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Exploring the Relationship Between School Level and a School Growth Mindset

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Abstract

A goal of this study was to provide an alternative lens to view the processes of student learning across school transitions such as elementary to middle, middle to high school, and high school to college or work. This study explored the theories of organizational learning and mindset theory. The framework included dialogical processes of boundary crossing and relative autonomy (Wenger, 1998; McGrew, 2011; Mays, 1965; Lacey, 1970; Corrigan & Frith, 1976; Willis, 1977/1981; Shor & Freire, 1987; Spector, 1988). Suchman (1994) described boundary crossing as “a person’s transitions and interactions across different sites.” Akkerman and Bakker wrote, “All learning involves boundaries” (p. 132 &133). Edwards & Fowler (2007) explained boundary theory has more recently been used in social theory to explore “marginal and decentered discourses of power” (p. 135). Recent literature in social theory described a multiple dimensional model of the individual mind connected to others in ways that continuously construct and reconstruct the identity through dialogical processes. The social dimension of knowledge construction is also found in Vygotsky’s (1978) and Bandura’s (1977, 1986, 1989, 1997, 2001) works grounded in social cognitive theories. These processes recognize the “interplay of research, politics, and social analysis” in developing and promoting recommendations for improvements in educational processes (Oakes, Welner & Renée, 2015, para. 5).

I. Purpose

This study sought to explore the relationship between the variables of school level and a school growth mindset culture (Blackwell, 2012). The What's My School Mindset? Survey is a unidimensional scale that quantifies a school growth mindset and including three subdomains; collaborative planning, shared leadership, and open communication & peer support (Hanson, Ruff, & Bangert, 2015, in progress). The results of the WMSM survey are used to assess school cultures and provide interventions to develop growth mindsets in students and faculty (Mindset Works, 2008-2012a-c). A review of mindset literature revealed teacher behaviors were shown to influence student academic behaviors that directly affected student transition success and completion rates (Blackwell, Trzesniewski, & Dweck, 2007; Farrington, et al., 2012, p. 47). Identifying variables influencing school culture and that vary with school level could be useful for administrators to begin dialogues with faculty regarding their perceptions, beliefs and worldviews that may differ from the organization and the students they teach (Hoy, Tarter & Kottkamp, 1991; Tarter & Hoy, 2004; Blackwell, 2012; Dweck, 2010). Research-based identification of malleable variables of teachers’ perceptions about their school practices could provide opportunities for opening communication and reflection on perspective taking that could result in transformations at the boundaries of differences (Akkerman & Bakker, 2011, p. 151). Using dialogical processes of growth school mindset may result in improved school cultures and teacher behaviors that support
all students in the development of positive psychosocial skills leading to increased academic engagement (Farrington et al., 2012). The independent variable used in this study was school level, and the dependent variable was school mindset.

II. Literature Review
A review of the literature in the area of school transition success revealed students in transition to middle school or high school dropped in academic engagement and performance (Eccles, Lord, & Midgley, 1991). Teachers in middle and high schools were reported as having fewer skills to address the psychosocial factors needed to develop student engagement in school. For example, secondary level teachers tended to reward ability rather than effort and emphasized social comparison. They also demonstrated increased control over students compared to elementary levels, increased whole class and group work, emphasizing social comparison, and used a higher standard in secondary school for grading performance. Teachers at the secondary level also used teaching practices that reduced student autonomy and had fewer teacher-student relationships (pp. 533-534; Spector, 1988; Blackwell et al., 2007).

Students transitioning to middle and high schools also experience increased psychological sensitivity due to cognitive changes in adolescence that increase their awareness of their social situation, self, and others. Student self-conceptions arise, such as the belief that if one has to work hard it reflects poorly on one's abilities compared to others (Farrington et al., 2012, p. 55). Students in school level transition are learning how to relate to changes in norms and values, as well as developing their new identities in the new context (Akkerman & Bakker 2011, p. 138). Secondary level teachers lack developmentally appropriate responses to students’ needs during transition years becoming a large contributor to reduced student academic and pro-social behaviors (Eccles & Wigfield, 2002; Farrington et al., 2012, p. 63). Akkerman & Bakker also identified a difference in worldviews between secondary teachers and students. They described a resource for student learning as building relationships and initiating dialogue to overcome such sociocultural differences between teachers and their new students (p. 136). Middle and high school teachers used judgments about student attitudes and behavior as direct factors when calculating student grades, not just student learning outcomes (Austin & McCann, 1992; Cross & Ferry, 1999).

As transitioning students experienced the changing school context, they demonstrated withdrawal behaviors resulting in a drop in grades. Reduced academic behaviors included absenteeism, incomplete homework, and failure to study (Farrington et al., 2012; Dweck, 2012; Blackwell et al., 2011). Multiples studies showed student course failure during transition years in high school predicted school dropout more than did grades. Students’ chances of dropping out of high school increased by 30% if they failed one semester course in the first year of high school (Allensworth & Easton, 2007). The middle and high school context included faculty use of behaviorist-style strategies to motivate disengaged students with threats of failure, reduced monitoring, and lack of feedback to students. These methods contributed to reductions in student perceptions of internal locus of control and withdrawal from engagement in school (Farrington et al., 2012, p. 49, 59, & 64; Spector, 1988). In contrast, faculty with a growth mindset were more likely to see growth potential in struggling students and to support persistence to mastery. Teachers with growth mindsets praised students for their effort rather than traits. They were also more likely to support school change efforts (King, 1973; Mueller & Dweck, 1998; Yeager, Johnson, Spitzer, Trzesniewski, Powers & Dweck, 2014). Applying growth mindset theory to develop growth
mindset cultures in schools could increase teacher skills to support student psychosocial needs and the development of academic skills. School mindset interventions aim to develop the faculty belief that their school can help all students grow and learn (Blackwell, 2012; Farrington, 2013). Teachers with growth mindset beliefs were more open to new information and demonstrated increased ability to resolve a conflict. They showed more tolerance, chose learning goals over performance goals, and demonstrated persistence in the face of setbacks. They also showed resilience in the face of obstacles and exhibited reduced stereotype behaviors (Sprengel & Spritts, 2012; Yeager et al., 2014; Briceno, 2013).

