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MEASURING ACCOMMODATION ON FACEBOOK BETWEEN SINGLE-A MINOR LEAGUE BASEBALL TEAMS AND FACEBOOK USERS

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Abstract

Social media has changed the ways in which a business communicates with their target consumers (Smith, 2009). While previous computer mediated communications involved businesses communicating through a one-way channel, social media has made businesses become more responsive to consumers by opening up online communications as a two-way channel. Businesses are not only a part of the social media revolution, but have also worked to increase their social media reach. Funk (2013) suggested that social media managers need to continually monitor the success of their posting strategies on all mediums to improve their overall quality of posting strategies. Yet, many of the available measures for Facebook are based off of post's *likes*, shares, and number of comments.

An avenue which may provide some deeper insights into the ways in which a Facebook page's fans are interacting with a host's page can be found through the communication accommodation theory (CAT). Dragojevic, Gasiorek, and Giles (2014) described the communication accommodation theory (CAT) as "[a theory that] seeks to explain and predict such communicative adjustments, and model how others in an interaction perceive, evaluate, and respond to them" (p. 1). CAT's flexibility has been observed in the ways in which people adapt their language to others (Chen, Joyce, Harwood, & Xiang, 2016), between professor and students (Gasiorek & Giles, 2015), and even on social media (Goode & Robinson, 2013; He, Zheng,

Zeng, Luo, & Zhang, 2016). These previous examinations overviewed the ways in which communicators act, but can there be a way to use CAT as a measure of social media post success?

These studies used CAT as a means of understanding the theory's interaction with traditional Facebook metrics, such as *likes* and number of comments. This was significant as the theory had yet to be applied in such a manner, and as previous research suggested, the results could be of great interest to sports organizations and social media in sport researchers.

The following research was designed to introduce CAT into a practical setting for social media managers while primarily examining Minor League Baseball (MiLB) at the Single-A level. Single-A baseball has not been examined solely in a social media setting, which was why this level of MiLB was selected. Study A was designed to measure the levels of accommodation across various posting strategies (neoliberal, social, team related, open code) and the subsequent number of *likes* and number of comments accompanying each post. The accommodation scores, measured through the Language Inquiry and Word Count software (LIWC, pronounced "Luke"), accompanied by a series of algorithms, and the traditional measures for traditional Facebook metrics were measured using a regression analysis. There was some evidence to suggest that number of comments was correlated to LSM scores, while various posting types were significant at the team level. Study B was designed to measure the differences between the most and least liked Single-A MiLB Facebook pages in terms of levels of accommodation. Again, this exploration utilized regression to measure accommodation's influence on *likes* and number of comments. As expected, traditional Facebook metrics such as *likes* and number of comments per post were higher for the team with more page likes, although accommodation scores were higher

for the team with fewer page likes. The implications of these studies, and future direction for social media academics and practitioners, are also explored.

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CHAPTER ONE

INTRODUCTION

The advent of social media sites (SMS) has changed how businesses communicate with target consumers (Smith, 2009). Businesses are no longer the sole producers of their own content as commenting, tweeting, posting, and other two-way communication channels have allowed consumers to shape the perceptions of products in an online setting. Heller, Baird, and Parasnis (2011) explained the true power of social media: "Social media holds enormous potential for companies to get closer to customers and, by doing so, facilitate increased revenue, cost reduction and efficiencies" (p. 30). Sports franchises have caught onto the social media trend as both players and teams have used social media to connect with fans. For example, franchises within Major League Baseball (MLB) have used Twitter as a means of reaching their fans, through a feature titled "Connect with the (team name)" (Witkemper, Lim, & Waldburger, 2012), corporate social responsibility messages (Haugh, 2016), and team information dissemination (Arth, 2016). While social media has been seen as a creative medium, many entities use social media in a similar fashion. Politicians, state public health departments, and other government agencies have all utilized a similar communication pattern when using social media by primarily posting information dissemination posts, although evidence of interactive posts has also been detected (Thackeray, Neiger, Smith, & Wagenen, 2012).

One way to measure similarities in communication patterns is through communication accommodation theory (CAT). CAT can be used as a means of investigating the ways in which conversation participants interact and feel about conversation topics (Giles, 2008). For example, individuals that are interested in a conversation may converge their linguistic style to that of other conversation participants (Hu, 2013). If individuals are not interested in the topic of conversation, they may start to diverge their language structure from that of other conversation participants (Hu, 2013).

CAT has been applied in a variety of academic investigations (Giles, Coupland, & Coupland, 1991) as this theory has shown to be very flexible in its use within the realm of academia. For example, Hajek (2015) found that gay men would communicate in converging and diverging ways when interacting with different age groups of other gay men, while Chen, Joyce, Harwood, and Xiang (2016) examined the ways that children would adapt their language styles to different types of adults (mean, nice, etc.). Converging one's language occurs when an individual shapes their communication patterns, accents, and sentence structures to that with whom they are speaking, while diverging (non-accommodation) occurs when communicators will intentionally divert their speech patterns from those whom they are communicating with (Giles, 2008). Within the social media setting, researchers have found that Dutch students on Twitter would converge their language style to that of a minority language to better connect with other students (Nguyen, Trieschnigg, & Cornips, 2015). Similarly, Tamburrini, Cinnirella, Jansen, and Bryden (2015) found that Twitter users would converge their language to a group norm when posting in different online communities. Although this body of literature exists, converging and diverging language structures within the context of sport and social media has yet to be observed.

Minor League Baseball (MiLB) allowed for a wide variety of groups to be observed with regard to language accommodation (i.e., convergence and divergence). According to MiLB.com, there were 244 teams across 43 states and US territories that composed the MiLB system at the start of this dissertation (2016). MiLB has been observed in the context of promotions (Howell, Klenosky, & McEvoy, 2015; Paul & Weinbach, 2013), attendance figures (Agha & Rhoads, 2016; Gitter & Rhoads, 2010; Roy, 2008), and history (Land, Davis, & Blau, 1994); yet examinations of social media usage within MiLB has been very limited to date (Williams, Heiser, & Chinn, 2012). Williams, Heiser, and Chinn (2012) surveyed patrons of MiLB games to see if more active social media users would be more likely to attend games than less active social media users. The results from their observation suggested that less vocal fans on social media actually attended games more frequently than their more vocal social media counterparts.

Academics and practitioners have found that the use of analytics is crucial to a successful social media campaign (Funk, 2013). Social media measurement tools have included Google Analytics, Radian6, and others. However, language accommodation has yet to be used as a tool for analyzing social media in practice. Giles (2008) found that individuals will converge their language styles towards communications that they have a particular interest in. From an organization's perspective, customers are willing to pay more money based on the ways that an organization communicates with them (Holmqvist, 2011). More specifically, consumers prefer businesses that converge with their own communication styles, as consumers demonstrated a willingness to pay more for a product with the convergent businesses than with businesses that did not converge with their own communication styles (Holmqvist, 2011). One way to measure language accommodation on social media websites would be through communications between an organization and its fan base. On Facebook, communications are bundled through a status update and subsequent comments from outside users/organizations. An organization will post a status update and this will allow for others to respond to said communication. Thus, given that previous research has established a link between language accommodation and interest in conversation, as well as purchase intent, these studies observed the extent to which language accommodation affects traditional Facebook measures (*likes*, number of comments) in MiLB.

Purpose of Study A

The purpose of study A was to measure the level of accommodation, in terms of linguistic-style matching (LSM) and immediacy, among three single-A minor league baseball franchises' Facebook posts within the state of South Carolina and subsequent comments from fans. Accommodation was measured across three different posting types found in previous literature: neoliberal (Dart, 2014), social (Blaszka, Burch, Frederick, Clavio, & Walsh, 2012), and team related posts (Waters, Burke, Jackson, & Buning, 2011). This state offered a unique point of observation as the lifespans of all three of the teams ranged from their first year of operation and affiliation (Columbia Fireflies, New York Mets), to having over 36 years of baseball in one city (Charleston Riverdogs, New York Yankees), to having a medium lifespan of ten years (Greenville Drive, Boston Red Sox). Accommodation of language has shown that individuals tend to enjoy the communication being portrayed, and thus have similar positive emotions (Giles, 2008). Thus, deciphering which types of posts generate the highest levels of convergence may aid in an organization's success. To further analyze this phenomenon, individual team scores across all measures and all posting categories will be assessed to see if teams have different regression scores for different posting types (examined through RQ3 below).

Purpose of Study B

The purpose of study B was to observe the differences in levels of accommodation between two Single-A MiLB baseball teams' Facebook posts and subsequent user generated comments. The two teams were selected from MiLB's Single-A full season division. The Single-A full season teams with the most Facebook page likes and the least Facebook page likes were selected for study B. As language accommodation has previously been seen to generate interest, in theory, the greater a user accommodates to an organization's Facebook post, the greater the post resonated with that individual. This study was the first to compare the differences, or similarities, between MiLB Facebook pages with a highly varying number of page likes.

Selection of Teams and Posts - Studies A and B

Single-A Minor League Baseball franchises were selected for these studies. MiLB has been observed in a variety of contexts, but not in terms of an organization's social media use. Further, small market MiLB franchises (Single-A) have scarcely been observed in previous research. These studies have shed greater light on the social media strategies utilized within Single-A MiLB franchises. MiLB Single-A teams were also chosen for these studies as social media is one of the limited communications outlets available to MiLB franchises. This is reasonable given the tight budgets of MiLB franchises, which leads to fewer paid communications to the MiLB franchise's host community. Three teams' Facebook pages from the South Atlantic League were chosen for study A: the Greenville Drive, the Charleston Riverdogs, and the Columbia Fireflies. The primary investigator's previous experiences in the South Carolina Single-A baseball market aided in the decision to choose these three franchises. Posts from these teams were first collected, then coded using a deductive thematic analysis. Following the deductive thematic analysis, a semi-randomly selected sample was analyzed for levels of accommodation. In their study of measuring language accommodation in an online setting, Goode and Robinson (2013) observed interactions between 80 original blog posts and 225 audience replies. For the current study, the primary investigator semi-randomly selected 90 Facebook posts per theme. First, a deductive thematic analysis was used to code each of the three team's posts for a one-year time frame. Then, a random number generator was used to select 30 posts per team per theme. Thus, each of the three teams submitted 30 posts to be observed in each category: neoliberal, social, team related, or newly found open codes. These posts, and their subsequent comments, were then run through the Language Inquiry and Word Count software (LIWC) to measure for levels of LSM and immediacy, which are described more in depth in chapter three. Following LIWC's analysis, these totals were run through a series of algorithms, which determined the accommodation scores for both LSM and immediacy. LSM and immediacy scores (ranging from 0-1) were then analyzed using regression, with *likes* and number of comments being measured in tandem the accommodation scores. The statistical software R was used to generate the regression plots and values.

Study B first observed the number of page likes per Facebook page for every Single-A baseball team in MiLB. Short season Single-A teams were not included in this analysis as an argument could be made that full season Single-A teams will garner more attention, and be in larger markets, than short season Single-A teams. After identifying the number of page likes per team across all full season Single-A MiLB teams on Facebook, the highest number of page likes and the smallest number of page likes were selected as the teams for this analysis. Eighty Facebook posts and subsequent comments from each of the two teams selected were used to measure levels of language accommodation through LSM and immediacy measures. These subsamples were selected through a random number generator. Each team's randomly selected posts and LSM/immediacy scores were again analyzed using regression in R. Facebook posts were gathered from September 10, 2015 to September 10, 2016.

Research Questions Study A

The primary researcher for Study A sought to answer the following research questions:

RQ1: What levels of accommodation (LSM, Immediacy) exist between user-generated comments and neoliberal, team related, social posts, or other open coded posts from South Carolina MiLB teams?

RQ2: What is the relationship between neoliberal, team related, social, and/or open coded posts, language accommodation measures (LSM, immediacy), and *likes* and/or number of comments?

RQ3: Across all teams, what is the relationship between coded posts (neoliberal, team related, social, open code), language accommodation measures (LSM, immediacy), and *likes* and/or number of comments?

Significance of Study A

As language accommodation has been tied to interest and purchase intent (Giles, 2008; Holmqvist, 2011), this study sought to explain which posting type (neoliberal posts, team related posts, social posts, or open code) generates the highest levels of language accommodation from Facebook users. The argument can be made that certain types of posts may bring in greater levels of interest for each organizations' Facebook page. Further, this study was one of the first two studies to examine primarily Single-A MiLB teams on Facebook. Every MLB franchise has a number of MiLB teams, which are located in cities outside of their MLB affiliate. Previous research has focused on Double or Triple-A baseball, while Single-A baseball had yet to be the focal point.

Social media pages need to utilize analytical tools to observe how well a page's posts are performing (Funk, 2013; O'Hallarn, Morehead, & Pribesh, 2016). To date, very few platforms exist for analyzing Facebook posts (Google Analytics, Facebook Insights, Radian6). Most of these software packages are used to measure post success in terms of *likes* or number of comments, the peak times in which Facebook posts perform well, the reach of a post (the number of times a post appeared in a user's Facebook timeline), and clicks to links embedded in Facebook posts. In general, the higher the number of *likes* a post receives, the greater chance the post has of going viral and reaching a very large audience. The primary investigator for study A intended to use CAT as a means for analyzing posts in a more quantitative manner to see which types of posting strategies are most successful for which teams. In this mixed methods approach, posts were micro analyzed using LIWC and a series of algorithms which led to posts being quantified (see chapter 3 for a more in depth explanation of this process). Using this metric, alongside a post's *likes* and number of comments, regression models were used to see if there were any correlation between posting types and *likes*/number of comments. MiLB teams will rely on free services, such as Facebook, to communicate with their target demographic. Thus, MiLB teams can use the results of this study to further craft their social media posting strategies.

The results of this study will help reveal how an organization should compose their Facebook posts through a two-part analysis. After coding each post into its own theme, measures for language accommodation and a comparison to *likes* and number of comments will occur. As Giles (2008) suggested that language accommodation will lead to a greater level of interest in a conversation, it stands to reason that Facebook users commenting on a Facebook post will be more interested in a post if they accommodate their language to the original post. This analysis will measure the LSM and immediacy score noted in each theme, and will show the correlation between *likes* and number of comments and LSM and immediacy scores for each theme. For example, if neoliberal Facebook posts had generally high accommodation levels, but this was not correlated with *likes* or number of comments (meaning the higher level of accommodation between the original Facebook post and the subsequent comments, the lower number of *likes* were produced), an organization should continue to post in ways that generate high levels of accommodation, which has been found to potentially sell more products. Thus, this across-team's comparison will directly benefit each of the teams in this analysis, and give deeper understanding of the overall results. All teams can use these findings in their own social media campaigns. For example, if a team has successful neoliberal Facebook posts (posts that try to sell a product or a sponsor over Facebook) well, other teams can use these posts in their own social media campaigns.

The results will also reveal the differences in levels of accommodation between all posting types among three different MiLB franchises. This can be very useful to each MiLB franchise as they can have a deeper understanding of their Facebook populace. For example, if the Greenville Drive have greater success at posting in neoliberal ways than the Charleston Riverdogs, this might suggest that either the Drive have a fan base that wants to purchase their products with greater intent, or that the Drive have found a way to sell their product through Facebook in a way that is more enticing than the Riverdogs. In this situation, the Riverdogs could benefit from understanding why the Drive were successful with their neoliberal posts. Further, these results will show how neoliberal, social, and team related posts fair in terms of *likes*, number of comments, and levels of accommodation.

