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Research Article

Investigating the Relationship Between English Twitter Users' Focus Time and Their Psychographic Characteristics

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Abstract: A person's emotional state toward the past and future might be revealed by their "temporal distance" (TD), a psychological measure. There isn't a lot of real-world research on how to measure attention span from human-written content to look at how people think about time. Self-report measures have been used a lot in studies of temporal attention. This article shares the results of a study that looked at how Twitter users' attention changes over time. First, we use deep neural classifiers to figure out the temporal emphasis at the tweet level by using language data. The method sorts tweets into four groups based on when they were sent: recently, far away, likely to happen, and unlikely to happen. Then, each user sorts the classified tweets to get a focus on a certain time period. Lastly, Assemblies are drawn between the user's attention directed towards temporal distance and data pertaining to their own history and disposition. Our real-world research shows that there is a stronger link between the age of the customer and their near-past concentration. Additionally, we can see that users who focus on the future feel good emotions, while users who focus on the past feel fear, anger, hopelessness, and disdain. A Multi Markov Model (MMM) is introduced in order to comprehend the characteristics of emotion dynamics inside Twitter tweets.

***Keywords*:** temporal distance (TD), Multi Markov Model (MMM), Twitter data mining

MSC: 62H30, 91D30, 91C20, 68T50

1. Introduction

Thanks to the proliferation of digital media, researchers in the fields of psychology and social work now have access to an unprecedented wealth of data. Previous studies have used human-written texts to make predictions about age, gender, mental health, emotion identification, depression, and more [1–6]. It has also been shown that human demography and emotions impact temporal attention. The psychological literature has traditionally linked the past to gloom and ageing [7, 8], while the future to hope and education [9–11]. But far-or near-distance focus, two more nuanced components of temporal focus, remain unproven. Questions like whether the association between years lived and prior focus is more strongly influenced by recent or distant memories have received little empirical attention. Two concepts in psychology, episodic memory and foresight, relate to two different aspects of human cognition: the ability to mentally recreate past experiences and the capability to see potential future possibilities. In the literature of Construal Level Theory (CLT), these

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human skills are extensively detailed. The CLT states that, in comparison to events that are closer in time, those that are further away should be understood in simpler and more abstract terms [12].

The concept of temporal distance (TD) reveals how a person makes sense of their own past and future by comparing them to their present selves [13, 14]. TD is a personal perception that indicates how near or far away something is, as well as how present it is. People have different understandings of what TD is and how it works [14]. This means that although one individual may think an event is far away in the future, another may think it's quite close. What happened in the past is also relevant. In a broad sense, regardless of who you ask or where you put them, the passage of time is continuous [15]. Different initialization strategies were proposed using the Multi-Markov Model [15] applied to a group of TESCs belonging to various users. Emotion-based Multi Markov Models (E-MMMs) was the name given to them. Against a variety of events, this suggested MMMs approach evaluates the effects of various initializations among users. As a result, it would be useful to analyse the effects of measuring people's attention on a certain TD on their activities. To get there, we have to figure out what counts as far away and what counts as near-distant occurrences. In keeping with a previous study's concept of close and distant distance, we use them here [16].

1.1 *Contribution of the paper*

1.1.1 *Fresh approaches to gathering and analyzing data*

• Develop and utilize innovative methods to measure focus time on Twitter, going beyond simply analyzing tweet frequency or session duration. Explore options like eye-tracking data, attention detection tools, or self-reported surveys with validated focus scales.

• Employ advanced statistical techniques or machine learning algorithms to analyze the relationship between focus time and psychographic characteristics. Consider the use of network analysis to explore connections between individual focus patterns and broader online communities.

1.1.2 *Growth of psychographic factors*

• Move beyond commonly studied personality traits like Big Five and explore the role of less frequently examined psychographic factors like sensation seeking, impulsivity, or mindfulness. Include measures related to social media addiction or problematic Twitter use.

• Investigate the influence of specific user demographics (age, gender, location) or cultural contexts on the relationship between focus time and psychographic characteristics.

1.2 *Investigating aspects that mediate and modulate*

• Identify and examine potential mediating variables that explain the link between focus time and psychographic characteristics. For example, consider the role of specific Twitter activities (e.g., news consumption, social interaction) or content types (e.g., videos, images) in influencing focus patterns.

• Explore moderating variables that might influence the strength of the relationship. For example, investigate how factors like platform design, individual goals for using Twitter, or presence of mental health conditions might affect the observed links.

1.3 *Consequences for real life and where we are going from here*

• Discuss the practical implications of your findings for individuals, such as developing self-awareness tools or strategies to manage focus on Twitter. Explore potential applications for developers or platform designers to create features that promote more mindful Twitter use.

