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# Language Style Matching as a Predictor of Social Dynamics in Small Groups

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## Abstract

Synchronized verbal behavior can reveal important information about social dynamics. This study introduces the linguistic style matching (LSM) algorithm for calculating verbal mimicry based on an automated textual analysis of function words. The LSM algorithm was applied to language generated during a small group discussion in which 70 groups comprised of 324 individuals engaged in an information search task either face-to-face or via text-based computer-mediated communication. As a metric, LSM predicted the cohesiveness of groups in both communication environments, and it predicted task performance in face-to-face groups. Other language features were also related to the groups' cohesiveness and performance, including word count, pronoun patterns, and verb tense. The results reveal that this type of automated measure of verbal mimicry can be an objective, efficient, and unobtrusive tool for predicting underlying social dynamics. In total, the study demonstrates the effectiveness of using language to predict change in social psychological factors of interest.

## Keywords

language style matching, verbal mimicry, small group, cohesiveness, team performance, pronouns, text analysis, LIWC

Human communication requires substantial coordination. Each participant regulates words, sounds, and motion in time with others, which can enhance mutual attraction and improve shared understanding (Giles & Coupland, 1991). This kind of coordination between individuals has been studied from a number of different perspectives and under the auspices of a number of different constructs. Burgoon and colleagues have described

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many of these constructs, including matching, mirroring, convergence, synchrony, interpersonal coordination, and mimicry (Burgoon, Stern, & Dillman, 1995). Although any of these terms can describe the range of behaviors that reflect coordinated communication, in the present article we use the term *mimicry* as it succinctly captures behavior that reflects the matching of identical behaviors between one person and another.

Mimicry appears to be a fundamental social behavior. The nonconscious impulse to mimic is thought to be linked to the human response to rhythms, including the rhythms of human movement and human language (Kendon, 1967), and it takes place across different communication channels. For example, it is observed in some of the earliest human interactions in the form of gaze entrainment between mothers and infants (Condon & Ogston, 1966). People will imitate one another's nonverbal movements and gestures (Bernieri & Rosenthal, 1991), individuals converge (and diverge) accents or rate of speech based on the quality of a relationship (Giles & Coupland, 1991), and verbal mimicry also occurs at the level of syntactic structure or even word-by-word matching (Pickering & Garrod, 2004).

The importance and function of the various forms of mimicry has undergone some debate in the past (Gatewood & Rosenwein, 1981), but mimicry has been frequently linked to social processes. Perhaps, the most common is the relationship between mimicry and affinity. That is, people who like one another produce similar styles of speech along multiple dimensions of speech (Giles, Coupland, & Coupland, 1991). Mimicry has also been linked to team performance (Kozlowski & Ilgen, 2006) or may facilitate language production and comprehension (Pickering & Garrod, 2004).

## Automated Analysis of Verbal Mimicry

Although mimicry is ubiquitous in social interaction and important to social relationships, it is extremely difficult and time consuming to code and quantify. The process involves first identifying the behaviors of interest (e.g., eye-gaze, gestures, linguistic features), coding those behaviors for each interlocutor, and then assessing the degree to which those behaviors co-occur across interlocutors. A classic study on nonverbal mimicry by Condon and Ogston (1966) illustrates the amount of effort required. Their microanalysis of body positioning required replaying the videotape of social interactions frame by frame. Each precise change in movement was recorded and coded as a particular form of gesture involving four or more classifications per gesture. This coding then had to be repeated for each participant. As Bernieri and Rosenthal (1991) noted, "an interaction lasting just a minute may generate a transcription many feet in length" (p. 414).

In the present article, we propose the linguistic style matching (LSM) metric, an algorithm used to automatically assess mimicry in language. To the best of our knowledge, the LSM metric is the first automated measure of mimicry. This algorithmic approach takes advantage of specific characteristics of language to calculate the LSM metric. First, with the development of automated text-analysis programs, language can be analyzed efficiently and objectively through use of computer-based text analysis tools (see Pennebaker, Mehl, & Niederhoffer, 2003). Entire conversations can be parsed into psychologically relevant dimensions quickly and with a high degree of accuracy. For instance, modern

parts-of-speech taggers are typically 90% to 95% accurate in identifying a word's grammatical function (Manning & Shuetze, 2003).

The second characteristic of language important to the LSM metric is an important category of words called *function words*, which have proven useful in identifying relationships between language and social psychological states (Campbell & Pennebaker, 2003; see also Chung & Pennebaker, 2007). In contrast to *content words* such as nouns and verbs, function words do not contain semantic information. Instead function words are the syntactic backbone of language. Categories of function words include prepositions, conjunctions, articles, and other content-free parts of speech.

Function words have several important qualities that make them potentially useful as a measure of LSM. Function words occur at a very high frequency, making them relatively easy to measure in dialogue. Although there are only about 400 different function words, they cover more than half of the vocabulary of daily speech (Rochon, Saffran, Berndt, & Schwartz, 2000). Also, because function words are context independent, they can be measured across all semantic domains, from informal social dialogue to task-based communication. Finally, similar to the nonconscious nature of mimicry, function words are nonconsciously produced, which makes it very difficult to manipulate one's function-word patterns (Pennebaker & King, 1999).