Research Questions Study B

The primary investigator for study B sought to understand whether Facebook users would accommodate their language more towards a team based on overall page likes. Interest in a conversation can be shown through conversation participants accommodating their language to one another (Giles, 2008). Could this mean that, in a Facebook setting, an organization would generate a greater number of *likes* based on levels of accommodation generated from Facebook users? The primary investigator wanted to investigate the following questions for Study B:

RQ1: What levels of language accommodation exist between the Single-A MiLB team with the highest number of page likes and the Single-A MiLB team with the lowest level of page likes?

RQ2: For the Single-A MiLB teams with the highest and lowest number of page likes, what is the relationship between language accommodation measures (LSM, immediacy), and *likes* and/or number of comments?

Significance of Study B

Study B furthered the knowledge base of social media language accommodation into the realm of sports by examining language accommodation between Single–A level MiLB teams on opposite ends of the spectrum in terms of page likes. Were accommodation levels the same for liked and less liked MiLB teams on Facebook? Language accommodation has shown to be a predictor of interest in a conversation (Giles, 2008). This tool could be used by practitioners as another measure of post success, regardless of how many page likes an MiLB team's Facebook page has. The new measurement's rationale is simple in theory- the greater level of language convergence, the greater the level of interest between commenters and the original post. However, it could be entirely true that a higher level of convergence on Facebook may lead to less *likes* and/or number of comments than lower levels of convergence between the original post and subsequent comments. The primary investigator for this study examined how accommodation relates to *likes* and number of comments between the most page liked Single-A MiLB team and the least page liked Single-A MiLB team on Facebook.

This study showed how comparisons can be made between two teams Facebook performance, regardless of overall team likes. By breaking down language accommodation and *likes* and number of comments into a regression model, a correlation can be detected. Further, *likes* and number of comments can be explained through LSM and immediacy measures through correlation. For example, when a social media manager for the San Diego Padres wants to compare their Facebook page performance to that of the New York Yankees, their comparison will show that the Padres may be underperforming due to the Yankees having a greater fan base. With this form of analysis, the social media manager can see how well fans are accommodating to the team's original post, and measure their overall effectiveness associated with higher or lower levels of accommodation. Very rarely do teams share a perfectly similar market, and thus they may find success in posting to Facebook through posts that do not lend themselves to accommodation. For example, if the Padres find that posts with low accommodation ratings earn more *likes* and/or number of comments than posts with higher accommodation levels, then they may find success in posting non-accommodating posts while the Yankees may find the opposite situation to be true.

As MiLB teams do not have the budget of MLB teams in terms of marketing their product, MiLB teams have to do more with less resources. Thus, every marketing opportunity is a chance for MiLB teams to grow. Facebook, as a generally free medium, has allowed for sports teams to engage further with their fan base (Williams & Chinn, 2010). MiLB teams need to maximize their effectiveness on Facebook to get their message out to as many fans as possible. This examination revealed the posting strategies for two MiLB teams with the most, and least, number of page likes in Single-A baseball. Examples of posts that perform well will be reported as a guide for future practitioners, as well as posts that do not generate as many *likes*, number of comments, and accommodation levels. Knowing what fans want to see on Facebook can help an organization grow, while at the same time avoiding Facebook posting pitfalls to continue to grow their fan base.

It is understood that not every geographic market is created equal in terms of the number of people in the market, their makeup in terms of demographics, salary expectations, etc. However, the challenge of all MiLB teams is to bring in as many fans as possible to the ballpark, regardless of how many people are in their market. Thus, MiLB teams need to establish themselves in their community, both at the community-wide and grassroots levels. This study will show how well the two teams selected interact with their fans on a deeper level than simply reporting *likes* and number of comments by showing simply how their fans respond to their posts. This will show how MiLB organizations can craft their Facebook posting strategies to maximize their Facebook audience and build a better relationship with their fans. Further, the results of this study are valuable to the two teams as correlations can be seen between LSM and immediacy when compared with *likes* and number of comments. It is entirely possible that one market may find that accommodation ratings equal higher amounts of *likes* and/or number of comments while the other does not. This will allow for practitioners to see how they can shape their posts to gain maximum Facebook exposure. For example, if a particular Facebook post from an MiLB team garners a greater amount of *likes* than the average post, and has a high level of accommodation, what was the substance of the post? If many posts show a high level of language accommodation and *likes* in tandem, then these posts should be replicated by MiLB teams to gain a higher level of exposure. This way, MiLB teams will gain the most exposure per post.

Limitations

As with any research, there were some limitations. The following limitations were identified:

- Facebook posts, as data points for these studies, will be collected after the season ended, and thus some posts may have been deleted.
- Levels of accommodation were measured in an online setting, which did not take into account nonverbal cues such as posture, facial, hand gestures, and other nonverbal responses to individuals viewing the Facebook posts.
- Five MiLB teams were selected based on geography or the highest/lowest number of page likes.
- Study A and Study B consisted of teams within only one level of play.
- The MiLB teams selected will have different makeups in terms of their markets, which includes size, demographics, and clientele.
- The size of the dataset limits the power of each analysis.
- This analysis observed only texts, videos and pictures were left out of the analysis.

Assumptions

- Teams will post in different ways.
- Teams will post a minimum of 90 Facebook posts over the course of a year (Study A).
- Teams will post a minimum of 30 Facebook posts per coded theme over the course of a year (Study A).
- Teams will post a minimum of 80 Facebook posts over the course of a year (Study B).

Definition of Key Terms

Conceptual Definitions of Key Terms

- Social Networking Sites (SNS): "… group of internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of user generated content" (Kaplan & Haenlein, 2010, p. 61).

- Facebook: Web-based networking tool that allows users to create a public profile, and build and control a social network of connections (boyd & Ellison, 2008).
- Accommodation: “It [accommodation] can function to index and achieve solidarity with or dissociation from a conversational partner reciprocally and dynamically… accommodation strategies can characterize wholesale realignments of patterns of code or language selection, although again related to constellations of underlying beliefs, attitudes, and sociostructurally conditions” (Giles, Coupland, and Coupland, 1991, p. 2).
- Convergence: “…to move towards each other or a common point” (Hu, 2013, p. 3).
- Divergence: “… To move away or to proceed in different directions from a point or from each other, in other words to move further and further apart” (Hu, 2013, p.3).
- Viral reach: “… refers to the volume of message viewing, sharing, and forwarding by Internet users carried out either online or offline” (Alhabash, et al., 2013, p. 176).
- *Likes* (on Facebook): “[*Likes*] can be considered a proxy measure of word of mouth and brand engagement” (Wallace, Buil, de Sheraton, & Hogan, 2014, p.3).
- Comments (on Facebook): Publically viewable passages left on status updates that are linked back to personal pages, and have the potential to generate more traffic to a story (Hille & Bakker, 2014).
- Neoliberal posts: Organizations will use social media, a generally free service, to sell their companies or products (Dart, 2014).
- Team related posts: Posts that informed Facebook users of team-related activities (Waters, Burke, Jackson, & Buning, 2011).
- Social posts: Posts that include messages of fandom or interactivity (Blaszka, Burch, Frederick, Clavio, & Walsh, 2012).

- Shares (on Facebook): “[Shares are] the value fetched from Facebook and the higher number of shares is considered a positive indicator for the company web site” (Seker, Cankir, & Arslan, 2014, p. 223).

Operational Definitions of Key Terms

- Page Likes: Refers to the number of likes of an organization’s Facebook page. This term does not refer to the number of *likes* within Facebook posts or comments made by an organization.
    - Most Liked MiLB Facebook Page: Refers to, in this instance, the Single-A MiLB team with the most likes on their Facebook page.
    - Least Liked MiLB Facebook Page: Refers to, in this instance, the Single-A MiLB team with the least amount of likes on their Facebook page.
- *Likes*: Refers to the number of *likes* a Facebook post has, for either a status update, a picture, a comment, and any other Facebook activity that allows users to *like* the post. This term does not refer to the number of page likes an organization’s Facebook page has. When the term *likes* is italicized, the use of the term refers to this definition.
- Convergent posts: When Facebook post language between an organization and a comment left by a user are similar in terms of LSM and immediacy.
- Divergent posts: When Facebook post language between an organization and a comment left by a user are different from each other in terms of LSM and immediacy.
- Linguistic-style matching (LSM): A metric used to measure the level of mimicry in language (Gonzales, Hancock, & Pennebaker, 2010). When conversation participants converge on each other’s linguistic styles, this shows a heightened level of interest in the conversation (de Siqueira & Herring, 2009; Gasiorek & Giles, 2015; Gonzales, Hancock,

& Pennebaker, 2009; Giles, Coupland, & Coupland, 1991; Giles, 2008; Ludwig et al., 2013).

- Immediacy: Refers to the ways in which a communicator interacts with others by way of "affective, evaluative, and/or preferential attitude(s) toward the objects, events, or people about which he communicates" (Mehrabian, 1966, p.26). These attributes have also shown positive emotions towards a conversation (McCroskey & Richmond, 2000).
- Traditional Facebook Metrics: Refers to *likes* and number of comments.
- Accommodation scores: Refers to immediacy and linguistic-style matching (LSM).

Summary

By measuring *likes* and number of comments as components of internet virality, this study has examined how organizations can maximize their viral reach. The goal of these studies was to provide insight and direction to future social media administrators in terms of posting strategies, and introduce CAT to social media in a sport setting. Study A specifically investigated how accommodation interacts with *likes* and number of comments through various Facebook posting strategies (neoliberal, social, and team related posts) for MiLB teams geographically centered in South Carolina. In this study, accommodation was reported generally through all teams' posts per category, as well as individual team posting strategy reports. Study B put forth a means by which teams may be compared with various levels of popularity. Study B compared the most and least liked pages of Single-A MiLB teams on Facebook, and compared correlations to see which team is actually performing better, given their language accommodation scores and *likes* and number of comments. This study gave further insights into successful posting strategies for MiLB teams with a high number of page likes, as well as pages with a low number of page likes.

CHAPTER TWO

LITERATURE REVIEW

This literature review is divided into three different sections. First, this literature review will give an overview of social media best practice studies in the corporate world, and conclude with an overview of social media studies conducted in the realm of sports. This setup was chosen as the investigator wanted to expand the tools available to social media researchers, while also acknowledging that the current research endeavor will add to the knowledge base of how businesses can use social media. Emphasis will be placed on the idealized self, and ways that individuals have acted on Facebook to converge or diverge their posting strategies toward either their idealized self or their actual self. Next, this literature review will examine various works within communication accommodation theory (CAT), and conclude with convergence and divergence studies performed in various online settings. The third and final section of this literature review will provide an overview of work conducted in and around Minor League Baseball, which will highlight the need for more scholarly attention on social media studies within the Minor Leagues.

Social Media

Social Media Introduction

Social media have changed the ways that the world uses the Internet, as Facebook has more users than some countries have citizens (Kaplan & Haenlein, 2010). When discussing social media (see definition in chapter one), there are a few other terms associated with the websites: user generated content and Web 2.0. User generated content refers to the ways in which users make use of social media (by posting, adding videos, tweeting, commenting, sharing, messaging, etc.). Web 2.0 is defined as "a new way in which software developers and end-users started to utilize the World Wide Web… as a platform whereby content and applications are no longer created and published by individuals, but instead are continuously modified by all users in a participatory and collaborative fashion" (p. 61). The authors go on to lay out various ways that companies can utilize social media, including using social media platforms differently and synergistically, be active and post in everyday language, and for social media pages to be honest and interesting.

Kietzmann, Hermkens, McCarthy, and Silvestre (2011) illustrated how social media have reshaped the internet. "Social media employ mobile and web-based technologies to create highly interactive platforms via which individuals and communities share, co-create, discuss, and modify user-generated content" (p. 241). Given this definition, it makes sense that a two-way communication system such as social media can influence one's perceptions about an organization. One two-way communication medium is Facebook. Facebook began as a private network for Harvard University students, but eventually allowed for users from all forms of life to join the medium, including businesses. The authors set forth a guide for businesses on how to use social media, termed the seven functional blocks for social media use. These terms included identity, conversations, sharing, presence, relationships, reputation, and groups. Identity represents the ways that individuals portray themselves on social media, while conversations shows how individuals communicate with other users on social media. In their terms, sharing shows the ways that users exchange, distribute, and receive content while presence refers to the availability of one's social network page(s). Relationships show the ways that users are related to one another, while reputation is how individuals are seen by other users in terms of social standing. Finally, groups represent communities and sub-communities. Most of these functional blocks exist today in some form on Facebook. The authors claimed that a four-step process would work in defining a company's social media policy: including cognize (know the social media landscape), congruity (make applicable social media strategies to each platform), curate (knowing when or if a company's page should chime into a social media conversation), and chase (always seek further information).

Smith (2009) further showed how social media changed the internet landscape in the mid-to-late 2000's. Within two years, this study found an increase in blog readership (from 54% to 77%) while also claiming that viewing video clips online jumped over 51% in total viewership over this same period of time (32% in 2006 to 83% in 2008). This author suggested that social media would shape the ways in which content would circulate. Instead of having a company control the dialogue surrounding their organization, consumer driven communications would begin to dictate the direction of conversations surrounding companies. User generated content surrounds products, and can have heavy influences on individuals' personal decisions (including purchasing intentions) online and offline. Smith further asserted that social media can create an opportunity for companies, given the ways in which social media have changed the ways that individuals and companies communicate. The new listening economy is a directive towards companies to listen to the public's opinions. Factors included in the listening economy include the notion that sharing opinions is normal, constant research will aid companies in marketing endeavors, these technologies have a global focus, and that they can be used to retrieve exposure ratings (or reach). This paper concluded that companies should embrace these research opportunities, and evolve through building an online community, work with brands, use external platforms, use web or technology based applications (apps), and collect data from all social media platforms.

There are a variety of social media platforms, or "different mechanisms or technological vehicles for connecting people and information" (McFarland & Ployhart, 2015, p. 1654). Facebook specifically has the ability to create a public profile, maintain a list of individuals whom a user shares a connection with, and allows for communication with other users within the system of Facebook. McFarland and Ployhart developed a contextual framework, which showed the versatility of social media, which led to a variety of implications for practitioners and theorists. For example, these authors suggested that social media could act as a vehicle for not only theory development, but discovery of new theories.

Social Media As Image Enhancers

Liking a Facebook page has been tied to an organization having better brand evaluations than those who did not like their Facebook page (Beukeboom, Kerkhof, & de Vries, 2015). In their study, these authors examined 197 participant responses to a painting sales organization's Facebook page. The participants were divided into three groups- current follower, new follower, and non-follower. Current followers had already liked this organization's Facebook page, and were identified in the participant recruiting stage of this study. New followers were instructed to like the page before the survey was distributed, and the non-follower group had no association with the organization's Facebook page. A premeasure questionnaire was distributed online, and after a month, the brand attitude, brand equity, net promoter score, and purchase intention were measured. After the experiment, a similar measurement instrument was used, with the inclusion of conversational human voice to measure conversational style. Their test concluded that liking a Facebook page can lead to an elevation in one's perceptions on the brand, and even increase their level of purchase intention.

