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Circadian rhythms and social media information-sharing

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Abstract. Large amounts of information are shared through social media. Such communication assumes users are sufficiently aligned, not only in terms of their interests but also in terms of their emotional and cognitive states. It is not clear how this emotional and cognitive alignment is achieved for social media, given one-to-one interactions are infrequent and discussion often spans loosely connected individuals. This study argues that circadian rhythms play an important physiological role in aligning users for information-sharing, as information shared at different times of the day is likely to encounter users with common physiological states. Data are gathered from Twitter to examine patterns of sentiment and text complexity in social media, as well as how these patterns affect information-sharing. Results suggest the timing of a social media post, relative to collective patterns of sentiment and text complexity, is a better predictor of information-sharing than the sentiment and text complexity of the post itself. Put differently, information is more likely to be shared when it is posted at times of the day when other users are primed for emotion and concentration, independent of whether that posted information is itself emotional or demanding in concentration.

Keywords: Circadian. Social Media. Sentiment. Text Complexity. Twitter.

1 Introduction

Social media provides an important means of gathering and distributing information. Yet the sheer volume of information limits what individuals can consume and share, i.e. the amount of information users may ‘convey’ significantly exceeds the amount of information upon which they may ‘converge’ [c.f. 9]. Key determinants of convergence and information-sharing have been identified as *sentiment* [14, 35] and *text complexity* [27, 34]. These qualities influence a recipient’s motivation and capability to engage with particular pieces of information. The influence of *sentiment* and *text complexity* on information-sharing is not absolute; rather, their impact depends on their alignment with the needs of recipients at some particular time. Failure to match the *sentiment* of recipients may result in posts appearing out of sync or ‘tone deaf’ [4, 36]. Similarly, more complex information is often less welcome when discussion is adversarial [27, 34] and more welcome when discussion is collaborative [8, 16, 19].

This need for alignment between communicators and recipients is typically developed over the course of one-to-one symbolic interactions [3] and physiological mirroring [29]. Yet social media-based information-sharing is rarely one-to-one and often occurs between individuals who do not frequently interact [13]. Hence it is not obvious how users achieve the alignment to interact effectively.

This study proposes the alignment of social media users relies partly on common circadian rhythms, i.e. daily light-entrained physiological oscillations that help to ensure individuals are most active during the day and most restful at night [1, 6]. Studies have shown circadian rhythms produce predictable patterns in the sentiment of social media posts. Notably, an extensive study by Macy and Golder [15] found consistent circadian patterns in social media sentiment across countries, seasons, and days of the week. Previous research has also shown that information-sharing on social media is disproportionally between individuals in geographical proximity [38], hence in similar time zones. Thus, there is an intuitive role for circadian rhythms as a mechanism for creating alignment between social media users.

2 Social Media and Circadian Rhythms

Circadian rhythms encourage us to be active at the times best suited for our environment, e.g. to crave food and increase in activity when food sources are typically plentiful [33]. Circadian rhythms regulate a range of biological processes, from hormonal changes, to body temperature, to mood [1, 25, 26, 32, 33]. These roughly 24-hour cycles are coded into the cells of most living things, creating a natural clock that oscillates between wakefulness and restfulness – even when environments are artificially manipulated to make days seem longer or shorter [1, 2, 7].

For mammals such as humans, daily circadian cycles are entrained by light through the suprachiasmatic nucleus (SCN), which fires to dorsomedial areas of the hypothalamus and links to neural pathways involved in the release of mood and effort-related hormones such dopamine [21], serotonin [33], and cortisol [10]. The SCN simultaneously inhibits the pineal gland from secreting melatonin, the hormone that accumulates to promote sleep states [2]. This results in dual-process cycle (see [33]) where (i) the ascending arousal system triggers hormones to promote activity/inhibit the release of sleep-inducing melatonin via the pineal gland, while (ii) the competing homeostatic sleep system gradually builds up pressure until it can overwhelm sleep-inhibitors and produce enough melatonin to inhibit the SCN, resulting in a ‘flip flop’ switch between wake-sleep transitions. A summary of documented daily circadian hormonal patterns is illustrated in Figure 1.