The LSM metric takes advantages of these aspects of language by measuring the degree to which two or more participants are producing similar rates of function words in their dialogue. The algorithm involves first calculating a score for each participant with respect to their use of the nine main function-word categories: auxiliary verbs (e.g., to be, to have), articles (e.g., an, the), common adverbs (e.g., hardly, often), personal pronouns (e.g., I, they, we), indefinite pronouns (e.g., it, those), prepositions (e.g., for, after, with), negations (e.g., not, never), conjunctions (e.g., and, but), quantifiers (e.g., many, few). Each individual's score is then compared with the scores of the other interaction participants to produce the dyadic or group LSM score. The final LSM score ranges from 0 to 1, where 1 reflects perfect function-word matching between participants in a conversation.

## The LSM Metric as a Predictor of Social Dynamics

To test the value of the LSM metric, we investigated its ability to predict two well-known aspects of social dynamics in small groups: cohesiveness and task performance. The first, cohesiveness, is related to previous findings that mimicry occurs in positive relationships. A wealth of work has supported the idea that social synchrony can be used as a metric of positively functioning social dynamics (Bernieri, Reznick, & Rosenthal, 1988; Chartrand & Bargh, 1999; Giles et al., 1991). For example, people who have high rapport tend to mimic one another more closely (Tickle-DeGnen & Rosenthal, 1987). Also nonverbal researchers have identified convergence of matching speech patterns when individuals like one another and divergence when individuals do not like one another (Giles et al., 1991). In this study, we test the relationship between cohesiveness and verbal mimicry as measured by the LSM metric to see if verbal mimicry of function words within a group predicts positive interactions.

The second social dynamic examined here is task performance. Can the proposed LSM metric also predict a group's performance on an information search task? Several domains of research suggest that it should. For instance, research on mimicry in psycholinguistics has demonstrated that language synchronization facilitates both language production and comprehension (Pickering & Garrod, 2004). Organizational research has also demonstrated links between synchronized communication and team performance (Kozlowski & Ilgen, 2006). For example, research examining mental models, which are cognitive structures that capture shared understanding (Klimoski & Mohammed, 1994), suggests that when group members share an implicit understanding of group goals and responsibilities they perform more effectively (Cannon-Bowers, Salas, & Converse, 1993). In light of the evidence that improved communication synchrony can improve a group's performance, if the LSM metric is indeed tapping mimicry, then it should positively predict task performance.

## **LSM Across Communication Media**

Given that the LSM metric focuses exclusively on verbal content, an important question is whether the medium of the communication affects LSM and its predictive abilities. For instance, does the LSM metric effectively measure mimicry in text-based computer-mediated communication (CMC), such as email, as well as more traditional face-to-face (FTF) interactions? Mediated communication is remarkable because it does not contain nonverbal information and therefore involves no additional channels for conveying mimicry. Previous research has provided evidence of mimicry in computer-mediated interactions (Niederhoffer & Pennebaker, 2002), although it is unclear how mimicry in computer-mediated interactions compares with FTF interaction. A research question explored in the present study is whether verbal mimicry will occur at equal rates in FTF groups and online groups, and whether LSM can predict cohesiveness and task performance in both media.

## **Additional Language Indicators of Cohesiveness and Performance**

Finally, in addition to mimicry, we are also interested in whether individual features of language use can predict rates of group cohesiveness or task performance. Investigative projects using automated text analysis have uncovered consistent patterns in language style across many different identity markers, including age (Pennebaker & Stone, 2003), psychological health (Mehl & Pennebaker, 2003; Stirman & Pennebaker, 2001), and sex (Newman, Groom, Handleman, & Pennebaker, 2008). Linguistic categories, such as pronouns, have been implicated as indicators of phenomena such as dominance relations, depression, deception, and social bonding (see Chung & Pennebaker, 2007). As a final exploratory analysis, we examined whether simple verbal features of the interaction, such as word count, pronoun patterns, and the use of future and achievement-oriented language, are indicators of cohesiveness and task performance.

*Word count.* Studies on both ‘traditional’ FTF workgroups (Riordan & Weatherly, 1999) and virtual workgroups (Weisband & Atwater, 1999) have found a positive relationship between the amount of group communication within the group and group cohesiveness. For this reason, word count should be positively associated with cohesiveness in both online and FTF.

*First-person pronouns.* Research on shared social stressors such as 9/11 (Cohn, Mehl, & Pennebaker, 2004), or smaller scaled tragedies (Gortner & Pennebaker, 2003), finds that people increase in first-person plural use in response to such events. These findings have been interpreted to suggest that when a group reacts to a common event it heightens the sense of groupiness or cohesiveness. In light of these findings, it is predicted that both online and offline groups will demonstrate a positive correlation between the use of first-person plural pronouns and self-reports of cohesiveness.