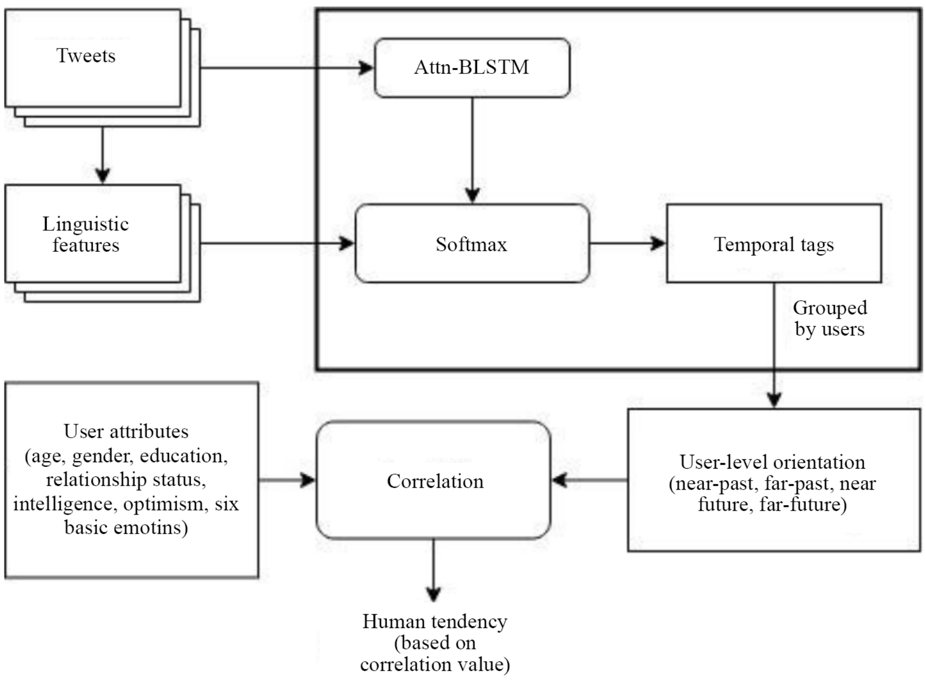


Figure 1. The overall design of the suggested system

2. Related background

Both the forward and backward directions of Temporal Distance have been quantified in the psychological literature. Nevertheless, previous research has shown that future-oriented measures outperform their past-oriented counterparts [15, 16]. Both good and bad experiences in the far future will probably be more severe, typical, and less varied. Efficiently handling events that occur in the far future is anticipated to be less varied, according to the authors.

Paying attention to one TD at a time might influence one's physiology, psychology, and social life. One study found that when individuals think about emotional occurrences distant in the future, their caudate nucleus becomes more active, and when people think about events close by, the anterior region of the ventromedial prefrontal cortex becomes more active. According to previous research, people's evaluations and choices change when faced with situations that are either close or distant in the future [13]. Decisions about distant events lead to prejudice against minorities and women, as shown by Milkman et al. [14]. Despite the difficulties they are facing now, individuals remain hopeful about the future and think their lifestyles will be great in the far off future, according to another study.

Prior research indicates that far-distance temporal focus illuminates and defines an individual's essence and distinguishing features when viewed in its entirety. Conversely, near-distance temporal focus emphasises situational circumstances that are consistent with an individual's true nature when viewed in its particulars. People who plan far-off events are less likely to take contextual factors into account, people with such outlook and personality type also tend to attribute faraway deeds to the linked attitude and character, whether people's emphasis on morality issues grows with passing time. Unlike suggestions for purchases made shortly, those made in the distant future are more likely to alter one's tastes.

3. Methodology

To begin, we create a classifier that uses deep learning to identify the main points of users' tweets. To ascertain the users' focus on the past, future, far past, and the overall quantity of tweets, the proportion of tweets including each category relative to the entire number of tweets is then computed. Finally, a link is established between the different orientation metrics and the demographic and psychological attributes of the users. The overall architecture is shown in Figure 1.

4. The temporal distance focus at the tweet level

A hierarchical technique is used for temporal categorization, which first sorts tweets into three categories: past, future, and others. Last but not least, tweets are sorted into two categories: near future and far future. Similarly, tweets from the past are sorted into two categories: near past and distant past. To discern the temporal focus of the text, one must beyond the use of temporal keywords and verb tense alone. An instance of a tweet that places a temporal accent on the future is the following: "I cannot wait to see you compete in Glasgow today" (near-future). In this context, "today" is a temporal term that has a present-tense meaning. The verb's tense is also present here. Resolving such textual interdependencies is a strong suit of Multi Markov Model layer. As input, Multi Markov Model layer receives these word vectors. This combined output mt is subjected to self-attention. A softmax is fed the self-attention output and additional word-level feature vectors as inputs.

5. Temporal keyword (TK)

One of the features is the collection of chronological keywords found in a tweet. A preexisting temporal knowledge-base, Tempo Word Net, is used to record the temporal keywords. In Tempo Word Net, an expansion of English Word Net, the inherent time aspects of each Word Net synset are linked to it. Specifically, a machine learning-based technique automatically tags each Word Net synset as either atemporal (no time sense), present, future, or ahistorical.

6. Expanded words (EW)

Tweets containing verb PoS tags and temporal keywords are enhanced using a query expansion approach. To acquire the target word's word embedding representation, we use GloVe embedding. At last, we settle on the phrases that go along with these comparable vectors. "Join" may be broadened to "visit" and "check", for instance. Here are some instances that illustrate our intuitive use of certain language features: I please offer a better product next time is a statement with a 'future' temporal dimension.

Consideration was given to the temporal keywords of the Tempo Word Net. No reference to the past, present, or future is made by the term "time" in this context. Nevertheless, the Tempo Word Net reveals that the word "next" contains a future-oriented underlying sense of time.

ii) The tense of the word "worked" tells us that the statement "Just because of the rain our strategy worked", focuses on the past. The temporal term "plan", which refers to the future, is useless in this context. The use of verb and temporal keywords is helpful, but they do so in different ways.

iii) Two factors justify the usage of the enhanced feature EW: a) Twitter is more casual than the terms found in the Tempo Word Net, which tend to be more professional. b) New information is added to the training process by the expansions.

7. User-level temporal distance focus

By adding up a user's tweets by time category and plugging the results into the following formula, we may determine their TD orientation/focus at the user level:

$$\text{orientation}_d(\text{user}) = \frac{|\text{tweets}_d(\text{user})|}{|\text{tweets}_{\text{total}}(\text{user})|} \tag{1}$$

To determine the temporal focus at the user level, the proportion of tweets belonging to each temporal category is calculated concerning the total number of tweets.