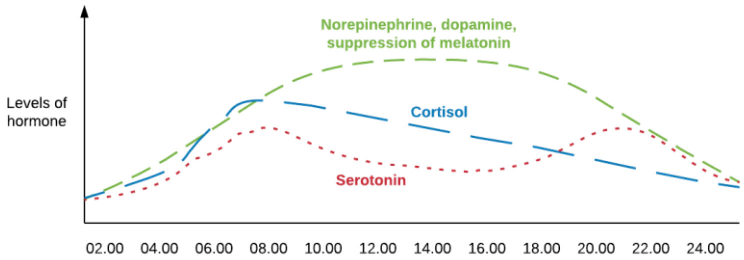

Fig. 1. Typical circadian levels of dopamine, serotonin, cortisol, and melatonin suppression.

The role of these hormones in regulating engagement and energy means these patterns are relevant for social media information-sharing in two ways.

First, increased engagement and energy are linked to higher levels of emotional affect [37]. Hence circadian rhythms tend to influence the mood of individuals at different times of the day in a way that harmonizes that mood with other social actors [25], even in where no interaction has occurred.

Second, increased engagement and energy are associated with an individual's willingness to engage in challenging behaviors [18]. Communication via social media changes the nature of communication, wherein individuals must decide which communications to ignore, which to prioritize, and which to share with others [22, 30]. More complex communications increase mental load for the recipient [31], increasing the pressure on specific intrinsic and extrinsic rewards [23].

Circadian hormone patterns have been used to predict collective shifts in mood and information-processing in social media use. This includes daily contribution patterns to Wikipedia [39], seasonal changes in depression-related information search [11], and changes in word volume variation [12]. Most comprehensively, Golder and Macy [15] found strikingly consistent daily *sentiment* patterns on Twitter across countries, seasons, and days of the week.

Thus, circadian rhythms may conceivably have a direct impact on the *sentiment* and *text complexity* of social media posts, as well as subsequent information-sharing behaviors of users (as users will be in different, common physiological states at different times of the day). It may further moderate the relationship between *sentiment*/*text complexity* and information-sharing by extending alignment between the communicator and the recipients.

3 Method

Data were gathered from Twitter Data on 8th August and 6th December 2018. For both dates, 1,000 English-language tweets were gathered from US social media users in each of the 50 states at 1-hour intervals (total N=2,400,000). Duplicates and retweets were removed, as were tweets from private accounts or accounts with no followers, and tweets with no text. *Sentiment* for each tweet was analyzed at a word level using the AFINN sentiment lexicon for microblogs [28], accessed through the tidytext library[1] for R (an open source data processing platform). *Sentiment* was scored according to positive affect (*PA*), negative affect (*NA*), *valence* (PA-NA) and *arousal* (PA+NA). Tweets with no scores for *sentiment* were removed to allow analysis to focus on discussion with some emotional content. This resulted in a final set of 404,946 tweets. *Text complexity* was then scored using the Gunning FOG index [17], the Dale-Chall measure [5] (later dropped for convergence issues), the Flesch-Kincaid Reading Ease Index (FRE) [20], and the Simple Measure Of Gobbledygook (SMOG) [24] (accessed via the quanteda library[2]).

4 Findings

Data show reliable circadian patterns of *sentiment* and *text complexity*, consistent with existing research (see Figures 2 and 3) [c.f. 15]. The predicted *sentiment* and *text complexity* at different times were estimated using separate locally weighted regression (LOESS) curves for each measure of *sentiment* and *text complexity*. These curves were tested against the patterns and effect size of comparative polynomials to ensure reliability. A series of negative binomial regressions (see Tables 1 and 2) also compared the impact of a tweet's *sentiment* and *text complexity* with the predicted *sentiment* and *text complexity* based on the time of day it was posted, i.e. the qualities of the tweet vs. the daily aggregate qualities of Twitter discussion at the time of posting. Hierarchical models were introduced that predicted information-sharing by adding the *sentiment/text complexity* of a tweet (model 1), then the circadian predicted *sentiment/text complexity* at the time that tweet was posted (model 2), then finally the interaction term (model 3).