Recommendations to develop a growth school mindset and improve teacher behaviors that support students include; providing professional development to support psychosocial skills, such as a growth mindset. Psychosocial skills include increased “self-awareness, self-management, social awareness, relationship skills, and responsible decision making" (Farrington et al., 2012, p. 49). Students with strong psychosocial skills showed improved social behaviors, autonomy, engagement and persistence toward academic goals, and reduced emotional stress (Greenberg, Weissberg, O’Brien, Zins, Fredericks, Resnik, & Elias, 2003; Vygotsky, 1962, 1978; Bandura, 1997 & 2001; Briceno, 2013). When schools have a growth mindset culture the faculty act according to the belief that all individuals in the school can grow and learn. This increases the group's willingness to choose challenging organizational goals and leads to school improvement (Dweck, 1986, 2010, 2014; Blackwell, 2012; Delaney, Dweck, Murphy, Chatman, & Kray, 2015) and has been demonstrated to significantly correlate with faculty collective efficacy beliefs (Hanson, Ruff, & Bangert, In Process).

III. Procedure
This study included a quantitative research design using SPSS version 22 analytical software (IBM, 2013) to perform a correlation analysis of variables and a multiple regression analysis of significantly correlated variables. Data collection used a combination of paper-based and online Likert-style surveys distributed to a stratified random sample of approximately 15 PK-12 schools districts across a large northwestern state. Data analyses were performed to determine covariance and correlations with an analysis of variance. Data for this study was collected using a demographic questionnaire and the What’s My School Mindset Survey (Blackwell, 2012). The participants included faculty and administrators (n=347) from a random, stratified sample of 30 PK-12 schools across a large northwestern state. The sample was selected from 417 school districts including 10,153 teachers and 142,349 students during the 2014/2015 school year (Meador, 2015). An approximate stratified random sample of schools by class size was selected through random number generator to obtain a representative sample. Table 1 in Appendix A shows the distribution of the stratified random sample. This sample size provided a 95% confidence level, and a 5.16 confidence interval indicating the results of this study would generalize to the population under study.

IV. Results
The results of this study revealed school level explained a significant difference in a school’s growth mindset mean as quantified in teacher and administrator self-reports on the What’s My School Mindset? Scale (Mindset Works, 2008-2012c). Results from a one-way analysis of variance (ANOVA) revealed that the elementary school What’s My School Mindset mean scores were significantly higher than those for middle school (p < .001, d = 1.80 and high school teachers
Exploring the Relationship Between School Level and a School Growth Mindset

(p < .001, d = 1.20). The effect sizes (Cohen’s d) for these comparisons ranged from moderate to large. However, there were no significant differences in What’s My School Mindset mean scores when comparing elementary teachers to teachers in combined schools levels represented by PK-12, elementary/middle and high school /middle. Results of a multiple linear regression analysis, although significant, found that school level explained only about 5.2% of the variance in school mindset scores ($F_{(1, 347)} = 19.112$), $p < .001$. Although, these results suggest that a small yet significant variation in teachers’ What My Mindset scores is explained by school level, results from the ANOVA show that this variability in WSMS mean scores is primarily due to differences found when comparing elementary teacher WMSM means to middle and high school WMSM teacher means. There was a no statistically significant interaction between school level and school size. Appendix B provides a table of these results and Appendix C shows a graph of WMSM means scores by school levels.

V. Conclusion and Implications

This study provides support for the literature that differences exist between school culture and teacher behaviors at the elementary and secondary school levels (Farrington et al., 2012; Blackwell et al., 2007). Akkerman & Bakker (2011) wrote boundaries can be “potential learning resources rather than barriers” (p. 137). Therefore, the results of this study could be used to create opportunities for faculty dialogue and reflection that “develops an expanded sense of perspectives…that informs future practice” (p. 146). The results of this study may also provide realistic ways to implement change by using research-based evidence to challenges assumptions and give sound reasons for new practices (Ruff, 2002; Sanders & Sheldon, 2009). Akkerman & Bakker (2011) explained confrontation of “some lack or problem that forces the intersecting worlds to reconsider their current practices and interrelations” is required for transformation to occur (p. 146). Research-based data may provide additional paths for administrators to help faculty collaborate on ways to support students during school level transitions that can help students succeed and increase school completion rates (Kearney, 2007; McGrew, 2011; Dweck, 2010, 2012; Delaney et al, 2015; Farrington et al., 2012; Farrington, 2015).

Administrators can use the WMSM scale as a boundary object to capture and quantify their school’s culture and to develop interventions that recognize the unique individual and school needs in their school context. Mindset culture interventions include providing opportunities for faculty participation in the decision-making and change processes, professional development that targets the development of teachers’ psychosocial skills in supporting student academic skills, and scheduled time for professional collaboration (Blackwell, 2012).