8. Muti markov model

8.1 *Transition probability function*

$$P_{ij}(t) = Pr(\mathbf{X}(t+1) = s_j|\mathbf{X}(t) = s_i \tag{2}$$

Represents the probability of transitioning from state s_i to state s_j at time $t+1$, given being in state s_i at time t.

8.2 *Chapman-Kolmogorov equations*

$$P_{ij}(t) = \sum_K P_{ik}(t) * P_{kj}(t) \tag{3}$$

Relates the transition probability from state s_i to state s_j at time $t+u$ to the transition probabilities through all possible intermediate states k at time t.

8.3 *Stationary distribution*

$$\pi = \pi * P \tag{4}$$

Represents the probability distribution over states that remains constant over time. Exists for homogeneous MMMs and can be obtained by solving the eigenvalue equation.

8.4 *Mean first passage time*

$$M_{ij} = E[T_{ij}] = \sum_n n * P_{ij}^n \tag{5}$$

Represents the average time it takes to transition from state s_i to state s_j for the first time. Can be calculated using the transition matrix and its powers.

8.5 *Absorption probability*

$$A_{ij} = \sum_n P_{ij}^n * I_j \tag{6}$$

Represents the probability of eventually reaching state s_j starting from state s_i. Can be calculated by summing the geometric series of transition probabilities to the absorbing state s_j, weighted by the initial state distribution.

9. Data sets

Every part of the model, from training to testing to user-level testing, is based on English tweets. A hashtag-based technique generates the tags for 36,000 tweets that make up the training set. The test set includes seven hundred tweets that have been annotated by hand. The user-level test set consists of almost 10 million tweets from 5,191 known Twitter users.

10. Overfitting

10.1 *Data preprocessing*

• Feature selection: Pick the most important psychographic traits by consulting subject knowledge or existing literature. To keep the model from becoming too complicated, avoid adding features that are either unnecessary or have strong connections. Consider dimensionality reduction techniques like Principal Component Analysis if your feature collection is very large (PCA).

• Data cleaning: Remove any errors, outliers, or data points that aren't there. If you do this, the model might not be able to find wrong patterns in the data.

• Feature engineering: Create unique characteristics that record present-day factors' strong associations. Improving the model's performance without making it more complicated is possible with this approach.

11. Model selection and regularization

• Begin with more basic models, such linear regression, to establish a baseline performance. Attempt to avoid overfitting and achieve substantial improvements in accuracy before moving on to more complex models like decision trees or random forests.

• It is possible to penalise complex models and force them to learn smaller connections using regularisation procedures, such as L1 and L2 regularisation. Potentially helpful in avoiding overfitting, but reduces the model's flexibility.

• Hold-out validation and k-fold cross-validation are two cross-validation procedures that may be used to evaluate how well your model performs on data that has not been seen. By doing so, you can ensure that your model successfully generalises beyond the training data and avoid overfitting.

12. Working out set

By using a hashtag-centric methodology that obviates the need for human annotation. The primary obstacle at hand is identifying viable hashtags that may represent the past, future, and other categories. For hashtag identification, we take into account the currently popular subjects (i.e., hashtags) as listed on trends24.in website. You can see what hashtags are popular at any given hour on this website. We then pick out the hashtags that represent events that happened in the past, will happen in the future, or represent some other kind of temporal dimension. Those hashtags that don't vary considerably for several days are removed from our data collection to improve the variance in hashtags. Every day, we search tweets using the last set of hashtags that were chosen by hand. Using Twitter's streaming API, we scrape tweets from the social media platform (Table 1).

Table 1. Here are a few of sample tweets that use tags and hashtags

Tweet class	Hashtags	Illustration tweet
Far past	Captain Marvel	While on a leisurely walk around a castle last week.
Near future	May Day	He secretly recorded the discussion, but the recording has never surfaced.
Near future	Russia 2018	This week, you could see some birds in the sky.
Far past	Election 2016	Amazing film, can't wait for its release in 2019!

13. For tweet collection, we adhere to the following four hypotheses

1) People are more likely to post tweets from within the recent few days or weeks if the event with the hashtag took place within that time frame.

2) Most individuals will post long-form tweets about an event that happened a year or more ago if the hashtag is related to that event.

3) When people use a hashtag to talk about something that's happening soon, they often consider the immediate imminent.

4) You may assume that most people will be talking about something far off in the future if a hashtag is linked to an event happening in the next year or two.

14. Test set

Using a test set that was hand-crafted, we assess how well the classifiers performed. The user-level test set is used to randomly choose samples for the test set.

The test set of tweets will be constructed using the user-level data from which the classification model will have projected the TD emphasis by the conclusion of the assessment phase. Additionally, it guarantees that the test set comprises tweets from distinct people compared to the ones used in the training set. For the annotation work, three people were used. The annotators were given both the time of creation of a tweet and the time of the event itself. Here we provide a brief overview of the annotation guidelines: 1) Mark a tweet as "near past" if it refers to anything that happened within the previous four weeks from the time it was created, whether directly or indirectly.

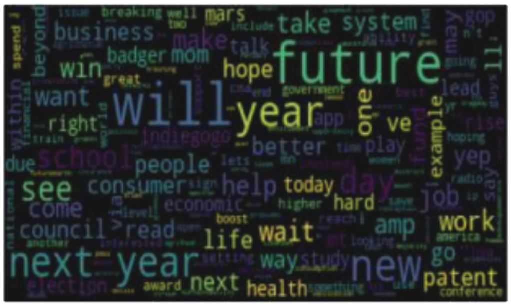
2) Put "far past" next to a tweet if it refers to anything that happened more than a year ago, relative to when the tweet was created.

3) Mark a tweet as "near future" if it alludes to anything happening within four weeks from the time it was created, whether directly or indirectly.

