword do not help. For example, the tweet *'it was great speaking to you again.'* has a *near-past* connotation but the classifier tags it as *far-past*.

The effectiveness of the EW feature can be noticed by the results of the ablation study in Table 5. We see that for the past and future, w/o using EW features the accuracy is better w.r.t. Using that feature. Here, we see that this feature is not that useful. One possible reason is that 'expansion also includes words of different temporal orientation'. For example, the word tomorrow's expansion also includes today which is a present related keyword. This tends to incorporate bias into the system (for a multi-class classification past vs future vs other). For fine-grained classification (near vs far) it improved the results (Table 6 and 7). The reason is that we are doing binary classification for each of the past and future separately. Which means Past tweets and future tweets are already separated. Now for example, even if near future related keywords like "tomorrow" include expansion as "today", the sentence won't be classified to the far future. The reason is that there are many sentences which include the keyword "today" but have a near-future connotation. For example, "I have to finish the work today" has a near-future connotation.

We visualize the sentence-level attention vectors using heatmaps for a few examples in Figure 3. The intensity of color signifies the importance of the words or the phrases. In the first example the word 'watched' was most useful to predict the tweet as 'near-past'. This observation shows that both the verb and temporal keywords play an important role in classification.

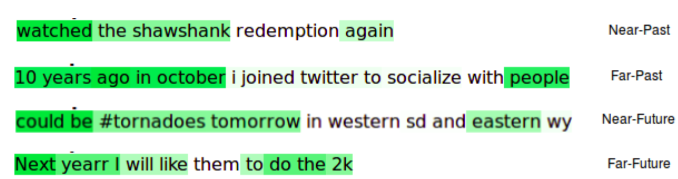


Fig. 3: Examples of sentence-level attention for some correctly classified tweets.

6 Correlation Results and Analysis

Here, we discuss the relationship between users' focus on *near past*, *far past*, *near future*, and *far future* and their different demographic and psychological attributes using correlation coefficient. All the analyses in this section are based on the correlation results obtained over the User-level Test Set. The correlation results are presented in Table 8 to Table 14. The p-values are obtained by Fisher' R-to-Z transformation (Bonferroni corrected). We only discuss the correlation values having p-values lesser than 0.05 for all subsequent analyses.

6.1 Demographic Correlates

Here, we describe correlations between users' focus on a TD and their age, gender, education, and relationship status.

6.1.1 Age

Results in Table 8 show that users' *past* focus (both near-past and far-past) is positively correlated to their 'age' while their

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TABLE 8: Correlation coefficient between users' near-past, far-past, near-future and far-future focus and their Age.

Attributes	Temporal Distance Focus			
	near-past	far-past	near-future	far-future
Age	0.34	0.16	-0.17	-0.31

TABLE 9: Correlation coefficient between users' near-past, far-past, near-future and far-future focus and their and Gender. Values with suffix * indicate not significant.

Gender	Temporal Distance Focus			
	near-past	far-past	near-future	far-future
Female	0.27	0.01*	-0.10*	-0.10*
Male	-0.02*	0.16	0.02*	-0.07*

future focus (both near future and far future) is negatively correlated to their 'age'. We also observe that users' *age* is more positively correlated to *near-past* focus (r=0.34) than *far-past* focus (r=0.16). This indicates that *near-past* focused users are more aged. Age is also more negatively correlated to *far-future focus* (r=-0.31) than *near-future* focus (r=-0.17).

6.1.1.1 **Analysis by Gender**: Females' *near-past* focus is positively correlated to *age* (r = 0.18) while males' *far-past* focus is positively correlated to *age* (r = 0.36).