Future studies in the area of the area of the influence of school transitions on student academic and non-cognitive behaviors could include qualitative study design to explore and develop a rich thick understanding of differences in teacher and student behaviors between elementary, middles school, and high school context and between school sizes. A quantitative study to explore the correlation between teachers’ epistemological beliefs at differing school levels and student academic and non-academic behaviors might reveal further influences that explain differences in teacher’s perceptions about their school’s ability to help all students learn and grow.
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References


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IBM Corp. (Released 2013). *IBM SPSS Statistics for MacIntosh, Version 22.0*. Armonk, NY: IBM Corp.
King, P., & Shuford, B. (1996). A multicultural view is a more cognitively complex view:
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Institute of Technology.


APPENDIX A

TABLE 1

Table 1. Table of the percent of public schools by size categories and number of responses collected.

<table>
<thead>
<tr>
<th>Calculation</th>
<th>&lt; 150</th>
<th>150 to 500</th>
<th>501 to 1000</th>
<th>&gt; 1000</th>
<th>Total</th>
<th>CL</th>
<th>CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent of total student population enrolled</td>
<td>17%</td>
<td>12%</td>
<td>23%</td>
<td>48%</td>
<td>100%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual number of responses collected</td>
<td>45</td>
<td>73</td>
<td>124</td>
<td>107</td>
<td>349</td>
<td>95%</td>
<td>5.16</td>
</tr>
<tr>
<td>Percentage of total responses collected</td>
<td>12.9%</td>
<td>20.9%</td>
<td>35.5%</td>
<td>30.7%</td>
<td>100%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: CL= confidence level, CI=confidence interval.
### Table 2

Table 2. ANOVA results Pearson correlations between building levels and standard deviations.

<table>
<thead>
<tr>
<th>School Level</th>
<th>n</th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pk-12</td>
<td>31</td>
<td>4.29</td>
<td>.82</td>
</tr>
<tr>
<td>Elementary</td>
<td>112</td>
<td>4.65</td>
<td>.72</td>
</tr>
<tr>
<td>Middle</td>
<td>56</td>
<td>4.18</td>
<td>.80</td>
</tr>
<tr>
<td>High School</td>
<td>95</td>
<td>3.87</td>
<td>.67</td>
</tr>
<tr>
<td>Elementary /Middle</td>
<td>25</td>
<td>4.27</td>
<td>.68</td>
</tr>
<tr>
<td>Middle/High School</td>
<td>28</td>
<td>4.23</td>
<td>.50</td>
</tr>
<tr>
<td>Total</td>
<td>347</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
APPENDIX C

Figure 1. WMSM Means Bar Graph at School Level (two-tailed test)

Figure 2. WMSM Means Line Graph at School Level
Abstract

With social media the de facto communication gizmo to disseminate one’s self-revelations such a profound disclosure often contains double-talk, peculiar insights, or contextual information about real-world events. Natural language processing is regularly used to uncover grammatical insight within a corpus. An attempt is made to better support predictive crime analysis by combining the two and identifying a relationship between social media and crime. Since it is known that geographic information system (GIS) risk terrain models (RTMs) are based on social behavior and represent predictive crime hot spots an attempt to ascertain the predictive capability of a social media corpus as a GIS RTM risk variable is examined. Gaining insight from such a corpus would exhibit ultimate crime stopping flexibility and wherewithal, and increase predictive crime capabilities. Therefore, a tweet corpus in terms of its grammar, structural foundation, and subsequent transformation into a functional GIS RTM risk layer is produced. Second, consideration is given to the necessary data flexibility a GIS RTM environment utilizes. Third, in a between-subject quasi-experiment design it is found that NLP processing of a social media corpus increased word identification by 1.73%. Last, the social media corpus was used as a GIS RTM risk input layer, which, produces a more robust architecture than the baseline model. The result supports an idealized question; therefore, yes social media corpora are robust enough to optimize, control, and use in a GIS RTM. In addition, the finished artifact was able to increase the predictive crime incident outcome with an overall $R^2$ increase of 7.3%.

Social media as a proxy for both social behavior and predictive capability of spatial temporal crime is largely unexplored. Incorporation of social media corpora, for instance, Twitter, RedIt, or FaceBook, with government-based crime data is a promising research thread. Furthermore, natural language processing (NLP) of a tweet corpus may better facilitate social understanding, reveal correlations between disparate data, or enhance existing predictive crime analysis solutions. Well-known researchers such as Hiruta, Yonezawa, Jurmu, and Tokuda (2012), Phillip Bramsen (Bramsen, Escobar-Molano, Patel, & Alonso, 2011), and Leslie Kennedy (Kennedy, Caplan, & Piza, 2011) provide theoretical insight and practical application of social media analysis, spatial correlation, and predictive crime, respectively. Although transdisciplinary research solutions via social media and crime facilitate promising results, only rudimentary solutions are currently implemented. Furthermore, a guiding framework supporting a significant solution attempting to correlate social media and crime—which, allows law enforcement agencies to efficiently and effectively predict criminal activity, allocate and manage crime prevention resources, and promote community crime awareness—does not exist. As a result of

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these claims, additional evidence and substantive theory, examination of noteworthy research, and construction of a formative social media grammar is fabricated.