*Achievement and future-oriented language.* If team coordination is critical to positive work outcomes, according to research noted above, language that reflects active intent to coordinate and plan for successful task completion should positively correspond with higher performance on an interdependent task. There are multiple categories of language that might indicate effective task performance. We specifically focus on achievement-oriented language (e.g., *ability, win*), which should reflect that groups are discussing the task, and future-oriented language (e.g., *will, should*), which should reflect that the groups are devising a team strategy. Both of these categories of language should occur more frequently in groups that are performing well.

## Study Overview

To examine these questions and predictions, work teams were put into groups of 4 to 6 people to work together on a problem-solving task. Approximately, half of the groups worked in the same room (FTF condition) and the remaining participants worked in individual rooms using online chat technology (CMC group). The study, which totaled 35 minutes, required participants to first get to know one another (10 minutes) and then come up with answers to 22 different questions in an information search task (25 minutes).

The language from the FTF condition was transcribed, and the language from the CMC condition was checked for spelling errors. The language from the entire interaction was then analyzed and compared with the outcomes of group cohesiveness and performance using an automated language analysis tool, Linguistic Inquiry and Word Count (LIWC; Pennebaker, Booth, & Francis, 2007). LIWC is a word count program with over 70 pre-defined grammatical dictionaries, including function-word categories, and psychological dictionaries, including achievement and future language categories. Use of this tool is a simple procedure in which the automated word count program analyzes the texts, all in a text document, simultaneously and nearly instantaneously. Output is based on the percentage of language from each category used during the interaction, with linguistic data from each individual, or in this case each group, displayed in a separate row.

Our expectation was that the LSM metric could assess mimicry in both the computer-mediated and FTF conditions, and that in both conditions the LSM metric would be

positively associated with levels of group cohesiveness and group performance. Lastly, we expected word count and pronoun patterns to predict cohesion, and achievement and future-oriented language to predict performance.

## Method

### *Participants*

A total of 324 students, 174 female and 150 male, participated in the experiment for course credit. Participants worked in same-sex groups of 4 to 6 people. Three groups were removed from the CMC condition due to technical problems with the communication system. Two CMC groups were also removed from analysis because participants knew one another. The final analysis included 34 CMC groups, 16 of which were male students and 18 of which were female students, and 41 FTF groups, 29 of which were male students and 22 of which were female students.

### *Procedure*

Participants were informed that the group with the highest score would receive a US\$15 gift certificate to a local video store for each group member. The additional motivation was effective, as a review of the text indicates that all groups worked to complete the task.

On arrival at the lab, participants were told that the study was designed to measure small group task performance as a function of group socialization. Groups were randomly assigned to interact FTF or online. After a brief introduction to the study, participants were taken to separate rooms to read and sign a consent form before beginning the study. After completing the consent form, participants reconvened in CMC or FTF. All groups were then given the instructions to, get to know one another, for the first 10 minutes of the interaction, before beginning the task. After socializing, the experimenter returned to introduce the task and choose a team leader at random who would be solely responsible for recording answers in an attempt to generate more language and increase interdependence. By having a single individual record answers, teams were required to maintain a minimum level of coordination and teamwork.

After explaining the task, the experimenter gave each group 2.5 minutes to strategize before beginning. When the strategizing session concluded, the experimenter returned with questions for each member as well as an answer sheet for the team leader. Participants were told that they would be given 20 minutes to work on the task. Midway through the task, groups were stopped by the experimenter for another 2.5 minute strategy session. During that time, participants were asked to close their books and discuss the effectiveness of their strategy. In all, task-focused dialogue constituted 25 minutes of the experiment. After completing the task, participants were taken to separate rooms where they were asked to fill out an Interaction Rating Questionnaire (IRQ; Niederhoffer & Pennebaker, 2002). On completing the questionnaire, participants were debriefed and dismissed.

## Measures

*Interdependent task.* The task consisted of finding answers to 22 questions in an almanac. Questions were in short-answer, true/false, and multiple-choice formats (e.g., What U.S. state was deemed the healthiest in 2006? Are there more registered vehicles in California than people in all of the states that begin with the letter M?). Each member was given one of three different 2007 almanacs. The task was designed to be relatively difficult and interdependent, often requiring information from multiple topics, or even books, in order to answer a single question. Participants were instructed not to exchange books during the task.

*IRQ.* The IRQ was administered following all group interactions. This measure was developed for previous use in conjunction with research on language style matching (Niederhoffer & Pennebaker, 2002). The scale consisted of 22 questions using a 7-point likert scale. Eight of these questions specifically addressed liking. Each group member's responses to those eight questions were summed and then averaged with other group members to create a group score (Cronbach's  $\alpha = .82$ ). Note that only the eight questions associated with liking were used to operationalize cohesiveness.