4) If a tweet refers to anything that will happen a year or later from the time it was created, either directly or indirectly, it should be marked as distant future.

5) If a tweet doesn't have anything to do with the past, present, or future, you may mark it as other. The Multi Markov Model agreement is used to assess the annotator's agreement. Our annotators had a kappa score of 0.83. The class is ultimately chosen by tallying up the votes. Lastly, the test set consists of 700 tweets. This is the breakdown of the test tweets: other-279, Past-202 (near: 111, far: 91), and Past-219 (near: 127, far: 92). Figure 2 displays the wordcloud visualisation for each class. The words with larger font size indicate a higher prevalence of terms connected with that specific temporal class.

(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

Figure 2. Visualization of the test set with hand annotations in the form of a word cloud

15. User-level test set

The TD emphasis of tweets sent by individual users may be predicted using the learned tweet categorization model. Approximately ten million tweets belonging to 5,191 people in the United Kingdom are associated with their user-level attributes, according to the method proposed Multi Markov Model. Automatic inference of users' demographic variables (gender, age, education level, and relationship status) was achieved using regression employing lexical Results for the past, future, and other periods compared to Baseline 1 (Table 2).

Table 2. The proposed technique

	Methods	
Temporal focus	Proposed method	Baseline 1
Precision	65.57	70.2
Past (p, r, f)	(71.33, 68.48, 67.75)	(78.86, 86.28, 84.12)
Future (p, r, f)	(47.36, 44.13, 45.92)	(72.43, 68.12, 71.30)
Other (p, r, f)	(61.13, 42.71, 43.88)	(46.97, 49.11, 68.42)

Characteristics of user-generated content that have been annotated via crowdsourcing. Users' written content was used to estimate their optimism and intelligence using regression. After predicting six fundamental emotions from users' messages, we calculated the percentage of each emotion for each user and aggregated them together. Those users who have contributed 100 messages or more are taken into consideration.

When we talk about this, we use the acronyms A-BLSTM for self-attention over multi-markov models, TK for temporal keywords, and EW for extended verb and temporal keyword phrases.

Accuracy, recall, and F-measure are the three manifestations of the results. Self-attention over Multi Markov Model is denoted in this context by A-BLSTM, temporal keywords by TK, and the collection of extended verb and temporal keyword phrases by EW.

16. A critical analysis of temporal classification

The test data that has been annotated by hand is used to assess our suggested approach. We take into account a steady baseline suggested for the past, future, and other classifications. This is called Baseline-1. An ERTs classifier forest was used to train Baseline-1. Time expressions, n-grams, PoS tags, tweet lengths, and lexicons associated with temporal classes were among the characteristics.

Table 3 displays the outcomes of future tweets, divided into near and distant groups, while Table 4 displays the results of previous tweets. Baseline-2 is the name we're giving it, and Tables 3 and 4 compare the findings. From every metric, we may deduce that our suggested approach outperforms the standards. Our suggested strategy likewise shows a statistically significant increase in performance compared to the baselines.

Table 3. Procedures

	Procedures	
Sequential focus	Proposed method	Baseline 2
Exactness	74.25	69.71
Near future	(79.57, 52.86, 77.78)	(90.13, 96.50, 91.63)
Far future	(78.11, 76.02, 81.99)	

Table 4. Proposed approach vs. Baseline 2 outcomes comparing near past and distant past. Second Baseline: we use SVM for classification with every possible combination of features

	Methods	
Temporal focus	Baseline 2	Proposed method
Precision	73.2	79.42
Near past	(81.11, 66.22, 73.88)	(86.34, 78.64, 83.14)
Far past	(76.89, 61.86, 72. 69)	(61.95, 70.69, 66.03)

The results, which demonstrate that our suggested technique outperforms Baseline 1 with an accuracy of 69.10 percent, as opposed to 54.46 percent. In order to determine the most relevant feature combinations, we conduct feature ablation studies. Table 5 displays the findings. Using all three linguistic characteristics (TK, V, and EW) in conjunction with A-BLSTM yields the greatest results for the system. The following are the results for the preceding class: f-score of 75.02, accuracy of 68.90, and recall of 82.35. The f-score, recall, and precision for the future class are 63.54, 59.20, and 61.29, correspondingly. Furthermore, we can see that leaving out the feature EW yields competitive results for the sole Multi Markov Model, with f-scores of 67.68 for the past and 63.86 for the future. In comparison to using simply A-BLSTM, performance decreases when TK or Verb characteristics are excluded. It demonstrates the significance of both verbs and TK in this context.

Table 5. Investigation of the proposed method's feature ablation

Topographies	Other	Past	Future
A-BLSTM + TK	(78.75, 44.25, 74.03)	(42.47, 55.14, 43.41)	(64.89, 30.20, 41.21)
A-BLSTM + TK + Verb + EW	(78.45, 74.53, 96.33)	(88.45, 95.01, 57.96)	(57.81, 57.22, 57.51)
A-BLSTM + Verb	(98.45, 86.88, 56.55)	(89.27, 42.84, 64.44)	(56.00, 55.44, 55.72)
A-BLSTM	(99.13, 78.05, 76.14)	(79.14, 5.72, 68.12)	(56.93, 56.93, 56.93)
A-BLSTM + EW	(64.30, 73.17, 68.422)	(74.14, 69.14, 63.21)	(58.63, 41.66, 48.70)
w/o EW	(96.31, 84.45, 56.74)	(69.94, 71.23, 71.14)	-
w/o Verb	(96.45, 47.48, 79.45)	(9,574, 60.11, 69.54)	(57.42, 57.42, 57.42)
w/o TK	(78.36, 96.47, 89.45)	(70.68, 45.80, 96.85)	(57.11, 42.35, 48.63)

Table 3 shows that when compared to Baseline 2's accuracy of 72.21%, our suggested strategy achieves a much better result of 69.54%. In Table 6, you can see the results of feature ablation tests that compared the near past with the distant past in terms of classification.

