Technical Report 1318

Language and Social Dynamics

James W. Pennebaker
Cindy K. Chung
University of Texas at Austin

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Authorized and approved for distribution:

Michelle Sams

MICHELLE SAMS, Ph.D.
Director

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14. ABSTRACT *(Maximum 200 words)*:

Some of the smallest words that people use in everyday life can reveal basic social and psychological processes. A series of studies were conducted to explore how basic group processes could be revealed by people's use of pronouns, articles, prepositions, and other function words. Through the analysis of transcripts of live and virtual working groups, informal groups, close relationships, and emails, it was possible to identify the relative status of group members as well as identify effective communication patterns. In addition, the computerized text methods were developed in ways that can capture near-real-time social processes in English and other languages. Implications of the findings include the ability to characterize group dynamics by the mere measurement of the words used in groups – a form of remote sensing. In addition, the studies point to ways of automatically shaping group dynamics in education or training so that they work more effectively. Finally, the current research provides a methodology to track real world group processes as they occur.

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group dynamics, social psychology, leadership, linguistics

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James W. Pennebaker
Cindy K. Chung
University of Texas at Austin

Foundational Science Research Unit
Gerald F. Goodwin, Chief

U.S. Army Research Institute for the Behavioral and Social Sciences
6000 6th Street, Bldg. 1464
Fort Belvoir, VA 22060

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LANGUAGE AND SOCIAL DYNAMICS

EXECUTIVE SUMMARY

Research Requirement:

Language is the basic currency of most social activity. To truly understand the dynamics of groups, researchers must track what different group members say to each other over time. Historically, such a task has been almost impossible due to the inability to efficiently analyze large samples of spoken text. In the last decade, advancements in computer technology have revolutionized our ability to analyze natural language in ways that can reveal how groups and members of groups are thinking, relating to each other, and behaving. The goal of the current contract was to use recent text analysis methods to better understand group identity, engagement, and roles and, at the same time, to refine text analytic tools.

Natural language can be analyzed by *what* people are saying and *how* they are saying it. Most artificial intelligence research focuses on the "what" question – that is, the content of language. The "how" question explores markers of linguistic style. Much of language style is revealed in a group of stealth-like words called *function words* – pronouns, prepositions, articles, auxiliary verbs, and a handful of other categories. These commonly-used but rarely noticed words are integral in shaping communication between people. Indeed, analyses of these words reveal that they are related to a host of social and psychological processes.

The current project examined function words to better understand three general dimensions of group dynamics. First, we sought to determine whether there are language markers of group identity. For example, do groups that use *we*-words (e.g., we, us, our) at higher rates have a greater sense of group identity and work more effectively together? Next, we validated a new measure of *language style matching* (LSM) or function word synchrony by group members in an attempt to identify group cohesiveness and productivity. Finally, we explored how the use of function words by group members reflects their roles. Specifically, to what degree can we identify status hierarchies, leaders, and subordinates through the ways group members talk with one another?

In parallel to these research questions, we developed a large number of new natural language research tools that are easy to use, Internet-friendly, and flexible enough to analyze large data sets across multiple languages. At the same time, we have been able to create an impressive corpus of hundreds of thousands of text files that include online chats, Internet bulletin board messages, telephone calls, face-to-face conversations, blog posts, essays, online ads, books, lyrics, poems, speeches, and other text samples in English, Spanish, Arabic, and other languages. Finally, we have been developing a range of new statistical methods that measures language style matching, provides real time online feedback about people's language use, and can extract language themes automatically.

Procedures:

With recent advancements in computerized text analytic tools, we now are able to efficiently measure language within and across groups, and in groups interacting face-to-face (FTF) or by computer-mediated communication (CMC). Using the computerized text analysis tool *Linguistic Inquiry and Word Count* (LIWC), we are studying language style in two ways. The first is to compare the actual rates of function word use by different people in a group or by different groups as a unit. For example, we can determine if successful groups use language differently from unsuccessful ones. The second is to examine how each person in a given group matches his or her function word rates with the other members of the group. This language synchrony measure is referred to as language style matching, or LSM. By isolating each person's ability to synchronize with others, LSM provides a unique look at social competence in a complex environment.

Findings:

Our various projects have produced a number of interesting and useful results. High points include:

- The degree of group member similarity in the relative use of function words is a consistent and relatively powerful marker of both cohesiveness and performance. The LSM metric is associated with small group performance, marital success, large online group collaboration, and even community-wide cohesiveness.

- In online blogging communities, the ways that people write and communicate with others predict positive psychological and health outcomes.

- The degree to which people identify with groups can be tapped through the use of we-words. However, the degree to which people identify with a group is not consistently related to the group's cohesiveness or performance.

- The ways that people use function words with each other reveal relative status across types of groups and across languages and cultures.

- We have developed a variety of text analytic tools that allow for cross-language analyses and for close-to-real-time feedback for individuals and groups.

Utilization and Dissemination of Findings:

Language analysis can be viewed as a form of remote sensing in that it is possible to unobtrusively detect people and groups by the words they leave behind. While researchers have always known that the content of what people say is important, our approach has focused on the more stealth-like function words in everyday language. It is these function words that can provide important information about group processes. Indeed, our research findings suggest that we can provide valuable information concerning the engagement level of trainees and military units, predict emergent leaders, and assess leadership effectiveness. We describe a fast, efficient, and relatively non-intrusive methodology to assess individuals and groups in terms of cohesiveness, functioning, and individual-group relationships. The research summarized in this report has a number of applications, such as allowing evaluators to bypass the use of self-reports and to instead use natural language within tasks, meetings, or missions as the primary behaviors to be assessed. Our methods also have the potential to be incorporated into online training related to group functioning (e.g., leadership training) in ways that could ultimately help predict and enhance leadership, group cohesion, and performance.

