Bursty Coordination in Online Communities

Completed Research Paper

Lei (Nico) Zheng
Stevens Institute of Technology
Hoboken, NJ
lzheng9@stevens.edu

Feng Mai
Stevens Institute of Technology
Hoboken, NJ
fmai@stevens.edu

Deborah M. Gordon
Stanford University
Stanford, CA
dmgordon@stanford.edu

Jeffrey V. Nickerson
Stevens Institute of Technology
Hoboken, NJ
jnickers@stevens.edu

Abstract

The collective intelligence of online communities often depends on implicit forms of coordination, given the fluidity of membership and the lack of traditional hierarchies and associated incentive structures. This coordination drives knowledge production. Studying temporal dynamics may help elucidate how coordination happens. Specifically, the rate of interaction with an artifact such as a Wikipedia page can function as a signal that affects future interactions. Many activities can be characterized as bursty, meaning activity is not evenly spread or random, but is instead concentrated. This study analyzes 3,260 Wikipedia articles and shows that the coordination pattern in the Wikipedia community is mostly bursty. More importantly, the extent of burstiness affects article quality. This work highlights the important role temporal dynamics can play in the coordination process in online communities, and how it can affect the quality of knowledge production.

Keywords: coordination, burstiness, productivity, temporal dynamics, Wikipedia

Introduction

How members collaborate and coordinate in online communities is an important topic in the information systems literature (Faraj et al. 2015; Howison and Crowston 2014; Malone et al. 1994; Maruping and Magni 2015; Ransbotham and Kane 2011). A core question is how self-organized communities can produce high-quality content (Arazy et al. 2011; Kane and Ransbotham 2016a; Liu and Ram 2011). Studies posit a kind of collective intelligence that goes beyond simply aggregating individual intelligence of the members (Aggarwal et al. 2019; Woolley et al. 2010). Such collective intelligence is likely to be influenced by both group compositions and group interactions, and can explain why groups perform well in collaborative tasks (Barlow and Dennis 2016; Kittur and Kraut 2008; Woolley et al. 2015). Successful collaboration, therefore, depends on factors such as individual intelligence, social sensitivity of group members, conversational patterns (Woolley et al. 2010), and team cognitive style (Aggarwal et al. 2019).

A less-studied feature of collective intelligence in online communities is the temporal dynamic of interactions. Scholars have long recognized the vital role of temporal patterns in IT-enabled organizations (Jackson et al. 2011; Massey et al. 2003; Saunders and Kim 2007; Shen et al. 2015). Prior research in this area suggests that a coordinated and predictable temporal pattern is a trait of effective teams (Maznevski and Chudoba 2000; Saunders et al. 2004). Yet online communities are different from conventional virtual teams in several aspects: they have a high membership turnover rate (Ransbotham and Kane 2011), a lack of traditional organizational structure (Ren et al. 2016), and an absence of monetary incentive (Chen et al. 2017). Therefore, it is unclear whether findings in other settings apply to online communities.

In addition, existing IS research related to time mainly focused on theoretical development or laboratory experiments with small groups (Massey et al. 2003; Massey and Montoya-Weiss 2006; Saunders and Kim 2007). Research using observational data of large collaborative communities is relatively scarce. In many instances, interactions in online communities can better be described as implicit coordination rather than collaboration (Kittur and Kraut 2008). Implicit coordination takes place when members dynamically adjust their behavior according to the actions of others and task demands, without direct communication or planning (Rico et al. 2008). Indeed, while collaboration depends on a common cause and shared interests, implicit coordination only needs a mechanism for creating signals others can see (Majchrzak and Malhotra 2016). On platforms such as Wikipedia, signaling can be accomplished through the interactions with artifacts such as articles (Bolici et al. 2016; Heylighen 2016; Rezgui and Crowston 2018); the interactions with the artifacts leave editing traces that others can see. We develop a theory to explain that contributors' behavior is affected by the temporal patterns of recent edits, not just the presence of past interaction. Studying these temporal patterns may offer new insights into the generation of knowledge.

In this paper, we seek to answer the following research question: What kind of temporal patterns are associated with successful coordination in online communities? We first analyze sequences of editing activities in Wikipedia and show that the editing activities on most articles exhibit a unique, bursty temporal pattern. This temporal pattern is characterized by long periods of inactivity following a small period of extensive activity. We use a distribution-based measure, burstiness, first proposed in the complex systems literature (Barabási 2005; Goh and Barabási 2008) to quantify the extent of the bursty temporal pattern on thousands of Wikipedia pages. A high value of burstiness corresponds to activities that cluster into short and separated segments of time, whereas a low value of burstiness represents more evenly spread activities.

We examine whether burstiness affects article quality. The investigation is in part motivated by a recent small group collaboration study that shows burstiness having a significant positive effect on team performance when controlling for members' skills and monetary incentives (Riedl and Woolley 2017). However, collaboration in online communities violates core assumptions of collaboration theories under small group settings (Faraj et al. 2011; Howison and Crowston 2014; Jarvenpaa and Majchrzak 2010; Kane and Ransbotham 2016b). That is, mechanisms that organize small group coordination, such as visible and stable membership, organizational structuring, the reliance on transactive memory and related cognitive processes are attenuated or absent in online communities (Faraj et al. 2011). As a result, new theory and empirical evidence are both needed to show that bursty coordination is an effective mechanism that enhances the quality of information generated by online communities.

We hypothesize that bursty activity patterns will yield higher quality content based on coordination theory (Malone et al. 1994) and social learning theory (Bandura and Walters 1977). We examine a comprehensive Wikipedia dataset with human-rated article quality measures. While many related studies were conducted on open software projects (OSS), we choose Wikipedia for several reasons. First, it provides a more general study sample, as contributions on Wikipedia do not need to be as technically sophisticated as those made to open software. Second, participation in Wikipedia is immediate, which means anyone can edit a page at any time, thus creating a more spontaneous temporal dynamics. Third, the evaluation process of the information quality is consistent thanks to a consistent quality grading scheme. All editing behaviors are also recorded and made public (Kane and Ransbotham 2016a; Stvilia et al. 2008). Thus, editing patterns on Wikipedia offers an ideal opportunity for us to study the consequences of different temporal patterns generated by the implicit coordination process. Our empirical analysis shows that the burstiness of coordination is a significant predictor of article quality while controlling for other factors. Furthermore, we use an instrumental variable (IV) approach to address endogeneity concerns. We exploit the exogenous variations of burstiness that can be attributed to external events propagating through the Wikipedia hyperlink network. The results suggest that the relationship between burstiness and article quality is likely to be causal.

This paper added to the literature on coordination in online communities by exploring the temporal dynamics of editing in Wikipedia. First, we find that the editing behaviors in Wikipedia follow a bursty temporal pattern that contains short bursts and long breaks. Second, we find the degree of burstiness has a positive effect on article quality. Third, by constructing endogenous instrumental variables for article burstiness, we offer causal empirical evidence for the effect of bursty temporal pattern on successful peer production work. Our finding suggests the editors may respond to the frequency of recent edits, leading to a fat-tail distribution of the inter-edit time. Based on coordination theory and social learning theory, the bursty temporal pattern serves as an implicit form of coordination, during which bursts of activities encourage more interpersonal synchrony and long breaks enable editors to absorb, conceptualize, and search for novel ideas. Together, our findings have important implications for platform design and associated tool development that can improve the quality of information generated by online peer production communities.