Social media has also been used as a supplement to television programs through the second-screen experience (Kätsyri, Kinnunen, Kusumoto, Oittinen, & Ravaja, 2016). These authors examined the attention spans of 38 participants watching a news program while also on a second-screen tablet. Tweets, or updates from Twitter accounts, would show up on the tablet that were related to the news program. As expected, these tweets took away viewers' attention from the television program. Tweets of a negative nature were observed for a longer time than positive tweets, and did not detract any more attention away from the news broadcast than positive tweets did. Thus, these findings suggest that negative stimuli on a social media network would solicit greater attention than positive stimuli. Although negativity was found through this examination to hold the reader's attention longer, this negativity could have an overall negative affect as users may see a social media page as a detractor from their personal lives.

Mangold and Faulds (2009) suggested that social media have many unique qualities, including the ability for users to communicate with one another via each platform. The authors argue that this new version of word of mouth communication can be harmful, and that marketers should try and shape the communications of social media users to that of a positive tone. Further, these authors suggest that social media posts by businesses should be in line with the mission and performance goals of the organization, which would in turn shape the conversations amongst social media users. Engaging customers via blogs, social media posts on all forums, and networking platforms (standalone or through social media) are all suggested as ways that companies can maximize their social media campaigns.

Social media have been seen as a way to enhance a company's image, but social media can also be used as more of a venting website for complaining and other negative circumstances (Gregoire, Salle, & Tripp, 2015). These authors acknowledge that customer complaints are becoming more frequent as over 21% of adults ages 18-34 would retaliate to a negative customer service experience via social media. This paper showed the various ways that customers would go about complaining on social media, which includes directly contacting the company online, boasting (when a company corrects a customer's problem), badmouthing the company without contacting the company directly, complaining to a third party for help, spreading negative publicity about your company, and allowing competitors to take advantage of one's complaints against a company and helping to spread the negative news. The first two situations are positive complaints a company could see online, the next two are bad, and the last two are downright terrible situations. To respond to each of these complaints, the authors suggested the following: for direct contacts, the company should acknowledge the problem within the first fifteen minutes. This should be done in a similar manner as the complaint was received. For boasting, organizations should take advantage of this opportunity and publicize their customer service victories. Being proactive will help companies that are the victims of badmouthing, or when an individual speaks ill on a company without directly contacting them. Companies should set up software packages to find those who talk about a company indirectly, so they may reach out to these customers to make reparations where possible. When individuals seek the help of third-parties online, companies should work to resolve the problem through said third-party. In this light, other individuals can see that the company is trying to make reparations. The next type of complaint, essentially the viral complaint, is almost impossible to overcome. Other than preventative measures, the authors suggest that companies fight a viral complaint by immediately compensating the individual, and analyzing the situation to ensure that similar situations do not happen again. Finally, when competitors take hold of a very negative situation, the host organization should respond with a humorous post or campaign.

Bernritter, Verlegh, and Smit (2016) suggested that users tend to endorse a brand to enhance or justify their identity. A brand's warmth, or being positive in nice, was found to be a better predictor of success than if a brand was perceived as more competent, or generally being good at doing something. For example, if an NFL team were to post various Facebook status updates depicting their star quarterback signing a football for a kid as opposed to this same team posting play-by-play game recap posts depicting a blowout victory, that the first football signing post would garner more success than the blowout victory posts. The authors' findings suggest that warmth type Facebook posts found greater success than competency type Facebook posts in supporting non-profits, although there was no difference between warmth and competence posts when observing solely for-profit organizations.

Social Media Advice For Managers

Benthaus, Risius, and Beck (2016) found that companies that use social media management (SMM) tools would, in general, make social media webpages more effective in their deliveries and strategies. SMM tools would include aspects such as monitoring capabilities (trend analyses, influence of a post), and would help organize and analyze workflow for user engagements (scheduling of posts, automatic replies to posts, and engaging multiple users through a post). The authors also suggest that the goals of social media need to be aligned with the goals for the organization. Their analysis examined posts from 100 Fortune 500 companies' Twitter accounts, while also interviewing six social media professionals from Denmark, Germany, and the United States. Results concluded that the use of SMM tools instead of general website development tools was very beneficial to social media pages gaining more exposure. This suggests that different web based applications should use specific tools to reach their maximum potential. In this example, web based tools were not as effective on social media. Thus, it would stand to reason that different tools should be used between different social media types.

Social media often develop separate social media strategies per platform, meaning that there will be a particular strategy for Facebook, Twitter, Instagram, and/or YouTube (Hanna, Rohm, and Crittenden, 2011). These authors suggested that organizations should adopt a more comprehensive social media posting strategy, which puts forth a communication strategy first approach. The paper suggested that social media managers look at social media as a whole, somewhat like an ecosystem. These authors used the 2010 Grammy Awards as a case study to observe the ways that the virtual online ecosystem was used to promote the event on social media websites. This case study revealed ways that companies can use social media websites to gain the most attention and interaction. The first way to improve social media performance was to visualize the ecosystem, or essentially planning out which messages should appear on which sites. Next, social media managers should keep track of key performance indicators, which would include the *likes* or reach metrics on Facebook. Having a clear story throughout the process was essential in having a great social media campaign. Each platform can add to the social media campaign in a different way, but having a clear focal point will make a campaign clearer towards all publics as opposed to having different strategies on different social media platforms. Elaborate productions are not necessary on social media, as most platforms are free to use and require minimum costs for advertising over the medium. Finally, the authors suggest that being unique plays a role in having a great social media campaign. For example, Manchester United's social media ecosystem has Facebook, Twitter, and Google Hangouts each working alongside one another. Manchester United often hosts Google Hangouts with prominent players on their team, which find sponsorships through the soccer club's various sponsors (typically their title sponsor).

Similarly, Ashley and Tuten (2015) found that businesses were using various social media platforms in different ways. In other words, these authors found that across 28 selected brands (from Interbrand's Best Global Brands valuation study), each brand used their Twitter, Facebook, and MySpace platforms in different ways. The authors used a content analysis across various message strategies (sales promotion, user-generated content, interactivity, etc.) and found that Twitter, Facebook, and socialized microsites were used most frequently, followed by YouTube, social bookmarking, photosharing, mobile apps, and social gaming. In short, these authors argued that marketers will go where the people are, and that they will adapt their social media strategy to each platform.

Ludwig and de Ruyter (2016) examined previous research, and found the importance of customer generated content placed on various social media websites, including an organization's comments section. These authors suggested that companies should dive into the specifics of how a review or social media post is written about their company, as subtle word choices can heavily influence the opinion of others. Next, there seems to be a saturation point for positive online reviews, as the authors suggested that too many positive online reviews would be seen as insincere by the public. An overload of information on social media can also alienate customers, as they may find sifting through a high quantity of comments to be too arduous of a task. This may leave these potential customers out of future purchasing intentions. The act of communication through an online dialogue and listening to social media channels is key for social media managers to run a successful campaign. Finally, practitioners should use text analytics to gain further insights into what the public is discussing about their products online.

Feng, Hu, Li, Stanley, Havlin, and Braunstein (2015) found that the spread of information across social media is somewhat geographically based. These authors found that the more individuals living within the same area as a social media post, the more likely the post will spread virally from a grassroots perspective. Further, the more friends a person has, the more exposures of a particular post are necessary for a post to spread. The authors found this through a micro-blog site Chinese Sina Weibo, a program similar to Twitter. Their examination looked at 286 viral messages sent through Weibo in December, 2012. Each time a message is seen, the authors measured how long it took the message to transmit from the original poster to subsequent reposts, and so on and so forth. A fractional SIR model was used to depict this trend. Thus, as a message was sent out to a social network, the closer in proximity to the message origination point a user is, the more likely they are to share it. This makes sense as individuals will try and portray an idealized self in any setting, thus identifying with a local entity may show one's roots in a particular area.

Arnaboldi and Coget (2016) argued that most organizations are misusing their social media pages, and that this misuse is leading to stunted results. These authors suggest that social media have been used, for the most part, as an exploitation tool so organizations can further their missions or profit lines. This form of thinking is argued as wrong, whereas arguments in favor of organizations adapting to and around social media will flourish in that particular environment.

These authors suggested four different tests to see if an organization is ready to adapt and evolve around social media or try and use social media for their own means. Knowing where one's organization falls on the social media acceptability spectrum is the first of four steps to diagnose if a company is ready to embrace social media. If a company's policy on social media is closed, and unwilling for its employees to take part in any social media forum, then this company may not be ready for social media. Understanding the needs and wants of a company's own stakeholders also is a test for social media applicability for a company. Although other studies would discredit this test, on the surface this argument makes sense- if your stakeholders and active publics do not want an organization to perform a certain task, then this company shouldn't perform this task. Next, understanding the climate surrounding the topics discussed on social media by your organization is paramount to success. For example, if a conservative company in the United States backs a very liberal presidential candidate, they may alienate their constituents. Finally, given the underlying assumptions of an organization, is said organization ready for the value that social media can bring to this organization? In this example, value can go both ways- as positive or negative feedback. Some companies may not be ready for negative feedback, and may be ill equipped to work with negative commentary.

Schivinski and Dabrowski (2016) detected a difference in responses to Facebook posts between user generated posts and firm created posts. A user generated Facebook post would be a post that originates from a Facebook user, while a firm created Facebook post would be a post generated by a corporation or business. A questionnaire was posted via 60 participating brands Facebook pages (within the brand categories of non-alcoholic beverages, clothing, and mobile network operators). 504 usable questionnaires were available, as the authors used structural equation modeling to find that firm created Facebook posts had a positive influence on brand equity and on consumers' brand attitudes. Brand attitude had a significant effect on brand equity, and both brand equity and brand attitude had a positive effect on purchase intention. Thus, given that Facebook can work in a negative light towards many organizations in terms of complaints, the positives of having a Facebook pages can include an increase in one's intent to purchase a product.

Hollenbeck and Kaikati (2012) found through a series of focus groups, semi-structured interviews, and two years of research that individuals would represent themselves on Facebook using various brands to portray their ideal and actual selves. This study's findings suggest that individuals will converge their outward appearances towards certain brands, or as the authors refer to as blend (congruous), while also diverging from their personal self to identify with other brands, or as the authors refer to as conflict (incongruous). For example, and individual may post pictures on Facebook of the individual user wearing a lot of workout apparel even if the individual does not work out just to be seen in a more idealized light. Although this portrayal doesn't truthfully represent this user's actual self, it does represent this person's idealized self through a conflicting (or diverging) representation. This examination also showed that individuals could portray multiple identities through Facebook. Furthermore, the authors found that individuals would not only represent themselves in an actual or idealized way, but would tend to blend the two representations to converge upon a middle-ground identity.

Social Media In Sports

Social media has also seeped into the world of sports, as social media has given users unprecedented access to their favorite athletes (Pegoraro, 2010). These athletes are seen in a new, more authentic, light, which had rarely been accessible to the general public. Before social media, the most that a consumer would receive from their sports heroes would come from press conferences (unless they had a personal relationship with said athlete). There have been bumps in the road in terms of acclimation to social media by athletes and leagues, as specific rules have been put in place for athletes on guidelines for using social media. In particular to this study, the author collected data from a one week period in January, 2010, from the top five Twitter accounts for many popular sports (NBA and NFL), while also collecting tweets from athletes in tennis, golf, soccer, and motor sports. The results showed that players in the NFL as well as golf used Twitter more than other sports. Further, athletes would give a glimpse into their personal lives. At the time, these results suggested that athletes were not taking advantage of Twitter in the ways that they could, meaning through brand promotion.

Clavio and Kian (2010) used Twitter as a means of identifying the demographic makeup of a retired female athlete. These authors also examined the ways in which this athlete used Twitter, through a uses and gratification lens. Their findings suggested that her Twitter followers were primarily white, educated, and older (40 years of age or older). It was suggested that followers of this athlete on Twitter followed her due to her expertise, followed by the athlete’s writing style. It was also suggested that women would follow this athlete because of her athletic prowess, while men would follow her because they found her physically attractive. Twitter users would also follow this athlete because it seemed that her posts were organic (originated from her, not perceived to be posts from a robot or third party), and interactivity (or the ability of Twitter users to garner a response when prompting one from the athlete).

Twitter was observed in a case study exploration of professional golfers during the Masters golf tournament (Hull, 2014). Twitter was used to show the audience the stresses of playing in such a prestigious and difficult tournament, while also showing a behind-the-scenes look at how athletes lived during the tournament. Some golfers also engaged with fans personally through Twitter.

A survey methodology was employed to interpret what factors the Twitter audience perceived to be important when they followed an athlete (Lebel & Danylchuk, 2014). Ten presentation strategies were defined for a sample of 377 survey participants, who suggested that the sport insider was the most sought after strategy when following an athlete. Further results indicated that discussions of athlete performance, fitness, and an athlete's expertise in a sport were also reasons that Twitter users would follow an individual on the medium. The investigators for this study also found that Twitter users were not as interested in the personal lives of athletes, which contradicted previous research.

Although athletes have used Twitter to show aspects of their personal lives, Zimmerman, Johnson, and Ridley (2016) found that football coaches at major NCAA Division 1 universities used Twitter as a means of information dissemination and program promotion. Coaches rarely used Twitter as a means for the public to see into their private lives. This examination encompassed 1,315 tweets from coaches after the 2012 season. These authors suggested that coaches used Twitter as a means of relationship marketing for themselves, and for their schools.

Twitter has also been used as a means for protesting the cancellation of collegiate athletics teams. Hull (2014, a) used a case study methodology to explore how Twitter was used as a protest medium to help save the UNC-Wilmington swimming and diving teams. The results of a content analysis of 1,775 tweets by 25 athletes, and a series of interviews, suggested that athletes could use Twitter as a way to become opinion leaders, disseminate information, and use the medium as a means of gathering others to support the UNCW swimming and diving team.

Instagram has also been observed in a sports setting, through an analysis of Instagram posts from institutions in the Southeastern Conference (Bowles, 2016). Two months of Instagram posts were collected from the fall of 2013. A thematic analysis of the photos posted to Instagram suggested that SEC teams posted in behind the scenes photos, action photos (in-game, during practice), fan photos, landmark photos, promotional photos, and photos of team success.

Major League Baseball (MLB) teams have also become involved with Instagram, as observed by Hull and Kim (2016). Their analysis selected 50 Instagram posts from each MLB team during the 2015 season. Their analysis found that teams were not posting on Instagram in ways that were deemed charitable, and when teams would post charity type photos, the responses from their fans were minimal. This showed that MLB teams were not using Instagram as an avenue to promote their corporate social responsibility efforts, but instead wanted to give fans other insights into their respective teams.

Athlete self-presentation on Instagram has also been examined (Smith & Sanderson, 2015). A collection of Instagram posts by athletes in various sports revealed that posted in various ways, including humanitarian posts which were civically driven, family driven which shared the personal lives of athletes, personality traits and interests which gave a more personal look at athletes' interests off the field, dedication which showed the hard work of training to be a professional athlete, endorser which portrayed a sponsorship or endorsement agreement between an athlete and a sponsor, and socialite which gave Instagram users a look into the personal lives of athletes. Many of these themes could be found across self-presentation strategies on Facebook and Twitter.

Other inquiries into sport and Instagram have shown that athletes may be using Instagram similarly to Twitter and Facebook (Geurin-Eagleman & Burch, 2016). Personal life photos, business life photos, and sexually suggested images were all posted by athletes on Instagram. Memes, pop culture, and reposting fan content were all found to a lesser extent in this analysis, which shows that athletes perceive that a glimpse into their personal life is what fans on social media are looking for.