LANGUAGE AND SOCIAL DYNAMICS

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Introduction

The study of groups and group dynamics is a messy job. Over the course of a day, the average person is a part of dozens of formal and informal groups, such as being with family, neighbors, friends, coworkers, or fellow shoppers and commuters. Most groups are surprisingly dynamic, with membership, roles, and agendas that constantly change. However, social scientists who study groups have historically been limited in the methods available to study important aspects of these group dynamics. The default research tactic has often been to focus either on the groups' products or on self-reports by individual group members about their perceptions of what happened while the group was functioning. Although useful, both of these approaches provide limited information about how groups think and interact with one another over time. Additional methods are needed to efficiently measure and analyze what people are saying to each other as the groups work together. Until recently, such natural language analysis was simply too time intensive, costly, obtrusive, and slow to realistically incorporate into group research.

In the last 15 years, a revolution in language measurement and analysis has begun. For the first time, social scientists now have tools that can capture the words people use across all types of groups. The current ARI-funded language project sought to develop ways to understand various social processes inherent in a wide range of groups using basic word counting strategies. Most of this work focused on a particular class of words, called *function words*, which include the most common words in English – pronouns, prepositions, articles, auxiliary verbs, and other stealth words that we rarely notice in spoken or written language. Because previous research has found that function words are closely linked to basic social and personality processes (Chung & Pennebaker, 2007; Pennebaker, Mehl, & Niederhoffer, 2003), it was hypothesized that these language dimensions would be particularly relevant to group processes.

Very broadly, the current project had three overarching goals. The first was to explore *group dynamics on the group level* through words used by the group members. This group-level analysis allows us to compare groups and to track their thinking and action over time. The group dynamic studies focused on issues surrounding group identity, group engagement and productivity, and group communication. The second goal was to identify the individual *roles within the group*; that is, we sought to use language analyses to reveal the social hierarchy and leadership structure in both formal and informal groups. The third goal was to develop our *language analysis toolkit* to better measure and understand natural interactions across groups, languages, and cultures.

The primary methods used to analyze natural language were based on a simple computerized text analysis tool *Linguistic Inquiry and Word Count* (LIWC; Pennebaker, Booth, & Francis, 2007). LIWC, pronounced "Luke," computes the percentages of words used by a speaker or author that are devoted to grammatical (e.g., articles, pronouns, verbs) and psychological (e.g., emotions, cognitive mechanism words, social words) categories. By analyzing the grammatical categories devoted to function words (e.g., conjunctions, negations, pronouns), we are able to assess markers of linguistic style.

This report reviews research conducted at the University of Texas at Austin on computerized text analyses of natural language to understand and to predict group dynamics.

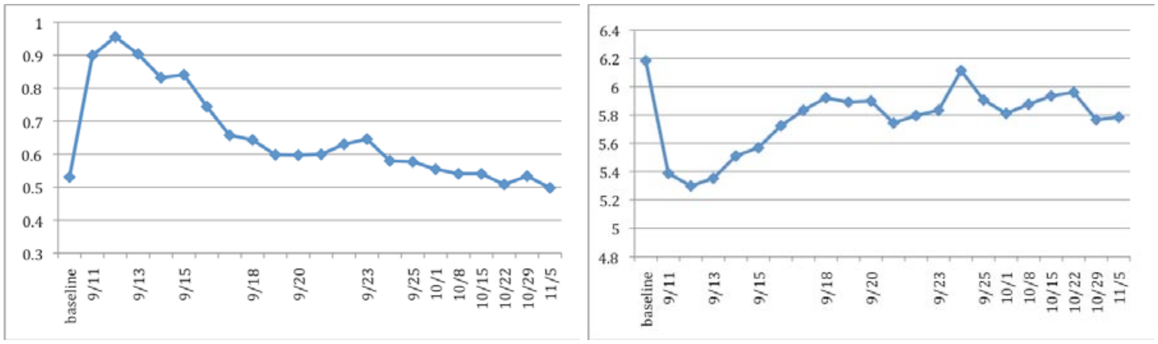
Over the course of this contract, we completed a series of experimental lab studies on small groups. Many of our findings were then validated on a variety of real world working groups and online communities. Our results point to fast and efficient metrics of group dynamics such as engagement, competitiveness, leadership, and performance based on natural language. Our research can be applied in assessment and evaluation contexts, and is especially amenable to online training environments. Because the details of these studies have been described in previously submitted annual reports, we report on the general conclusions, implications, and applications that can be drawn from this research.

Language Markers of Group Dynamics

From a social-psychological perspective, three dimensions of group processes stand out as centrally important. The first concerns group identity, or the group's sense of being a group. The second, more substantial, question explores group engagement; that is, when and how do members of groups work efficiently together? The third question examines how group communication can facilitate individual and group goals. As described below, language analyses can inform our thinking about each of these dimensions of group dynamics.

Group identity. Historically, much of the research on groups in the social sciences has revolved around feelings of group identity. Wars, prejudice, and discrimination are based on the psychological distinction between "us" and "them." Many popular business models attempt to build on this by trying to establish a sense of we-ness among their employees with slogans such as "There is no 'I' in team."

The analysis of the use of we-words (e.g., we, us, our) suggests that feelings of group identity are far more complicated than one might imagine. When appropriately primed, people naturally fuse their identity with groups of importance to them. In classic experiments, Cialdini and his colleagues (1976) demonstrated that people were more likely to embrace their college football team's identity after a win than after a loss. This "we won"/"they lost" phenomenon was particularly strong when people were interviewed by someone from another state rather than by someone from their own community. Similarly, when groups are threatened from the outside, the usage of we-words increases dramatically. Analyses of pronouns in 75,000 blog entries from about 1,000 bloggers in the weeks surrounding 9/11 demonstrated a dramatic and statistically significant jump in we-words and drop in I-words immediately after the terrorist attacks. These pronoun effects persisted in moderated form for up to a month after the attacks (reanalysis of Cohn, Mehl, & Pennebaker, 2001 data; in Pennebaker, 2011). Several studies have demonstrated that when interviewed by others, couples that use we-words when talking about their marriages are more likely to remain married (Seider, Hirschberger, Nelson, & Levenson, 2009) or to evidence better physical health (Rohrbaugh, Mehl, Shoham, Reilly, & Ewy, 2008).