Bursty Temporal Pattern and Burstiness

Prior research about time in the IS literature mainly focused on temporal dispersion (O'Leary and Cummings 2007), defined as the extent to which the working hours of team members differ. Existing empirical studies provide both positive and negative views on the influence of temporal dispersion. On the one hand, temporal dispersion decreases the likelihood of synchronous interactions, which result in reduced real-time problem solving and disjointed discussions (Maznevski and Chudoba 2000; Mcgrath 1991; Ocker et al. 1995; Warkentin et al. 1997). Thus, studies found that temporally dispersed teams face more coordination problems and have lower team performance (Espinosa et al. 2007, 2015; Montoya-Weiss et al. 2001). On the other hand, studies found that temporally dispersed teams can increase team performance by utilizing asynchronous communication (Colazo and Fang 2010; Yamauchi et al. 2000). This is because asynchronous communication eliminates time and space constraints on communication. In addition, it also allows individuals to take more time to consider the problem and consult other resources to improve problem-solving (Borges et al. 1999; Rasters et al. 2002).

Despite recent progress, most empirical studies only considered time as a categorical construct, by either comparing distributed teams to co-located teams (differentiating the presence of temporal dispersion) or by differentiating sets of teams based on the variation in team members' time zones. However, as temporal dispersion affects coordination through altering the pattern, timing, and content of interactions (Massey and Montoya-Weiss 2003; Mcgrath 1991), we argue that it is not the temporal dispersion but the temporal pattern of interactions that matters. This is especially true in the fluid context of online knowledge collaboration (Faraj et al. 2011; Jarvenpaa and Majchrzak 2010; Kane et al. 2014). For example, a timely response may trigger a sequence of consecutive edits that help elaborate a spark of an idea into a thorough form of knowledge. In the context of Wikipedia, such interactions are mediated through the articles that groups of editors are dedicated to contributing to. In this case, the article is not only the shared work of editors but also the medium that delivers information about what needs to be coordinated (Bolici et al. 2016; Heylighen 2016; Rezgui and Crowston 2018). Editors follow digital traces made by other contributors, including edits and their location in the article, and allocate their effort to extend or modify other's work. In this way, the time series of edit timestamps serve as an indicator of how group members interact with others and allocate their work.

We use burstiness as defined by Goh and Barabási (2008) to measure each article's temporal pattern of editing. To understand this variable, consider a system whose activities are recorded in a series of timestamps – in this case, edits to a Wikipedia article. This measurement first calculates the time interval between two consecutive edits and represents it as a random variable τ, whose probability function is $P(\tau)$. Let m_τ and σ_τ be the mean and standard deviation of $P(\tau)$. Burstiness is defined as:

$$B = \frac{(\sigma_\tau / m_\tau - 1)}{(\sigma_\tau / m_\tau + 1)} = \frac{(\sigma_\tau - m_\tau)}{(\sigma_\tau + m_\tau)}$$

B has a value in the bounded range (-1, 1), and its magnitude correlates with the signal's burstiness: an activity pattern which is completely time-independent, a Poisson process, will yield a neutral B=0, where B=1 is the most bursty signal and B=-1 corresponds to a completely regular signal with even intervals. Thus, higher values of B correspond to spiked patterns of intensive activities, while lower values of B correspond to more regularly spread activities.

This measurement captures the degree to which editors of an article concentrated their work during relatively contained time periods versus spreading them out over the entire article history, leading to a more uniform distribution of wait times. Figure 1 below compares the editing timestamps of two pairs of Wikipedia articles with a similar number of edits but different B, where each line represents one edit in the article history. Figure 1 (a) and (c) show two articles with higher B. We observe dark stacked lines as the result of intensive edits in a brief time interval. In Figure 1 (b) and (d), the articles have lower B, which represents there is only a few edits happened in a relatively long period of time.

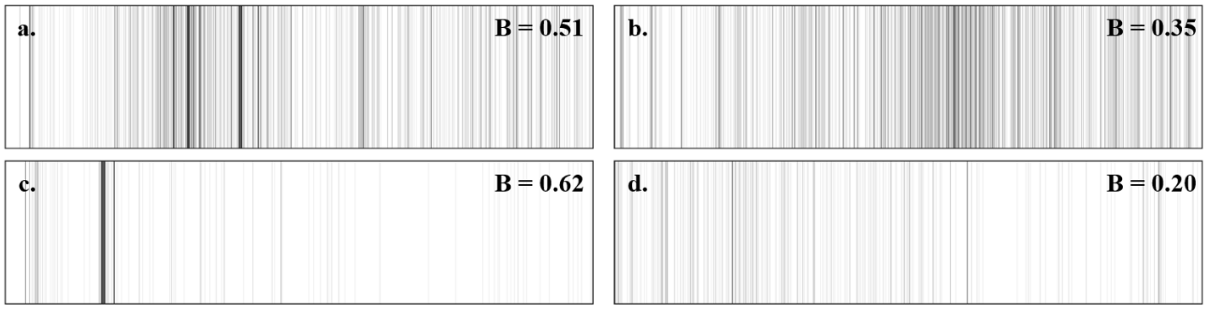

Figure 1. Editing Timestamps and Burstiness of Different Articles.

Note: Each line represents one edit in the article history. (a) NeXT page with a high burstiness B = 0.51, Total Edits = 1714; (b) Unity (game engine) page with a moderate burstiness B= 0.35, Total Edits=1770; (c) PowerBook_100 page with a high burstiness B= 0.62, Total Edits=465; (d) AirPlay page with a low burstiness B=0.199, Total Edits=457.

Relationship Between Burstiness and Article Quality

Coordination Theory

One theoretical perspective that provides a base for understanding knowledge production processes is *coordination theory* (Malone et al. 1994). Coordination is defined as a mechanism that manages dependencies between activities, so that tasks can be better allocated given limited resources (Malone et al. 1994). Coordination can be explicit or implicit (Espinosa et al. 2004). Explicit coordination refers to team members using task programming mechanisms such as schedules, plans, and procedures, or communicating verbally, in writing, virtually or face to face to allocate tasks to the appropriate person. Implicit coordination refers to team members coordinating without necessarily planning the time and nature of the activity. Implicit coordination is based on shared knowledge (Cannon-Bowers and Salas 2001) about the tasks as well as other team members. Under implicit coordination, team members dynamically adjust their behaviors based on expectations of the behaviors and needs of others.

Coordination can also be explicit or implicit with respect to time (Jackson et al. 2011; Saunders and Kim 2007; Shen et al. 2015). In conventional virtual teams, members face various temporal patterning problems including temporal distance (Espinosa et al. 2015), temporal ambiguity, conflict temporal interests and requirements, and scarcity of temporal resources (McGrath and Kelly 1986) that hinder productive collaborations. Related explicit coordination mechanisms include scheduling (deadlines), synchronization (alignment of the pace between members), and allocation of resources (specification of time to be spent on specific tasks) (Marks et al. 2001; Mcgrath 1991). Empirical studies found that these explicit coordination mechanisms have a positive effect on team performance (Massey et al. 2003; Maznevski and Chudoba 2000; Saunders et al. 2004). Yet, in the context of Wikipedia, even though editors could communicate explicitly on articles' talk pages and each other's user page, evidence shows that editors mainly use implicit forms of coordination (Kittur and Kraut 2008). Reidl and Woolley (2017) point out that in highly distributed environments, temporal patterns of coordinating may still be important. Burstiness is one way of measuring these temporal patterns of coordination: the more bursty, the less evenly spread out is the communication, and the more interpersonal synchrony may be at work.