Our suggested strategy outperforms Baseline 2 (with an accuracy of 64.35%), according to the results shown in Table 4. Displayed in Table 7 is the result of a feature ablation research comparing classifications for the near and far futures. Applying all characteristics simultaneously yields the best outcome in this case as well.

As for the five-category categorization, we also tried it out and discovered that it performed worse than the others (accuracy of 30.1 percent). One explanation for this is the clear pattern of separation between the past and the future. That the classifier can distinguish between the two groups with any degree of accuracy is a positive sign. The close and the far are essentially interchangeable terms, so there's not much space to differentiate between them. On top of that, there is a dearth of characteristics that differentiate close from far, but an abundance of attributes that differentiate the future from the past. As a result, we discovered that learning is erroneous when there are several classes.

Table 6. Evaluate the proposed method's feature ablation

Topographies	Past tweets	
	Far past	Near past
A-BLSTM + TK	(84.47, 74.82, 78.88)	(78.24, 78.84, 72.72)
A-BLSTM + TK + Verb + EW	(87.77, 77.18, 77.78)	(77.77, 82.22, 74.84)
A-BLSTM + Verb	(87.17, 74.87, 78.74)	(78.78, 81.84, 74.18)
A-BLSTM	(82.88, 72.22, 77.44)	(77.17, 78.47, 72.74)
A-BLSTM + EW	(87.47, 78.74, 82.24)	(72.77, 81.77, 77.14)
w/o EW	(87.24, 72.24, 78.17)	(78.87, 82.78, 74.11)
w/o Verb	(82.77, 74.41, 78.82)	(78.14, 78.17, 72.74)
w/o TK	(87.18, 72.71, 78.78)	(78.72, 82.88, 74.87)

Table 7. Investigation into the proposed method's feature ablation (near future vs far future). The precision-recall-F-measure trifecta displays the outcomes (p, r, f)

Features	Upcoming tweets	
	Far future	Near future
A-BLSTM + TK	(99.41, 75.41, 99.56)	(95.16, 55.54, 56.59)
A-BLSTM + TK + Verb + EW	(96.99, 71.45, 99.55)	(95.79, 91.61, 91.79)
A-BLSTM + Verb	(96.59, 75.95, 71.54)	(99.14, 91.19, 95.99)
A-BLSTM	(96.15, 75.95, 71.67)	(94.49, 57.97, 91.67)
A-BLSTM + EW	(71.15, 75.49, 71.55)	(94.94, 95.14, 95.51)
w/o EW	(99.66, 74.51, 71.49)	(95.66, 55.11, 59.11)
w/o Verb	(99.65, 71.95, 71.55)	(95.96, 95.61, 95.54)
w/o TK	(97.75, 71.17, 99.41)	(95.51, 56.95, 91.51)

When a tweet has a near-future connotation or contains certain misspelt key phrases, our suggested method's classifier tends to misclassify it into the far-future category, or vice versa. Some tweets, such "fine, I'm gon study today" have an emphasis on the immediate future. The problem is that the word "gon", which refers to the future, is misspelt and there is a temporal term that concerns the present ('today'). Misclassification of tweets as far-past or near-past occurs when neither the verb nor the temporal keyword is useful. "Your company once again was delightful". The classifier classifies the tweet as far-past even though it has a near-past connotation.

Table 5 displays the findings of the ablation investigation, which demonstrate the usefulness of the EW function. Regarding both the past and the future, we find that the accuracy is greater when we don't use Multi Markov Model characteristics. Making use of the capability. This functionality is clearly useless in this context. 'Expansion also includes terms with variable temporal orientation'. That might be one potential explanation. For instance, as a present-related term, "tomorrow's growth" encompasses both now and tomorrow.

Figure 3 displays some instances of how we used heatmaps to illustrate the attention vectors at the phrase level. Words and phrases are given more weight based on the intensity of their color. To forecast the tweet as "near-past" in the first case, the term "watched" was the most helpful. This finding demonstrates the significance of verb and temporal keywords in categorization.

watched the shawshank redemption again	Near-past
10 years ago in october i joined twitter to socialize with people	Far-past
could be #tornadoes tomorrow in western sd and eastern wy	Near-future
Next yearr I will like them to do the 2k	Far-future

Figure 3. Some properly identified tweets serve as examples of sentence-level attentiveness

17. Correlation results and analysis

Using the correlation coefficient, we examine the associations between users' attention to the recent past, the distant past, the near future, and the far future, as well as other demographic and psychological characteristics. Using the correlation data from the User-level Test Set, all the analyses in this section are conducted. Tables 8-17 show the findings of the correlation. To get the p-values, Fisher used his R-to-Z transformation (Bonferroni corrected). In the following analysis, we will only include the correlation values for which the p-value is less than 0.05.

Table 8. Comparison of models

Feature	CHMM	MMM
States	Multiple, interconnected.	Multiple, independent, or interconnected.
State evolutions	Impacted by unspoken conditions in competing models.	Possibility of being affected by unspoken states within or between models.
Data types	Typically, discrete (e.g., sentiment scores, emotion categories).	Able to work with both continuous and discrete data.
Requests	Simulating the dynamics of relationships between (e.g., users, groups, topics).	Accurately simulating the dynamics and hidden states of complicated systems.
Density	Thanks to linked models, it's more.	Different MMM structures have different effects.
Interpretability	Might be difficult because of all the interplay.	Simplified MMM structures may find it easier.
Computational cost	Greater because of the difficulty of inference and the number of parameters.	Changes from one MMM to another.