We-words I-words

Figure 1. Pronoun use by bloggers before and after September 11, 2001. Graphs reflect percentage of we-words (left) and I-words (right) within daily blog entries of 1,084 bloggers in the 2 months surrounding September 11, 2001.

Outside of interviews and naturalistic interactions, however, we have not found compelling evidence to suggest that the use of we-words is associated with greater marital satisfaction (Slatcher & Pennebaker, 2006), group cohesiveness, or group productivity (based on reanalyses of data from Kacewicz, Pennebaker, Burris, David, & Rodgers, 2010; Gonzales, Hancock, & Pennebaker, 2010). Indeed, we have now conducted at least five studies where, despite having successfully manipulated people's use of we-words, no corresponding changes in group identity were ever observed. For example, some studies subtly manipulated the use of we-words or I-words when writing about their college experiences. Other studies were more direct. In one condition of a bogus business school team-building study, participants were told that the group must use we-words and not I-words in their interactions (the logic being that there is no 'I' in team). Although it is possible to increase or decrease people's rates of use of we-words, no study found that this manipulation actually changed feelings of group solidarity or group performance.

The question remains, then, what does the use of we-words signal? Across various contexts, from weekly therapy groups (Odom, 2006), to airline cockpit crews (Sexton & Helmreich, 2000), to the Beatles 10-year collaboration (Petrie, Pennebaker, & Sivertsen, 2008), we-words are linked to group longevity. That is, the longer a group has been together, the more the people in the group use we-words when talking with each other (Chung & Pennebaker, in press; Pennebaker, 2011).

Standing back, the evidence suggests that the use of we-words reflects a general feeling of being allied with whatever group has been made salient as well as group longevity. We-words serve as reflections of social feelings rather than as causal elements. That is, merely changing people's language to use we-words does not affect their feelings of closeness with the group. The we-words finding illustrates that it is possible to get a rough measure of commitment to a particular group. Feelings of commitment, however, are not necessarily helpful predictors of group performance or even group cohesiveness. To the degree that researchers seek to understand how groups function, more dynamic language measures must be employed.

Engagement and language style matching (LSM). Although a sense of group identity may be important in bringing people together and giving them a sense of group solidarity, it is not clear that group identity is sufficient to get a group to work well together. In the study of group dynamics, it may be more important that the group members all think about their tasks in the same way; that is, they have a shared mental model of team- and task-based outcomes (Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, 2000). It is also important that this measure of group cohesiveness is based on the measurement of actual behaviors as the group interacts rather than on self-reports collected before or after any group interaction due to social desirability, lack of self-awareness, or other dynamic features of groups that may influence mental models. Much of the work has been devoted to developing a language-based measure of group engagement that we refer to as language style matching, or LSM.

Basic psychometrics of LSM. Across a large number of studies, we have been exploring how groups of people tend to use function words at comparable rates while interacting with each other. As a reminder, function words can be broken into nine independent categories: personal pronouns, impersonal pronouns, conjunctions, articles, prepositions, auxiliary verbs, negations, common adverbs, and quantifiers. As can be seen in Table 1, these nine dimensions—that are made up of fewer than 500 English words—account for almost 60 percent of the words people use in their daily speech and writing

Table 1

Function Word Categories in the LSM Metric

Category	Examples	Percentage
Personal pronouns	I, us, your, she, them	10.1
Impersonal pronouns	Any, it's, somebody	5.0
Prepositions	To, for, above	12.9
Articles	A, an, the	6.3
Conjunctions	And, or, but, whereas	6.4
Auxiliary verbs	Am, have, are	8.5
Common adverbs	Very, really, so	4.6
Negations	No, not, never	1.7
Quantifiers	Few, lots, much	2.5
Total		58.0%

Note. Percentage refers to percent of total words that each category averages across multiple genres including conversations, essays, novels, etc (from Pennebaker et al., 2007).

The idea of LSM is that two or more people in an interaction should, in theory, match in their levels of function words when interacting as they are establishing common ground. For example, when two people are chatting about Jedidiah's bouillabaisse, they can both use "he" and "it" instead of each repeatedly having to say "Jedidiah" and "bouillabaisse." The more engaged they are with each other, the greater the synchrony. Although there are several ways to measure LSM, our goal was to create a metric that people could calculate without the use of a complex computer system. For example, if we have a telephone transcript between two people, we could calculate the degree to which their personal pronouns matched with the following equation:

$$1 - \frac{|\text{Person 1's pronouns} - \text{Person 2's pronouns}|}{(\text{Person 1's pronouns} + \text{Person 2's pronouns} + .001)}$$

Note that the absolute difference between the personal pronouns assures that the number is always positive and the addition of .001 in the denominator guarantees no division by zero. In addition, the fraction is subtracted from 1.0 so that LSM ranges from 0 to 1.0, with higher numbers indicating greater matching. The equation above is applied to all nine function word categories listed in Table 1 and averaged.

The psychometrics of LSM are straightforward. Across multiple studies, the LSM of one function word category is positively correlated with the LSM of the other function word categories. Together, these yield internal consistency reliabilities of the LSM statistic ranging from Cronbach's alphas of .49 to .80 across multiple studies (Gonzales et al., 2010; Ireland & Pennebaker, 2010; Ireland et al., 2011). Depending on the sample, we find that LSM scores can range from as low as .30 for Wikipedia editor interactions (Tausczik & Pennebaker, 2010) to .93 for speed dating interactions (Ireland et al., 2011). This wide range of LSM scores reflects, in part, the degree to which the group members are actively engaged with one another in the here-and-now. Very low LSM scores among Wikipedia editors reflect interactions that may take place across vast gaps in physical space and time between questions and answers. Note that while LSM was initially devised as a dyadic measure, it can be calculated between any sets of text, including people in groups, written text such as emails, or even between two or more articles by the same person. We have recently developed an online calculation tool available to anyone (it has not yet been released to the general public): http://www.utpsyc.org/synch/.