A recent study in collective problem solving provides experimental evidence related to temporal patterns of communication (Bernstein et al. 2018). When people are allowed to interact with each other, such interactions introduce both benefits and costs. Since people know and learn from each other's solutions, the benefit is the team will have a higher average solution quality. In contrast, since they are influenced by others' solutions, individuals reduce their effort in searching for novel answers, hence the team will have a lower maximum solution quality when compared with independent problem-solving. In the experiment, subjects were randomly separated into three treatments with constant social influence (interact all the time), intermittent social influence (interact with breaks), or no social influence (no interactions). The result showed groups in the intermittent social influence treatment had the best performance. Members found the best solution frequently and also had a high mean performance score. In other words, intermittent social influence allows team members to learn from each other while maintaining a high level of individual exploration.

Social Learning Theory

A second theoretical perspective related to knowledge production is *social learning theory*, which suggests that people learn by observing others; they will begin to perform similar actions without extra incentives (Bandura and Walters 1977). The effect of social learning (anti-social or pro-social) has been generalized to many other domains and is widely used in the IS literature (D'Arcy et al. 2009; Santhanam et al. 2008; Wang et al. 2013). Social learning theory identifies four steps of the learning process: attention, that people observe behavior; retention, that people remember behavior; reproduction, that people are capable of reproducing similar actions; and motivation, that people have a motivation to perform similar actions. Wikipedia provides the necessary components for social learning to happen. Editors can observe an article's edit history, including information on who, when, and how an edit was made. Upon noticing a recent edit, editors may be prompted to act by performing another edit – out of altruism or reciprocity (Zhang and Zhu, 2011), or because they are otherwise stimulated to edit.

Bursty coordination can have a positive influence on article quality through repeated interactions. First, interactions keep people engaged. Recent studies about motivations in social network sites reveal that people feel a sense of reward when receiving responses from their friends (Burke et al. 2009, 2011). Similarly, observing someone editing the same article at about the same time could also entice the observer to further contribute. Thus, frequent contributions could trigger more contributions that result in a larger number of total contributions in a short time span. Second, interactions foster attachment to the community. The sense of belonging is one of the key motivations that encourage continued participation in online communities (Bateman et al. 2011; Fang and Neufeld 2009; Lampe et al. 2010). Therefore, repeated interactions in bursty sessions could build bonds among the editors who interact, thus increasing their motivation to contribute more (Joyce and Kraut 2006; Kittur et al. 2009). Third, interactions stimulate innovations (Hutter et al. 2011; Perks et al. 2012). During the knowledge co-production process in Wikipedia, editors build new knowledge based on previous edits of others. Thus repeated interactions in a short time window could allow editors to clarify their ideas, extend other's work, or elaborate new ideas that are based on each other's ideas.

Moreover, bursty coordination can have a positive impact on article quality through long breaks. In cognitive psychology, studies consistently found there is an incubation effect in solving creative tasks: taking a break from the unsolved problem may eventually facilitate the problem-solving process and lead to a better solution (Sio and Ormerod 2009; Smith and Blankenship 1989, 1991). This positive incubation effect is stronger when people face divergent thinking tasks or have a longer incubation period (Sio and Ormerod 2009). Several studies show that selective forgetting is likely to be the cause of incubation: when people are constrained by the initial thwarted attempt, taking a break will allow them to forget some false assumptions and start again with a fresh view of the problem (Smith 1995; Smith and Blankenship 1991). The same phenomenon could also happen in online communities. The community members are more likely to reach a temporary convergence after a bursty period of extensive editing. Then a long period of inactivity allows the members to search external resources and reconsider the current article from a fresh viewpoint.

One objection to the applicability of social learning theory to this context is that Wikipedia editors don't necessarily know each other. Their communication is mediated through the articles. But mediation may be enough. Coordination theory is based on interactions mediated through shared resources (Rezgui and Crowston 2018). Indeed, even insects coordinate without explicit collaboration; in particular, they respond to their frequency of interactions with other insects, in that way improving the quality of task allocation (Davidson et al. 2016). Thus, even if conscious processes of learning are not at work, patterns of interaction, and in particular certain frequencies of interaction, can trigger self-exciting processes that can improve quality. In sum, based on the two theoretical perspectives, we present our main hypothesis as follows:

Burstiness Hypothesis: Bursty coordination is positively associated with high article quality in Wikipedia.

Research Method

Data Description

Established in 2001, the English version of Wikipedia offers approximately 5.6 million distinct articles. We focus our empirical analysis on the Apple Inc. WikiProject, an active sub-community focused on developing information related to Apple Inc. and its products. A WikiProject refers to a group of editors who are dedicated to develop, maintain, and organize articles associated with a specific topic area. At the time of writing, the Apple Inc. WikiProject consists of 3,260 articles created by 366,294 unique contributors. We gathered the full-text history of 1,158,279 revisions of 3,260 articles in the Apple Inc. WikiProject from 2001 until October 2017 using publicly provided APIs. For each revision of an article, we recorded the editor's identity, the text of the edit, a description of the edit, and the time of the edit. We also gather the daily page view history of all the articles started from July 2015.

Dependent Variable: Information Quality

To assess article quality, we took advantage of Wikipedia's article assessment project, which has evaluated over 5,971,036 articles by peer review in a consistent and uniform manner[1]. For the period of our analysis, peer reviewers assessed all articles in Apple Inc. Project on a seven-point scale (from lowest to highest quality: Stub, Start, C, B, Good, A, Featured). This rating system is a good proxy for information quality in Wikipedia (Kane and Ransbotham 2016a; Kittur and Kraut 2008). We use this human-rated article quality score as our dependent variable.

To avoid quality changes caused by further editing after the peer reviewers' assessments, we removed all the revisions that occurred after the date that the article was evaluated. This left a total of 1,110,939 revisions. We coded the article quality using seven-point scale integers (where Stub is 1, Start is 2, ..., Featured is 7). Table 1 shows the number of articles in each quality level.

Table 1. Distribution of Article by Quality

Article Quality	Number of Articles
Stub	1267
Start	1451
C	454
B	41
Good	36
A	2
Featured	9
Total	3260

Table 1. Distribution of Article by Quality

Independent Variable: Article Burstiness

We use the burstiness measurement described before as our independent variable. We first address the question of whether the coordination pattern in Wikipedia is bursty. By definition, a set of non-bursty, time-independent edits will be a Poisson Process and yields a burstiness of 0. We calculate each article's burstiness and test whether this measurement has a mean value of zero. Figure 2 shows the empirical distribution of article burstiness, which is a bell-shaped curve. The article burstiness ranges from -0.88 to 0.92 and has a mean value of 0.283. In our sample, only 3.7% of the articles have a burstiness level less than or equal to zero. A one sample t-test produces a t-statistic of 99.81 ($p < 0.01$). Hence we can confirm that editing behavior in Wikipedia is bursty.