One way that athletes have used Facebook was observed as a crisis communication related tool (Sanderson, 2010). During Tiger Woods' infidelity scandal, fans flocked to his Facebook pages to show sympathy for the way that the media was prodding into his personal affairs. This Facebook textual analysis was completed in conjunction with a textual analysis of print media (newspapers), which framed Woods as a fallen hero. Data were collected between December 2, 2009 and February 20, 2010 through the Lexis-Nexis Academic Database for print media, as well as through Woods's official Facebook page during that same time period (128 discussion threads with 650 postings throughout). Further results from this study revealed that print media would simply transfer Woods's tenacity on the golf course to a similar tenacity for sexual craving. On Facebook, fans saw this scandal as a way that made Woods more human, as these acts of infidelity portrayed in imperfect human being. There was also evidence that the portrayal of Woods leaned toward more of an idealized self before this scandal, and that individuals were having a difficult time understanding Woods' actual self. This study showed how Facebook could be used by a public figure as a means of generating positive commentary when being attacked by a traditional media source.

Frederick, Stocz, and Pegoraro (2016) found that athletes would not only find positive commentary through Facebook during times of crises, but would also find individuals who would attack them. This examination looked at Facebook user generated responses to Tony Stewart's official press release after he ran over, and killed, Kevin Ward, Jr., at a dirt track race.

Leximancer software was used to qualitatively analyze 14,888 comments, which generated two frames (judgment and knowledge) containing five themes (fault, accident, conviction, racing knowledge, and evidence). All of these themes had positive and negative sentiments sent towards Stewart, but also users would attack each other. Examples throughout this dataset were seen of individuals attempting to portray themselves in a positive light through exemplifying their knowledge of all forms of racing. These users would use facts about Tony Stewart or racing in general in an attempt to sway other users to their side. Although there was a plethora of comments in this examination, each type of post could be coded into a general theme or frame. These themes would work bi-dimensionally, but would contain very similar linguistics to other Facebook posts.

Similar to the previously mentioned sports social media studies, Frederick, Lim, Clavio, and Walsh (2012) found that users will follow athletes for personal reasons, although these reasons were explored more in depth. These authors found that users felt a sense of interpersonal closeness with these athletes through a survey (distributed through Facebook and Twitter), but only if the athlete matched the user's individual communication style. These authors found that followers of a social athlete, or one who posted in interactive ways by engaging their Twitter audience (typically through the @ symbol to signify a personalized tweet towards one audience member), tended to follow that athlete due to their interactive qualities. Thus, a user would follow this athlete and may find themselves in an online dialogue with this athlete. On the other hand, followers of the more parasocial athlete tended to seek information and believed they were a part of a community surrounding the athlete. These results once again show how individuals will use social media to associate themselves to an idealized self.

Similar to Beukeboom, Kerkhof, and de Vries (2015), Walsh, Clavio, Lovell, and Blaszka (2013) found that if users used Facebook alongside an event (not necessarily a two-screen experience, but if they followed the event via Facebook) that they would value the brand higher than those who did not use Facebook. An instrument that measured brand personality items (including exciting, passionate, entertaining, intense, competitive, fan-friendly, skilled, elite, and fast-paced) was distributed to 3,334 individuals with a response from 1,523 (45.7%). A MANOVA test showed a significant difference between the Facebook user group and the non-Facebook user group for exciting, passionate, entertaining, intense, competitive, fan-friendly, skilled, and elite at a minimum at the alpha level. This examination showed that Facebook did have an effect on one's perception of a brand.

In further identifying why individuals use Facebook to connect with their team(s), Kim, Kim, and Hur (2015) found that individuals consumed Facebook pages through motivations of social voyeurism, self-enhancement, economic value, fan connection, team connection and support, entertainment value, and convenience. These individuals used a mixed-methods approach, of using focus groups, an exploratory factor analysis, an expert panel, and a survey to generate these results. Further, these authors found that consumers of sport Facebook pages would be constrained by self-protection, time, and lack of interest in terms of viewing these pages. For practitioners, this signifies that social media managers should keep their posts somewhat brief (but not as brief as a Twitter post).

Sports Organizations on Social Media

During the early stages of social media integration into an organization's setting, Waters, Burke, Jackson, and Buning (2011) found that sport franchises were hesitant to post information on Facebook. In the early stages, organizations would post content directly to their franchise's own webpage, as the authors suggested that organizations tended to promote relationship building tactics through their own pages as opposed to Facebook or other social media platforms. These authors' findings also suggest that teams were posting to Facebook and their own webpages in different ways. These findings suggested that organizations felt the need to control the messages surrounding their team, which is typical of users of Web 1.0 software packages. While Web 2.0 allowed for users to become producers, Web 1.0 software allowed for organizations to control the entirety of the message as webpages were seen more as static one-way communication outlets. This finding represented the need for organizations to grow around Web 2.0 (and eventually social media) to survive in an ever-changing environment.

One way that organizations would need to "grow" would be through the attraction of fans through the idea of authenticity. Pronschinske, Groza, and Walker (2012) found through an econometric model that teams need to post to their social media accounts in ways that are deemed as authentic to stimulate their Facebook audience and build an engaged Facebook fan network. The authors claim that authenticity is comprised of showing trust throughout the marketing process (towards fans), acting in transparent ways when making decisions on an organization, properly engaging a team's own fan base, and being truthful. These authors claim that two general variables help to determine if a team's Facebook strategy will impact the number of fans a team receives; first, the team must show that posts generated were actually performed by the team. Second, the team must support a Facebook environment of a two-way dialogue. For practitioners, the first criteria can be met through filling out the impressum section on Facebook. Completing this section is one of the steps for an organization's Facebook page to be the "official" page for an organization. This is signified through a blue check mark next to the organization's name.

Sport Organization Social Media Posting Strategies

O'Hallarn, Morehead, and Pribesh (2016) put forth a set of guidelines for universities when using social media to promote their athletic teams. The authors used a case study methodology to compare the strategies of Old Dominion University to Funk's framework for social media practices. These results were compared with those from five peer institutions' social media websites. Funk (2013) suggested that social media managers utilize the following strategies: 1) target influential social media users who have a lot of connections, 2) post in a fun and interactive manner, 3) address complaints, and 4) measure social media campaigns' success with analytical tools (such as Facebook Insights and Google Analytics). Based off of this work, O'Hallarn, Morehead, and Pribesh (2016) proposed the acronym, STEAM, as a strategy for campaigns generated by sport media managers. The acronym stands for steal (or learn from other organizations' successful posts), team (posting not just ticket sales status updates, but also team updates), engagement (engaging with the fan base), analytics (using statistical software to measure social media campaign effectiveness), and mavens (recruiting the help of highly identified fans to spread the word about an athletic department on social media).

Wallace, Wilson, and Moloch (2011) found that sport organizations on Facebook were using the medium as a way of posting a variety of content (that changed with each sports season), as a means for fan interaction, and branding techniques. This examination looked at the differences between the NCAA organization Facebook page and the individual pages for the Big 12, to see their posting strategies. All parties involved would post with different frequencies throughout the year (divided by season), with the Big 12 Pages posting primarily in the fall while the NCAA would post the most in the spring. The NCAA was more likely to post a status update with a link, although all pages would primarily post updates with a link with the NCAA posting this way with more frequency. All pages would post in ways to raise brand awareness, while Big 12 pages would more frequently post general information about their teams than the NCAA. This study showed how sports organizations have posted to Facebook previously.

In keeping in line with posting strategies for organizations, Thompson, Martin, Gee, and Eagleman (2014) found that tennis National Sports Organizations (NSO), such as the U.S. Open, should post content year around, and use social media to the strengths of said social media. This finding once again suggests that not all social media platforms are created the same, and managers should use these differences to gain a more diverse, and higher number, of patrons for their social media accounts. These authors found these results through a qualitative based survey, which was distributed through online means. Further results included, similar to Frederick, Stocz, and Pegoraro (2016), participants' desire for NSO's to foster fan to fan discussions, create an emotional connection, using social media as an exclusive first look at entities surrounding events hosted by the NSO's, and interactions between the NSO and users.

Further examinations of NSO's were performed by Abeza and O'Reilly (2014) as they observed three Canadian NSO's use of Facebook and Twitter. Their examination found that Canadian NSO's were not using Facebook and Twitter as a two-way communication medium, but instead were using these platforms as a way to communicate in a one-way fashion with fans. Along with this finding, users rarely engaged the NSO's status updates. This study found that performance did not match time on a platform (AKA when the NSO signed up for a Facebook or Twitter page). Lastly, these authors found that NSO's tend to communicate through Facebook more than Twitter. This article showed managers what not to do on social media. In acting in more of a Web 1.0 manner of solely using each platform as a communication medium, users would rarely engage the NSO.

Further fan expectations for organizations' posting strategies for social media were discussed by Parganas and Anagnostopoulos (2015). These authors interviewed the social media managers for Liverpool Football Club (FC), one of the most identifiable soccer clubs in the world. This case study used semi-structured interviews with two senior social media marketing managers for Liverpool FC. These managers claimed that their social media strategy includes making a close connection with fans through generated content, engage fans through interactive posts, monetizing social media through sponsorships and generating money from clicks to a website, and successfully resolving challenges and customer complaints. One of the ways that individuals can make money off of social media would be through live internet streaming of players and/or coaches through applications such as Google Hangouts. In this scenario, a selection of major players could be selected for the "Liverpool FC Hangout, Presented by Standard Chartered."

Miranda, Chamorro, Rubio, and Rodriguez (2014) examined professional sports teams across the United States and Europe to see their posting strategies as compared to the Facebook Assessment Index. The Facebook Assessment Index (FAI) measures three dimensions of posting strategies for the Facebook Medium: interactivity, popularity, and content. Results indicated that the highest level of posting scores went to the English Premiere League. Interactivity posts were measured through the number of visible posts on a team's wall, as well as global interactivity, *likes* per post, number of post shares, and comments per post. The content category was measured by the completeness of profile by teams, including filling out the impressum section, standard information, contact information, address, and other pertinent Facebook information. Finally, popularity was measured by the number of page likes, which ranged from 5,000 to over

30 million. This study showed the importance for practitioners to have a complete Facebook profile, and the ways that Facebook assesses they can get more fans.

Boehmer and Lacy (2014) found that interactivity had no direct effect on the number of clicks onto a host's website on a Facebook in a post-by-post observation. These same authors also found that having a Facebook strategy that is overall interactive did lead to a host's website having more clicks to the webpage overall. These authors studied a popular German web page, SPOX.com, and their linked Facebook account for this analysis. Facebook Insights and Google Analytics were used as measurement tools to see how many unique users clicked off of Facebook onto the host's webpage, but would only account for the number of unique visitors, not the number of times each unique visitor clicked off of Facebook into the host's webpage. This article showed that interactivity was a solid posting strategy for organizations on Facebook.

Many of the previous studies detected significant findings suggesting that social media would be useful in discovering purchase intentions or clicks onto a host's webpage. Bayne and Cianfrone (2013) found that Facebook could be used to build awareness of an event on a university campus. These authors found that liking this Facebook page would not lead to generating any more interest in an event nor intention to attend this event. These authors tested a relatively low number of participants (55) through a pre-and post-test analysis with a Facebook group and non-Facebook control group. They tested both groups' awareness, interest, and intention of participating in a campus organized adventure race. As stated before, the Facebook group was made more aware of this event than the control group, but they were not significantly more inclined than the control group to attend the event or show interest in the event. This could be due to the perceived high level of personal participation in an adventure race. This study could be replicated to a more traditional sports fan setting, such as attending a sporting contest, and show different results.

Excitement was assumed to be positive influences on one's intent to post content to social media; however, Wakefield and Wakefield (2016) found through surveying attendees of a National Association for Stock Car Auto Racing (NASCAR) event that this was not the case. Through a survey of 328 patrons for a NASCAR event, these authors found that affect (or excitement) did not lead to desire for one to post to Facebook or Twitter. Further results indicated that patrons of this NASCAR event were enjoying themselves. Thus, the implications of this study are that excitement alone will not build a fan base on social media. A company must invoke other methods to generate social media posts from their fans.

Seng and Keat (2014) set up an experiment between similar products and audience reception between a minimal information Facebook page and a positive, flourishing with information Facebook page. The authors set up a fictitious sporting good Facebook page for the control and experimental group. The control group was routed to a Facebook page with only a company description, a mission statement, and the year that the company was founded, while the experimental group was sent to a page that contained all of the above factors, but also included positive comments for the brand in a wall type of section. This section was also shown the number of *likes* each fictitious comment received. After the exposure, the participants completed a four-item instrument to measure purchase intention, and involvement in sport. The results found that those who had low involvement with sport were more affected by the positive Facebook page in terms of purchase intention and willingness to speak highly for the product than the general information page. This study showed how powerful a completed Facebook page can be for a company in bringing in individuals who aren't necessarily interested in a product to becoming potential consumers.

This section of the literature review primarily gave an overview of social media and Facebook, as well as setting forth a comprehensive strategy guide for social media managers. Throughout the literature, it can be argued that a universal convergence of posting strategies occurred, as academics and practitioners set forth their strategies. The final article in this section of literature review suggested that converging one's language can lead toward more comments, *likes*, and RSVP's on Facebook (Hodge, Pederson, & Walker, 2015). The different types of Facebook posting styles used were forceful (example: be there to support our team), passive (example: you should come to the game so we can beat our opponents on the court and in the stands), personal (example: we'd really like to see you at our game), impersonal (example: fan encouragement is necessary for us to defeat the other team), colorful (example: our amazing success this season and storyline continue this Friday), and less colorful (example: the [home team] will play against the opposing team this Friday). Adapting one's personal communication style, in this study, led to individuals commenting with more frequency on an invitation type post surrounding a women's varsity volleyball match, while personal and colorful posts lead to a greater number of *likes* on a Facebook post. Further results indicate that less colorful posts would lead to more shares, while colorful, forceful, and personal types of posts would lead to a greater number of RSVP's. Thus, managers can converge their language style to one of the above-mentioned categories to receive more attention through Facebook.