LSM validation studies. Style matching in an interaction occurs almost immediately (Niederhoffer & Pennebaker, 2002). If one person begins a conversation with a stranger using a very formal tone, the other adapts. One of the more compelling examples concerns written LSM among college students completing written course assignments (Ireland & Pennebaker, 2010). Across two semesters, almost 2,000 Introductory Psychology students were required to complete an online writing assignment that asked them to give examples of four social psychological principles. Each of the four questions was written in a different style. One was pompous and arrogant ("Since time immemorial, laymen have doggedly adhered to pearls of folk wisdom…"), another informal or ditzy ("OK, we haven't talked about cognitive dissonance much in class.… I mean, it's so cool because it's super easy…"), etc. The last sentence was the same for everyone asking them to give an example of the principle.

In answering the various questions, participants' linguistic styles tended to match the prompts, with LSM coefficients ranging between .67 and .75. LSM itself was consistent from one question to another (intraclass correlation coefficient = .45). As an individual difference, LSM was positively related to gender (females higher), social class, and overall performance in the class based on multiple choice exams (all Cohen's *d* effect sizes ranged between .08 and .27). An interesting feature of this approach is that the LSM metric is inherently relational. In natural conversations, the participants are generally adjusting to each others' styles on a turn-by-turn basis. Capturing LSM in a static setting is one of the few ways to think of it as an individual difference measure.

In another study, 74 students were given two pages of text from each of three novels written in very different styles. All the students were then asked to "please finish the story… be realistic about what likely happened in the scene after the one you read." Half of the students received additional instructions to "…maintain the author's voice and style: Write as though you are the author." As before, all participants matched the novelists' styles at high rates (mean LSM = .77). Ironically, direct instructions to emulate the target style were not successful. In fact, the direct style matching instruction revealed slightly lower LSM than no matching instruction at all. The direct instructions to attend to and to monitor smaller details of language style may have produced more cognitive load and less rapport relative to higher level and less constrained instructions to take the perspective of another. These results suggest that LSM does not reflect attention to rates of word use, per se; rather LSM might reflect shared perspective more generally.

It should be noted that we compared LSM with the more traditional latent semantic analysis, LSA (Landauer, Foltz, & Laham, 1998). Note that LSA compares the content similarity between text samples whereas LSM focuses only on linguistic style. Independent judges were asked to compare the language style between the prompts and the writings. Interestingly, ratings of style similarity were correlated with content words as measured by LSA coefficients and unrelated to style words as measured by LSM. What this means is that even judges are unable to detect writing style and naturally confuse it with writing content.

Taken together, style matching appears to occur automatically, outside the control of the speaker or writer, and is difficult to detect by independent judges. Nevertheless, it is a reliable, internally consistent measure related to a small number of demographic factors but not reliably linked to traditional personality measures (Ireland & Pennebaker, 2010). In the following section, we describe how we are using LSM to identify and understand group dynamics.

LSM and group behavior in the lab: Cohesiveness and performance. The LSM approach is a potentially powerful method by which to tap ongoing group behavior. Traditionally, social scientists have been forced to rely on self-report questionnaires to measure group processes. Furthermore, the questionnaires are generally completed after the group has disbanded, affording the possibility of recall biases and distortions. LSM and other language analysis methods provide a new window into communication in ongoing groups.

In a series of studies in small group behavior, our first question addressed whether group-level LSM was related to group cohesiveness and performance. In one of our first studies, approximately 300 students were assigned to same-gender groups of 4–6 people to work together on a problem solving task (Gonzales et al., 2010). Half of the groups worked together in the same room (face-to-face, or FTF condition) and the remaining participants worked in individual rooms using online chat technology (computer-mediated communication, or CMC condition). Language analyses of the FTF and CMC groups revealed that the LSM of the group (see Gonzales et al., 2010 for a discussion on alternate ways to compute LSM) was positively related to subsequent ratings of group cohesiveness. That is, the more the group members tended to use function words at comparable levels, the more they felt a sense of support and shared perspectives with others.

More interesting were the results of the group performance measures. Groups were required to work together to answer a series of complex multiple choice questions that required different group members to gather information from a variety of unique sources. If the members did not work together, the group would perform poorly. Overall, LSM was positively correlated with group performance. Interestingly, this effect was significantly stronger for the FTF than the CMC condition.

In an extension of this project, we reanalyzed data from a simulation study conducted at the University of Illinois Business School (Burris, Rodgers, Mannix, Hendron, & Oldroyd, 2009; also Kacewicz et al, 2010). In the study, 41 four-person groups worked on a business task simulation for about an hour. The project was sufficiently complex that each person in the group had to work closely with the others. Independent judges rated the quality of the group's performance and the members of the group itself rated the group dynamics. As you can see in Figure 2, the results paralleled those from the Psychology Department study. The LSM metric from the group interaction (i.e., the mean of each member's rates of function word use relative to the remaining group members) was significantly related to ratings of group cohesiveness. Although not statistically significant, the pattern of effects for group performance was in the expected direction.