State-of-the-art prediction of criminal activity, law enforcement resource use, and public safety would experience important foresight by finding a solution to implement a social media grammar. A second important and correlated issue contends with processing, analyzing, and interpreting social media’s big data characteristics and government-based structured crime reporting data. On one hand, social media data are streaming, in many instances in real-time, and there are vast amounts of it to collect, process, and analyze. On the other hand, law enforcement data are structured, stateful, and comparable. To accurately combine both data, and for example, train a classification model via social media’s big data criteria, exhibits great difficulty and is extremely expensive in terms of both human and machine resources. Further research and implementation of solutions are needed to improve the status quo and solve issues at a much deeper level.

A 21st century solution needs to classify an extremely large social media corpus given its limited grammatical structure and sparse textual content. To begin with, application of a natural language processing technique to a Twitter corpus is critical as the solution needs to make assessments about a tweet’s English-like grammar. Moreover, extreme content sparseness is a frequent problem with social media corpora that must be addressed with for tokenization and part of speech tagging prior to assigning a classification label. To help life-long scholars and practitioners in building an adequate predictive crime solution the relationship between social media grammar and their dynamic capabilities, and an improved crime performance solution must answer the question; do social media corpora better support predictive crime solutions?

I. Literature Review
Short text classification research explores the NLP continuum from serendipitous feature extraction to frequency of bigrams for syntactic labels. A key component of short text classification ultimately rests on tokenization of the corpus as results are used for metadata analysis or text-based keyword lookup for each token found in the corpus. Well-known researchers such as Frantzi et al. (Frantzi, Ananiadou, & Mima, 2000), Hirst and Feiguina (Hirst & Feiguina, 2007), Phan et al. (Phan, Nguyen, & Horiguchi, 2008), Sriram et al. (Sriram, Fuhry, Demir, Ferhatosmanoglu, & Demirbas, 2010), and Piao and Whittle (Piao & Whittle, 2011) provide great insight into the theoretical, practical, and evaluation concepts of the area. Although many of their topics are of great recent interest, others in the community tend to focus on corpora of a more structured type and use of metadata when conducting research. Sriram et al. (Sriram et al., 2010) alters this trend by conducting research in the more ambiguous unstructured realm, i.e., nonuse of metadata for text classification, but only with respect to natural language processing based on word emphasis. Despite this direction, subsequent work from Piao and Whittle (Piao & Whittle, 2011) supports the more traditional view of metadata analysis.

The work of Hirst and Feiguina (Hirst & Feiguina, 2007), Phan et al. (Phan et al., 2008), Sriram et al. (Sriram et al., 2010), and Piao and Whittle (Piao & Whittle, 2011) have many research traits in common. First, all of them identify critical NLP features in order to build robust learning models. The learning models are used to classify a short text corpus. Second, each work calculates a baseline for their respective project’s corpus based on what best lends itself to
linguistic component analysis and easy comparison. In all four cases a simple subject matter expert analysis is not enough for evaluation; each provided better analysis as statistical values were presented. The Piao and Whittle (Piao & Whittle, 2011) project is instrumental in that it extends Frantzi et al. (Frantzi et al., 2000) in calculating automatic recognition of n-grams based on the c-value metric. In other words, they use an evaluation metric based on linguistic and statistical analysis. The Sriram et al. (Sriram et al., 2010) project presents foundational principals in terms of metadata tagging. It gives a general statistical overview of its corpus, and its design is somewhat familiar with respect to the project proffered by Piao and Whittle (Piao & Whittle, 2011), i.e., both feature and evaluation components are present. Phan et al. (Phan et al., 2008) leverage a novel framework for building classifiers given short and sparse text inputs, but conclude that the foundation for their bad results is based on sparse text inputs. Along the same line of reasoning, Hirst and Feiguina (Hirst & Feiguina, 2007) reinforce the concept of working with short texts and again identify with the fact that text sparseness makes things difficult within a natural language process artifact.

As seen, commonalities among research are present, but substantial differences do exist in each of the projects. First, Piao and Whittle (Piao & Whittle, 2011) form a theory base using the art of making unsought findings, i.e., use of serendipity. This is a novel approach and directs them to the feature set of users’ tweet ID, number of user tweets, and existence of hyperlinks. Evaluation here strongly considers the work of Frantzi et al. (Frantzi et al., 2000) and the c-value calculation. The Sriram et al. (Sriram et al., 2010) work used seven feature components in their linguistic analysis: ID of user, word emphasis, time-based events, and various other metadata tweet tags. Phan et al. (Phan et al., 2008) simply used known words from 48 million words taken from Wikipedia and MEDLINE, as such; the words were well-defined with only moderately sparse content. Last, Hirst and Feiguina (Hirst & Feiguina, 2007) relied on the use of bigrams of labels from a partial parse to provide a solution for part-of-speech tagging. In this case it can be noted that the corpus was the full-length work of two distinct authors and the solution was to provide author discrimination. Thus, while the former three solutions leveraged metadata this latter work did not. The only component necessary for the latter project was the text’s content. Comparison of all evaluation methods show Piao and Whittle (Piao & Whittle, 2011) exploited only the c-value calculation. In Sriram et al. (Sriram et al., 2010), Phan et al. (Phan et al., 2008), and Hirst and Feiguina (Hirst & Feiguina, 2007), each used the tried and true foundational concept of accuracy to represent their results.