[1] https://en.wikipedia.org/wiki/Wikipedia:WikiProject_Wikipedia/Assessment#Quality_scale

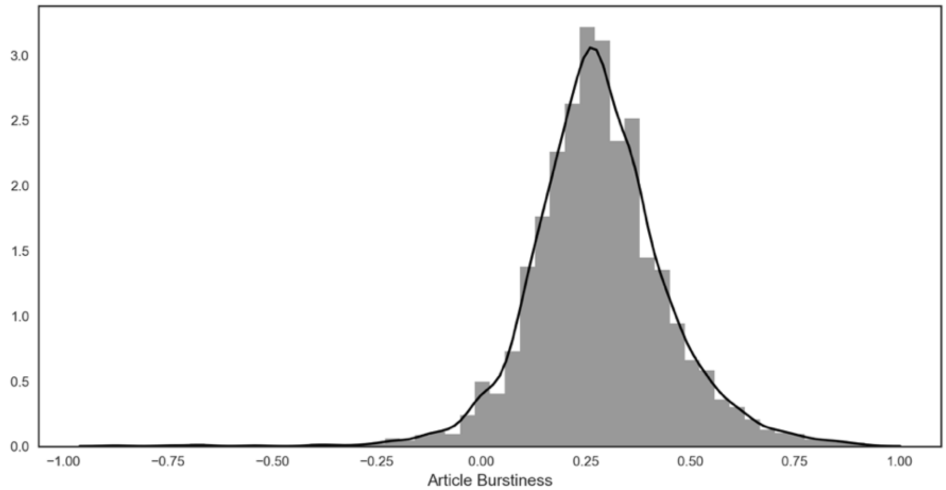

Figure 2. Article Burstiness Distribution in Wikipedia

Control Variables

Previous studies identified that content and collaboration drive knowledge quality in online communities (Kane and Ransbotham 2016a). Content studies link the characteristics of an article to its quality; characteristics include age, length, readability, the number of edits (Aaltonen and Seiler 2016; Blumenstock 2008; Okoli et al. 2012; Stvilia et al. 2008), and position in the network (Kane and Ransbotham 2016a). Collaboration-based studies explain the quality of the collaboration output using the characteristics of the article's contributors. Factors at work include the experience of editors (Halfaker et al. 2009), roles of editors (Liu and Ram 2011), and group composition (Arazy et al. 2011; Ransbotham and Kane 2011; Ren et al. 2016).

length, number of distinct contributors, readability
As in previous studies (Kane and Ransbotham 2016a), we controlled for the following variables: article age, article length, number of distinct contributors, readability, section depth, number of external references, number of internal links, number of multimedia content and anonymity. Table 2 shows the definitions of these covariates.

Table 2. Variables Definitions

Variable Name	Description
Age	Article age since it was first created (in days)
Length	Article length (in characters)
Total Edits	Number of total edits in the article
Topic Popularity	Average daily page view
Readability	Automated Readability Index (ARI)
Section Depth	Number of sections in the article
Multimedia Content	Number of images in the article
Internal Links	Number of links to other Wikipedia articles
External Reference	Number of references
Distinct Contributors	Number of distinct contributors
Anonymity	Percentage of anonymous contributors
Burstiness	Article burstiness
Quality Rating	Seven-point scale quality rated by Wikipedia peers

Table 2. Variables Definitions

Age: Article maturity influences quality (Kane and Ransbotham, 2016; Kittur and Kraut, 2008), since the longer an article exists, the more editors may contribute to it, thus will have higher article quality. We control for this effect by adding article age into the regression.

Length: Article length also relates to quality, since longer articles may be appearing to be more informative, and more informative articles may be recognized as being of higher quality. Previous studies showed that article length could be a significant predictor of article quality (Aaltonen and Seiler, 2015; Blumenstock, 2008). We measure article length using a log transform of the number of characters in the article.

Total Edits: Article total edits influence quality (Stvilia et al., 2008), since more edits are a result of more work having been done on the page. We control for this effect using the number of total edits.

Topic Popularity: An article's topic popularity also influences quality (Kane and Ransbotham, 2016; Zhang and Zhu, 2011), since more popular topics may attract more people to contribute. We use the log transform of the article's average daily page view as a proxy for topic popularity.

Readability: Article readability also influences quality. A more sophisticated writing style may influence article quality, either because it is perceived as being more authoritative or, conversely, less accessible. We control for the article readability using the Automated Readability Index (ARI) (Senter and Smith, 1967), which is a standard measurement used to capture the understandability of English text. The lower the ARI score, the more accessible the article. The ARI is calculated as:

$$\text{ARI} = \left(\frac{4.71 \times letters}{words} + \frac{0.5\ \times words}{sentences} - 21.43\right)/1000$$

Section Depth: The article structure influences quality (Stvilia et al., 2008), since the section title in a Wikipedia article can be informative and leads readers to the right location on the page. We control for this using the number of sections. Since the number of sections is related to the length, we divide it by article length, as was done in previous studies (Kane and Ransbotham, 2016).

Multimedia Content, Internal Links, External References: According to Wikipedia Quality Rating Criteria[2], a high-quality article requires reliable sources, appropriate in-line citations, images, and other media content Stvilia et al. (2008). We control the number of multimedia content elements, internal links, and external references.

Distinct Contributors: The number of distinct contributors is associated with the quality of the page (Kittur and Kraut, 2008). We include the number of distinct contributors in the model.

Anonymity: The contributors' anonymity is also related to quality (Kane and Ransbotham, 2016). People can make edits whether they log into the Wikipedia system or not. We control for the influence of anonymity using the percentage of anonymous editors.

The article topic may also affect how people coordinate. Therefore, we control for different article topics using their categories. We first retrieve all categories and their subcategories follow the category hierarchy of the Apple Inc. WikiProject3. For each article, we define a set of dummy variables that indicate whether the article belongs to a topic category. For instance, if an article belongs to the "Apple Inc. hardware" category or one of its subcategories, the associated variable will be 1, otherwise 0. We controlled for five categories that are most frequently used (hardware, software, people, products, and platforms) and aggregated articles that don't belong to any of them into "others".

Based on the research hypotheses presented above, we set up the following article level econometric model:

$$Q_i = \beta_0 + \beta_1 B_i + \beta_n C_i$$

[2] https://en.wikipedia.org/wiki/Wikipedia:WikiProject_Wikipedia/Assessment

[3] https://en.wikipedia.org/wiki/Portal:Apple_Inc.

In this model, information quality (Q_i) depends on article burstiness (B_i) and control covariates (vector C_i). Since our dependent variable, information quality, is ordered and categorical, we used an Ordered Logistic Regression to study the relationship between burstiness and quality. To make the regressor's coefficient comparable, we also standardize all the variables to have a mean of zero and a standard deviation of one.

Results

Main Regression

We presented the summary statistics and correlations between the variables in Table 3.