## Analytic Strategy

The calculation of LSM scores required a series of analytic steps. The first was to measure the degree to which each group member used nine types of function words: auxiliary verbs (e.g., to be, to have), articles (e.g., an, the), common adverbs (e.g., hardly, often), personal pronouns (e.g., I, they, we), indefinite pronouns (e.g., it, those), prepositions (e.g., for, after, with), negations (e.g., not, never), conjunctions (e.g., and, but), and quantifiers (e.g., many, few). For each participant, the percentage of total words for each of the nine function words was calculated. For personal pronouns, for example, the percentage use might be 6.4% for Person 1, 5.7% for Person 2, and so on.

In dyadic comparisons of LSM, the absolute value of the difference between two speakers was divided by the total for each category. The resultant LSM score was between 0 and 1, with scores closest to 1 reflecting high degrees of style matching. For example, in the case of percentage of personal pronouns (pp) between Persons 1 and 2, the calculation was as follows:

$$\text{ppLSM} = 1 - (|\text{pp1} - \text{pp2}| / (\text{pp1} + \text{pp2})).$$

Or, in the example from above, where the two people used 5.7% and 6.4% personal pronouns, their personal pronoun LSM score would be as follows:

$$1 - |5.7 - 6.4| / (5.7 + 6.4),$$

or

$$1 - 0.7 / 12.1 = 1 - .058 = .942.$$

There are multiple ways by which to calculate LSM scores for entire groups. One way is to calculate separate LSM scores for all the possible pairs of group members, Person 1 with Person 2, Person 1 with Person 3, and so on, and then to average the scores. This pairwise approach assumes that group interactions occurred on the dyadic level. An alternative approach is to compare each person's language with the overall percentage of the remaining group members. We followed this second strategy, which resulted in four separate LSM scores—one each for each group member and his/her language in comparison to the remaining group members. Mathematically, personal pronoun LSM was calculated in the following way:

$$\begin{aligned} pp1 &= 1 - (|pp1 - ppG| / (pp1 + ppG)), \\ pp2 &= 1 - (|pp2 - ppG| / (pp2 + ppG)), \\ pp3 &= 1 - (|pp3 - ppG| / (pp3 + ppG)), \\ pp4 &= 1 - (|pp4 - ppG| / (pp4 + ppG)), \end{aligned}$$

resulting in

$$\text{Group } ppLSM = (pp1 + pp2 + pp3 + pp4) / 4,$$

where ppG was the percentage of personal pronoun use of the remaining group members determined by taking their total number of personal pronouns and dividing it by their total word count. For pp1, then, ppG would be composed of words from Persons 2, 3, and 4; for pp2, for Persons 1, 3, and 4, and so on.

Recall that there are nine separate dimensions of function words that make up the overall LSM score. Comparable calculations were made for each person within each group for each function-word category. For each group, then, the nine separate mean LSM scores for each category were averaged to yield a group total LSM score. Function-word LSM scores were correlated with each other and resulted in an internally consistent synchrony measure, Cronbach's  $\alpha = .73$  (Table 1).

## Results

### *LSM as an Indicator of Group Cohesiveness*

Recall that group cohesiveness was calculated using the IRQ. Individual ratings of the group were averaged to form an overall group cohesiveness score. LSM was calculated by averaging individuals' LSM scores within a group to create a single group LSM score.

LSM scores, group size, sex, and communication medium were entered into an ordinary least squares (OLS) linear regression model predicting cohesiveness (see Table 2). We expected that, after controlling for other factors in the model, language style matching would positively predict group cohesiveness. As expected, LSM predicted group cohesiveness ( $b = .28, p = .04$ ), when controlling for medium, sex, and number of people in the group. That is, for every standard deviation increase in the group LSM score, cohesiveness ratings increased by .28 standard units. Medium, sex, and number of people in the group



**Table 1.** Mean Category LSM Score and Total LSM Score

Category LSM Score	Examples	<i>M</i>	<i>SD</i>
Adverb	completely, often	0.89	0.06
Article	a, an, the	0.88	0.06
Auxiliary verb	am, have	0.91	0.04
Conjunction	and, but, or	0.85	0.06
Indefinite pronoun	it, those	0.90	0.04
Negation	no, not, never	0.79	0.10
Personal pronoun	I, you, we	0.92	0.04
Preposition	at, for, into	0.91	0.05
Quantifier	all, few, some	0.85	0.07
Total LSM score		0.88	0.03

Note: Mean scores refer to the average LSM score between each group member and the sum of the remaining group members. *SD* refers to the standard deviation of mean LSM scores across all 75 groups. Total LSM score is calculated by averaging the category LSM scores. LSM = language style matching.

did not significantly influence changes in group cohesiveness. Overall, the model explained 17% of the variation in group cohesiveness ( $R^2 = .17, p < .01$ ), suggesting that verbal matching within a group is a significant indicator of how well members of that group like one another.

To examine whether the communication medium affected the relationship between LSM and cohesiveness, a second model that included an interaction term for medium and LSM was tested. An incremental *F* test of Model 1 and Model 2 revealed that the model with the LSM  $\times$  Medium interaction term did not account for more variance than the first model ( $F = 1.33, p = .25$ ). Furthermore, the interaction term did not reach statistical significance ( $b = 6.16, p = .14$ ), suggesting that LSM's ability to predict cohesion was not affected by medium.