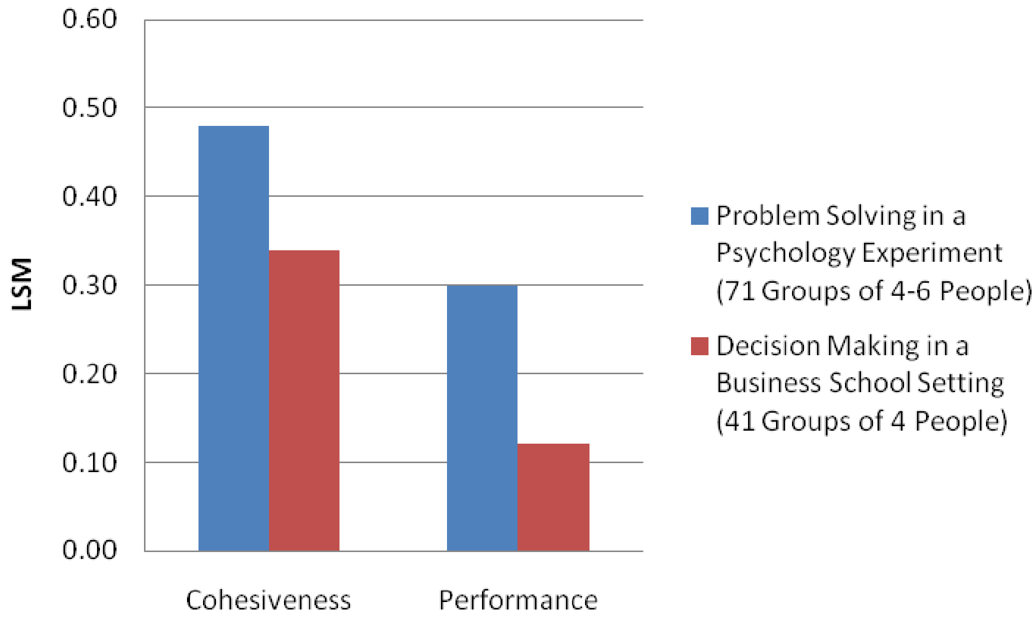


Figure 2. Correlations of LSM with cohesiveness and performance across two studies.

Real world group dynamics: LSM in Wikipedia. Remarkably few real-world studies have been conducted that track ongoing interactions over time. The current generation of text analytic tools is allowing us to do this for the first time. One venue of particular interest to group dynamics researchers is Wikipedia. Wikipedia, which started in 2001, is an online encyclopedia-like information source that has more than 3 million articles. Many of the articles are written by experts on a particular topic and have been carefully edited by dozens, sometimes hundreds, of people. For the most commonly-read articles, an elaborate informal review takes place. Often, a single person will begin an article on a particular topic. If it is a topic of interest, others will visit the site and frequently make changes to the original article. Each Wikipedia article is a repository of group collaboration. The casual visitor sees only the current final product. However, by clicking on the "talk" and "read" tabs, it is possible to see archives of conversations among the various contributors.

Wikipedia discussions are a naturalistic record of interactions among the various editors of each article. Recently, we have analyzed the discussion threads of about 70 Wikipedia articles (all on the subject of separate American mid-sized cities) that had been edited multiple times by at least 50 editors over several years (Tausczik & Pennebaker, 2010). By comparing the language of each discussion entry, it is possible to calculate an overall LSM score. As in the two previously mentioned lab studies, LSM for the group was computed by taking the mean of each editor's rates of function word use relative to the remaining editors for that article. In terms of outcome measures, Wikipedia sponsors an elaborate rating system that categorizes articles as being exemplary, very good, good, adequate, or poor.

Across the 70 Wikipedia entries, the higher the LSM of the discussions, the higher the rating for the entry, r (68) = .29, $p < .05$. Unlike other data sets we have worked with, the LSM levels for discussion groups were quite low, averaging .30. Nevertheless, the highest, mid-level, and lowest rated articles had LSM coefficients of .34, .30, and .27, respectively. In other words, Wikipedia discussions that indicated that the editors were corresponding in more similar ways to each other tended to develop better products.

LSM and more intimate social dynamics. The previous LSM projects have focused on groups of varying size where group-relevant outcomes were objectively measured. Can the same linguistic processes be applied to more informal interactions? Two recent experiments suggest that the answer is yes (Ireland et al., 2011).

An analysis of speed-dating sessions showed that LSM could predict which of the interactions would lead to both parties being interested in going out on a real date. The transcripts came from a series of heterosexual speed-dating sessions offered on the Northwestern University campus. Forty men and forty women participated in 12 4-minute interactions with members of the opposite sex. Following each interaction, participants rated how attractive and desirable the other person had been. On the day following the speed-dating sessions, each person indicated whether or not they would be interested in dating each of the partners with whom they had interacted. Both parties had to agree they were interested for a “match” to occur, and only then were they given contact information to set up a potential date in the future. Our analyses showed that “matches” were far more likely if LSM during the speed-dating interactions was above the median. Particularly interesting was that the LSM measures actually predicted successful matches better than the post-interaction ratings of the individuals. In other words, we could predict if they would subsequently go out on a date better than the couples themselves.

Whereas the speed dating project focused on strangers seeking partners, we also have been curious to know if LSM could predict the long term success of people who were already dating. In a reanalysis of an older study (Slatcher & Pennebaker, 2006), the instant messages (IMs) between 86 heterosexual romantic couples were downloaded before, during, and after participation in a psychology study. LSM between the couples was computed over 10 days of IMs. Almost 80% of couples with high LSM (above the median) were still together 3 months later, whereas only half of the couples with low LSM (below the median) were together 3 months later. LSM was able to predict the likelihood of a romantic couple being together 3 months later over and above self-reported ratings of relationship stability.

We have also explored how LSM can generalize to historical relationships based on archival records. For example, LSM was assessed between well-known pairs of colleagues and authors. For example, the correspondence between Sigmund Freud and Carl Jung is famous in tracking their close initial bonds and subsequent feud and falling out. The poetry of Elizabeth Barrett and Robert Browning as well as Sylvia Plath and Ted Hughes was also analyzed in the years before the couples met, during the happy times of their marriage, and the less-than-happy times. LSM reliably changed in response to times of relationship harmony (higher LSM) and in times of relationship disharmony (lower LSM). Interestingly, even without the use of self-reports, LSM was able to reliably indicate relationship dynamics over time (Ireland & Pennebaker, 2010). Since these language samples had been recorded for purposes other than assessing group dynamics, they provide evidence regarding the robustness of LSM to predict real world outcomes beyond a controlled laboratory study.