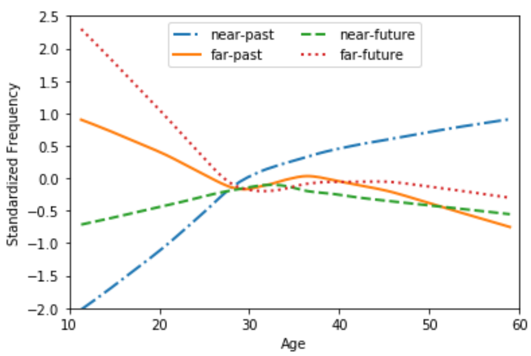

Fig. 4: Standardized near and far temporal distance focus of the users over their age. Loess smoothing estimates [42] was used for smoothing.

Figure 4 explains how the users' *near-future* and *far-future* focus vary from age 10 to 60. We observe that users' *near-past* focus increase steadily over the age. Users' *far-past* focus decrease up to the age of 28 sharply and then decrease slowly. Users' *near-future* orientation increase slowly up to the age of 32 and then becomes almost steady. Users' *far-past* focus decrease sharply up to the age of 29 and then becomes steady.

6.1.2 Gender

We investigate the correlation between users' focus on TD and their gender in two categories: *female* and *male*. The genders are predicted by regression by Preoţiuc-Pietro et al. [19] and the values are normalized between -5 and +5 where a more positive value indicates more chances of being female. As we use those values, we consider the top 700 positive values as females and the top 700 negative values as males for our evaluation. The correlation results between gender and focuses on TD are shown in Table 9. Results suggest users' *near-past* focus is positively correlated to gender female (r=0.27) while their *far-past* focus is positively correlated to gender male (r=0.16). We do not find other significant values in the Table.

6.1.2.1 **Analysis by Age Group**: For this type of analysis, we group the users in two parts-users with age less than 30 and users with age more than equals to 30. The reason for considering 30 as a partition point is intuitive. The intuition we get from the results shown in Figure 4 where we find a change of trend near the age of 30. We find that *near-future* focus is positively correlated to less than 30 aged females (r = 0.23) while *near-past* focus is negatively correlated to more than 30 aged females (r = -0.19). *Near-future* focus is also positively correlated to females with age more than 30 (r = 0.33).

TABLE 10: Correlation coefficient between users' near-past, far-past, near-future and far-future focus and their Education. Values with suffix * indicate not significant.

Education	Temporal Distance Focus			
	near-past	far-past	near-future	far-future
Degree	0.03*	0.01*	-0.09	0.06
Graduate_degree	-0.01*	-0.01*	-0.09	0.05
High_school	-0.02*	-0.00*	0.10	-0.02*

6.1.3 Education

We measure users' focus on TD and their 'education' in three sub-categories: *degree*, *graduate_degree*, and *high_school*. In literature, future orientation is related to education [9], [10]. Our results in Table 10 show that users' education has no significant relationship with the past distance focus (near-past or far-past), but has a significant relationship with the future distance focus. We observe that people graduate_degree are far-future focused while people having a high_school degree are near-future focused. Here, we can see that when people get higher educated, they become more far-future oriented.

6.1.3.1 **Analysis by Gender**: We do not find any significant relationship between females' temporal distance focus and education. For males, we find that near-past focus has a negative correlation with education_degree (r = -0.15) while a positive correlation with education_high_school.

6.1.3.2 **Analysis by Age Group**: For below 30 aged users, near-future focus is negatively related to education_degree (r = -0.16) and education_graduate_degree (r = -0.1334) while positively correlated to education:high_school (0.17). For this same group of users, far-future focus is positively correlated to education_degree (r = 0.05) and education:graduate_degree (r = 0.13) while negatively correlated to education:high_school (r = -0.08). For above 30 aged users, we do not find any significant correlation between temporal distance focus and education.

6.1.4 Relationship

We discuss the correlation between users' TD focus and relationship status in four different sub-categories: divorced, in_a_relationship, married and single. The results in Table 11 show that *far-future* focus has a positive correlation with relationship: divorced (r=0.10) while past focus (both near and far past) has a negative correlation with it. It signifies that divorced users focus more on *far-future*. We do not find any significant relationship between users' focus on

TABLE 11: Correlation coefficient between users' near-past, far-past, near-future and far-future focus and their Relationship. Values with suffix * indicate not significant.