Table 3. Summary Statistics and Correlation of the Variables

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Age	1633.806	1055.470	1.00												
2. Length	1092.085	1402.733	0.32	1.00											
3. Total Edits	340.081	1368.412	0.14	0.38	1.00										
4. Topic Popularity	147.897	645.571	0.13	0.47	0.34	1.00									
5. Readability	0.019	0.008	-0.02	-0.01	0.05	0.04	1.00								
6. Section Depth	0.001	0.002	0.04	0.16	0.06	0.06	0.02	1.00							
7.Multimedia Content	0.001	0.002	-0.04	-0.18	-0.06	-0.07	0.02	-0.07	1.00						
8. Internal Links	0.041	0.029	-0.04	-0.24	-0.02	-0.03	0.28	-0.03	0.15	1.00					
9.External Reference	0.004	0.006	-0.07	0.13	0.12	0.08	0.30	0.04	-0.12	-0.07	1.00				
10.Distinct Contributors	112.360	272.284	0.33	0.68	0.53	0.60	0.04	0.11	-0.09	-0.06	0.13	1.00			
11. Anonymity (%)	0.293	0.165	0.29	0.43	0.24	0.17	-0.05	0.17	-0.09	-0.09	0.06	0.42	1.00		
12. Burstiness	0.283	0.162	0.11	0.42	0.21	0.21	0.01	0.14	-0.18	-0.16	0.19	0.33	0.36	1.00	
13. Quality Rating	1.825	0.852	0.37	0.64	0.27	0.24	0.03	0.14	-0.20	-0.22	0.17	0.43	0.39	0.41	1.00
N	3260														

Table 3. Summary Statistics and Correlation of the Variables

The Ordered Logistic Regression and OLS estimation results are shown in Table 4. In Model 1 and Model 3, we find both models' predictive power increased after adding article burstiness into the regression. Model 2 presents the Ordered Logistic Regression result. We find the coefficient of article burstiness is positive and significant, with an odds ratio equal to 1.177[4]. This means when other variables in the model are held constant, a one standard deviation increase in burstiness increases the odds of a higher quality article by a factor of 1.177. Compared with the control variables, burstiness is more effective than several traditional predictors, such as section depth, multimedia content, internal links, and external reference. To check the robustness of the result, we also run a standard OLS regression (Model 4), which also provides a similar result. Burstiness is still positive (β=0.056) and significant ($p<0.01$). This result supports our hypothesis and burstiness is a significant predictor of article quality.

Table 4. Regression Results: Effect of Burstiness on Article Quality.

	Ordered Logistic		OLS	
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Burstiness		0.163***		0.056***
		(0.053)		(0.012)

4 calculated using e^0.163

Age (in day)	0.337***	0.362***	0.086***	0.094***
	(0.046)	(0.048)	(0.013)	(0.013)
Length (in char)	2.421***	2.377***	0.410***	0.398***
	(0.148)	(0.149)	(0.037)	(0.037)
Total Edits	0.624***	0.547***	0.152***	0.119***
	(0.127)	(0.127)	(0.035)	(0.033)
Topic Popularity	0.231***	0.248***	0.042**	0.051***
	(0.074)	(0.074)	(0.018)	(0.018)
Readability (ARI index)	0.398***	0.386***	0.082***	0.080***
	(0.113)	(0.104)	(0.022)	(0.021)
Section Depth	-0.071	-0.072	-0.021**	-0.022**
	(0.048)	(0.049)	(0.010)	(0.010)
Multimedia Content	-0.043	-0.035	-0.017	-0.014
	(0.034)	(0.033)	(0.012)	(0.012)
Internal Links	-0.042	-0.028	0.142***	0.146***
	(0.085)	(0.086)	(0.034)	(0.033)
External Reference	0.062	0.058	0.039	0.036
	(0.087)	(0.087)	(0.032)	(0.032)
Distinct Contributors	-0.230***	-0.238***	-0.071***	-0.071***
	(0.062)	(0.063)	(0.023)	(0.023)
Anonymity	-0.338***	-0.328***	-0.077***	-0.075***
	(0.065)	(0.064)	(0.014)	(0.013)
Constant			1.825***	1.825***
			(0.010)	(0.010)
Page Topic Fixed Effect	Yes	Yes	Yes	Yes
Observations	3,260	3,260	3,260	3,260
$\chi^2(18)$	1247.490	1263.010		
Log Likelihood	-2170.563	-2165.612		
Pseudo R-squared	0.410	0.411		
R-squared			0.570	0.573

Table 4. Regression Results: Effect of Burstiness on Article Quality.

Note: The sample includes 1,110,939 revisions of 3,260 articles from February 2001 to October 2017. All variables are standardized. *** p<0.01, ** p<0.05, * p<0.1

Causal Interpretation through Instrumental Variables

In both the Ordered Logistic and OLS models, we find the effect of article burstiness on article quality is positive and significant. This suggests that successful online knowledge co-production follows a bursty temporal pattern, that contains shot activity bursts followed by long breaks. However, the estimation in Table 4 may have endogeneity issues. The omitted variables may bias the coefficient of our main independent variable. There might also be the issue of simultaneity, i.e. the burstiness of an article can also be influenced by the quality of the article. To argue for a causal interpretation of our results, we introduce two instrumental variables (IVs) for article burstiness. Suitable instrumental variables should be those that exogenously relate to article burstiness, but have no theoretical reasons to affect information quality. The variation of an instrumental variable induces variation in the proposed cause (article burstiness), and we may estimate its effect on information quality.

Our first instrumental variable is the *shortest path from famous deaths* to the focal page in our sample. The hypothesis is that famous death will cause a sudden traffic increase in the celebrity's biography page (Goldenberg 2018). Some editors will follow the hyperlinks to our focal page and decide to make an edit. In this way, the famous deaths will increase the burstiness of the articles that are linked from the biography pages but have no theoretical reason to directly affect article quality of the focal page. At the same time, pages with shorter shortest paths will be more easily influenced by famous deaths because it is more likely for editors to reach these pages following the hyperlinks. To construct this IV, we first collect all the 123,983 famous deaths pages under "Wikipedia deaths" category and their page link information from 2001 to 2018. To ensure that the instrument also meets the exclusion restriction, and would not be likely to affect information quality, we removed all the celebrities (including employees, executives, directors, and ex-employees) whose biography is part of the Apple Inc. WikiProject. This left us with 123,954 famous deaths pages. Then, for each article A_i in our sample, we count the shortest path required from the closest famous death to A_i and use it as our first instrument.

Our second instrumental variable is the *average burstiness of related articles* that are pointing to the focal page. This instrument also strips out the variation in burstiness that are attributable to the particular articles. The rationale is that if editors of those related articles edit in a bursty way (due to either external events or editing habits), some of them will follow the hyperlinks to the focal page and influence its burstiness. To ensure those pages do not contain any information related to the focal page, we rule out all the pages that are part of the Apple Inc. WikiProject. Thus, this instrument measures the average burstiness of 30 related pages that are outside the Apple Inc. project and point to the focal page.