### *LSM as an Indicator of Task Performance*

As noted above, task performance was determined by the percentage of correct responses to 22 short questions. Each group worked on the task together and received a single group score. LSM scores, group size, sex, and medium were entered into an OLS linear regression model predicting task performance. As can be seen in Table 3, this initial model was not significant, and none of the coefficients were statistically significant.

A second model was tested that included the interaction term between medium and LSM, regressing task score on group size, sex, medium, LSM, and the Medium  $\times$  LSM interaction term. This model was statistically significant, explaining 19% of the overall variance in group performance ( $R^2 = .19, p = .01$ ). An incremental *F* test between Model 1 and Model 2 revealed an improvement in variance accounted for between the models ( $F = 8.82, p < .01$ ). The results also revealed that LSM and medium interacted to influence task score ( $b = -13.32, p < .01$ ). The interaction was decomposed by evaluating the predictive value of

**Table 2.** Standard Deviation Change in Group Cohesion Due to Medium, Sex, Group Size, and Language Style Matching (LSM)

Independent Variables	Main Effects Model	Main Effects and Medium $\times$ LSM Model
	$\beta$	$\beta$
Medium (0 = CMC, 1 = FTF)	.17	-5.90
Sex (1 = Male)	.00	-0.01
Group size	-.04	0.01
LSM	.28*	0.15
Medium $\times$ LSM		6.16
$R^2$	.17	0.20
Adjusted $R^2$	.13	0.45

Note: LSM refers to the mean group LSM score, range 0 to 1. Cohesiveness is determined using the Interaction Rating Questionnaire that taps the degree that groups get along, range 8 to 56. Medium refers to online and face-to-face groups. Group size is the number of people in each group, from 4 to 6 people.

\* $p \leq .05$ . \*\* $p \leq .01$ .

LSM on task performance in each medium separately. FTF groups produced a significant positive relationship between performance and LSM. For each standard deviation increase in LSM scores, FTF groups performed better by .58 standardized unit increase in score ( $b = .58, p < .01$ ). In contrast, online groups produced a negative relationship between LSM and performance, although this value did not achieve significance ( $b = -.18, p = .38$ ). Finally, as might be expected, group size improved group performance ( $b = .32, p < .01$ ).

### Additional Language Indicators

Group cohesiveness and task performance were also analyzed in relation to specific language characteristics to determine if they predict group social dynamics.

*Language indicators of cohesiveness.* An OLS regression analysis that controlled for medium, group size, and sex examined the relationship between group cohesiveness ratings and LIWC categories. To begin, after controlling for other variables, word count was a positive predictor of group cohesiveness ( $b = .70, p < .001$ ).

The analysis also revealed that groups that used fewer first-person plural pronouns (“we”) were more cohesive ( $b = -.32, p < .001$ ). That is, for every standard deviation increase in first-person plural pronoun use, group cohesiveness score decreased by .32 standard units. This finding was counter to the prediction that first-person plural pronouns would be positively correlated with group cohesion and is further explored in the discussion.

*Language indicators of performance.* An OLS regression analysis that controlled for medium, sex, and group size also examined the relationship between task performance scores and LIWC categories. The analysis yielded a positive relationship between the use of future-oriented language (e.g., *could, should, will*) and task performance ( $b = .34, p < .01$ ). This finding was consistent with expectations. However, there was an

**Table 3.** Standard Deviation Change in Task Performance Due to Medium, Sex, Group Size, and Language Style Matching (LSM)

Independent Variables	Main Effects Model	Main Effects and Medium × LSM Model
	$\beta$	$\beta$
Medium (0 = CMC, 1 = FTF)	.05	-13.07**
Sex (1 = Male)	.20	0.18
Group size	.20	0.32**
LSM	.04	-0.24
Medium × LSM		13.32**
$R^2$	.07	0.20
Adjusted $R^2$	.02	0.14

Note: LSM refers to the mean group LSM score, range 0 to 1. Performance is based on a percentage of correct answers on the group task, range 0 to 22. Medium refers to online and face-to-face groups.

Group size is the number of people in each group, from 4 to 6 people.

\* $p \leq .05$ . \*\* $p \leq .01$ .  $t$  values in parentheses.

unexpected result for the relationship between achievement language and performance. Achievement-oriented language (e.g., *ability*, *progress*, *work*) was negatively related with performance on the task ( $b = -.33$ ,  $p < .01$ ).

## Discussion

The primary goal of this analysis was to develop an efficient means of assessing mimicry from language and to determine whether such a metric could predict two social dynamics identified in the previous literature as being related to mimicry. The results demonstrate that a mimicry metric that calculates the degree to which group members produce similar rates of function words can, like other hand-coded measures of mimicry, predict key group dynamics such as cohesion and performance.