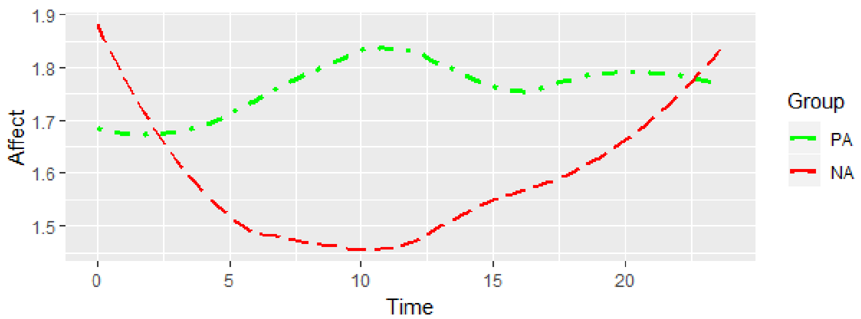

Fig. 2. LOESS curves for *positive affect (PA)* and negative affect (*NA)* based on avg. *sentiment* for time

[1] Tidytext version 0.1.8, available at https://cran.r-project.org/web/packages/tidytext/index.html
[2] quanteda ver. 1.3.4, available at https://cran.r-project.org/web/packages/quanteda/index.html

Table 1. Results of negative binomial regression for circadian predicted sentiment on retweets

	Model 1			Model 2			Model 3		
	B	*SE*	*exp*	*b*	*SE*	*exp*	*B*	*SE*	*Exp*
Arousal	.026**	.006	1.026	.024***	.006	1.024	-.531**	.189	.588
PredictedArousal				.817***	.134	2.257	Ns	-	-
Ar*PredictedAr							-.165**	.056	.848
Hashtags	.131***	.014		.135***	.014		.135***	.141	
Mentions	-.291***	.018		-.289***	.018		-.289***	.178	
Urls	.319***	.025		.336***	.025		.335***	.025	
Log(followers)	.557***	.009		.559***	.009		.559***	.009	
Log(activity)	-.179***	.009		-.181***	.009		-.181***	.009	
AIC	77604			77563			77563		
Valence	-.011**	.004	.989	-.010	.004	.990	Ns	-	-
PredictedValence				-1.122***	.101	.320	-1.118***	.101	.321
Val*PredictedVal							Ns	-	-
Hashtags	.131***	.014		.133***	.014		.133***	.014	
Mentions	-.291***	.018		-.285***	.018		-.285***	.018	
Urls	.312***	.025		.339***	.025		.339***	.025	
Log(followers)	.557***	.009		.562***	.009		.563***	.009	
Log(activity)	-.181***	.009		-.187***	.009		-.188***	.009	
AIC	77615			77492			77492		
PA	ns	-	-	ns	-		Ns	-	-
PredictedPA				-2.785***	.296	.053	-2.469***	.399	.075
PA*PredictedPA							Ns	-	-
Hashtags	.128***	.014		.123***	.014		.123***	`.014	-
Mentions	-.294***	.018		-.288***	.018		-.288***	.018	
Urls	.308***	.025		.309***	.025		.309***	.025	
Log(followers)	.556***	.009		.559***	.009		.559***	.009	
Log(activity)	-.179***	.009		-.185***	.009		-.185***	.009	
AIC	77623			77535			77535		
NA	.029***	.069	1.029	.027***	.006	1.027	Ns	-	-
PredictedNA				1.182***	.122	3.277	1.159***	.153	3.218
NA*PredictedNA							Ns	-	-
Hashtags	.134***	.014		.138***	.014		.138***	.014	-
Mentions	-.287***	.018		-.285***	.018		-.285***	.018	
Urls	.319***	.025		.346***	.025		.346***	.025	
Log(followers)	.558***	.009		.563***	.009		.563***	.009	
Log(activity)	-.182***	.009		-.186***	.009		-.186***	.009	
AIC	77602			77512			77514		

* p < .05, ** p < .01, *** p < .001, † p < .1, ns = not significant

Table 2. Results of negative binomial regression for circadian predicted sentiment on retweets