Communication Accommodation Theory (CAT) and Convergence/Divergence Studies

Introduction to CAT

Dragojevic, Gasiorek, and Giles (2014) described the communication accommodation theory (CAT) as "[a theory that] seeks to explain and predict such communicative adjustments, and model how others in an interaction perceive, evaluate, and respond to them" (p. 1). CAT was originally developed in the 1970's as speech accommodation theory, but renamed communication accommodation theory to encompass a broader scope of communications (including nonlinguistic and discourse). CAT can be used as an interpersonal and intergroup communication examination tool, as well as in the ways that speakers can adjust their speech patterns. CAT examines the ways in which participants in a conversation communicate with one another. For example, if conversation participant mimics the ways in which the interlocur, or conversation originator, communicates, this is a measure of CAT (specifically convergence). These adjustments include objective speech variables, which include convergence, divergence, and maintenance. Convergence, in practice, includes the ways in which a conversation participant mimics the interlocur's conversation patterns. Convergence of communication refers to adjusting one's communication behaviors to another individual's communication behaviors in terms of accent, length of dialogue, pitch, and language. For example, if an interlocur says "The sky is blue," a conversation participant may respond with "Yes, the sky is blue." This sequence would have a high level of language convergence. Divergence "refers to adjusting communicative behaviors to accentuate verbal and nonverbal differences with others, to appear more dissimilar" (p. 4). For example, if the interlocur in a conversation says "The sky is blue," a divergent conversation participant may say "No, the sky is not blue, it is in fact green. I believe you may need contacts." Maintenance refers to when one keeps their own communication pattern without adjusting to other individual’s speaking patterns. For example, if the interlocur says “The sky is blue,” and later may say “The ocean is blue,” regardless of what the other conversation participant is saying. Within convergence, upward and downward convergence can be witnessed as upward convergence is shifting one’s speech patterns to a more prestigious speech pattern, while converging downward refers to one adjusting their speech level toward a less prestigious way of speech. For example, in a conversation between a college freshman and a tenured professor, if the college freshman shifts their speech pattern to that of the tenured professor’s speech pattern, this would be an example of upward convergence; however, if the tenured professor shifts their speech pattern to that of the college freshman, this would be considered a downward convergence. Emphasizing one’s own lower-prestige speech patterns while in the presence of upper-class individuals is referred to downward divergence, while upward divergence refers to when one speaks in more prestigious ways when talking amongst the same as the speaker or lower-class speaking individuals. In the same scenario as seen above, if the college freshman over emphasizes their own speech patterns while talking with a tenured professor, this would be an example of downward divergence. An upward divergence example would be if the college professor began to use a higher level of intellect in their conversation with the college freshman. Some instances see a symmetrical convergence occur when speakers converge their speech patterns to the originator, while asymmetrical convergence occurs when individuals will not reciprocate the original speaker’s speech patterns. For example, symmetrical convergence may occur in a scenario where three individuals are having a conversation, and individual one, the interlocur, begins to speak in French, and participant number three speaks in French. Asymmetrical convergence would occur, in this example, if participant number two began to speak in a language other than French. Further, accommodation can occur on a unimodal or multimodal level. Unimodal accommodation occurs on a single dimension, such as posture or accent, while multimodal occurs on multiple dimensions, such as speech pattern, accent, posture, etc. An example of unimodal accommodation would be when a conversation participant adopts the accent of the interlocur. Multimodal accommodation, in this example, would be if this conversation participant adopted the interlocur's hand gestures, accent, rate of speech, etc. during the conversation with the interlocur. For the purposes of these studies, and in the context of social media, a unimodal accommodation approach will be necessary.

Giles, Coupland, and Coupland (1991) gave a general overview of CAT literature. These authors examined various ways that individuals converge their language, as observed through previous literature. Many factors that have been previously examined in terms of convergence included utterance length, information density, expression of opinions/orientations/solidarity and jokes, as well as vocal intensity. Utterance length refers to the length of the phrase. Convergence would be observed, in terms of utterance length, if conversation participants speak with similar phrase lengths. For example, if the interlocur states "The sky is blue," and the other participants respond with "Yes, the sky is blue," this would be considered convergence of utterance length. Information density refers to the depth or quantity of information transferred. For example, if two co-workers are gossiping on coworkers, they may exchange information on certain coworkers. "I was told that Alex was going to get promoted," may begin the conversation, followed by "Alex told me she was getting promoted, but she had to move to the south branch. Convergence of expression means that whichever expression an interlocur has adopted (joking, opinionated, etc.), each conversation participant will adopt. For example, if Alex takes on a joking expression, the degree to which each subsequent conversation participant adopts a joking expression would be a measure of convergence. Vocal intensity refers to the level of noise generated from a conversation. An example of vocal intensity convergence would be if the interlocur begins a conversation by yelling at a conversation participant, and the participant begins to yell back. Although they may be disagreeing, they are converging upon the volume of one another's conversation. These authors also propose that individuals may highlight differences in their speech patterns to portray themselves in a positive light. Although this is occurring in a divergent manner, the thought here is that by showing this seemingly positive attribute, the subsequent response would be positive and may even lead to a greater convergence of language from the responsive group.

Further, Giles (2008) set forth four principles of CAT. The first principle says that individuals will gradually accommodate greater levels communication patterns of individuals that speakers interacting with to form greater bonds with. For example, if an individual wanted to talk more with one individual in a group, they would accommodate their language to that individual throughout the course of a conversation. Next, the more that an individual perceives positive intent in an interaction, the greater the level of perceived accommodation will occur. In the previous example, if two individuals are having a positive perceived conversation, it is considered that the conversation is interesting to both participants. Diverging from one's communication patterns is considered a sign of dissatisfaction with the other individual. Thus, if one individual in the previous conversation talks about elephants, and another participant begins to talk about quantum physics, this would be perceived as dissatisfaction in the conversation on elephants by the quantum physics conversationalist. Finally, communication patterns of dissatisfaction signify unfriendliness and will be accepted negatively by other individuals. In the previous conversation, the quantum physics conversationalist will be seen as unfriendly to the elephant conversationalist, and vice versa. Thus, if a person is diverging, the receptor of this divergent language will not see the other individual in a positive light.

Rubin (1987) found that oral and written forms of communication both have instances where they diverge and converge upon each other. An example of written communication convergence would be if two individuals conversing through online instant messaging write similar messages back and forth with each other, in terms of writing style and length. While some individuals found writing to take away from the act of learning, others believed that writing was a tool for cognitive development. The differences between oral and written communications are vast, as written communications tend to be more thought out while oral communications are more spur of the moment. Although antiquated by today's standards, this article showed that convergence and divergence can exist between written communications.

Accommodation can occur in almost every context, as Gnisci (2005) used a sequential analysis to observe the accommodation patterns between lawyers and witnesses. It was found that lawyers and witnesses would reciprocate behaviors, as well as accommodate to the spoken word of one another. Thus, as the lawyer is typically the interlocur in conversations such as these, the witness would converge upon the lawyer's statement. Lawyers would use maintenance and control strategies when dealing with a hostile witness. A maintenance strategy is when an individual continues to use their own style of speech regardless of others' behaviors. In other words, no matter the response from the witness, a lawyer would continue to speak as they had previously, or would try to control the conversation. The back and forth nature of this observation also revealed those in a power position (lawyer) tended to accommodate less to those not in power (witness).

Similarly, Gasiorek and Giles (2015) found that converging communication patterns can be perceived by individuals as helpful or positive. Students for one of the authors signed up via an online questionnaire to an overaccommodation or underaccomodation vignette through random sampling. The scenario placed the students in a foreign land, speaking in their non-primary (not English) language with a primary speaker of this language. Two scenarios were given: the first where the primary speaker spoke slowly and translated their passage into English, while the second where the primary speaker spoke very quickly and would not repeat themselves. Results indicated that overaccommodating the non-primary speaker was perceived as helpful and positive. This study suggested that overaccommodating would lead to more positive evaluations while underaccommodation would lead to less positive evaluations. Further, this study showed that positive perceptions can be detected through an online medium, in this case, an online survey with a scenario. For example, in an online medium such as Reddit, where users can log onto a number of different conversation threads, one might choose to ask a question in the home improvements Subreddit (a thread within Reddit). In this thread, the interlocur might ask about the best methods for installing a sink. A response that thoroughly describes the process of installing a sink, as well as including supplemental materials and 'how to' videos, would be considered an accommodating response. This response would elicit positive feelings from the interlocur. On the other hand, a response that simply says "Call a plumber," would not be received as well by the interlocur as the post clearly indicates that the interlocur wants to install this sink themselves. The interlocur would then feel negative feelings toward the user who posted this response.

Ireland (2011) used a language style matching metric to observe any similarity of language and the act of liking that has been reported in previous CAT studies. In other words, this work attempted to examine if language accommodation would lead to future intent for individuals to meet one another. This study observed the conversation structures between men and women, and measured their accommodation ratings through the Language Inquiry and Word Count Software (LIWC). This author's dissertation found that men would be interested in contacting women that matched their style of communication. Further, this author found that both men and women were interested in contacting the opposite gender in instances where the conversation had a converged style of language. Thus, this dissertation found that language convergence was related to liking, as well as influencing future behavior (meeting up with conversation participants). In other words, the more the conversation accommodated towards each participant's speaking style, the greater chance that the two individuals would want to meet up again after the observation. For example, if two conversation participants are speaking in very similar manners, an argument could be made that both participants have positive feelings toward each other (Giles, 2008), and that they would enjoy having conversations with each other again in the future (Ireland, 2011). The implications of this can become a measure by which social media managers view the quality of their posts. If language accommodation can be measured as a means of actual intent, as suggested, then social media managers can use the LIWC and accompanying measures to measure the levels of accommodation present between their post, as the interlocur, and the subsequent comments from social media users.

CAT in Computer-Mediated Communications Settings

Language software (LIWC), as well as a subsequent set of equations, has been used to measure levels of adaptation between television star posts to a blog and responses from their fans through a comments section (Goode & Robinson, 2013). The blog posts observed were written by three soap opera stars from various television programs, with 1,335 replies to 120 blog posts

(40 posts per character analyzed, the authors analyzed 80 posts total). As first explained by Penne baker, Francis, & Booth (2001; 2007), Goode and Robinson (2013) used LIWC software to measure accommodation patterns in written messages, with an accompanying set of questions. For this examination, these authors used LIWC to examine LSM and prevalence of immediacy styles. In the current studies, the LIWC software will be used to break down the Facebook post into various measures, described below. From there, each percentage of the breakdown will be run through a series of equations to determine the level of accommodation between the original post and one comment. Each post will have a number of comments with accommodation scores, which will then be averaged together to see the level of accommodation number as an average.

Convergence and divergence type studies have occurred in a variety of forms across the internet, including an examination on the choice of news article that journalists and their audience choose to read (Bukowski, Mitchelstein, & Walter, 2011). The authors took a sample of journalists and current news consumers in Western Europe and Latin America to see if there was a difference in what stories both groups would like to read. Further, the authors sought to understand if there was a convergence of news stories towards certain news topics worldwide or if there was a divergence towards more local or different types of stories. Their findings suggest a disconnect between the news stories read by consumers and journalists, as journalists went for the more newsworthy types of stories. In other words, journalists and news consumers tended to want to read different types of stories online, which suggests that journalists may not have a firm grip on what their consumers want to read. The authors did find a pattern of convergence upon certain types of news stories (public affairs) as a majority, with little instances of divergence present. This suggests that even across nations, there could be some form of universal convergence when it comes to news stories portrayed online.

Computer-mediated communication styles have been shown to portray differences between ethnic cues (Hansen, Fabriz, & Stehle, 2015). In this study, the authors emailed internet users via a purposive sampling manner as a scholar looking for assistance. Emails were sent to students with German or Chinese backgrounds. Responses to the initial email were coded and measured, in terms of length, style, and wording. Results showed that cultural cues would aid in the response email, and that wording convergence was not present throughout the study. In other words, cultural cues would lead to a greater level of accommodation in terms of style. This would mean that if cultural cues were used, say for a German student when asking a Chinese student, in looking for help with a paper in the early 20th Century Chinese history, that the Chinese student would be more willing to help the German student than if the German student simply just asked for help. Wording convergence simply referred to the number of words a response would elicit, and the results found that results would not necessarily converge upon the original email.

Although the previous study's authors did not find convergence in terms of politeness (or referred to as style), Bunz and Campbell (2004) found that respondents to an email message would converge towards politeness cues. For this study, a scenario was set up in which college students were recruited for a visiting professor's study, and signing up for this study would fulfill a course requirement. The email asked for a response as to why they would be good fits for the study itself, and the results found that email responses did in fact have a level of politeness accommodation (in terms of greeting, signature, etc.). One explanation for this politeness can come from the perceived power structure of the conversation, in which the fate of the students' grade relies upon participation in the visiting professor's study. This study would suggest that using politeness cues, such as "Dear Dr. _______," and "Sincerely, [signature]," in an email would lead toward the email recipient sending an email with similar language. This can be useful for individuals who are emailing a recipient that may have something the interlocur needs. For example, if a graduating student were to write an email to a potential employer, it would be beneficial for the student to write said email with polite language, and view the response from the potential employer. If the potential employer sends back a polite email in return, this may mean the student is still in contention for the job, whereas an impolite email may mean the student should look elsewhere for a job.

The academic setting was again used to observe communication accommodation as de Siqueiros and Herring (2009) observed the communication patterns between academic advisors and students in an instant messaging (IM) setting. The surveyors used Skype's IM service over the course of a few months to measure different language backgrounded students whom all were fluent in English. The results showed that the academic advisor would accommodate their typing speed to that of their students, which suggested a presence of an IM rhythm. Further, throughout the duration of the study's parameters, the authors found that individuals would not sway from their own style of typing, thus representing each individual's own style for communicating. Similar to Giles, Coupland, and Coupland (1991), these communication patterns may represent the pride that one has in their own heritage, as they may be attempting to represent a form of their most positive self through these IM messages. This maintenance strategy shown by the participants may also mean that the English as a second language students have a limit for how quickly they can type in a foreign language. In a real-world setting, the results of this study would show that a person in power (instructor) would accommodate their typing speed to those who are overseen by them (students).

To follow on the findings of de Siqueira and Herring, Hesse, Werner, and Altman (1988) asserted that quicker responses to an author's original post in an online setting would send a more positive message towards the original sender. This paper set forth a framework for computer mediated communications through a transactional lens, which claimed that the environment (social and physical), time (linear and cyclical), and people (individual, dyad, group, psychological processes) all played a part in the temporal processes of message sending through computers. One of the conclusions of this study was that quicker response times to a post would show interest in the post. For example, if an email was sent by a graduating student to a potential employer asking about the status of their application, the quicker the student receives a response, the more positive a response the graduating student would feel.

Riordan, Markman, and Stewart (2012) defined various ways that computer mediated communications have been examined in the context of CAT. First, lexical convergence has been used to measure the level of converging in conversations pertaining to the following items: perceptions of rapport, trust, politeness, and gendered sayings. For example, lexical convergence online could be observed in an IM setting between a student and professor, where the student may call the professor "sir," and use politeness cues such as "please," or "Could I trouble you for…". Should the professor respond with these cues, then lexical convergence would be detected. Structural convergence refers to longer or shorter messages, as well as response times. The results of this study, which observed undergraduates communicating online with various individuals and groups (strangers of higher stature/standing), concluded that the amount of time that a subject would converge their language would decrease overtime. Thus, the closer the length of time between responses between conversation participants, the higher level of structural convergence. The second study observed friends interacting through a similar test, which found that these friends would tend to converge their language structures more throughout the experiment. This is an interesting finding, as many convergence/divergence studies identified individuals whom would accommodate to important individuals. Thus, conversation participants would accommodate their language towards both people in power or those who are friends with them.

Individuals in an online chat room setting have shown that they can accommodate their language structures to that of other individuals in a scenario where they can earn theoretical money for forming a coalition (Huffaker, Swaab, & Diermeier, 2010). This study examined how students would interact with simple three-person groups in a chat room setting as the authors gave every person a different personality. The greater that a group cooperated with each other, the greater the theoretical cash reward. The various group makeups included personality types that were designed to clash with each other, but the researchers found that personality types would begin to mirror each other. This type of language convergence was found throughout the dataset, while positive emotions didn’t necessarily lead to agreement. In this situation, monetary compensation was shown to lead toward a higher level of personality convergence. In reality, this tends to happen every day as many different individuals makeup a group within a company. Each employee’s salary is somewhat dependent upon their ability to interact and work within that group, thus personality convergence can be seen in the workplace.