The LSM metric predicted group cohesiveness regardless of the communication medium, the gender of the group, or how many individuals were in the group. In both online and FTF groups, the more individuals liked their groups, the more members of the group used the same rate of function words. This positive relationship between the LSM metric and group cohesiveness is consistent with previous findings on mimicry (Bernieri et al., 1988; Chartrand & Bargh, 1999; Giles et al., 1991).

The results also revealed a positive relationship between the LSM metric and task performance, but only in the FTF condition. When interacting FTF, the more teams matched their production of function words, the better they did on the task. The positive relationship between the LSM metric and team performance is consistent with previous work on the role of shared mental models as being predictive of team-performance measures (Cannon-Bowers et al., 1993).

## *Contributions of the LSM Metric*

In addition to producing findings similar to hand-coded measures of mimicry, the novel LSM metric of mimicry has three important attributes. First, the LSM metric is a uniquely efficient tool. As an automated metric of mimicry, it is both objective and unobtrusive. Automated text analysis is much less time consuming than human coding (see Bernieri & Rosenthal, 1991) and reduces the risk of coder error. Unlike previous studies on mimicry, the LSM metric does not require line-by-line analysis of interaction. Instead, an entire interaction can be analyzed at once. This may be seen as a weakness relative to computerized linguistic analysis techniques that reveal a more detailed analysis of a text. Nevertheless, the results demonstrate both the strength of the effect and the power of this approach.

Second, function words, which are the underlying features of the LSM metric, are effective measures of mimicry because they are frequently used, nonconsciously produced, and context independent (Chung & Pennebaker, 2007; Pennebaker et al., 2003). Even with great effort, it is difficult to intentionally manipulate function-word use, making them a relatively pure measure of social dynamic. Also, because function words are context independent, it is possible to ensure that the dynamics measured are not artifacts of a particular content domain. Further, because the rate of function-word mimicry is based on percentages of the text (i.e., the percentage of the text comprised of function words) and therefore controls for volubility, it is unlikely that LSM is determined solely by member involvement.

Third, the study demonstrated that mimicry occurs in both online and offline groups. The fact that verbal mimicry takes place in a nonvisual environment is an important finding that replicates earlier work (Niederhoffer & Pennebaker, 2002) and highlights the fact that although nonverbal communication may support coordination, it is not required for verbal mimicry to occur. Furthermore, the fact that mimicry takes place in CMC suggests that there is more to mimicry than synchronization based on physical rhythms (Kendon, 1967). Across the wide body of research on mimicry and other forms of interpersonal coordination, there are multiple interpretations of the exact role of synchronizing behavior (see Burgoon et al., 1995). Some authors have linked mimicry to early forms of language learning. Indeed, vocal mimicry may have evolved using mirror neurons similar to those used when evoking physical mimicry (Studdert & Goldstein, 2003). Evidence of mediated verbal mimicry is further proof that this process is not solely due to physical priming but must also require internal cognitive representations of mimicry.

## *Additional Language Indicators of Cohesiveness and Performance*

*Predictors of cohesiveness.* Aside from research on LSM, we also undertook an exploration of specific language indicators of task performance and cohesiveness. Although there were significant effects between predicted language variables and the dependent variables, not all of the relationships were in the predicted direction.

To begin, the relationship between word count and cohesiveness was observed as expected. This finding is consistent with previous research on liking and interaction (Riordan & Weatherly, 1999; Weisband & Atwater, 1999), and this is not altogether surprising. However, there was an unexpected negative relationship between first-person plural pronouns (“we”) and group cohesiveness. It is possible that mention of the group identity by its members may have been an indication that groups were trying to create cohesiveness in an otherwise noncohesive group. In other words, perhaps the use of “we” suggests that liking, which is rarely explicitly stated, was being compensated for by actively unifying the group linguistically.

*Predictors of performance.* Key performance related activities, such as planning and task orientation, were expected to be reflected through achievement- and future-oriented language. The prediction that future-oriented language would be positively associated with group performance was supported. In the LIWC dictionary, future language includes any use of auxiliary verbs, *could*, *would* *should*, *must*, *ought*, and *will*. In a task setting, this language reflects goal orientation, real time planning (e.g., “Who will answer no. 5?”), and cognitive complexity, as individuals mull over behavioral choices together (e.g., “Should we answer ‘Mexico’ for no. 8?”). Such responses indicate that a group is working together on the task in a manner that facilitates performance.

Unexpectedly, the more that groups used achievement-oriented language, the more poorly they performed on the task. As in the case of “we,” it is possible that referencing the task was an indication that the group was perhaps trying to compensate for a poor performance. It seems plausible that, particularly in a task setting, words such as *success* and *work* may indicate that a group is talking about the task because they are not performing well. Additional research is required to understand whether the explicit mention of achievement or explicit references to the group via first-person plural pronouns indicate groups that are struggling.