II. Problem Description and Solution
Within the purview of natural language processing, to classify a large corpus with very, very limited data structure, many problems manifest and challenges exist. For example, a Twitter corpus with each tweet having only 140 characters for message content exhibits a significant amount of noise that needs cleaning to determining its meaning. A very novel and significant solution is needed in order to crack a tweet’s code and make assessments about its content, especially when considering a classification label for it. Much research suggests a tweet’s sparseness must be overcome before classification, and this is not an easy problem to address and at best very difficult to solve. The natural language processing component of this project originates from approximately 415,000,000 tweets collected between September 1, 2014 and April 21, 2016. Each original tweet consisted of thirty fields; only the content field was used for analysis. Figure 1 represents the process overview (corpus collection, NLP processing, and...
evaluation) with respect to cracking the grammatical structure of a tweet to be consumed by the GIS solution.

A very terse description of the process flow would be as follows:

- Obtain tweet corpus via Twitter stream, JSON format;
- Preprocess and clean tweets, Python NLTK;
- Tokenization, Python NLTK;
- Token lookup, WordNet;
- Calculate token hits and misses, Excel;
- Acronym lookup and mapping, Excel;
- Recalculate token hits and misses, Excel;
- Evaluate result, Excel;
- Build processed tweet corpus, Excel; and
- Import processed tweets, GIS Solution.

Select steps of the process are shown in Figure 2 with each individual figure labeled and subsequently explained.
The procedure was completed on a Dell laptop in the CIS research lab of the College of Engineering at California Baptist University. The computer was loaded with Java, Python and NLTK, and Microsoft Office. Upon commencement of the experiment a Python script was executed. This script had two functions, tokenize the tweet corpus, previously preprocessed in Java (Figure 2a), and conduct a WordNet lookup of all tokens, this is denoted by Figure 2b and Figure 2c. All tokens not found were saved to a file. Next, a second Python script was executed and the saved tokens were matched to a lookup acronym list, donated in Figure 2d. Count was kept as to how many additional tokens could be identified (Figure 2e). As pictured in Figure 2f all calculations for the project were computed in Excel then transferred into Table 1 located the results section of this work.

III. Experiment Design NLP

Research Design. The goal is to conduct a controlled experiment to test the relationship between a Twitter corpus and an NLP treatment. With the use of random selection within the tweet corpus there is one treatment condition with one condition being the baseline.

Hypothesis. Based on preceding arguments, the qualities needed to proffer a better solution revolve around the three-step solution and algorithm previously shown. To investigate the outcome of this situation and help readers better understand the landscape Figure 1 was presented; thus, the following hypothesis is offered:

Hypothesis 1: The accuracy of tokenizing short text messages will improve when acronym lookup is conducted as an integral component of the NLP algorithm.
The hypothesis will focus on the independent NLP treatment variable of a tweet corpus and the dependent variable of accuracy. Stated in other words, greater accuracy of word-based token lookup depends on the NLP process used for its identification. As a result the multidimensional aspects of the research model will now capture many facets of the processed Twitter corpus as depicted in Figure 1.

**Independent Variable.** This is the different treatment of the NLP process used to increase overall accuracy of tokenization. The independent variable of an improved NLP process will be measured using precision, recall, and accuracy. The improved process represents the result of how much better the NLP algorithm tokenized a tweet corpus. In effect, the task reflects how well the acronym lookup list was able to match tweet content tokens to collected and well known social media acronyms.

**Dependent Variable.** Total or overall accuracy will be used for the dependent variable and is selected because its calculation is deemed to be significantly influenced by the improved or degraded NLP process being used to further tokenize content.

**Sampling Corpus.** The general descriptive statistics used for demonstration purposes in this work considered 200 randomly selected tweets. Subsequently, using NLTK and breaking on space only, this corpus was tokenized into 1,730 tokens. These tokens were assigned to the treatment and baseline condition. In standard fashion the purpose of the baseline treatment will act as a group without any further treatment.

**Evaluation Plan.** After the preprocessing removal of author and time the purpose of evaluation is at the word level. Each individual tweet’s content will have a tokenization treatment applied. One treatment is the baseline the other a modified NLP tokenization treatment. Then, both the baseline case and the NLP treatment case allow for the following metrics to be applied:

--Calculate TP
--Calculate TN
--Calculate FP
--Calculate FN
--Calculate Precision
--Calculate Recall
--Calculate Accuracy
--Calculate F-score

Furthermore, formulas for the project are presented as follows:

- Precision (P): number retrieved and relevant items / number retrieved items;
- Recall (R): number retrieved and relevant items / number relevant items;
- Accuracy (A): (TP + TN) / (TP + TN + FP + FN); and
- F-score (F-S): 2 * (Precision * Recall) / (Precision + Recall).

**Results NLP**

After preprocessing and upon conducting a WordNet lookup of the tweet corpus, which identified 1,730 total tokens, 859 tokens were retrieved. Along with 59 tokens being cleaned-up and relabeled, only 800 tokens were found to be relevant. The remaining 871 unidentified tokens...
represent the list of tokens attempting to be identified by conducting the acronym lookup. The acronym lookup list compiled (Figure 2d) incorporated 2,444 social media acronyms. Table 1 provides important calculations and is subsequently reviewed.

Thus, comparison of the proposed artifact is a large component of evaluation; results are shown in Table 1 and represented in terms of a baseline versus treatment model. Baseline calculations are based on a break on space approach for tweet content tokenization. Although from the expert-observer perspective one might suggest only simple observation of the proposed new approach will yield better results, without quantifiable calculations it is hard to compare. Theoretically, the evaluation proposed will provide overall better results based on the NLP treatment stated. Thus, the given calculations in Table 1, and the overall comparison for the solution being based on total accuracy were needed. The new artifact proposed yields approximately a 1.73% gain or what equates to .983-.966 difference with respect to a post and pre artifact accuracy metric.