Summary of LSM effects: What do they mean? The series of studies we have conducted have established that LSM is a reliable measure of engagement within dyads and groups. Across widely varying samples, LSM has been shown to reflect feelings of group cohesiveness and is predictive of important behavioral outcomes such as group task performance, economic equality within a community, and relationship longevity. Taken together, LSM might be viewed as the degree to which any two or more people are motivated to be coordinated in their thinking styles.

Overall, LSM is more a reflection rather than a cause of a group's social dynamics. LSM occurs automatically and outside of conscious awareness. External judges are able to detect when people are talking on the same topic and with a similar style or tone. However, judges and group members themselves have difficulty assessing the degree to which their function words are entrained to their interlocutors, despite the strong relationships of LSM with behavioral outcomes of an interaction. For example, recall that LSM outperforms self-reports in predicting "matches" in speed-dating interactions. LSM, then, can be viewed as an implicit and less biased reflection of social dynamics than self-reports.

Other language markers of group dynamics. Across several studies, we have been able to assess group dynamics that are unavailable for real-time or near real-time measurement using traditional methods. Indeed, one of the primary benefits of language analyses as markers of group dynamics is that we are able to assess underlying psychological processes with far greater ecological validity than data collected in artificial lab settings using self-report questionnaires. The advantage of our language analyses is that the same metrics that have been carefully studied in the lab generalize to real world settings, meaning the same methods and tools used for training sessions can be used for evaluation in real world missions and operations.

Sending and receiving: Interactions in the blog world. The examination of larger groups such as blog communities can be used to understand how communication patterns affect performance for common goals. Although not often appreciated by data miners, blog communities are actively social. Typically, when individuals post stories or personal observations, others will respond to the posts in individualized comments. Indeed, the comment sections of blog posts serve as an indirect marker of the bloggers' popularity, networks, and social support.

A particularly rich source of social engagement surrounds blog sites devoted to self-help issues. Over the last 2 years, we have been examining how language can be used to assess goal success and social dynamics within an online community of blogs devoted to weight loss (Chung, 2009; Chung, Jones, Liu, & Pennebaker, 2008; Chung & Pennebaker, 2010). As part of her dissertation, Cindy Chung tracked the complete blog records of 186 frequent contributors to dietdiaries.com, including the comments that each blogger sent and received. Of particular relevance was that each person posted their actual weight at the beginning of each blog entry. In other words, we were able to compare the change in weight of the various dieters as a function of how they wrote and how they interacted with others.

Overall, two striking findings emerged from the project. First, the ways people wrote in their blog posts were modestly related to successful weight loss. Specifically, people who wrote more personally (e.g., using more I-words) while conveying positive emotions benefited far more than individuals who focused just on what and when they ate. Second, and not predicted, social integration into the blog community predicted weight loss. That is, the more bloggers made comments on other people's blogs, the more they themselves lost weight. Giving comments was even more predictive of weight loss than receiving them.

Tracking the reading of and searching for information. In addition to being a source of social connections, much of Internet traffic is devoted to people searching for information. By analyzing where people go for information, we get a deeply personal sense of their interests and concerns. Only recently have we begun to make the connection between emotional experiences and people's need for specific types of information.

In late April, 2009, the World Health Organization announced the potential danger of a new form of flu, based on the H1N1 virus, more commonly known as the swine flu. Over the next 10 days, a tremendous amount of media attention and international anxiety was aroused. Using a new search system, we were able to identify almost 10,000 blogs that mentioned swine flu on a day-by-day basis. Our goal was to determine how swine flu-related blogs differed from non-flu blogs in their language. At the same time, we were curious if we could also track people's searching for information online using Wikipedia (Tausczik, Faasse, Pennebaker, & Petrie, 2012).

Analyses of the blogs revealed an initial spike in anxiety-related words that returned to baseline within a few days, followed by an increasing level of anger and hostility words. Searching for information on Wikipedia, however, tended to lag behind the swine flu mentions on blogs by about 3 days. The pattern of results suggests that after hearing about a potentially threatening disease, most of the public lets it stew for a few days before actively searching for information about its symptoms, time course, and treatment. Note that this strategy of information seeking complements key word search strategies reported by Google and others (Ginsburg et al., 2009) where online symptom searches actually lead diagnoses of flu across time and over regions.

Individual Level Social Dynamics

Most of the research discussed so far has focused on the relationships between group-level language and group behavior. Another important dimension to understanding group processes is evaluating the relative roles of people within the group. Over the course of the ARI contract, we have explored how the language among individuals within a group can reveal the groups' overall social hierarchy. An outgrowth of this work has resulted in additional research on the correlates of leadership, personality, and social networks.

Using group language to determine social hierarchy. Virtually all social animals quickly establish a social hierarchy when in groups. In humans, the social hierarchy within a group is partially dependent on variables such as the attractiveness, strength, wealth, experience, and age of its members. Even in purely social CMC pairs where interactants never see one another, pairs quickly come to agree on who has more status based on a few "innocent" questions: where are you from, what's your major, what year in school are you, etc. More striking, however, is the degree to which relative status is revealed through function words– especially pronouns.

Across multiple studies, we have found that the use of I-words is reliably associated with low self-esteem, depression, youth, and lower social class (see Chung & Pennebaker, 2007 for a review). It would follow, then, that within any interaction between two people, the person using fewer I-words would be the person with the higher status. Over the last few years, we have analyzed a number of studies that support this idea (Kacewicz et al., 2010).