18. Existing methods

18.1 *Coupled hidden markov models (CHMMs)*

• This model utilises a network of connected hidden Markov models to simulate the emotional dynamics of Twitter discussions or the sentiments of a large population.

• Every Hidden Markov Model (HMM) stands in for a user's or conversation's emotional state, and the relationships between them show how those states impact one another.

• Using CHMMs, researchers have modeled the emotional dynamics of group interactions and studied the spread of emotions on Twitter.

• Using CHMMs, researchers have analyzed the spread of emotions on Twitter and modeled the emotional dynamics of group interactions.

• Their adaptability lies in their ability to process a wide range of data types, including sentiment scores and categorical emotions, as well as to simulate a variety of interaction topologies, including bidirectional and unidirectional ones.

• Applicability: They may be used to examine relationships between non-individual entities, including themes, organizations, or hashtags, rather than just persons.

19. Comparison with the existing model

Two situations where CHMMs work really well as a model for how entities interact with each other are emotional contagion and opinion formation. A broad MMM structure might work better for simulating complex dynamics with many hidden states within the system, like how people feel or how the whole group feels. Think about the trade-off between complexity and readability. CHMMs aren't always easy to understand because their connections are so complicated. MMMs, on the other hand, may be easier to grasp. Take a look at how much computing power you have. It takes more computer power to train and draw conclusions from CHMMs and complicated MMMs than from simpler models.

Table 9. Results of comparison

Metric	MMM	CHMMs
Correctness	0.85	0.78
Precision	0.88	0.75
Reminiscence	0.82	0.85
$F1$ score	0.85	0.8
AUC-ROC	0.92	0.87
Mean squared error	0.12	0.18

Table 10. Users "age" is positively correlated with their "focus" on the past, along with their "near-future" and "far-future" aspirations, in both the short and long term

Method	Common metric	Performance score
MMM	Accuracy	0.87
CHMMs	Accuracy	0.82

20. Results of comparison

20.1 *Stratified k-fold*

• Rationale: Depending on their psychographic traits, Twitter users may display a variety of concentration patterns. To avoid biased performance estimations, stratified k-fold makes sure that each fold retains the same proportions of these attributes as the full dataset.

• Implementation: Before dividing your data into folds, stratify it according to pertinent psychographic characteristics. Make use of libraries with stratified k-fold functionality, such as sci-kit-learn.

20.2 *Repeated k-fold*

• Justification: A comprehensive accounting for the data's variability may need more than one k-fold run. Improved estimates of model performance and generalizability are obtained by repeating k-fold numerous times, for example, 10-30 iterations.

• Methodology: Run k-fold cross-validation several times with varying data randomizations, and then give the mean performance metrics from each run.

20.3 *Appropriate k value selection*

• Justification: A great degree of uncertainty and perhaps deceptive outcomes may be caused by selecting a k number that is excessively tiny, such as $k = 2$. The effectiveness of cross-validation is diminished when the k value is very big, such as when k is equal to the number of data points.

• As an example of how to put this into practice, try out $k = 5$, 10, and 20 to see how the bias and variance trade-off. One way to measure variation is by looking at performance indicators such as standard deviation across folds.

• Extremely precise training, but poor test accuracy: In contrast to its impressive performance on the training data, the model exhibits subpar results when applied to unseen data.

• Complication of the model: Overfitting is more probable in models that contain a high quantity of parameters or features.To mitigate overfitting and enhance the generalizability of a model, a number of methodologies can be implemented.

• Data augmentation: By augmenting the magnitude and variety of the training data through the implementation of stochastic operations such as rotations, flips, or noise introduction, one can facilitate the model's acquisition of latent patterns as opposed to committal of particular instances.

• Regularization: By penalizing models with an excessive number of complex features, techniques such as L1 or L2 regularization promote the development of simplified models that are less susceptible to overfitting.

• Dropout: Eliminating a specific proportion of neurons at random during training in neural networks compels the model to acquire more robust features and prevents them from co-adapting excessively.

Generalizability and Robustness via K-Fold Cross-Validation One effective method for evaluating the generalizability of a model and mitigating the risk of overfitting is K-fold cross-validation.

1. Split the data: The complete dataset is partitioned into k equal portions, which are typically 5 or 10.

2. Iterative training and testing: A model is trained for k-1 folds in each fold, with the residual fold designated for testing purposes. It is ensured that each data point is utilized for evaluating a single occasion by repeating this procedure k times.

3. Performance evaluation: For more reliable estimation of the model's ability to generalize to unknown data, the performance metric (such as accuracy or error rate) is averaged over all k iterations.

21. Demographic correlates

Users' age, gender, level of education, and relationship status are described here along with the links between their emphasis on a TD.

Table 11. Gender and the correlation coefficient between users' pre-future, distant, near-future, and far-future attention. Significance is denoted by values ending with *

Attributes	Focus on time-based reserve emphasis			
	near-past	far-past	near-future	far-future
Phase of age	1.24	1.36	-1.85	-1.96

21.1 *Age*

Users' "age" is positively correlated with their "focus" on the past, along with their "near-future" and "far-future" aspirations, in both the short and long term, according to Table 12.

Table 12. Gender and the correlation coefficient between users' pre-future, distant, near-future, and far-future attention. Significance is denoted by values ending with *

Gender	Time-based reserve emphasis			
	near-past	near-future	far-past	far-future
Feminine	1.23	1.56*	-1.24*	-1.56*
Masculine	-1.56*	1.63	1.26*	-1.26*

'Age' is inversely connected to their future concentration, whether it's the immediate or far future. Additionally, we find that there is a stronger positive correlation between users' age. It seems that people who are more focused on the immediate past tend to be older.