Relationship Status	Temporal Distance Focus			
	near-past	far-past	near-future	far-future
Divorced	-0.08	-0.06	-0.03*	0.10
In_a_relationship	0.00*	0.01*	0.01*	-0.01*
Married	0.03*	0.00*	-0.06	0.00*
Single	-0.00*	0.02*	0.05	-0.03*

TABLE 12: Correlation coefficient between users' near-past, far-past, near-future and far-future focus and their Intelligence. Values with suffix * indicate not significant.

Intelligence	Temporal Distance Focus			
	near-past	far-past	near-future	far-future
Much_above	-0.04	-0.03*	-0.08	0.09
Average	0.05	0.02*	-0.01*	-0.04
Below_average	-0.08	-0.02*	0.10	0.01*

TD and attribute in_a_relationship. Users' *near-future* focus is negatively correlated to relationship: married while the users *far-future* focus is positively correlated to relationship: single.

6.1.4.1 **Analysis by Gender**: For females, we do not find any significant relation between temporal distance focus and relationship. For male, near-past focus is negatively correlated to relationship:divorced (r = -0.17) and positively correlated to relationship:single (r = 0.19). Males having far-future focus are found to be more in_a_relationship (r = 0.14).

6.1.4.2 **Analysis by Age Group**: For under 30 aged people, far-future focus is positively correlated to relationship:divorced (0.14) and relationship:married (r = 0.08) while negatively correlated to relationship:single (r = -0.10). For this same group of people, near-future focus is negatively correlated to relationship:married (r = -0.11) and relationship:divorced (r = -0.06) while positively correlated to relationship:in_a_relationship (0.07) and relationship:single (r = 0.06). For above 30 users, near-past focus is negatively correlated to relationship:divorced (r = -0.10). For same group of users, far-future focus is positively correlated to relationship:divorced (r = 0.06).

6.2 Psychological Correlates

We use intelligence, optimism and six basic emotions (joy, sadness, anger, disgust, surprise, and fear) as the psychological attributes.

6.2.1 Intelligence

We investigate intelligence in three sub categories: intelligence: much_above, intelligence: average and intelligence: below_average. The correlation results between users focus on TD and intelligence are shown in Table 12. The results suggest that users having *far-future* focus have intelligence much_above. Users having *near-past* focus are found to have average intelligence. Users' *near-future* and *near-past* focus are found to be related to below_average intelligence.

6.2.1.1 **Analysis by Gender**: For male, near-past focus is negatively correlated to intelligence:much_above (r = -0.17). We do not find any significant results for female users.

TABLE 13: Correlation coefficient between users' near-past, far-past, near-future and far-future focus and their Optimism. Values with suffix * indicate not significant.

Optimism	Temporal Distance Focus			
	near-past	far-past	near-future	far-future
Optimist	0.02	-0.05	0.04	-0.03*
Pessimist	-0.01*	0.08	0.00*	-0.02*

6.2.1.2 **Analysis by Age Group**: For users aged below 30, *near-past* focus is negatively correlated to intelligence:below_average (r = -0.10) while near-future focus is positively correlated to intelligence:below_average (0.18) and negatively correlated to intelligence:much_above (r = -0.10). Far-future focus for the same group of people is positively correlated to intelligence:much_above (r = 0.14). For users above 30, near-past focus is negatively correlated to intelligence:much_above (-0.06).

6.2.2 Optimism

The results shown in Table 13 suggest that near-future focused users are more optimists while *far-past* focused users are pessimists.

6.2.2.1 **Analysis by Gender**: For gender-based analysis, we do not find any significant correlation between temporal distance focus and optimism.