CAT has been used to measure an individual’s level of confidence, as Liao, Bazarova, and Yuan (2016) measured both face-to-face interactions and computer mediated communication patterns among graduate students. In face-to-face interactions, individuals with a lower level of confidence on a particular topic would tend to converge upon the discussions of those perceived to have a high level of confidence, while online groups showed no difference between confident and non-confident individuals when discussing a topic in an online chatroom scenario (through Skype's IM feature). An example of the face-to-face interaction accommodation would be if a group of students are discussing European history, and a graduate student joins the group. This graduate student then begins to talk about their Master's thesis on the Renaissance period. The conversation may not shift to the thesis, but the Renaissance period in general. This study also found that accommodation was found through status cues, as more confident members in the computer mediated setting would accommodate their language to that of less confident individuals in computer mediated groups. This finding is similar to the findings of de Siqueira and Herring (2009), as confidence would exert a sign of inferred power. Thus, in a computer mediated setting, these two studies have found that the perceived leaders, or holders of power, will accommodate their language to the other conversation participants. Furthermore, Danescu-Niculescu-Mizil, Lee, Pang, and Kleinberg (2012) found that, in an online setting, individuals would exercise their power through posting experienced based knowledge or presenting their status alongside of their credentials on Wikipedia. Given these three studies, the argument could be made that power structures can further be identified in online settings through individuals accommodating their language towards those who control the conversation on social media platforms. This again makes sense, as an instructor will attempt to explain difficult terms in ways that particular students can understand.

Ayoko, Härtel, and Callan (2002) found that groups of individuals in a business setting would be impacted by the communication behaviors of other group members during times of conflict. Semi-structured interviews and results from a questionnaire showed that cultural differences added or started conflicts, and that having a diverse workgroup led to longer and more frequent conflicts in general. Task related, interpersonal, and process conflicts were observed through the survey results, as individuals at different levels of experience would change their communication style to reflect their experience, which in turn would cause conflicts throughout all of the above-mentioned conflicts. Thus, in an emergency, different linguistic styles would lead employees to act in divergent ways. For example, if a long-winded individual announced a fire in a building through a lengthy dialogue, many individuals would find an issue with this individual as they could have just said fire, and not had a long talk about various aspects of the fire.

Yilmaz (2016) observed if groups of individuals in an online setting working through a task would benefit from converging their linguistic style to that of the group. This author arranged for thirty-four groups of individuals (four per group) to complete a decision-making task in a chat room setting. The tasks for the group are set around a scenario in which a college basketball star approaches a teaching assistant with a bribe for a better grade. This author found that the language convergence in terms of style was found to be a predictor of team success in working through this scenario (how they respond to the basketball star), suggesting that individuals would be more prone to listening to people who have similar language structures to their own. In this example, it would take a more divergently communicating group longer to respond to the basketball star. Outside of this example, a group of students from the United States, the UK, and Germany may have a harder time coming to a consensus on how to respond to a bribe than three students from within Germany.

He, Zheng, Zeng, Luo, and Zhang (2016) found that individuals would converge upon each other's social media posting types when they were posting about a highly emotional topic. Through examining the social media websites LiveJournal and Sina Weibo, these authors found that users would post in very similar fashions to one another when discussing very emotional topics. For example, if an individual were to post about Prince's death, this post would be very similar in structure to similar posts about Prince, according to these authors.

Aside from individuals posting in converging and diverging ways from one another, Lisiecka et al (2016) found that communication technologies users will use different communication strategies depending on the communication channel that they are using. For example, radio and television would broadcast information differently, while Facebook and Twitter will also have different types of posts associated with each medium. These authors found, through communicating through chat rooms, face-to-face, and mobile phones, that users will maximize the use of each medium to complete a task. In other words, individuals were found to accommodate their communication style to that of a particular communications medium. Again, a person or organization would not post a particular story in the same manner when posting on Facebook and Twitter. For Twitter, the post will be shorter than the Facebook post, which would go a little more in depth. Both mediums can deliver a story, but the ways in which users deliver the story on these mediums is, and should be, different.

Ludwig et al. (2013) examined customer reviews listed on Amazon.com. The authors looked at 591 entities for sale (books), and collected 17 weeks of data from the reviews left on the website (18,682). This study found that positive comments left on reviews would lead to a slight convergence by subsequent posts. Further, these findings suggested that similarity in linguistic styles between reviewers could lead towards more positive reviews online. Thus, if one review of an online product is positive, and is written in a way that appeals to other online users, then subsequent positive reviews could be seen. One limitation of this study was that it observed only books, and the reviews left for these products. This may not be the case for other products, such as dog toys or music.

CAT in Various Contexts.

Although performance was shown to be affected by the language convergence of others, Dougherty, Kramer, Klatzke, and Rogers (2009) found that individuals may converge towards various symbols, although their interpretations of meanings would diverge across groups. In their example, the authors noticed that a sample of individuals would converge towards terms of sexual harassment, but these terms may have different meanings to each individual. This study showed the differences in general terms we use throughout our lives, even though the sample spoke the same language. CAT research can be performed in instances involving just one language, and can still find significant results. This study's findings can be seen in different contexts. For example, the word "micromanage" would find some convergence in terms of feelings toward the term (negative), while the term's definition might be different from participant to participant. The term micromanage could be agreed upon as negative, although the definition would be different from person to person.

Hajek (2015) interviewed middle aged gay men to gain insights into their levels of convergence and divergence when in the company of younger gay men. This author used a grounded theory perspective to code the interview transcripts under the general CAT framework. The interview's results found that not all groups (in this instance, gay men) feel within the same group, suggesting that a major base of individuals (gay men) may have smaller subsects that do not communicate well with each other. Gay men would converge their language to that of the younger generation of gay men to act more as a mentor, but overwhelmingly would not associate with the younger generation at all. Previous CAT research has found that positions of power, be it real or perceived, have responded to other conversationalists with accommodating language (Danescu-Niculescu-Mizil, Lee, Pang, & Kleinberg, 2012; deSiqueira & Herring, 2009; & Liao, Bazarova, & Yuan, 2016). In this situation, the older individual would have perceived power as a mentor, and this individual would accommodate their language to that of their mentoring group.

When observing the differences between age groups, Chen, Joyce, Harwood, and Xiang (2016) found that college aged students would respond in a myriad of ways when dealing with older adults. Students were told that they were in a plane sitting next to an elderly woman that demonstrated one of six different styles (sociable and friendly, competent and intelligent, trustworthy and sincere, and the opposite of each of the scenarios above). The results showed that each individual's accommodation style would change based more off of the style of their communication partner as opposed to the age of the individual. These authors suggested that individuals rehearse their communication patterns with different types of individuals, which suggested that the participants have been in similar situations previously. To illustrate the results in a different light, imagine an individual is going into an interview for a job. To prepare for this interview, the job candidate will research the people whom they are interviewing with. The candidate will then accommodate their language to the findings of their research, and interact with the interviewers in ways their research says they should interact.

Many research inquiries in CAT observed the ways that individuals from various language backgrounds (different languages, various language dialects) interact with one another. Gasiorek, Van de Pole, and Blockmans (2015) suggested that medical doctors working in a multilingual hospital setting would try to accommodate with those who did not speak their language by using personal experiences, while using unconventional means to communicate medical issues. An open-ended questionnaire was sent to doctors, which also revealed that doctors would use technology to accommodate to others' dominant language. Hand gestures and the use of other colleagues were also utilized. These types of communication styles are prevalent for those who travel to a place where the populace does not speak the interlocur's primary language. For example, an English speaker that travels to Russia will use hand gestures or other forms of communication to communicate with the Russian people they encounter (unless they are fluent in Russian).

Toma and D'Angelo (2014) found that users in an online medical setting were more likely to be actual medical doctors if they had a very long posting length and avoided possessive pronouns. Undergraduate students were asked to examine messages from 16 advice tips via medhelp.org, and fill out a questionnaire following their examination. Further results indicated that fewer anxiety related terms also amplified the perception that these users were doctors and other medical personnel. In further observing the health community, Wang, Reitter, and Yen (2014) measured language alignment in terms of lexical convergence and syntax. These authors observed health communities online, and overall found that linguistically, individuals are speaking in the same manners and length.

Watson and Gallois (1998) also observed the ways in which medical personnel interact with patients. An audience would watch film on interactions between health professionals and patients, and would rate the interactions based on various items derived from CAT. The results of this study found that healthcare professionals would interact with patients in either an intergroup or individual communication type, and that the audience believed that this communication was all towards the benefit of the patient. Further results show that the more interpersonal, one-on-one dialogue a healthcare professional would engage in, the more likely the audience would see the healthcare professional in a positive light. Further, the results indicated that interpersonal communications had a higher chance of bringing patients back for future visits as opposed to an intergroup type of communication. Thus, individualized attention seemed to positively enhance the relationship between client and healthcare professional, and could lead to a higher chance for follow up visits.

CAT on Social Media.

Given some of the constraints with social media in terms of observing CAT, Danescu-Niculescu-Mizil, Gamon, and Dumais (2011) tested Twitter data to see if it was robust enough to conduct CAT examinations. These authors measured tweets through 14 different dimensions, and created a probabilistic framework that successfully measured tweets on a large scale. These authors found that social media are an applicable site for CAT studies, and the authors suggested that long-time analyses would be beneficial research endeavors moving forward.

CAT research has not only been confirmed, but also utilized, in a Twitter setting. Pavalanathan and Eisenstein (2015) found that users would accommodate their tweets towards that of a group if the group's participant numbers were low. Thus, geotagged groups would receive tweets similar to that of that geographic location's language and dialects. As seen throughout CAT research, these authors claimed that this level of language convergence helped the users integrate into the group, while claiming a positive standing with other members within the group or area. The authors warn that not every tweet will be used to portray an individual in a positive light on every international stage, as would be the case with the United States given the different dialects and language structures seen throughout the nation. If, for example, a newcomer to Spain from the United States wanted to become a well-followed individual in Spain, this student would start to tweet in Spanish dialects, specific to the particular part of Spain the student is currently living.

Similar to the previous study, Nguyen, Trieschnigg, and Cornips (2015) found that Dutch Twitter users would converge their language, and structure, to that of the popular language in a particular region. There are a number of minority languages present in Dutch, and as users would communicate with users of a particular group, these authors found that they would converge their language to that of the minority language group's. These authors also found that tweets would begin in Dutch, but during conversations, would switch to a minority language (from retweets). From there, retweets would converge upon the previously diverged language. Again, in practice, this study found that individuals would accommodate their social media language to that of the dominant language found in the area.

Tamburrini, Cinnirella, Jansen, and Bryden (2015) similarly found that individuals would converge their language (type, structure, and affectively) to that of the group via Twitter. These authors' findings suggested that individuals are aware of the identity of a group, and if they want to be included, these users will adapt their language to the most popular of the group. This measurement of convergence also suggested that the more isolated a group, the more likely it is that individuals from the isolated group would accommodate their language further to that of the main group's norm. In terms of frequency, the more involved a member was with the group at large, the more likely they would be to converge their language. This finding suggests that language accommodation may be used as a means of group identity, as the user adopted the linguistic style of the group. For example, if new fan to a football team wanted to quickly identify as a fan for the team, they would quickly converge their language upon the trends of the majority of the group.

Noble and Fernandez (2015) proposed that an individual's success on social media may be related to the ways in which their language types identify with the particular platform. For example, a long-winded speaker may not find utility or succeed on Twitter, which consists of 140 character excerpts, but may be more inclined to join Facebook as there are no character limits. In their study, the authors examined Wikipedia's Talk Page, where editors can discuss current happenings on Wikipedia without changing the outward content of a page. These authors used function words as linguistic style markers, including: quantifiers, personal pronouns, impersonal pronouns, articles, auxiliary verbs, conjunctions, prepositions, and adverbs. This study found that individuals would use the same language as those whom were perceived to be the center of attention, or most in control, of the dialogue. Again, this study showed that individuals would accommodate their language to that of those whom are perceived to have the most inferred or real power. For example, if someone wants to join into a community, they would change their linguistic style to that of those in charge.

Language Inquiry and Word Count Software (LIWC) and Equation Measures

The Language Inquiry and Word Count Software (LIWC, pronounced "Luke") is a software package that provides "… a transparent text analysis program that counts words in psychologically meaningful categories" (Tausczik & Pennebaker, 2010, p. 24). The LIWC's roots can be traced back to the 1980's, as developers of the software sought to develop a program which "looked for and counted words in psychology-relevant categories across multiple text files" (Tausczik & Pennebaker, 2010, p. 27). The LIWC has two features that work in tandem to analyze various texts- the processing feature and the dictionary. The dictionary of the LIWC refers to the various grouping variables available in the LIWC, and the words that are put into said categories. For example, the category for "articles" refers to the words "a," "an", and "the." There are over 80 categories in which words would identify as. The processing feature takes texts, such as a poem, social media post, speech, etc., and compares each word within the text against the word entry in the LIWC's dictionary. For example, the LIWC would analyze each word within a Facebook post such as "The Greenville Drive host the Charleston Riverdogs tonight at 7:05 pm at Flour Field in historic downtown Greenville. It will be a hot evening, so be sure to leave the coat at home!" In this post, the LIWC will recognize every single word in the post, and compare it to the LIWC's dictionary. "It," for example, would be searched for within LIWC's dictionary, and would be counted towards a certain category total. Each word within the sentence will add to the percentage of each category. Thus, the LIWC's output will be in percentages (such as 12.57%) The LIWC, after processing the passage against the LIWC's dictionary, will then give the LIWC operator a breakdown of each category's percentage of the total sentence. For example, possessive pronouns may make up 10.57% of a sentence, verbs would constitute 15% of a sentence, and so on.

Pennebaker and King (1999) established the reliability of the LIWC through three separate studies. These studies revealed that all 72 language categories had a Cronbach's alpha of .59. Although this total is considered a generally poor overall rating, various measures within the LIWC had better ratings (Six letter words, α= .88; Pronouns, α= .78; Articles, α= .75; Present Tense, α= .72; Negations, α= .63; Prepositions, α= .65).