	Model 1			Model 2			Model 3		
	B	*SE*	*exp*	*b*	*SE*	*Exp*	*B*	*SE*	*Exp*
FOG	.017***	.003	1.017	.012***	.003	1.012	ns	-	
LOESS FOG.				-.259***	.046	1.308	-.238**	.084	1.287
FOG*LOESS							ns	-	
Hashtags	.129***	.014		.133***	.014		.133***	.141	
Mentions	-.288***	.018		-.287***	.018		-.287***	.178	
Urls	.286***	.025		.303***	.025		.303***	.025	
Log(followers)	.553***	.009		.555***	.009		.555***	.009	
Log(activity)	-.178***	.009		-.179***	.009		-.179***	.009	
AIC	77603			77574			77576		
FRE	.018***	.003	1.018	.019***	.003	1.019	ns	-	
LOESS FRE				-.251***	.049	1.299	-.229**	.079	1.267
FRE*LOESS							ns	-	
Hashtags	.132***	.014		.136***	.014		.136***	.014	
Mentions	-.285***	.018		-.284***	.018		-.285***	.018	
Urls	.279***	.025		.294***	.025		.294***	.025	
Log(followers)	.552***	.009		.554***	.009		.554***	.009	
Log(activity)	-.177***	.009		-.178***	.009		-.178***	.009	
AIC	77594			77570			77572		
SMOG	.015***	.004	1.015	.016***	.004	1.016	ns	-	
LOESS SMOG				-.372 ***	.055	1.464	-.338**	.125	1.416
SMOG *LOESS							ns	-	
Hashtags	.131***	.014		.135***	.014		.135***	.014	
Mentions	-.289***	.018		-.288***	.018		-.288***	.018	
Urls	.286***	.025		.305***	.025		.305***	.025	
Log(followers)	.552***	.009		.555***	.009		.555***	.009	
Log(activity)	-.177***	.009		-.179***	.009		-.179***	.009	
AIC	77609			77567			77569		

* p < .05, ** p < .01, *** p < .001, † p < .1, ns = not significant

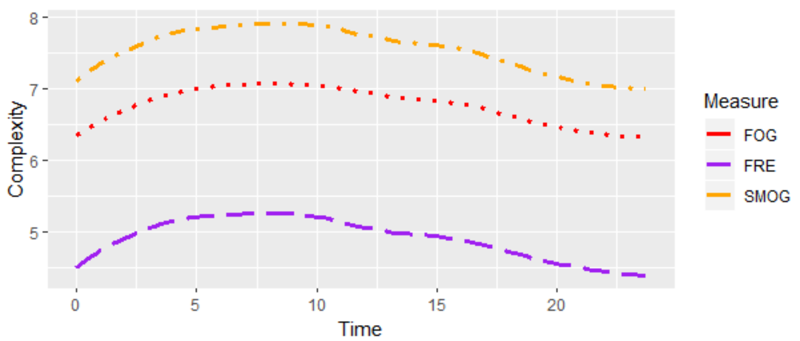

Fig. 3. LOESS curves for FOG, FRE, and SMOG, based on avg. text complexity for time

5 Discussion

Findings from this study support previous observations of circadian patterns in the *sentiment* of social media discussion. They also extend these patterns to *text complexity*, the first study to do so, to the author's knowledge.

More importantly, findings from this study suggest collective circadian patterns of *sentiment* and *text complexity* provide stronger predictions of information-sharing than the *sentiment* and *text complexity* of individual posts. Put differently, information is more likely to be shared when it is posted at times of the day when other users are primed for emotion and concentration, independent of whether that posted information is itself emotional or demanding in concentration.

More broadly, this study provides an explanatory physiological mechanism for how loosely connected individuals can achieve the emotional and cognitive alignment required for information-sharing. This has obvious practical implications for social media, e.g. perhaps posted information should be delayed for users in other time zones. However, this finding also has implications beyond social media discussion. For example, the circadian model proposed in this study may help to explain communication and relationship-building difficulties in distributed organizational teams.

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