**Solution GIS**

Research in GIS crime analysis suggests that it is associated with three specific, yet closely interrelated, dimensions of artifact design. The association between these dimensions—social media normalization, crime, and social behavior—are examined to uncover quantifiable results and qualitative visualization relationships often found in both retrospective and predictive crime analyses. Crime and census data, combined with a tweet corpus, and Supplemental Nutrition Assistance Program locations were used to produce sophisticated crime maps, and such variables are unconventional compared to environmental criminology’s traditional use of time, place, and crime. Nevertheless, such critical crime layers are key proxies for predictive crime, and with spatial autocorrelation and hot spot analysis applied, a complex and robust predictive solution was created. Within this defined theoretical framework, the research model in Figure 3 is presented and supports an artifact that is to be visualized and scrutinized in quantitative and qualitative ways; as a result, a hypothesis is considered.

**Hypothesis 2.** Risk terrain model predictive capability will be highest in the grammatically tagged tweet corpus condition, when compared to a standard tagged or untagged social media corpus operationalized as a GIS risk layer.

The solution will test the relationship between social media and crime when controlling for multiple levels social behavior. A favorable outcome will produce a GIS RTM artifact with better capability to predict crime. In addition to testing such a relationship, operationalization variables of a social media corpus are observed.
Results GIS

To accept the hypothesis, consideration of how much variation in the dependent variable (crime) has been explained by the model (in particular each NLP treatment). Table 2 present OLS diagnostic results. Artifact construction is associated with three NLP corpus treatments. First, the crime, SNAP, population, and noNLP layers. It yields an $R^2$ of .606 and is the baseline value and control group for the project. Ensuing NLP tweet corpus layers with the ability to incite positive predictors will need to better this value to explain variations in the dependent variable.

<table>
<thead>
<tr>
<th>Artifact Construction</th>
<th>noNLP</th>
<th>medNLP</th>
<th>hiNLP</th>
<th>Total Treatments</th>
</tr>
</thead>
<tbody>
<tr>
<td>R$^2$ values</td>
<td>0.606</td>
<td>0.522</td>
<td>0.679</td>
<td>3</td>
</tr>
</tbody>
</table>

Second, the crime, SNAP, population and medNLP treatment model yields an $R^2$ of .522. Last, the crime, SNAP, population, and hiNLP solution produces the best result with an $R^2$ of .679.

IV. Conclusion and Limitations

This inquiry investigated the application of an NLP treatment to evaluate its role in the accuracy of GIS crime prediction. It is proposed because opportunity exists to fill the gap between retrospective hot spot mapping and its less researched counterpart of sparse or acronym-based short message social media being used as a social behavior crime predictor. By conducting this project the hypothesized link between social media, with an appropriate NLP treatment, and crime prediction was tested and verified. The contribution here suggests that advanced development of social media corpora NLP treatments are needed as they can support a positive and more predictive crime artifact.

Limitations of the work include corpus collection and tokenization. The former incorporates the concept of random selection. Currently more than half a billion tweets are sent via Twitter every single day. The issue becomes whether or not the corpus collected was a representative sample given this enormity. This view can be seen from two perspectives; one, time and location of tweet selection; two, API used to collect the tweets from the Twitter stream. The tweet corpus used here was collected using the standard REST API. However, other projects, e.g., the corpus collected by Stanford University via Twitter’s firehose API collect a sizable sample from the Twitter stream. Thus, one cannot be certain a time component did not influence overall results even with the randomization process used. Also, it is not known what region or location the collection was captured from. Therefore, results presented will need to be compared with a clean capture of tweets given these know circumstances.
Another limitation stems from the simple tokenization method applied to the corpus. As noted the process was break on space. More sophisticated treatments should be used in order to test for enhanced or tainted results. This will also direct future work with respect to extending the NLP algorithm in attempting to research greater accuracy and should be considered.
GIS Investigation of Crime Prediction with an Operationalized Tweet Corpus

References


Three-dimensional Leadership Graphic Inventory for School Administrators (3D GISA)

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Abstract

This paper reports on a new survey scale developed from a review of the relevant literature on ethical leadership (EL) and the California Professional Standards for Educational Leaders (CPSEL) Standard 5: Ethics and Integrity (CTCC, 2014, p. 9). The scale can be used as an assessment and reflection tool for developing goals for administrator candidates. In 2001, California formally adopted the first set of Professional Standards for Educational Leaders (CPSEL). The CPSEL have been a part of the California’s education leader preparation continuum; adapted from the national Interstate School Leaders Licensure Consortium (ISLLC) Standards for School Leaders (1996) to fit the California context and emerging accountability expectations. In 2004, the CPSEL were adopted as part of the standards-based program for the Administrative Services Clear Credential used to license a broad range of education leaders, school principals, district superintendents and directors, county and state program administrators, and administrators in nursing, special education, counseling and technology.

Evidence of competencies in the area of EL is a mandatory part of the California Commission on Teacher Credentialing (CTCC) California Professional Standards for Educational Leaders (CPSEL) Standard 5: Ethics and Integrity. The Educational Leadership Department team at Azusa Pacific viewed the CPSEL 5: Ethics and Integrity as the foundational standard for all other five standards in the CPSEL. Figure 1 shows a model of the six CPSEL. The GISA scale may prove useful for both aspiring educational administrator candidates as well as current practitioners. Using results of the survey as data driven feedback, administrators may set goals to develop an increase in the frequency of EL behaviors; operationalized as constructs reflecting behaviors of EL school leaders.