Table 2

Effect Sizes of Word Categories That Indicate Status

	Study 1: Business school	Study 2: IM	Study 3: Get to know you	Study 4: E-mail	Study 5: Iraq Letters	Overall Effect Size	*p*-value
Word count	1.08	.86	.69	.16	–1.40	.58	0.00
All Pronouns	–.53	–.84	–.14	–.53	.16	–.42	0.00
Personal pronoun	–.40	–.67	.00	–.61	1.50	–.20	0.07
1st person singular	–1.02	–1.30	–.62	–.86	–.21	–.85	0.00
1st person plural	.77	.71	.30	–.02	.16	.49	0.00
2nd person	.27	.10	.30	.07	1.13	.29	0.01
3rd person singular	–.17	.10	.24	.00	–.25	.03	0.76
3rd person plural	–.04	–.42	.55	–.18	–.25	–.01	0.95
Impersonal pronouns	–.41	–.51	–.18	.02	–.31	–.34	0.00

Note: (from Kacewicz et al., 2010). Cells indicate effect sizes (Cohen's *d*). The overall effect size is a mean weighted by sample size across the five studies. A positive number denotes that high status individuals use that particular category more than lower status individuals.

Table 2 summarizes the results of five studies. Study 1, described earlier, involved groups of 4 people where the leader was assigned by the experimenters. Studies 2 and 3 were informal interactions in the lab where people were simply asked to get to know the other either online (Study 2) or face to face (Study 3). In Studies 2 and 3, independent measures of status were collected by self- and other-ratings of status in each interaction using the Interaction Rating Questionnaire (IRQ; see Niederhoffer & Pennebaker, 2002). Study 4 was an in-depth analysis of the emails of 10 people comparing their outgoing and incoming emails to/from a minimum of 10 other people. Study 5 was an analysis of recovered Iraqi Army letters between a person of high status and someone of lower status (see also Hancock et al., 2010).

As can be seen in the table, the person with higher status talks more, uses fewer I-words, more we-words and you-words, and fewer impersonal pronouns. The effect sizes are reasonably strong and consistent across studies. Particularly impressive is that the effects hold up for both natural evolutions in leadership as well as manipulated leadership.

Comparable effects have been found for real-world, long-lasting groups. In an analysis of an online collaboration of 18 engineers, economists, technology experts, and others in a DOD-sponsored workgroup, we were able to track the language of the group over an 18-month period (Scholand, Tausczik, & Pennebaker, 2010; Tausczik, 2009). During this time, the group underwent several hardships, eventually losing funding. Consistent with the lab studies, relative use of pronouns in general and I-words in particular were strong correlates of group members' ratings of the target's status in the group.

Why are I-words so consistently correlated with lower standing in the social hierarchy? One argument is that the use of I-words reflects people's focus of attention (Tausczik & Pennebaker, 2009). People who are depressed or insecure have been found to be more self-focused in general. One can see similar patterns in people's body language. When threatened or forced into a subordinate position, humans and other social animals look away from the high status individual and often focus on their own body. As has been emphasized before, relative use of I-words is likely reflecting the status hierarchy rather than influencing it. Indeed, people consistently believe that the use of I-words is a marker of high status when, in fact, it is just the opposite. Indeed, in a recent survey of over 2,000 linguists, the overwhelming majority made this error (see http://www.utpsyc.org/itest/).

Attempts to Predict Leadership by Word Use. In the original proposal, one question we posed asked if it would be possible to use baseline language use to predict leadership in small groups. Our attempts to answer this question have not yielded particularly promising results.

Perhaps the strongest test of the idea involved the recruitment of more than 750 Introductory Psychology students who participated in a single online dyadic interaction for 15 minutes. Basically, the students signed onto the computer at prearranged times and were randomly linked to one other student with whom they would chat. At the end of the interaction, the two would fill out independent questionnaires assessing status and leadership of the two. As we have found in previous studies, people generally agree about who has more status and is the implicit leader–even though it is just a get-to-know-you conversation.

In addition to the interaction, all of the students had previously completed a stream of consciousness writing sample earlier in the semester where they had been asked to track their thoughts and feelings on paper for 20 minutes. These written samples were analyzed with the LIWC program to assess relative use of pronouns and other markers of status. Overall correlations between the earlier independent writing samples and the use of language in the online interactions failed to reveal any meaningful patterns. In other words, the way people naturally write in one context did not have direct bearing on the relative status of the two people once they began a real conversation. It should be noted that no self-reports or other data we had on the participants predicted relative conversational status.

Other relevant projects. We are currently engaged in a host of other projects tapping the links between natural language use and social psychological dimensions. Those most relevant to ARI include:

● Development of a complete social hierarchy index within a group through language analysis. To date, we have only been able to focus on the likely leader of a group. We are now developing models that should be able to establish relative status of the entire group. In addition, drawing on the Wikipedia data set, we are attempting to distinguish natural group structure. That is, some groups evolve a clear hierarchical structure whereas others are more egalitarian. Yet others border on chaotic. We seek to determine if there is a language method that can distinguish these group structures.

● Automatic detection of language communities. We have recently developed an application to study the personality of people who use Twitter (see www.analyzewords.com). Through this online application, almost 100,000 twitter IDs have been examined, leaving traces of well over a million twitter posts. In our preliminary analyses, we are finding that social networks share emotional tone and other language features. What rules determine when friends talk like other friends? If I use a high rate of positive emotion words, so will my friends. But what about their friends? How wide is this dispersion of language?

● Creating automated feedback for writing and education. Is it possible to train people to write in particular styles that could be healthier? We have been developing a toolkit of methods that tracks people's natural writing and then provides feedback to them about their writing (see www.utpsyc.org/write). So far, more than 200 people have participated in our online projects to determine if automated feedback is helpful. The basic system can be applied to tracking online group interactions and providing feedback to groups about their interaction styles.