6.2.2.2 **Analysis by Age Group**: Below 30 aged users' *far-past* focus is negatively correlated to optimist (r = -0.06) and positively correlated to pessimist (r = 0.08). For users aged above 30, *near-future* focus is positively correlated to optimist (r = 0.07) while *far-past* focus is positively correlated to pessimist (r = 0.11).

6.2.3 Joy

Future orientation is related to the emotional attribute *joy* in the psychological literature [11]. The results in Table 14 suggest that users' *near-future* focus has more positive correlation with *joy* (r= 0.27) than their *far-future* focus (r= 0.11). As the correlation values suggest, people having *near-future* focus are more joyful than those having *far-future* focus. *Far-past* focus has also significant negative correlation with *joy* (r = -0.41).

6.2.3.1 **Analysis by Gender**: Here, we discuss the gender-based correlation analysis on users' emotional attributes. We found that males having focus on *near-future* (r=0.28) are more joyful than the male having focus on *far-future* (0.16). We also find that joyful male has less focus on the past (both near and far) and Females become more joyful when they are *near-future* oriented (r=0.15).

6.2.3.2 **Analysis by Age Group**: People with age less than 30 who are *far-future* oriented are found to be more joyful (r = 0.29). People with age more than 30 who are *near-future* oriented are found to be more joyful (r = 0.43).

6.2.4 Sadness

People's *past* focus has been associated with sadness in the psychological literature [7], [8]. The sad emotion generally persists for a long time in humans' minds. In Table 14, we see that users' *far-past* focus has a significant positive correlation with sadness (r = 0.17). It signifies that users

TABLE 14: Correlation coefficient between users' near-past, far-past, near-future and far-future focus and their Six basic emotions. Values with suffix * indicate not significant.

Emotions	Temporal Distance Focus			
	near-past	far-past	near-future	far-future
Joy	-0.10	-0.41	0.27	0.11
Sadness	-0.01*	0.17	0.02*	-0.03*
Disgust	0.08	0.40	-0.07	-0.13
Anger	0.14	0.37	-0.15	-0.15
Surprise	0.01*	0.00*	-0.16	-0.02*
Fear	0.14	0.50	-0.29	-0.09

having more focus on *far-past* seem to be sadder. The correlation results between remaining temporal distance focus and *sadness* are not found to be significant.

6.2.4.1 **Analysis by Gender**: We found that *near-past* focused males are more sad (r=0.40) while *far-past* focused females are more sad (r=0.35). Both males and females who are *near-future* focused are negatively correlated to sadness (r=-0.34 and -0.16, respectively).

6.2.4.2 **Analysis by Age Group**: Less than 30 aged people who are *far-past* focused are more sad (r = 0.26). In this group of people who are *near-future* focused are also found to be sad (r = 0.19). More than 30 aged people who are *near-past* focused are more sad (r = 0.26). In this group, who are *far-past* focused are also found to be sad (r = 0.25).

6.2.5 Disgust

In literature, the relationship between people's temporal focus on TD and *disgust* was not mentioned. In our experimental results in Table 14, we observe that people with disgust attitude has a focus on the past distance. In the past dimension disgusted people have more focus on far-past (r=0.40) compared to the focus on near-past (r= 0.08). We also found a significant negative correlation with *far-future* focus (r= -0.13) and disgust. It shows that focus on near-future reduces the disgust emotion of users.

6.2.5.1 **Analysis by Gender**: *Near-past* focused male users are found to be more disgusted (r=0.27) than the *far-past* focused male users (r=0.25). *Far-past* focused females are found to be more disgusting (r=0.29) while other correlation results for female are not significant.

6.2.5.2 **Analysis by Age Group**: *Far-past* focused below 30 year aged people are found to be more disgusted (r = 0.31) while *far-past* focused above 30 years old people are also found to be more disgusted (r = 0.53).