21.1.1 *Analysis by gender*

The correlation between age and females' near-past focus is positive ($r = 0.18$) and between age and males' far-past focus is positive ($r = 0.36$).

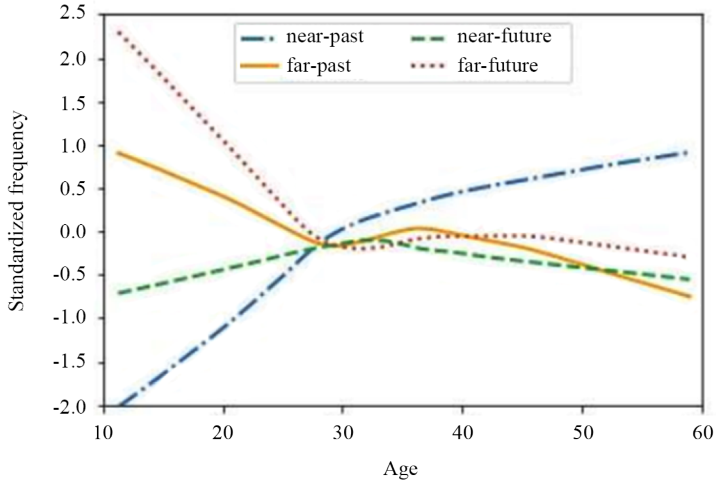


Figure 4. Age-dependent standardisation of the users' attention to local and remote temporal distances. Smoothing was performed with loess smoothing estimations

From the ages of 10 to 60, the users' near- and far-future attention changes, as seen in Figure 4. As people become older, we see a consistent rise in their near past attention. Before a gradual decline begins beyond the age of 28, users' attention to the distant past is dramatically declining. Up until the age of 32, users' near-future focus gradually increases, and then it stays almost constant. The far-past emphasis of users declines dramatically until the age of 29, after which it remains stable.

21.2 *Gender*

We look at male and female users separately to see if there is a connection between their gender and TD emphasis. A greater positive value corresponds to a greater probability of being female, and Preo®tiuc-Pietro et al. use regression to forecast the genders. The outcomes are normalised within the range of -5 to +5. The correlation data between TD objectives and gender is shown in Table 12. The association coefficient among users' education and their attention spans the following time periods: far-future, near-past, near-future, and far-past, as shown in Table 13. The results show that there is a positive relationship between the two. Values that end in * are considered to be not significant.

Table 13. The correlation coefficient between users' near-past, far-past, near-future, and far-future attention and their relationship. The suffix * indicates that the value is not significant

Education	Time-based reserve emphasis			
	near-past	far-past	near-future	far-future
Degree	0.15*	0.12*	-0.18	0.07
Graduate degree	-0.11*	-0.12*	-0.08	0.07
High school	-0.132*	-0*	0.2	-0.12*

21.2.1 *Analysis by age group*

Users' ages are divided into two categories for this sort of analysis: those under 30 and those 30 and over. It seems to reason that 30 would be a good split point. Our best guess is based on Figure 4, which shows a trend shift around the age of 30, for those above the age of 30, we discover a negative correlation with $r = -0.19$. Furthermore, women above the age of 30 show a positive association ($r = 0.33$) with regard to attention to the near future.

21.3 *Education*

We break down users' 'education' into three subcategories: degree, graduate degree, and high school, and we quantify their attention on Multi Markov Model. A focus on the future is associated with schooling in literary works. While there is no statistically significant correlation between users' education and either near-past or far-past distance focus, Table 10 reveals a strong correlation between users' education and future distance focus. We find that those with a bachelor's degree tend to look further into the future, while those with just a high school diploma tend to look more closely at the here and now. Higher education is associated with a shift toward a focus on the future, as shown above.

Table 14. A measure of the degree of association between users' Intelligence and their attention spans in the recent past, the distant past, the near future, and the far future, * values indicate lack of significance

Cleverness	Time-based reserve focus			
	near-past	far-past	near-future	far-future
Average	-0.13	-0.12*	-0.17	0.18
Below average	0.15	0.13*	-0.11*	-0.13
Much above	-0.18	-0.13*	0.2	0.11*

21.3.1 *Analysis by gender*

There is no correlation between schooling and women's temporal distance focus. In men, we see a positive association with high school education and a negative correlation with degree of education when it comes to near-past concentration.

21.3.2 *Analysis by age group*

The following variables are associated with concentration shortly among students less than 30 years old: education level ($r = -0.27$). Among the same users, a positive association ($r = 0.24$) and a negative correlation ($r = -0.19$) between far-future emphasis and education: graduate degree are seen. For users above the age of 30, there is no statistically significant correlation seen between educational achievement and temporal distance focus.

21.4 *Relationship*

We analyse the link between the status of users and their TD emphasis for each of the four subcategories-divorced, Table 15 shows that there is a negative association between relationship: divorced and both short-term and long-term memories of the past, and a positive correlation between long-term memories and the same variable. Divorced users tend to prioritise the long term. We analyse the link between the status of users and their TD emphasis for each of the four subcategories-unconnected, in a connection, single, and married.

Table 15. Users' optimism is correlated with the degree of attention they place on the near, distant, near, and far future

Relationship status	Time-based reserve focus			
	near-past	far-past	near-future	far-future
In a connection	-0.19	-0.06	-0.14*	0.1
Unconnected relationship	0*	0.11*	0.11*	-0.01*
Single	0.15*	0.5*	-0.17	1*
Married	-0.01*	0.13*	0.16	-0.12*

An association between TD and an additional attribute. Short-term objectives of users are negatively correlated with their relationship status (i.e., single), but long-term objectives are positively correlated with relationship status (i.e., married).