Table 5 reports the IV estimators obtained by Generalized Method of Moments (GMM) regression. The result shows that the positive effect of burstiness on article quality holds when using two exogenous instrumental variables. For the shortest path instrument, the under-identification test (Kleibergen-Paap LM statistic = 18.78, $p<0.01$) and the weak-instrument test (Cragg-Donald Wald statistic is 20.807, which exceeds the critical value of 16.38 for a maximal size of 10% for the Wald test in 2SLS) show that the model is well identified. For the average burstiness instrument, the result of the under-identification test (Kleibergen-Paap LM statistic = 13.809, $p<0.01$) and the weak-instrument test (Cragg-Donald Wald statistic = 19.054) show consistent result that the second IV regression model is also well identified.

Table 5. IV GMM Regression Results.

Variable	IV Reg: Shortest Path Model 1	IV Reg: Average Burstiness Model 2
Burstiness	0.246*	0.449**
	(0.147)	(0.185)
Age (in day)	0.123***	0.150***
	(0.024)	(0.029)
Length (in char)	0.369***	0.321***
	(0.048)	(0.059)
Total Edits	-0.007	-0.121
	(0.092)	(0.108)
Topic Popularity	0.093***	0.119***
	(0.028)	(0.032)
Readability (ARI index)	0.074***	0.065***
	(0.021)	(0.023)
Section Depth	-0.025**	-0.026*
	(0.012)	(0.014)
Multimedia Content	-0.000	0.014
	(0.014)	(0.016)
Internal Links	0.152***	0.168***
	(0.035)	(0.038)

External Reference	0.024	0.011
	(0.035)	(0.036)
Distinct Contributors	-0.074***	-0.077***
	(0.024)	(0.026)
Anonymity	-0.068***	-0.058***
	(0.016)	(0.019)
Constant	1.821***	1.822***
	(0.010)	(0.012)
Observations	3,158	3,158
R-squared	0.539	0.432

Table 5. IV GMM Regression Results.

Note: The sample includes 3,158 articles from February 2001 to October 2017. All variables are standardized. *** p<0.01, ** p<0.05, * p<0.1

Conclusion and Future Research

Wikipedia is an online community that builds a socially important artifact, an encyclopedia. There is no explicit hierarchical control of the editors (Ren et al. 2016), there is a great deal of fluidity in terms of membership (Ransbotham and Kane 2011), and there are no monetary incentives to reward good contributions (Chen et al. 2017). There are good reasons to study how such communities coordinate in producing high quality knowledge. In this study, we look at an important aspect of collective work: time. Specifically, we explore the temporal dynamics of knowledge production and how the temporal pattern of editing is associated with article quality. We draw on coordination theory and social learning theory to formulate our hypothesis and test it on a comprehensive Wikipedia dataset. We adopted instrumental variable techniques to rule out potential endogeneity issues.

We find the editing activities in the Wikipedia community follow a bursty temporal pattern that contains shot activity bursts followed by long breaks. Moreover, we show that article burstiness has a strong positive effect on article quality when controlling for other factors (Kane and Ransbotham 2016a). Our findings suggest there may be a new kind of implicit coordination at work: editors may be responding to the frequency of recent edits by others. Thus recent edits may excite more edits, creating a cascade of contributions that lead to the high quality of articles. The activity bursts are important for members to coordinate, as they encourage more interpersonal synchrony. The long breaks are also crucial, allowing editors to conceptualize current work and search for new ways of expressing their ideas.

Our results suggest that the quality of pages can be improved by strengthening this implicit coordination mechanism. For example, Wikipedia could program its notification system to promote articles that recently experienced a bursty session; this might bring even more people to the article. Platforms can also highlight recently changed content so as to trigger more reactions. As more sophisticated recommender systems are applied to Wikipedia (Cosley et al. 2007; Warncke-Wang et al. 2013), measuring the temporal characteristics of article pages may help such tools to make better suggestions to the human editors. Moreover, bots can be designed to serve as specialized co-editors that respond in a way that triggers further bursty edits by human editors. While bots often do serve to remind editors of missing items, more sophisticated bots might suggest information that could be converted into article content (Zheng et al. 2019). In sum, what is learned from the temporal patterns that lead to higher quality articles can be applied to the design of social and artificial systems that increase the productivity of human workers.

References

Aaltonen, A., and Seiler, S. 2016. "Cumulative Growth in User-Generated Content Production: Evidence from Wikipedia," Management Science (62:7), INFORMS, pp. 2054–2069.

Aggarwal, I., Woolley, A. W., Chabris, C. F., and Malone, T. W. 2019. “The Impact of Cognitive Style Diversity on Implicit Learning in Teams,” Frontiers in Psychology (10), p. 112.

Arazy, O., Nov, O., Patterson, R., and Yeo, L. 2011. “Information Quality in Wikipedia: The Effects of Group Composition and Task Conflict,” Journal of Management Information Systems (27:4), Routledge, pp. 71–98.

Bandura, A., and Walters, R. H. 1977. Social Learning Theory, (Vol. 1), Prentice-hall Englewood Cliffs, NJ.

Barabási, A.-L. 2005. “The Origin of Bursts and Heavy Tails in Human Dynamics,” Nature (435:7039), pp. 207–211.

Barlow, J. B., and Dennis, A. R. 2016. “Not As Smart As We Think: A Study of Collective Intelligence in Virtual Groups,” Journal of Management Information Systems (33:3), Routledge, pp. 684–712.

Bateman, P. J., Gray, P. H., and Butler, B. S. 2011. “Research Note—The Impact of Community Commitment on Participation in Online Communities,” Information Systems Research (22:4), INFORMS, pp. 841–854.

Bernstein, E., Shore, J., and Lazer, D. 2018. “How Intermittent Breaks in Interaction Improve Collective Intelligence,” Proceedings of the National Academy of Sciences of the United States of America (115:35), National Acad Sciences, pp. 8734–8739.

Blumenstock, J. E. 2008. Automatically Assessing the Quality of Wikipedia Articles.

Bolici, F., Howison, J., and Crowston, K. 2016. “Stigmergic Coordination in FLOSS Development Teams: Integrating Explicit and Implicit Mechanisms,” Cognitive Systems Research (38), pp. 14–22.

Borges, M. R. S., Pino, J. A., Fuller, D. A., and Salgado, A. C. 1999. “Key Issues in the Design of an Asynchronous System to Support Meeting Preparation,” Decision Support Systems (27:3), Elsevier, pp. 269–287.

Burke, M., Kraut, R., and Marlow, C. 2011. “Social Capital on Facebook: Differentiating Uses and Users,” in Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI ’11, New York, NY, USA: ACM, pp. 571–580.

Burke, M., Marlow, C., and Lento, T. 2009. “Feed Me: Motivating Newcomer Contribution in Social Network Sites,” in Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI ’09, New York, NY, USA: ACM, pp. 945–954.

Cannon-Bowers, J. A., and Salas, E. 2001. “Reflections on Shared Cognition,” Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior (22:2), Wiley Online Library, pp. 195–202.

Chen, W., Wei, X., and Zhu, K. 2017. “Engaging Voluntary Contributions in Online Communities: A Hidden Markov Model,” MIS Quarterly, Management Information Systems Research Center, University of Minnesota, March 2.

Colazo, J. A., and Fang, Y. 2010. “Following the Sun: Temporal Dispersion and Performance in Open Source Software Project Teams,” Journal of the Association for Information Systems (11:11), Association for Information Systems, pp. 684.