### *Limitations and Future Research*

One possible reason the performance effect was limited to the FTF condition may be the nature of the task. Hancock and Dunham (2001) pointed out the difficulties in cognitive allocation when switching between and online and offline tasks. Because verbal synchronization takes time, the constant shift of attention between the computer and the almanac may have detracted from the ability to verbally entrain with the group. The inability to fully attend to the task is supported by the lower scores for CMC groups. These results figure into a diverse body of literature on channel effects and task performance (see Martins, Gilson, & Maynard, 2004) and speak to the need for future research of LSM in additional task scenarios to determine the generalizability of LSM as a performance indicator. Specifically, future research should explore LSM in tasks when channel switching is not required, as in a computer-based information seeking task, so that moving from the task to the keyboard does not interfere with mimicry.

Also, we should note that a major limitation of this study is that we cannot determine the causal relationship between LSM and either of the dependent variables. With this experimental design, we can only conclude that there is a positive relationship between language matching and cohesion, and language matching and performance in FTF interaction. Previous studies have found evidence that increased mimicry can have a causal effect on increased rapport (Giles & Coupland, 1991); however, because we did not manipulate mimicry, it is impossible to determine whether changes in social dynamics altered the amount of mimicry in real time or whether changes in the amount of mimicry influence the social dynamics. Additional research is required to examine the causal nature of these relationships.

One possible contribution of future research that may address questions of causality will be to compare changes in mimicry over time. Such an analysis would serve to better situate the LSM metric within previous research that has examined changes in mimicry over the course of a conversation (e.g., Burgoon et al., 1995; Giles et al., 1991). While our intention was to demonstrate that a group of strangers with little personal history (10 minutes) will demonstrate varying degrees of mimicry that will influence cohesiveness and even task effectiveness, future research can begin to explore the nuances of LSM depending on the nature of the interaction, the length of the interaction, and so on. For example, it may be possible to determine what type of dynamics foster LSM by manipulating the relationship and interaction of participants prior to working on a task. Just as real-world work groups see differing existing social dynamics within their groups, it may be possible to simulate some of these different relationships to see how initial dynamics shape language patterns as well as consequent dynamics.

## **Conclusion**

In expanding previous findings on verbal mimicry, the outstanding quality of the LSM metric is that it can be easily and widely applied. Because it is an automated syntactical measure, it can be applied across conversational contexts in online or offline conversation in dyadic or group settings. This measure holds substantial promise for both academic and nonacademic enterprises. Researchers may take advantage of the plethora of public dialogue on the Internet to understand covariates of liking and performance. At the same time, real-world team managers can use the metric to easily get a sense of team cohesiveness and team performance.

In addition to being a tool with a broad range of applications, the objective and unobtrusive nature of computerized linguistic analysis make this resource less vulnerable to demand characteristics than traditional self-report measures. We do not mean to suggest that objective text analysis should or could do away with self-report methods of data collection. However, development of a self-report measure requires effort and careful consideration, as the order and composition of the questions can have a significant influence on the outcomes (Shwarz, 1999). Automated text analysis can be a useful complement to self-report data and may provide a means of analyzing group dynamics when self-report data cannot be collected.

The LSM metric expands on a large body of established work linking mimicry to social dynamics. Much of this literature focuses on nonverbal and paralinguistic mimicry (Bernieri, et al., 1988; Chartrand & Bargh, 1999; Giles et al., 1991; van Swol, 2003); however, findings from this study reveal that human synchronization also takes place at a nonconscious level with the words people use. It is striking to note that something as fundamental as entrainment between parent and child (Condon & Ogston, 1966) has been translated into language. Future research should continue to explore links between verbal mimicry and social dynamics in dyadic and group interactions to determine the role of function-word mimicry in the larger body of research on interpersonal coordination.

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### **References**

- Bernieri, F., Reznick, J. S., & Rosenthal, R. (1988). Synchrony, pseudosynchrony, and dis-synchrony: Measuring the entrainments process in mother-infant interactions. *Journal of Personality and Social Psychology, 54*, 243-253.
- Bernieri, F., & Rosenthal, R. (1991). Interpersonal coordination: Behavior matching and interactional synchrony. In R. Feldman & B. Rime (Eds.), *Fundamentals of nonverbal behavior. Studies in emotion and social interaction* (pp. 401-432). New York: Cambridge University Press.
- Burgoon, J., Stern, L., & Dillman, L. (1995). *Interpersonal adaptation: Dyadic interaction patterns*. New York: Cambridge University Press.
- Campbell, R. S., & Pennebaker, J. W. (2003). The secret life of pronouns: Flexibility in writing style and physical health. *Psychological Science, 14*, 60-65.
- Cannon-Bowers, J. A., Salas, E., & Converse, S. A. (1993). Shared mental models in expert team decision making. In N. J. Castellan (Ed.), *Individual and group decision making: Current issues* (pp. 221-246). Hillsdale, NJ: Erlbaum.
- Chartrand, T., & Bargh, J. (1999). The chameleon effect: The perception-behavior link and social interaction. *Journal of Personality and Social Psychology, 76*, 893-910.
- Chung, C. K., & Pennebaker, J. W. (2007). The psychological function of function words. In K. Fiedler (Ed.), *Social communication: Frontiers of social psychology* (pp. 343-359). New York: Psychology Press.
- Cohn, M. A., Mehl, M. R., & Pennebaker, J. W. (2004). Linguistic markers of psychological change surrounding September 11, 2001. *Psychological Science, 15*, 687-693.