As mentioned before, the LIWC will take a series of text and break down the text into different category percentages found in a passage. This information, although helpful, will not inform investigators on the similarities or differences between and among conversation participants. Gonzales, Hancock, and Pennebaker (2010) showed how investigators can compare outputs from the LIWC across different conversation participants to measure accommodation. First, the researcher must specify what they are trying to measure. For example, Goode and Robinson (2013) specified that they were measuring levels of linguistic-style matching (LSM, described later) as well as immediacy measures (described later). For the specific measures, there are dimensions of each text that will be included in the equation (described later). The LIWC can report all of these dimensions. Second, the investigator must run all texts through the LIWC to obtain various scores for each text. The LIWC will report various percentages of the passage, including prepositions, possessive pronouns, negations, six letter words, pronouns, articles, transitions, and many other measures. Third, the researcher will compare the individual scores of each dimension (pronouns, prepositions, etc.) between conversation participants. This dyadic comparison, as shown by Gonzales, Hancock, and Pennebacker (2010), is “the absolute value of the difference between two speakers was divided by the total for each category” (p.9). The resulting scores will be between 0-1. The closer the score was to 1, the higher degree of style matching was detected (Gonzales, Hancock, and Pennebacker, 2010, p.9). In the study that follows, the primary investigator wanted to measure the levels of accommodation, in terms of LSM and immediacy, between each individual Facebook commenter and the organization’s original post. One measure for immediacy is articles (a, an, the). Thus, the dyadic comparison between the original post and the average of all comments would be analyzed as follows (for articles):

$$CmprTR_1ART_Z = 1-(|TR_{1\ ART} - ART_Z|)/(TR_{1\ ART} + ART_Z)$$

$$CmprTR_1ART_B = 1-(|TR_{1\ ART} - ART_B|)/(TR_{1\ ART} + ART_B)$$

$$CmprTR_1ART_C = 1-(|TR_{1\ ART} - ART_C|)/(TR_{1\ ART} + ART_C)$$

In this equation, “Cmpr” stands for compare, “TR” is the post indicator for Study A (or will be the team indicator for Study B), the subscript number next to the team indicator refers to the status number, “ART” refers to measuring articles, and the subscript number to the right of “ART” signifies which comment number matches to which specific status number (status number is seen next to the team indicator). The subscripts “Z,” “B,” and “C” refer to different user comments, while the subscript 1 refers to the post number. For ease of observation, as the aggregate total is what is being sought, all individual scores for each dimension will be averaged, and a comparison will be made between the original post scores and the average scores (signified below by a subscript "A") for each dimension.

$$ART_{A} = ART_{Z} + ART_{b} \ldots ART_{YYYYYYY} / \text{Number of Comments}$$

$$CmprTR_{1}ART_{A} = 1 - (|TR_{1ART} - ART_{A}|)/(TR_{1\,ART} + ART_{A})$$

All dimensions for two pre-selected measures of accommodation (LSM and immediacy) will be compared between the commenter's post and the original post, but an overall accommodation measure will not be assessed in this work. This means that an overall accommodation measure will not be taken, meaning that a measure will not take place where all comments posted to a status update will be compared with each other.

After all scores per dimension have been decided within one post, an average of all accommodation scores will be calculated to obtain the post-to-commenter accommodation score. This will be done by first averaging all dimensions separately from one another. This means that articles, prepositions, etc., will be averaged among themselves. Next, LSM and immediacy scores will be calculated by averaging each dimension's average, per category (LSM or immediacy). The results of this LSM and/or immediacy score, as mentioned in Gonzales, Hancock, and Pennebaker (2010), will signify how accommodating every commenter's post was to the original MiLB post, with scores closer to 0 being more divergent and scores closer to 1 being more convergent.

For example, in the studies to follow this literature review, the interlocur post (original post from the host MiLB organization) will be compared with all comments via LSM and immediacy scores in various situations. For a post from the Charleston Riverdogs, for example, measures such as auxiliary verbs, common adverbs, conjunctions, indefinite pronouns, negations, personal pronouns, prepositions, and quantifies will be taken for LSM. First, each comment and the original post will be analyzed through the LIWC. Scores, such as common adverbs, will be reported as a percentage. From there, a series of dyadic comparisons between the original post and each subsequent comment will be separately conducted through the equation list described above. The original post will be compared with each comment, separately, per dimension. After running every equation, the averages for every dimension will be calculated individually. So, common adverbs will be averaged by themselves at this point, as will conjunctions, etc. Following these calculations, all dimensions within LSM (mentioned above) will be averaged together to get an accommodation score for LSM, and immediacy, between each original post and each comment.

Linguistic-style matching (LSM) is a metric used to measure the level of mimicry in language (Gonzales, Hancock, & Pennebaker, 2010). This algorithm metric, shown above, was specifically designed for use in tandem with the LIWC. These authors use function words as the subject for these algorithms, as function words help identify relationships between social and psychological states and language (p.5). These authors identified nine different function words: auxiliary verbs, articles, common adverbs, personal pronouns, indefinite pronouns, prepositions, negations, conjunctions, and quantifiers. The average of all of these dimensions' scores will identify the level of mimicry present between two individuals in a conversation.

Mehrabian (1966) suggested that immediacy is a good measure to investigate the relationship between conversation participants. As Giles (2008) suggested, the act of liking (not in terms of Facebook) can be seen through accommodating one's language, immediacy measures should also be observed. Further, McCroskey and Richmond (2000) suggested that immediacy can also cause someone to like a conversation. In other words, those who show immediacy in their conversations are more likely to like the conversation. Five dimensions make up the immediacy category- articles, indefinite pronouns, personal pronouns, short words and present tense verbs (Biber, 1988; Cegala, 1989; Goode & Robinson, 2013; Pennebaker & King, 1999). The use of first person and present tense verbs, as well as articles, were found to be an indicator of immediacy (Biber, 1988; Goode & Robinson, 2013; Pennebaker & King, 1999) while expressions of certainty (personal pronouns) were also indicators of immediacy (Cegala, 1989; Goode & Robinson, 2013).

The LIWC does have its setbacks. For example, the word “mad” can have multiple meanings (Tausczik & Pennebaker, 2010). The word mad, in the LIWC, is counted in the anger, negative emotion, and overall affect categories in LIWC’s dictionary. It is reasonable that the word “mad” can have a different meaning in sports. For example, a post may say “Frank Smith, Batting Practice, Mad Skills.” It is obvious from this theoretical post that the word “mad” doesn’t signify a negative emotion, but is rather a positive descriptor of the batter’s ability at the plate. Further, the LIWC does not understand irony, sarcasm, or metaphor.

The creators of LIWC created a standardized score sheet for various texts, including passages of computer mediated passages (Pennebaker, Boyd, Jordan, & Blackburn, 2015). Over 37,000 blog files and over 35,000 Twitter posts were analyzed. Below is a table of all measurements used to calculate LSM and immediacy. Table 1 also includes the standardized score for these dimensions for blogs and Twitter posts.

Table 1

Standardized Scores

Measurement	Blogs	Twitter
Auxiliary Verbs[M]	8.75	8.27
Articles[I]	6.00	5.58
Common Adverbs[M]	5.88	5.13
Conjunctions[M]	6.43	4.19
Indefinite Pronouns[M, I]	5.53	4.60
Negations[M]	1.81	1.74
Personal Pronouns[M, I]	10.66	9.02
Prepositions[M]	12.60	11.88
Present tense verbs[I]	17.03	16.33
Quantifiers[M]	2.27	1.85
Short words[I]	14.38	15.31

Note. [I] signifies aspects calculated within immediacy, while [M] signifies aspects calculated within LSM. Dimensions can be included in both immediacy and LSM measures.

Limitations of CAT

Like any theory, CAT has limitations. For example, Burgoon, Dillman, & Stern (1995) suggested that CAT was too divisive when observing conversations from a convergence-divergence perspective. These authors argue that conversations cannot be broken down to such a level where they can be micro analyzed. Throughout the course of a conversation, these authors would argue that a conversation is too complex to measure it via solely convergence and divergence. Further, they suggest that the theory doesn't take history between the conversation participants into account. For example, a conversation between two representatives from warring parties may seem civil and cordial from the surface level, but both parties may have a deep hatred for each other that may not be detected. For a sports example, a conversation between a middle of the line player and a coach in the game of football may look accommodating, although a player may not be receiving appropriate playing time or if the coach thinks the player isn't trying hard enough. Most conversations between football players and coaches are a command from the coach, and a "yes sir," or "no sir," response from the player, with exceptions being a player's explanation of the play to the coach. Thus, although a player may be saying "yes sir," they may in fact be diverging on an unseen, and/or unheard, level so their coach will not notice it. This way, the player can maintain or increase their paying time. Further, convergence/divergence can happen within a conversation on certain points. For example, if a player is watching film, and feels that they played well on a football play that led to a loss of yards, yet the coach blames the team for playing poor on an ill-chosen play, then the player may converge upon the bad play call statement, but diverge in the way that they executed on that play. Last, these authors believe that the consequences of conversations cannot fully be explained by the convergence or divergence between conversation participants. Convergence in conversations has shown to lead toward a liking of conversations (Giles, 2008; Ireland, 2011), yet the consequences of convergence in a conversation have not been thoroughly examined, in the eyes of Burgoon, Dillman, and Stern (1995).

Minor League Baseball

Minor League Baseball (MiLB) has been a staple in most states, and has drawn considerable attention from various local. Knight (n.d.) claims that over 38,690,622 patrons attended MiLB games across all types during the 2015 season. By comparison, the New York Yankees brought in 2,299,409 fans during the 2014 season (Baseball Almanac, n.d.). This highlights the demand for MiLB games as this league has brought in patrons from various locals that are not large enough to host an MLB club team. Throughout history, MiLB has proven to be a staple in both society in the United States and the success of the MLB (Land, Davis, & Blau, 1994).

The MiLB started in the late 1800’s as part of the Tripartite Agreement, which kept the Northwestern League in check as an inferior league to the American League and National League (Land, Davis, & Blau, 1994). This agreement allowed each league territorial rights to players, as well as each league acknowledging the other leagues’ player contracts. Various agreements such as the Tripartite Agreement were reached throughout the early days of professional baseball, but the Tripartite Agreement was seen as the catalyst for organizing professional baseball. On a club level, until the early 1900’s, teams would disband and players would join with other clubs in a Darwinist survival of the fittest model. The National Agreement of 1921 allowed for MLB franchises to own MiLB franchises. This began the farm system as we know it today, by allowing teams to develop their own talent from the bottom up. The St. Louis Cardinals and the New York Yankees were the first organizations to buy into this strategy, whereas other clubs would have to purchase contracts from MiLB franchises to obtain the rights to a player. The same process exists in today’s farm system, but the process was far less streamlined. Many other clubs bought into buying MiLB franchises, although most MiLB franchises were independently owned until the 1950's. Today, there are few remaining independently owned MiLB franchises, although independently owned leagues, such as the Florida League, still exist to promote college talent to MLB franchises.

Recent academic inquiries have focused on MiLB franchise sustainability, attendance figures, and promotions. In looking at the sustainability throughout a season, Agha and Rhoads (2016) found that short-term winning for an MiLB franchise does not necessarily equate to an increase of success in terms of attendance. Their observation looked at MiLB teams that won the first half of their season (which guarantees them a playoff spot, regardless of their second half season performance). In terms of attendance numbers, these were unaffected by a team winning the first half of their season; however, this could be due to a tradition of winning as the authors reported that these teams had 30% greater attendance numbers than the rest of the teams in their league. Gitter and Rhoads (2010) similarly found that winning did bring attendees to MiLB games, as well as increases of MLB ticket pricing, and MLB player strikes.

In aiding with attendance numbers, previous studies have found that promotions, special events, and non-workdays (including holidays and weekends) all have a positive effect on attendance numbers for an MiLB game (Howell, Klenosky, and McEvoy, 2015). Firework usage at an MiLB game is typically reserved for weekends or special events; however, Paul and Weinbach (2013) found that firework usage can be effective in drawing attendance numbers on many different days throughout a season. Stadium development has been seen in a very negative light as sports stadium financing has moved away from the public funding model recently; however, Agha (2013) found that building a new stadium for AAA baseball teams can have a positive effect on attendance, and the surrounding area of the ballpark. Further, Roy (2008) found that for the MiLB franchise, a new stadium can have an increase of attendance up to 74% for up to five years as opposed to the older attendance numbers.

In terms of marketing, Lachowetz, Dees, Todd, and Ryan (2009) used the now defunct Savannah Sand Gnats (now the Columbia Fireflies) franchise to describe how a small market sports team can make a profit and positive impact in a local community. The Sand Gnats hosted on of the few remaining MiLB parks that Babe Ruth hit a home run in, but that nostalgic feeling did not equate to success in terms of boosting fan attendance. Ballpark renovations were identified as a top priority for the organization, as they committed over $5 million to various stadium projects. Further, the Sand Gnats agreed to make the ballpark more family friendly, with various programs and activities dedicated towards the family experience. Community engagement was another priority for the Sand Gnats, as they made an attempt to bring individuals from within an hour and a half radius of the ballpark to games through fireworks nights, beer specials, community ticket giveaways, and merchandise giveaways. Local identity was considered a large issue in their study, while other studies have looked at how a name can transform an MiLB franchise's merchandising woes. Dwyer, Le Crom, Tomasini, and Smith (2011) argued that the naming of a franchise can enhance or deter from an organization's image. These authors looked at the naming process for the Richmond Flying Squirrels, who chose this name for their organization despite the numerous name entries and contests (over 15,000 names were entered) and the media firestorm that followed the franchise throughout the naming process. There were other names that had more local ties, such as the Richmond Hush Puppies or the Richmond Rock Hoppers, but the organization settled on the Flying Squirrels instead. Many other MiLB franchises base their merchandising sales off of their logos, including the Montgomery Biscuits and Ogden Raptors.

To date, only one study has primarily looked at social media usage surrounding the MiLB. Williams, Heiser, and Chinn (2012) found that those who post to social media with less frequency (or lurkers) were more likely to attend an MiLB game than those who posted to social media with greater frequency. This finding suggested that lurkers are not seeking attention from posting about a team on social media, but rather were using social media to enhance their fan experience, and not necessarily their self-presentation.

The studies presented will further examine social media within the context of Minor League Baseball. While this in itself is new territory, incorporating the communication accommodation theory into social media usage in and around sport field will also be an introduction. The following two studies will begin to incorporate both of these entities into the mainstream of SMS in sport research, and set forth the universal convergence hypothesis. This test will first be performed on a local level to see if geographic convergence is occurring through the SMS Facebook, then testing this hypothesis against a national sports organization. The following study will test if individuals are accommodating their language on Facebook to that of local MiLB franchises. This study will examine if user comments are being accommodated with more or less frequency on previously established codes for sport organizations. In other words, are fans accommodating their language more to social Facebook posts or team related Facebook posts?

MiLB Team Background

Each of the teams selected were chosen for specific reasons. In Study A, the Charleston Riverdogs, the Columbia Fireflies, and the Greenville Drive were selected. Single-A baseball teams have been included in previous literature, but have not been solely observed in a social media observation.

The Charleston Riverdogs are the Single-A affiliate of the New York Yankees, and play in the South Atlantic League (Charleston Riverdogs, n.d.). The Riverdogs name comes by way of a Charleston urban legend, where sailors would claim that giant rats seen on nearby rivers looked like ‘river dogs.’ This was the chosen name for the organization in 1994 through a public name-the-team contest. Originally, the Riverdogs were known as the Charleston Royals, a farm team for the Kansas City Royals, when they were founded in 1980. In 1985, the Charleston Royals changed their name to the Charleston Rainbows, and became affiliated with the San Diego Padres, and with the Texas Rangers until 1996. The renaming of the Rainbows to the Riverdogs occurred in 1994 to generate interest, after the Charleston franchise had run into losing slump. The Riverdogs changed affiliation to the Tampa Bay Devil Rays until 2004, until they changed one last time to the New York Yankees Single-A affiliate in 2005. The Riverdogs currently play at Joseph P. Riley, Jr. Park (AKA The Joe), which holds up to 6,000 patrons. According to the City of Charleston Planning, Preservation, and Sustainability commission (n.d.), the total city area of Charleston, without water, is approximately 112 square miles. The population for the city of Charleston for 2016 was 137,447, West Ashley was 60,878, and the various island and peninsula population totaling 76,569. In total, the Charleston Riverdogs’ potential market encompasses an estimated 274,894 people. Table 2 below shows the results and attendance figure for the Riverdogs, dating back to 2005 (MiLB.com, n.d.; MiLB.com, n.d.).