Cosley, D., Frankowski, D., Terveen, L., and Riedl, J. 2007. “SuggestBot: Using Intelligent Task Routing to Help People Find Work in Wikipedia,” in Proceedings of the 12th International Conference on Intelligent User Interfaces, IUI ’07, New York, NY, USA: ACM, pp. 32–41.

D’Arcy, J., Hovav, A., and Galletta, D. 2009. “User Awareness of Security Countermeasures and Its Impact on Information Systems Misuse: A Deterrence Approach,” Information Systems Research (20:1), INFORMS, pp. 79–98.

Davidson, J. D., Arauco-Aliaga, R. P., Crow, S., Gordon, D. M., and Goldman, M. S. 2016. “Effect of Interactions between Harvester Ants on Forager Decisions,” Frontiers in Ecology and Evolution (4), Frontiers, p. 115.

Espinosa, A., Lerch, F. J., Kraut, R. E., Salas, E., and Fiore, S. M. 2004. “Explicit vs. Implicit Coordination Mechanisms and Task Dependencies: One Size Does Not Fit All,” Team Cognition: Understanding the Factors That Drive Process and Performance. American Psychological Association, Washington, DC, academia.edu, pp. 107–129.

Espinosa, J. A., Nan, N., and Carmel, E. 2015. “Temporal Distance, Communication Patterns, and Task Performance in Teams,” Journal of Management Information Systems (32:1), Routledge, pp. 151–191.

Espinosa, J. A., Slaughter, S. A., Kraut, R. E., and Herbsleb, J. D. 2007. “Team Knowledge and Coordination in Geographically Distributed Software Development,” Journal of Management Information Systems (24:1), Routledge, pp. 135–169.

Fang, Y., and Neufeld, D. 2009. “Understanding Sustained Participation in Open Source Software Projects,” Journal of Management Information Systems (25:4), Routledge, pp. 9–50.

Faraj, S., Jarvenpaa, S. L., and Majchrzak, A. 2011. “Knowledge Collaboration in Online Communities,” Organization Science (22:5), INFORMS, pp. 1224–1239.

Faraj, S., Kudaravalli, S., and Wasko, M. 2015. “Leading Collaboration in Online Communities,” MIS Quarterly (39:2), Management Information Systems Research Center, University of Minnesota.

Goh, K. I., and Barabási, A. L. 2008. “Burstiness and Memory in Complex Systems,” EPL (81:4), IOP Publishing, p. 48002.

Goldenberg, R. (n.d.). “Life After Death on Wikipedia,” The Pudding. (https://pudding.cool/2018/08/wiki-death/, accessed August 2018).

Halfaker, A., Kittur, A., Kraut, R., and Riedl, J. 2009. “A Jury of Your Peers: Quality, Experience and Ownership in Wikipedia,” in Proceedings of the 5th International Symposium on Wikis and Open Collaboration, WikiSym ’09, New York, NY, USA: ACM, pp. 15:1–15:10.

Heylighen, F. 2016. “Stigmergy as a Universal Coordination Mechanism I: Definition and Components,” Cognitive Systems Research (38), Elsevier, pp. 4–13.

Howison, J., and Crowston, K. 2014. “Collaboration Through Open Superposition: A Theory of the Open Source Way,” MIS Quarterly (38:1), Management Information Systems Research Center, University of Minnesota, pp. 29–50.

Hutter, K., Hautz, J., Füller, J., Mueller, J., and Matzler, K. 2011. “Communitition: The Tension between Competition and Collaboration in Community-Based Design Contests,” Creativity and Innovation Management (20:1), Wiley Online Library, pp. 3–21.

Jackson, S. J., Ribes, D., Buyuktur, A., and Bowker, G. C. 2011. “Collaborative Rhythm: Temporal Dissonance and Alignment in Collaborative Scientific Work,” in Proceedings of the ACM 2011 Conference on Computer Supported Cooperative Work, CSCW ’11, New York, NY, USA: ACM, pp. 245–254.

Jarvenpaa, S. L., and Majchrzak, A. 2010. “Research Commentary—Vigilant Interaction in Knowledge Collaboration: Challenges of Online User Participation Under Ambivalence,” Information Systems Research (21:4), INFORMS, pp. 773–784.

Joyce, E., and Kraut, R. E. 2006. “Predicting Continued Participation in Newsgroups,” Journal of Computer-Mediated Communication: JCMC (11:3), Narnia, pp. 723–747.

Kane, G. C., Johnson, J., and Majchrzak, A. 2014. “Emergent Life Cycle: The Tension Between Knowledge Change and Knowledge Retention in Open Online Coproduction Communities,” Management Science (60:12), INFORMS, pp. 3026–3048.

Kane, G. C., and Ransbotham, S. 2016a. “Research Note—Content and Collaboration: An Affiliation Network Approach to Information Quality in Online Peer Production Communities,” Information Systems Research (27:2), INFORMS, pp. 424–439.

Kane, G. C., and Ransbotham, S. 2016b. “Content as Community Regulator: The Recursive Relationship Between Consumption and Contribution in Open Collaboration Communities,” Organization Science (27:5), INFORMS, pp. 1258–1274.

Kittur, A., and Kraut, R. E. 2008. “Harnessing the Wisdom of Crowds in Wikipedia: Quality Through Coordination,” in Proceedings of the 2008 ACM Conference on Computer Supported Cooperative Work, CSCW ’08, New York, NY, USA: ACM, pp. 37–46.

Kittur, A., Pendleton, B., and Kraut, R. E. 2009. “Herding the Cats: The Influence of Groups in Coordinating Peer Production,” in Proceedings of the 5th International Symposium on Wikis and Open Collaboration, WikiSym ’09, New York, NY, USA: ACM, pp. 7:1–7:9.

Lampe, C., Wash, R., Velasquez, A., and Ozkaya, E. 2010. “Motivations to Participate in Online Communities,” in Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI ’10, New York, NY, USA: ACM, pp. 1927–1936.

Liu, J., and Ram, S. 2011. “Who Does What: Collaboration Patterns in the Wikipedia and Their Impact on Article Quality,” ACM Trans. Manage. Inf. Syst. (2:2), New York, NY, USA: ACM, pp. 11:1–11:23.

Majchrzak, A., and Malhotra, A. 2016. “Effect of Knowledge-Sharing Trajectories on Innovative Outcomes in Temporary Online Crowds,” Information Systems Research (27:4), INFORMS, pp. 685–703.

Malone, T. W., Malone, T. W., and Crowston, K. 1994. “The Interdisciplinary Study of Coordination,” ACM Comput. Surv. (26:1), New York, NY, USA: ACM, pp. 87–119.

Marks, M. A., Mathieu, J. E., and Zaccaro, S. J. 2001. “A Temporally Based Framework and Taxonomy of Team Processes,” AMRO (26:3), Academy of Management, pp. 356–376.

Maruping, L. M., and Magni, M. 2015. “Motivating Employees to Explore Collaboration Technology in Team Contexts,” MIS Quarterly (39:1), Management Information Systems Research Center, University of Minnesota.

Massey, A. P., Montoya-Weiss, M. M., & Hung, Y. T. 2003. "Because Time Matters: Temporal Coordination in Global Virtual Project Teams," Journal of Management Information Systems (19:4), , pp.129-155.