● Predicting academic success. Working with the University of Texas Admissions Office, we have begun analyzing more than 50,000 admissions essays from more than 25,000 students over the last 4 years. We have been able to compare the language of their essays with their subsequent performance at college, including grades, years to graduate, dropout status, and other indicators of academic success. We are able to predict academic success at rates approaching standardized tests (e.g., SAT, ACT) by simply counting pronouns, articles, and auxiliary verbs. We are now discussing how these findings may be relevant to students' subsequent educational training upon arriving at college.

Language Analysis Tool Development

Tools in other languages. Given the multicultural nature of many working groups within the Army and within the world in general, understanding the degree to which cultural backgrounds or native languages can affect our assessment of individuals and groups is important. Just as it is desirable to calibrate any assessment tool with known systematic individual differences or demographics that may affect leadership, performance, or cohesiveness, it is important to understand how the assessment of natural language may be affected by subcultures or other languages.

We have completed an Arabic text analysis program of function words based on the LIWC program that uses an English categorization scheme that would read Arabic text (Hayeri, Chung, & Pennebaker, 2010). For the validation phases of the dictionaries' development, we have compiled one of the largest corpuses of Modern Standard Arabic texts. We hope to give people who work with translators and translations an insight into dimensions of a culture that may be invisible to someone unfamiliar with the other language or culture. Our work in the development of text analytic tools is nearing completion for the Chinese, French, Russian, and Turkish versions of LIWC with the help of experts around the world.

Multidisciplinary methods. In addition, we have collaborated with artificial intelligence experts and computational linguists to extend the types of language features that we study to include various parts of speech (which we are finding to be associated with academic performance; see also Chung & Pennebaker, 2008), and speech acts (i.e., automatically classifying phrases based on the pattern of the first words stated in an utterance, which we are finding to be associated with relative status in an interaction). Through these multi-disciplinary collaborations, we have been able to apply our text analysis toolkit to investigations that range from gender differences in communication (Ireland & Pennebaker, 2010; Newman, Groom, Handelman, & Pennebaker, 2008) and in literary works (Pennebaker & Ireland, 2008) to author identification tasks within online communities (Argamon, Koppel, Pennebaker, & Schler, 2009).

In collaboration with the consultants and with several other collaborators, we devised Social Language Processing (SLP), an interdisciplinary approach to assess social features in communications by terrorist organizations and authoritarian regimes (Hancock et al., 2010). The SLP paradigm represents a rapprochement of theories, tools, and techniques from cognitive science, communications, computational linguistics, discourse processing, language studies, and social psychology. SLP has been used to study cohesion, status, and deception in a corpus of documents and letters exchanged within Saddam Hussein's administration (Hancock et al., 2010).

Overall, we have developed our computerized text analysis toolkit with expansions into various parts of speech, complex algorithms, and machine learning methods. Although our toolkit has expanded with much more sophisticated and precise measurement techniques, we continue to interpret our findings in light of theories developed in psychology and in the communications field to distribute our findings as practically relevant. Ultimately, we believe that our findings can be informative of group dynamics and language processes, and that our tools can be applied not just for understanding social dynamics, but also for training effective groups and leaders.

Summary, Conclusions, and Applications

Language is generally thought of as a tool that we consciously manipulate. Changes in one's pitch or rate of speech happen outside of conscious awareness, but language is generally assumed to be a highly intentional communication channel. Our findings suggest that even the words we use are susceptible to influence by the affective nature of social dynamics; certain language categories, such as function words, may be as much a sign of how we feel as they are a tool for expressing it. The analysis of function words provides important clues about the social relationship between a speaker and the audience, the psychological state of the speaker, and information about the speaker's social role and status in the community.

Over the past several years, we have extended our function word metrics to be able to measure the dynamics of groups and their members by establishing a metric of verbal synchrony called language style matching (LSM). What makes LSM a particularly compelling measure is that group coordination is not always discernible by conversation topics or by keywords. For example, even very positive words without context can be misinterpreted: "Fantastic" can mean that the speaker is evaluating performance as outstanding, or that the speaker is sarcastically groaning about the poor progress that has been made. Slang is a way to indicate that a subculture shares a unique code. Human judges are able to code for sarcasm, sentiment, slang, and topics in natural language quite reliably. However, the measurement of linguistic style across various topics is only practically possible using computerized text analysis. Computerized text analyses are much faster, more reliable, and more efficient. Computerized metrics of linguistic style provide psychologically meaningful information for dyads, small groups, cities, and online communities.

We intend to apply our metrics to educational settings in an effort to improve the ongoing dynamics of working groups. Using our knowledge of function words and style matching, we are developing real-time feedback systems to alert group participants about the quantity and quality of their group role and participation in an attempt to improve learning and make social communication more efficient.

While part of our research is focused on the development of text analytic modules for training tools, our metrics may allow for the assessment of extant training systems using natural language. Our research methods and tools do not necessarily require elaborate new studies to be conducted. Instead, we can take advantage of recordings and archived training sessions in which natural language had been recorded for purposes other than text analysis. For example, our analyses of online discussion boards, forums, and community-level metrics tap broader group processes. With the examination of online communities and social media, we have the ability to look at real-world groups within larger communities and assess the overall influence of events or challenges at each level. We can examine widespread reactions or changes within a community and assess how group dynamics change in response. Indeed, it is critical to understand group dynamics in the larger context within which they function.

We are entering a new era of language assessments in psychology. Our findings have been shown to be reliable across various modalities, genres, and groups. These findings provide a solid foundation upon which to develop training systems or to assess existing recordings to make group assessments, while moving away from a heavy tradition of self-reports or external expert evaluations by human judges. Our metrics offer a unique perspective of the author or speakers within a task in ways beyond what self-reports offer. While our research aims to uncover group dynamics through language use, we are continually developing our data mining and text analysis toolkits that may be used for basic and applied research across the small groups domain. We offer fast and efficient metrics that are reliable remote sensors for a variety of group processes.

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