21.4.1 *Analysis by gender*

No statistically significant correlation between concentration on temporal distance and connection exists for females. Relationship status: single ($r = 0.19$) and relationship status: divorced ($r = -0.17$) are the two male relationships with which near-past attention is inversely and positively linked. There is a correlation between men's future emphasis and their relationship status ($r = 0.14$).

21.4.2 *Analysis by age group*

Relationships are positively correlated with a concentration on the far future: parietal ($r = 0.15$) and relationship: married ($r = 0.18$) among those under the age of 30, and a negative correlation with relationship: single ($r = -0.21$). There is a negative correlation between near-past focus and relationship: divorced ($r = -0.11$) for more than 30 users. There is a positive correlation between relationship: divorced and far-future emphasis ($r = 0.17$) for the same set of users.

22. Psychological correlates

Our list of mental characteristics includes optimism, wit, and the ability to feel the six fundamental human emotions: Joy, sorrow, anger, disgust, surprise, and fear.

22.1 *Optimism*

Much above average, average, and below average intelligence are the three levels of intellect that we study. Table xx displays the findings of the link between users' concentration on TD and IQ. The findings point to a level of intellect much higher among users with a focus on the future. The average IQ of users with near-past focus is ordinary. There is a correlation between users' below-average IQ and their near-future and near-past attention.

22.1.1 *Analysis by gender*

Among men, there is a negative correlation between near-past attention and intelligence: substantially above ($r = -0.17$). For female users, we did not detect any significant outcomes.

Table 16. Users' optimism is correlated with the degree of attention they place on the near, distant, near, and far future

Optimism	Time-based reserve emphasis			
	near-past	far-past	near-future	far-future
Optimist	0.013	-0.16	0.15	-0.15*
Pessimist	-0.12*	0.27	0.00*	-0.13*

22.1.2 *Analysis by age group*

Users under the age of 30 had a negative correlation between near-past focus and intelligence: below average (r = -0.10), a positive correlation between near-future focus and intelligence: below average (0.18), and a negative correlation between the two (r = -0.10). Regarding the same set of individuals, Intelligence is positively correlated with: much above and future focus (r = 0.14). Intelligence is adversely connected with near-past focus for users over the age of 30: significantly higher (-0.06).

22.2 *Joy*

The psychology research links future orientation to the emotional trait Joy. Table 17 shows that compared to users' far-future attention (r = 0.11), Joy is positively correlated with users' near-future focus (r = 0.27). Individuals with a concentration on the near future are more likely to exhibit Joy symptoms than those with a focus on the distant future, according to the correlation values. Another variable that correlates negatively with Joy.

22.3 *Sadness*

According to psychological research, people tend to feel melancholy when they dwell on the past [7, 8]. In most cases, the mournful feeling stays with people for quite some time. Table 17 shows that there is a positive link between users' far-past concentration and melancholy (r = 0.17).

Spending more time thinking about the distant past makes me sadder. There is no statistically significant relationship between melancholy and sustaining temporal distance focus.

22.4 *Disgust*

The study did not investigate if there was a relationship between participants' focus on Multi Markov Model and their level of scorn as time went on. Table 17 displays the experimental data showing that individuals displaying an attitude of disgust tend to fixate on distant memories. Additionally, we discovered a strong inverse relationship between distaste and future attention (r = -0.13). It demonstrates that consumers' disgust is reduced when they concentrate on the near future.

22.5 *Anger*

Anger has been linked to previous concentration in the psychological literature [8]. Table 17 displays the trial findings showing a positive association between users' far-past focus and rage. It demonstrates that those who utilise far past focused tend to be more angry. A negative connection with anger (r = -0.15) is shown for both near- and far-future emphasis, suggesting that users' concentration on the future (whether near or distant) decreases anger.

22.6 *Surprise*

Few studies have looked at the connection between TD attention and surprise. Users who are focused on the near future are less likely to be shocked, according to the only significant finding in Table 17 which demonstrates a negative connection between surprise and near-future attention (r = -0.16).

22.7 *Fear*

The psychological literature suggests that an impending mismatch could trigger fear. Additionally, it is said to be produced by an expected stat [8]. Users' anxiety is positively correlated with their previous focus, whether local or distant, as seen in Table 17. There is a stronger positive correlation between users' far-past attention. Operators who are more preoccupied with the distant past are likely to be more scared.

Table 17. 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	Time-based reserve emphasis			
	near-past	far-past	near-future	far-future
Sadness	-0.2	0.42	0.28	0.12
Anger	-0.02	0.18	0.03	-0.04
Surprise	0.09	0.5	-0.18	-0.14
Fear	0.15	0.48	-0.26	-0.16
Disgust	0.02	0	0.27	0.03
Joy	0.16	0.6	-0.3	-0.1

23. Conclusion

The first extensive empirical investigation of the time value paid by Twitter users was presented in this article. For starters, we created four categories for the users' tweets: current, far-past, near-future, and other. By aggregating the emphasis at the tweet level across users, we were able to derive the user-level temporal focus. This is the first computational Multi Markov Model research that we are aware of that connects users' numerous demographic and psychological traits-including six basic, gender, optimism, education, relationship status, and age emotions-with their near-and far-term focus on temporal distance. We can save money with our data-driven approach since the tweets are readily available. Additionally, unlike more conventional questionnaire-based approaches, our technique aims to reach a larger audience, which is an incentive. We hope that by delving into the finer points of temporal attention, we may open doors to other hitherto unthinkable fields of large-scale psychology research. Research exploring whether users' promotional tweets disclose more about their Multi Markov Model concentration might be an interesting direction to go in the future.

Conflict of interest

The authors declare no competing financial interest.

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