Massey, A. P., and Montoya-Weiss, M. M. 2006. "Unraveling the Temporal Fabric of Knowledge Conversion: A Model of Media Selection and Use," MIS Quarterly (30:1), Management Information Systems Research Center, University of Minnesota, pp. 99–114.

Maznevski, M. L., and Chudoba, K. M. 2000. "Bridging Space Over Time: Global Virtual Team Dynamics and Effectiveness," Organization Science (11:5), INFORMS, pp. 473–492.

Mcgrath, J. E. 1991. "Time, Interaction, and Performance (TIP): A Theory of Groups," Small Group Research (22:2), SAGE Publications Inc, pp. 147–174.

McGrath, J. E., and Kelly, J. R. 1986. Time and Human Interaction: Toward a Social Psychology of Time, Guilford Press.

Montoya-Weiss, M. M., Massey, A. P., and Song, M. 2001. "Getting It Together: Temporal Coordination and Conflict Management in Global Virtual Teams," Academy of Management Journal (44:6), Academy of Management, pp. 1251–1262.

Ocker, R., Hiltz, S. R., Turoff, M., and Fjermestad, J. 1995. "The Effects of Distributed Group Support and Process Structuring on Software Requirements Development Teams: Results on Creativity and Quality," Journal of Management Information Systems (12:3), Routledge, pp. 127–153.

Okoli, C., Mehdi, M., Mesgari, M., Nielsen, F., and Lanamäki, A. 2012. The People's Encyclopedia under the Gaze of the Sages: A Systematic Review of Scholarly Research on Wikipedia.

O'Leary, M. B., and Cummings, J. N. 2007. "The Spatial, Temporal, and Configurational Characteristics of Geographic Dispersion in Teams," MIS Quarterly, Management Information Systems Research Center, University of Minnesota, pp. 433–452.

Perks, H., Gruber, T., and Edvardsson, B. 2012. "Co-Creation in Radical Service Innovation: A Systematic Analysis of Microlevel Processes," Journal of Product Innovation Management (29:6), Wiley Online Library, pp. 935–951.

Ransbotham, S., and Kane, G. C. (jerry). 2011. "Membership Turnover and Collaboration Success in Online Communities: Explaining Rises and Falls from Grace in Wikipedia," MIS Quarterly (35:3), Management Information Systems Research Center, University of Minnesota, pp. 613–627.

Rasters, G., Vissers, G., and Dankbaar, B. 2002. "An Inside Look: Rich Communication Through Lean Media in a Virtual Research Team," Small Group Research (33:6), SAGE Publications Inc, pp. 718–754.

Ren, Y., Chen, J., and Riedl, J. 2016. "The Impact and Evolution of Group Diversity in Online Open Collaboration," Management Science (62:6), INFORMS, pp. 1668–1686.

Rezgui, A., and Crowston, K. 2018. "Stigmergic Coordination in Wikipedia," in Proceedings of the 14th International Symposium on Open Collaboration, OpenSym '18, New York, NY, USA: ACM, pp. 19:1–19:12.

Rico, R., Sánchez-Manzanares, M., Gil, F., and Gibson, C. 2008. "Team Implicit Coordination Processes: A Team Knowledge–Based Approach," AMRO (33:1), Academy of Management, pp. 163–184.

Riedl, C., and Woolley, A. W. 2017. "Teams vs. Crowds: A Field Test of the Relative Contribution of Incentives, Member Ability, and Emergent Collaboration to Crowd-Based Problem Solving Performance," Academy of Management Discoveries, journals.aom.org.

Santhanam, R., Sasidharan, S., and Webster, J. 2008. "Using Self-Regulatory Learning to Enhance E-Learning-Based Information Technology Training," Information Systems Research (19:1), INFORMS, pp. 26–47.

Saunders, C., and Kim, J. 2007. "Editor's Comments: Perspectives on Time," MIS Quarterly (31:4), Management Information Systems Research Center, University of Minnesota, Iii–xi.

Saunders, C., Van Slyke, C., and Vogel, D. R. 2004. "My Time or Yours? Managing Time Visions in Global Virtual Teams," Academy of Management Perspectives (18:1), Academy of Management, pp. 19–37.

Shen, Z., Lyytinen, K., and Yoo, Y. 2015. "Time and Information Technology in Teams: A Review of Empirical Research and Future Research Directions," European Journal of Information Systems (24:5), Taylor & Francis, pp. 492–518.

Sio, U. N., and Ormerod, T. C. 2009. "Does Incubation Enhance Problem Solving? A Meta-Analytic Review," Psychological Bulletin (135:1), psycnet.apa.org, pp. 94–120.

Smith, S. M., and Blankenship, S. E. 1989. "Incubation Effects," Bulletin of the Psychonomic Society (27:4), Springer, pp. 311–314.

Smith, S. M., and Blankenship, S. E. 1991. "Incubation and the Persistence of Fixation in Problem Solving," The American Journal of Psychology (104:1), JSTOR, pp. 61–87.
Stvilia, B., Twidale, M. B., Smith, L. C., and Gasser, L. 2008. "Information Quality Work Organization in Wikipedia," Journal of the American Society for Information Science. American Society for Information Science (59:6), Wiley Online Library, pp. 983–1001.
Wang, Y., Meister, D. B., and Gray, P. H. 2013. "Social Influence and Knowledge Management Systems Use: Evidence from Panel Data," MIS Quarterly (37:1), Management Information Systems Research Center, University of Minnesota, pp. 299–313.
Warkentin, M. E., Sayeed, L., and Hightower, R. 1997. "Virtual Teams versus Face-to-Face Teams: An Exploratory Study of a Web-Based Conference System," Decision Sciences (28:4), Wiley Online Library, pp. 975–996.
Warncke-Wang, M., Cosley, D., and Riedl, J. 2013. "Tell Me More: An Actionable Quality Model for Wikipedia," Proceedings of the 9th International Symposium on Open Collaboration. ACM, 2013.
Woolley, A. W., Aggarwal, I., and Malone, T. W. 2015. "Collective Intelligence and Group Performance," Current Directions in Psychological Science (24:6), SAGE Publications Inc, pp. 420–424.
Woolley, A. W., Chabris, C. F., Pentland, A., Hashmi, N., and Malone, T. W. 2010. "Evidence for a Collective Intelligence Factor in the Performance of Human Groups," Science (330:6004), pp. 686–688.
Yamauchi, Y., Yokozawa, M., Shinohara, T., and Ishida, T. 2000. "Collaboration with Lean Media: How Open-Source Software Succeeds," in Proceedings of the 2000 ACM Conference on Computer Supported Cooperative Work, CSCW '00, New York, NY, USA: ACM, pp. 329–338.
Zhang, X. (michael), and Zhu, F. 2011. "Group Size and Incentives to Contribute: A Natural Experiment at Chinese Wikipedia," The American Economic Review (101:4), pp. 1601–1615.
Zheng, L. (nico), Albano, C. M., Vora, N. M., Mai, F., and Nickerson, J. V. 2019. "The Roles Bots Play in Wikipedia," Proc. ACM Hum.-Comput. Interact. (3:CSCW).