6.2.6 Anger

In the psychological literature, *past* focus has been related to anger [8], [43], [44]. Our experimental results in Table 14 show that users' *far-past* focus has positive correlation with anger. We see that users' *far-past* focus has a relatively more positive correlation with the anger (r= 0.37) compared to their *near-past* focus (r= 0.14). It shows that far past focused users possess more anger. We also observe that both *near-future* and *far-future* focus have a negative correlation with anger (r= -0.15) which signifies that users' focus on future (both near and far) reduces anger.

6.2.6.1 **Analysis by Gender**: *Near-past* focused male users are found to be more angry (r=0.20) than the *far-past* focused male users (r=0.17). We also found that *far-future* focused males has reduced level of anger (r=-0.19). *Far-past* focused females are found to be more angry (r=0.42).

6.2.6.2 **Analysis by Age Group**: *Far-past* focused below 30 year aged people are found to be more angry (r = 0.33) while *far-past* focused above 30 years old people are also found to be more angry (r = 0.41).

6.2.7 Surprise

The relationship between TD focus and *surprise* is not studied extensively in the literature. The lone significant result we found in Table 14 shows that users' near-future focus has a negative correlation with surprise (r=-0.16) which indicates that *near-future* focused users tend to be not surprised.

6.2.7.1 **Analysis by Gender**: *Near-past* focused males are found to be more surprised (r=0.35) while *far-past* focused females are found to be more surprised (r=0.18).

6.2.7.2 **Analysis by Age Group**: *Near-past* focused below 30 year aged people are found to be more surprised (r = 0.09) while *near-past* focused above 30 years old people are also found to be more surprised (r = 0.11).

6.2.8 Fear

Fear has been said to happen in response to a pending mismatch in the psychological literature [45]. It is also said to be generated by an anticipated state [8], [46], [47]. From the results in Table 14, we observe that users' *past* focus (both near and far) is positively correlated to fear. We also observe that users' *far-past* focus is more positively associated to fear (r=0.50) than their *near-past* focus (r=0.14). It indicates that users having focus on *far-past* are more fearful.

6.2.8.1 **Analysis by Gender**: *Far-past* focused males are found to have more fear (r=0.54) while *far-future* focused males have reduced level of fear (r=-0.24). Females having focus on *far-past* are also have more fear (r=0.18) while *near-future* focused females are negatively related to fear (r=-0.17).

6.2.8.2 **Analysis by Age Group**: *Far-past* focused below 30 year aged people are found to be more fearful (r = 0.38) while *far-past* focused above 30 years old people are also found to be more fearful (r = 0.54).

7 Limitations of the Study

We mention here some limitations of our current study. We formulated the definition of *near* and *far* distance following recent literature which best suits the Twitter context and for general users. We also agree that individual differences for perceiving temporal distance exist which are not easy to incorporate separately by computational techniques. Thus, our approach is more generalized which is also dependent on the context (here Twitter). The hashtag based tweet collection technique does not cover all the events especially local events which never come as a trending topic. Some users may use keywords instead of hashtags to express something which will not be collected. Conversations in a tweet thread omit the hashtags thus those kinds of tweets will be avoided. Also, hashtags are more geographic-specific and thus the content depends on where the hashtag is trending. Our user-level data is of the UK population, and the findings may vary for the other demographics.

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8 Conclusion

In this article, we have shown a first large scale empirical study to find Twitter users' focus on a temporal distance. We at first classified the tweets of the users in either of *near-past*, *far-past*, *near-future* and *far-future* categories. We then grouped the tweet-level temporal focus over users to get user-level temporal focus. The associations between the users' focus on *near* and *far* temporal distance and their different demographics (age, gender, education, relationship status) and psychological attributes (intelligence, optimism and six basic emotions) are somewhat novel in the context of computational psychology studies. Our data-driven approach is less expensive as the tweets are easy to access. Our approach is also intended to cover a more general audience than the traditional questionnaire-based methods. We believe that our investigation on the fine-grained aspects of temporal focus will open many doorways in psychological studies which were not possible earlier on a large scale. In the future, an interesting way of investigation would be whether users' tweets about themselves give more insight about their focus on TD.

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