The 3D GISA measurement instrument quantitatively captures participants’ self-reports on 35 items related to key concepts from the California Professional Standards for Educational Leaders (CPSELs), particularly Standard 5: Ethics and Integrity. The GISA instrument is delivered online and results are displayed for the learner in a concise radar graph using Excel software. The administrator can use the results to identify areas for improvement. Appendix A shows figures of the graphics provided in the GISA scale.

I. Purpose
A primary purpose of the 3D GISA is to assist administrators in developing goals for growth during their program studies and as a planning tool for practicing administrators in the process of clearing their administrative credential. A school administrator’s personal values have been shown to be a significant variable influencing individual choices for behaviors that contribute to the
improvement of organizations (Brown, Treviño & Harrison, 2005, p. 120; Lawton & Páez, 2015). Current recommendations from the research include a need for an instrument that compares the administrator’s self-reports with his or her followers (Yukl, Mahsud, Hassan, & Prussia, 2013). A review of the literature on ethics and integrity in school leadership revealed an abundance of articles on the importance of EL in organizations. Ethical leadership consists of, “the demonstration of normatively appropriate conduct through personal actions and interpersonal relationships, and the promotion of such conduct to followers, through two-way communication, reinforcement, and decision-making” (Brown et al., 2005 in Lawton & Páez, 2014, p. 641). Few studies were found providing a method of quantifying and measuring an individual administrator’s ethics and values. The GISA scale uses administrators and followers’ self-ratings by objective measures such as frequency of observed behaviors.

The six state standards identified by the California Commission on Teacher Credentialing requires demonstration of competency by administrators for clearing their California credential (CCTC, 2014). Standard 5: Ethics and Integrity. Not understanding the underlying constructs representing the CPSEL standards, or not having a valid scale, may lead to misinterpretation of a candidate’s skills and to faulty conclusions about his or her progress. For those using the CPSELS to understand and evaluate a candidate’s growth and competencies in meeting CCTC standards valid measuring tools are necessary to accurately judge progress. Candidates may not fully understand the expectations of the Standards without valid and reliable means to determine a measurable level of attainment or expectations. Therefore an objective instrument for capturing and quantifying administrator behaviors from a 360 degree feedback method can support administrator goals based on data and provide artifact evidence of growth for meeting Standard 5: Ethics and Integrity. Therefore, development and exploration of the factor structure of a new instrument for this purpose is warranted.

II. Literature Review

The concept of virtue and integrity, as embodied in one’s values and ethics, can be traced to Aristotle (1947). Virtue has been described as the foundation from which springs “the good life” and integrity as the foundation to ethical leadership. Ethics and integrity suggest a coordination between one’s beliefs and actions, a wholeness and consistency that exemplifies moral behavior (Lawton & Páez, 2014, p. 641). This perspective is consistent with the model developed by the Azusa leadership department team and shown in the Figure 1 model of CPSEL Standards: core expectations for administrators (CCTC, 2014). The CCTC CPSEL 5 provides the recommendation that principals reflect on their values, use of ethical behaviors, and organizational citizenship behaviors to influence their school culture. This may result in professional growth and support transformations of their school culture resulting in improved school outcomes (Sadeghifar, Ashrafnejad, Mousavi, Nasiri, Vasokolaei, Zadeh, et al., 2014; Tarter & Hoy, 2004; Tschannen-Moran, 2003).

The nomological net provided in the literature on ethics, integrity, values, as aspects of EL include social exchange theory, social learning theory, and open systems organizational learning theory. Studies described scales used to capture EL and results included correlations with increases in employee commitment to the leader, openness to share work related problems, perceptions of effective leaders by the followers, accomplishing ethical organizational goals, development of future ethical leaders, collective efficacy, and organizational citizenship behaviors (Tarter & Hoy,
Ethical leadership has been quantified, explored, and reported in the literature as both a unidimensional and multidimensional construct. Lawton and Páez suggested a model of three overlapping circles for their framework of EL. The three factors in their model include leadership practices, purposes, and virtues.

Researchers are currently exploring meta-theories of organizational purpose based upon virtue theory including recognition of the common good and EL (p. 645). Ethical leadership has further been linked to outcomes such as trust and employee effectiveness (Kalshoven, Den Hartog, & De Hoogh, 2011). This is consistent with Tarter and Hoy (2004) in their enabling school structures research showing the influence from ethical behaviors of the administrator on the organization. The variables quantified in the GISA scale have been shown to compare favorably with variables in the literature shown to be malleable to administrator influence and related to improved school outcomes.

Figure 1. Model of CPSEL Standards: core expectations for administrators (CCTC, 2014).

III. Procedure
The GISA instrument was developed from a review of the literature, personal knowledge gained by the authors from study and experience as school administrators, and a review of the CCTC CPSEL standards. The GISA instrument operationalizes seven factors using items to measure ethics and integrity behaviors of administrators. The factors of professional development, personal development, justice and fairness, communication, decision-making, transformational leadership, and role model are considered separate constructs that contribute to an overall concept of ethical leadership demonstrated by school administrators. These factors, purported to comprise the ethical leadership concept, are each considered to have distinct antecedents. The 3D GISA goes further than the scales presented in the literature to date. The
The usefulness of the 3D Leadership Graphic Inventory for School Administrators (GISA) instrument is its ability to provide multidimensional feedback regarding essential school administrator behaviors. Potential uses of the GISA graphic organizer include as a measure for administrator hiring/screening processes; professional development of practicing administrators; and as part of a 360 degree survey tool.