- Condon, W. S., & Ogston, W. D. (1966). Sound film analysis of normal and pathological behavior patterns. *Journal of Nervous and Mental Disease, 143*, 338-347.
- Gatewood, J. B., & Rosenwein, R. (1981). Interactional synchrony: Genuine or spurious? A critique of recent research. *Journal of Non-Verbal Communication, 6*, 12-29.
- Giles, H., Coupland, J., & Coupland, N. (1991). *Contexts of accommodation: Developments in applies sociolinguistics*. New York: Cambridge University Press.
- Giles, H., & Coupland, N. (1991). *Language: Contexts and consequences*. Pacific Grove, CA: Brooks/Cole.
- Gortner, E. M., & Pennebaker, J. W. (2003). The archival anatomy of a disaster: Media coverage and community-wide health effects of the Texas A&M Bonfire Tragedy. *Journal of Social and Clinical Psychology, 22*, 580-603.
- Hancock, J., & Dunham, P. (2001). Impression formation in computer-mediated communication revisited: An analysis of the breadth and intensity of impression. *Communication Research, 28*, 325-32.
- Kendon, A. (1967). Some functions of gaze directions in social interaction. *Acta Psychologica, 32*, 1-35.
- Klimoski, R. J., & Mohammed, S. (1994). Team mental model: Construct or metaphor? *Journal of Management, 20*, 403-437.
- Kozlowski, S. W. J., & Ilgen, D. R. (2006). Enhancing the effectiveness in work groups and teams. *Psychological Science, 7*, 77-124.
- Manning, C. D., & Schuetze, H. (2003). *Foundations of statistical natural language processing*. Cambridge, MA: MIT Press.
- Martins, L. L., Gilson, L. L., & Maynard, M. T. (2004). Virtual teams: What do we know and where do we go from here? *Journal of Management, 30*, 805-835.
- Mehl, M. R., & Pennebaker, J. W. (2003). The sounds of social life: A psychometric analysis of students' daily social environments and natural conversations. *Journal of Personality and Social Psychology, 84*, 857-870.
- Newman, M. L., Groom, C. J., Handelman, L. D., & Pennebaker, J. W. (2008). Gender differences in language use: An analysis of 14,000 text samples. *Discourse Processes, 45*, 211-236.
- Niederhoffer, K. G., & Pennebaker, J. W. (2002). Linguistic style matching in social interaction. *Journal of Language and Social Psychology, 21*, 337-360.
- Pennebaker, J. W., Booth, R. J., & Francis, M. E. (2007). *Linguistic Inquiry and Word Count (LIWC): A computerized text analysis program*. Austin, TX: LIWC.net.
- Pennebaker, J. W., & King, L. A. (1999). Linguistic styles: Language use as an individual difference. *Journal of Personality and Social Psychology, 77*, 1296-1312.
- Pennebaker, J. W., Mehl, M. R., & Niederhoffer, K. (2003). Psychological aspects of natural language use: Our words, our selves. *Annual Review of Psychology, 54*, 547-577.
- Pennebaker, J. W., & Stone, L. D. (2003). Words of wisdom: Language use over the life span. *Journal of Personality and Social Psychology, 85*, 291-301.
- Pickering, M. J., & Garrod, S. (2004). Toward a mechanistic psychology of dialogue. *Behavioral and Brain Sciences, 27*, 169-226.
- Riordan, C. M., & Weatherly, E. W. (1999). Defining and measuring employees' identification with their work groups. *Educational and Psychological Measurement, 59*, 310-324.



- Rochon, E., Saffran, E. M., Berndt, R. S., & Schwartz, M. F. (2000). Quantitative analysis of aphasic sentence production: Further development and new data. *Brain and Language, 72*, 193-218.
- Schwarz, N. (1999). Self-reports: How the questions shape the answers. *American Psychologist, 54*, 93-105.
- Stirman, S. W., & Pennebaker, J. W. (2001). Word use in the poetry of suicidal and non-suicidal poets. *Psychosomatic Medicine, 63*, 517-522.
- Studdert, K. M., & Goldstein, L. (2003). Launching language: The gestural origin of discrete infinity. In S. Kirby, & M. Christiansen (Eds.), *Language evolution* (pp. 235-254). New York: Oxford University Press.
- Tickle-Degnen, L., & Rosenthal, R. (1987). Group rapport and nonverbal behavior. *Review of Personality and Social Psychology, 9*, 113-136.
- van Swol, L. M. (2003). The effects of nonverbal mirroring on perceived persuasiveness, agreement with an imitator, and reciprocity in a group discussion. *Communication Research, 30*, 461-480.
- Weisband, S., & Atwater, L. (1999). Evaluating self and others in electronic and face-to-face groups. *Journal of Applied Psychology, 84*, 632-639.

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