IV. Results
The concept of ethical leadership, or exemplar conduct that motivates and communicates norms, and that promotes a vision of the common good, was central to the development of standards for school administrators (CCTC, 2014; Lawton & Páez, 2014). The model used by the Azusa team to frame the teaching of the CPSELS to administrator candidates includes the historical perspective of ethics and integrity as the foundational concept that influences the decisions and behaviors of the administrator related to all other Standards in the CPSELS. Though an individual’s values were shown to have an indirect effect on one’s personal choice of behaviors and outcomes, research on the relationships between ethical leadership, social exchange theory, and employee commitment revealed the administrator's direct interaction effects on employee outcomes such as OCB, trust, collective efficacy, and school outcomes (Tarter & Hoy, 2004; Hansen et al., 2012). School administrators can benefit from understanding the complex variables of the administrator’s ethical leadership on the organization through the use of a GISA tool that provides research-based data for reflection and planning (Dweck, 2010; Kearney, 2007; Lawton & Páez, 2014). The scale items will be reviewed by a panel of experts for consistency with the literature and their effectiveness to
Three-dimensional Leadership Graphic Inventory for School Administrators (3D GISA)

communicate the qualities of ethical leadership behaviors to the survey participants. A pilot study is planned to test the usefulness, usability, content and construct validity, and the reliability of the instrument. Subsequent modifications will be made and an empirical quantitative validation study will be performed.

V. Conclusion
The 3D GISA scale is the only model that has data and reflections from four possible data sources; the administrator’s supervisor, the candidate, the subordinates, and other stakeholders. Other EL scales reviewed included input from the leader’s followers. The developers of the 3D GISA scale purport the items comprise seven distinct sub-factors and are considered useful for quantifying leadership behaviors. The scale can be used for the purpose of developing goals for professional growth and providing research-based evidence of administrator competency on CPSEL Standard 5: Ethics and Integrity. Effective use of reflective practices begins with collecting sound data of administrator behaviors.

Implications of the review performed in this paper suggest principals can compare their overall results from a pre assessment to the post assessment to determine growth on CPSEL Standard 5: Ethics and Integrity. When an administrator’s growth plan is developed from sound data for purposes of reflection, then growth is more likely to occur. Additionally, a valid and reliable scale can provide research-based evidence of competencies on the CPSEL Standard 5 that support university recommendations for clearing administrator credentials in CASC programs. Further, data provided by the disaggregated sub-factors will provide opportunities for beginning dialogues with administrators, their faculty, school board members, and stakeholders regarding their perceptions of the administrator’s behavior on the culture in their school.

Principals may use their GISA scale results and the results of this research to begin conversations with their staff. Principals must understand that just recognizing their influence on the school organization is not enough to promote a positive employee outcomes. School leaders can begin by developing goals for growth and structures that support positive relational behaviors and perceptions of organizational justice by identifying organizational purpose, and leadership behaviors related to ethics and integrity (Lawton & Páez, 2014). The process includes providing explicit information regarding ethics and integrity, a measure to identify a baseline, and reflection to develop a plan for growth. University coaches can provide support to explicitly question a candidate administrator's understanding of the practices related to factors identified in the GISA. Reassessment and comparison with the baseline provides an artifact for educational leaders to validate their own perceptions and those of others they lead related to their influence on the organization.

Candidates in educational leadership programs and practicing administrators can use the information to inform professional development efforts in collaboration, planning, and practicing new learning together with the faculty in the work environment. This requires establishing organizational routines that include professional development in the area of ethical leadership, personal development, justice and fairness, open communication, the processes of shared decision making and the influence of decision making on others, transformational leadership practices, and role modeling. Improving school cultures is a matter of developing principal skills in recognizing the indirect influence of his or her personal theories, beliefs, ethics, values, and integrity of
behaviors on the development of a positive organizational culture at their school (DiPaola & Hoy, 2005; Dweck, 2010; Hansen et al., 2012; Reed et al., 2011).

VI. Summary
There are many implications for using research-based data from scales, such as the GISA Scale, for quantifying administrator ethics and integrity behaviors. Survey research is just a beginning to finding realistic ways to implement growth in a candidate or practicing school administrator (Netemeyer, Bearden, & Sharma, 2003). Principals can provide the research-based evidence from the GISA scale for developing a growth plan, the reassessment as evidence of growth, and for demonstrating competencies in ethical leadership behavior to meet CPSEL Standard 5: Ethics and Integrity. School districts can use the GISA instrument, based upon logic and theory from the literature on EL, to plan professional development for administrators and faculty in their district. University administrator preparation programs may include the GISA instrument in their candidate screening process, for developing coursework, and provide the GISA to candidates for personal reflection. Another potential use of the GISA graphic organizer is as a measure for school district administrator hiring/screening processes and as part of a 360 degree survey tool. The GISA scale and micro learning supports seeks to help fill the need of obtaining objective and quantifiable measures of EL useful for developing school leaders and providing artifacts for growth.
Three-dimensional Leadership Graphic Inventory for School Administrators (3D GISA)

References


APPENDIX A

Sample of the Graphic Displays of the 3D GISA Instrument
APPENDIX A continued

Sample of the Graphic Displays of the 3D GISA Instrument