Table 2

Charleston Riverdogs Attendance Figures and Record

Year	Record	Attendance (Year)	Attendance Per Game
2006	78-62	267,908	3,999
2007	78-62	284,718	4,126
2008	80-59	279,606	4,173
2009	74-65	268,985	4,015
2010	65-74	269,023	3,899
2011	55-85	265,465	3,962
2012	76-63	254,002	3,791
2013	75-63	283,274	4,292
2014	71-69	280,075	4,309
2015	66-74	292,661	4,368
2016	76-63	293,161	4,311

The Clinton LumberKings are the Single-A affiliate for the Seattle Mariners, and are located in Clinton, Iowa (Clinton LumberKings, n.d.). Clinton has a history dating back to the 1930's, although Clinton joined the Midwest League in 1956, and are the oldest franchise in the Midwest League. The LumberKings have played at Ashford University Field since 1937, which can host 5,500 fans. Throughout the years, Clinton used the name of the MLB team they were affiliated with until the 1994 season, which included the Brooklyn Dodgers, New York Giants, Chicago Cubs, Pittsburgh Pirates, Chicago White Sox, Milwaukee Pilots/Brewers, Detroit Tigers, Los Angeles Dodgers, San Diego Padres, Cincinnati Reds, Montreal Expos, and the

Texas Rangers. According to the US Census Bureau (n.d., b), Clinton County had a population of 47,768 people, with a median household income of $50,498. Table 3 shows the Lumberkings' attendance figures and records, dating back to 2006 (MiLB.com, n.d.; MiLB.com, n.d.).

Table 3

Clinton Lumberkings Attendance Figures and Records

Year	Record	Attendance (Year)	Attendance Per Game
2006	45-94	108,301	1,570
2007	70-67	116,261	1,735
2008	78-59	114,662	1,711
2009	69-68	107,665	1,656
2010	74-65	123,553	1,817
2011	63-76	115,253	1,746
2012	71-67	111,760	1,644
2013	67-72	113,880	1,779
2014	61-77	111,329	1,713
2015	46-93	105,405	1,573
2016	86-54	124,154	1,910

The Columbia Fireflies (n.d.) are the Single-A affiliate for the New York Mets. The Greenville Drive and the Columbia Fireflies are connected as the beginning of the Greenville Drive started when the then Columbia Bombers moved to Greenville following the 2004 season. Baseball left the State's Capitol from 2004 until 2016, when the Savannah Sand Gnats moved to Columbia following the 2015 season. In October, 2014, Minor League Baseball granted

Columbia approval to have a team move to the State's Capitol. At the start of the 2015 season, the Savannah Sand Gnats announced they would move the team to Columbia, and the new Spirit Communications Park. The 'Fireflies' name derived from a naming contest. Spirit Communications Park can seat up to 9,077 patrons. According to the US Census (n.d., a), Columbia city limits have a population of 4,961,119 people, with a median household income reported at $45,483 (in 2015). The land area in square miles for Columbia's city limits was reported at 30,060 miles in 2010. Table 4 shows the attendance figures and record for the Fireflies during their first season (MiLB.com, n.d.; MiLB.com, n.d.).

Table 4

Columbia Fireflies Attendance Figure and Records

Year	Record	Attendance (Year)	Attendance Per Game
2016	67-73	261,134	3,785

The Greenville Drive Baseball Club is the Single-A affiliate of the Boston Red Sox (Greenville Drive, n.d.). The Drive relocated from Columbia, South Carolina, before the 2005 season (Capital City Bombers). The mascot for the drive is a frog named Reedy Rip'it, a nod to the Reedy River which runs through downtown Greenville, South Carolina. The origins of the Drive began in Shelby, North Carolina, as the Shelby Reds were formed in 1977. In 1983, this team relocated to Columbia and was named the Columbia Mets. The Columbia Mets were granted permission from the MiLB to move to Greenville in 2005, and gained the Red Sox affiliation shortly before the move was granted. In their first year, the now Greenville Bombers played at Greenville Municipal Stadium until their new field, Fluor Field, was constructed at 2006, where they've remained ever since. After the 2005 season, the Bombers announced a name change to the Greenville Drive, which was a nod to Greenville's history in the automotive industry. According to the Greenville Area Development Corporation (n.d.), Greenville County hosts a population of 482,752 people, with a per capita income reported at $36,525. Table 5 shows the attendance figures and team record for the Drive dating back to 2006 (MiLB.com, n.d.; MiLB.com: South Atlantic League, n.d.).

Table 5

Greenville Drive Attendance Figures and Record

Year	Record	Attendance (Year)	Attendance Per Game
2006	67-73	330,078	4,784
2007	58-81	339,356	4,991
2008	70-69	349,116	5,060
2009	73-65	335,159	4,857
2010	77-62	337,918	4,969
2011	78-62	327,558	4,747
2012	66-73	347,042	5,104
2013	51-87	300,402	4,768
2014	60-79	346,187	5,017
2015	72-68	346,828	5,100
2016	70-69	331,911	4,810

The West Michigan Whitecaps, a Single-A MiLB team affiliated with the Detroit Tigers, became a staple in Grand Rapids, Michigan, after they moved from Madison, Wisconsin (Madison Muskies), in 1994. When the Whitecaps came to Grand Rapids, Michigan, they were affiliated with the Oakland Athletics, and transitioned to the Tigers' farm system in 1997. The Whitecaps play at Fifth Third Ballpark, just north of Grand Rapids, which can hold 9,684 patrons. The ballpark was originally build in 1994, but changed names when Fifth Third Bank purchased the ballpark in 2000. According to the U.S. Census Bureau (n.d., c), Grand Rapids has a population of 195,097 people, with a median household income of $40,355 people. This total encompassed 44.40 square miles. Table 6 shows the attendance figures and record for the Whitecaps, starting during the 2006 season (MiLB.com, n.d.; MiLB.com, n.d.).

Table 6

West Michigan Whitecaps Attendance Figures and Record

Year	Record	Attendance (Year)	Attendance per Game
2006	89-48	356,155	5,238
2007	83-57	377,412	5,470
2008	72-65	367,532	5,569
2009	81-59	356,642	5,245
2010	62-77	371,575	5,385
2011	70-69	372,555	5,561
2012	72-68	362,554	5,179
2013	69-70	377,948	5,558
2014	82-58	391,653	5,595
2015	75-64	391,055	5,667
2016	71-65	386,416	5,683

CHAPTER THREE

METHODS

The purpose of study A was to explore if there was a difference in levels of language accommodation between Facebook user comments and team posts. Specifically, this study observed Facebook posts from different Single-A MiLB organizations within a similar geographic region (South Carolina). Each of the following observations were made on a day-to-day basis over the course of one year (365 days) by retroactively collecting data. Finally, each examination explored if there were any correlational differences between various posting types (neoliberal, social, or team related posts). All model assumptions were met, and are available via email to the primary investigator.

Data Collection and Sample Rationale – Study A

Data were retroactively collected on February 1, 2017 by using the NVivo qualitative data gathering and analysis software. NVivo has been used in previous Facebook investigations (see Frederick, Stocz, & Pegoraro, 2016) as a means of data collection. The data collection timeframe was set from September 10, 2015 to September 10, 2016. The three teams that were observed in Study A (Charleston Riverdogs, Columbia Fireflies, and Greenville Drive) were all Single-A baseball teams from that state of South Carolina.

The September 10, 2015 to September 10, 2016 timeframe was selected to encompass the various posting strategies of Single-A MiLB teams throughout the season, spring training, and offseason. The purpose of this analysis was to see the effectiveness of posting strategies in terms of measures of LSM and immediacy as they relate to *likes* and/or number of comments over time. One of the reasons for this study was to begin to examine potential correlations on MiLB Facebook pages between language accommodation (LSM, immediacy) and *likes*, and number of comments.

The primary investigator chose three teams from the state of South Carolina, which was both a limitation and an opportunity to view a traditional baseball market with a lack of a Major League Baseball franchise in the state. The recent success of baseball teams throughout South Carolina has been viewed nationwide, especially at the collegiate level (National Championships won by the University of South Carolina and Coastal Carolina University, and Clemson University with 12 College World Series appearances). The three MiLB teams selected each were in unique markets as well. The Charleston Riverdogs and Columbia Fireflies drew fans from mostly their host cities, while the Greenville Drive drew fans from two mid-sized cities (Greenville and Spartanburg, South Carolina). The Charleston Riverdogs were situated in a city with beach access, while Columbia and Greenville were more inland. The Columbia Fireflies play near the State's Capital, while the Greenville Drive have been credited with restoring a major sector of Greenville, and the Charleston Riverdogs were partially owned by actor Bill Murray. Thus, although these teams were seemingly the same due to sharing the same host state, there were a lot of nuances to each team that cannot be seen in other areas of Minor League Baseball. Further, the primary investigator's experiences with the Greenville Drive and the South Atlantic League sparked an interest in observing these three teams.

Methodology – Study A

The primary investigator examined accommodation in daily posting strategies (neoliberal, team related, social, open code) between three geographically similar MiLB teams on Facebook. Convergence and divergence studies date back to the beginnings of communication accommodation theory (see Fischer, 1958). A linguistic survey in New England found that children would accommodate their speech patterns specific to the situation and/or setting they were in, and they would focus on certain individual's speech patterns. Fischer termed this comparative idiolectology, which Giles (1973; 2008) eventually would develop into communication accommodation theory. The means of analysis within convergence and divergence studies have changed as more recent inquiries into accommodation research have not only utilized the internet as a setting, but have used social media as their point of observation (Danescu-Niculescu-Mizil, Gamon, & Dumais, 2011; Noble & Fernandez, 2015; Nguyen, Trieschnigg, & Cornips 2015; Pavalanathan & Eisenstein, 2015; Tamburrini, Cinnirella, Jansen, & Bryden, 2015).

Research Question 1: What levels of accommodation (LSM, Immediacy) exist between user-generated comments and neoliberal, team related, social posts, or other open coded posts from South Carolina MiLB teams? To answer RQ1, the primary investigator first observed every post throughout a one year period for the three Single-A baseball teams in South Carolina (Charleston Riverdogs, Columbia Fireflies, and Greenville Drive). These posts underwent a deductive thematic analysis. This deductive thematic analysis was used to code each post as neoliberal (Dart, 2014), social posts (Blazska, et al, 2012), team related posts (Waters et al, 2011), and an open code for new themes that may emerge from the data set. Following this deductive thematic analysis, 90 posts and comments from each theme were selected for the language accommodation algorithms. The number of posts from each theme were run through a random number generator, which randomly selected 30 posts per theme. Each post had a number associated with it. For example, if there were 120 team related posts for one of the teams in the sample, the random number generator selected 30 numbers out of the 120 sample to be analyzed. Each team added 30 posts per category. Thus, after the deductive thematic analysis, a random number generator selected 30 random posts per category per team. If there are less than 30 posts for one specific theme for one of the teams, the posts collected from the other teams for that theme would still input 30 posts for that particular theme. Finally, a regression analysis was used to see if there is a correlation between levels of accommodation (LSM and Immediacy), and *likes* and/or number of comments between the themes. The following sections explain this process in greater detail.

RQ2: What is the relationship between neoliberal, team related, social, and/or open coded posts, language accommodation measures (LSM, immediacy), and *likes* and/or number of comments? First, the researcher manually coded each of the MiLB franchise's Facebook posts through a deductive thematic analysis. The deduced themes came from previous research (Blaszka, et al, 2012; Dart, 2014; Waters, et al, 2011). The Facebook post themes described by these authors were team related posts, social posts and neoliberal posts. This deductive thematic analysis also allowed for new themes to arise from the dataset if they are observed. Team related posts described team activities, such as player trades, player highlights, game previews or reviews, player/staff honors, etc. Social posts represented forms of institutional interactivity, as well as charity related posts, mascot posts, etc. Finally, neoliberal posts attempted to sell products or generate money for an organization. Facebook posts had elements of multiple coding categories present. Thus, Facebook post categorization for this study were based on the most prevalent theme in the post. Table 7 below shows the code abbreviations.

Table 7

Code Abbreviations

Team	Abbreviation
Neoliberal Posts	NL
Social Posts	SO
Team Related Posts	TR
Open Code	OC

To measure for accommodation, two variables from previous research were selected: immediacy and LSM. Immediacy has been seen as a way in which communicators have revealed the relationship between communicators (Mehrabian, 1966). In the context of communication, immediacy refers to the ways in which a communicator explicitly communicates via “affective, evaluative, and/or preferential attitude(s) toward the objects, events, or people about which he communicates” (Mehrabian, 1966, p.26). In other words, immediacy refers to the ways in which one says a statement. For example, the phrase “Ted is married” can take on different meaning given the ways that this could be said. If the phrase “Ted is married” was said in a calm, collected manner, this would show that the conversation participant was simply updating the other conversation participants on updates with Ted’s life. If the phrase “Ted is married” was yelled in an argument, this would suggest that one conversation participant was angry with another participant for a reason relating to Ted’s marital status. Further, immediacy has been found to have a connection to liking (McCroskey & Richmond, 2000). In accommodation studies, positive attributes have been associated between two communicating parties who converge upon others’ linguistic styles (de Siqueira & Herring, 2009; Gasiorek & Giles, 2015;

Gonzales, Hancock, & Pennebaker, 2009; Giles, Coupland, & Coupland, 1991; Giles, 2008; Ludwig et al., 2013). LSM shows another level of accommodation as those who communicate in similar sentence structures are working in converging ways (Gonzales, Hancock, & Pennebaker, 2009; Wang, Reitter, & Yen, 2014).

Similar to the design of Goode and Robinson (2013), as well as Gonzales, Hancock, and Pennebaker (2009), LSM and immediacy were both totaled with a combination of the LIWC software and a comparison between each element within both measures. To start this process, each team's Facebook posts and subsequent comments were organized by file names in Microsoft Excel. This way, the LIWC software was able to analyze each document separately. Each post had a separate file while each comment was embedded in the file but was analyzed separately. For example, a neoliberal post from Facebook was be saved as "NL1". The next step was to run each individual file through the LIWC software and interpret the results.

The results from each LIWC computation were then placed into an Excel spreadsheet. Each measure (LSM, Immediacy) was compared between the original Facebook post and the average of all components of each measure for all comments. For example, when comparing immediacy scores between a post and all comments, a comparison was made first between each variable that makes up the overall immediacy score (articles, indefinite pronouns, personal pronouns, present tense verbs, short words). The comparison took place between the original post and the comments' average in terms of comparing articles, comparing indefinite pronouns, comparing personal pronouns, comparing present tense verbs, and comparing short words. Thus, if the percentage of present tense verbs came to 2 for the original post, and the average present tense verbs per comment came out to 3.1, these results would be run through the equations described in the literature review and below. Following these comparisons, all elements (articles, indefinite pronouns, personal pronouns, present tense verbs, short words) for immediacy were averaged to give the immediacy score between the original post and the subsequent comments for this post. The same process occurred for LSM, except the comparisons were made between the original post and the comments' average for use of auxiliary verbs, common adverbs, conjunctions, indefinite pronouns, negations, personal pronouns, prepositions, and quantifiers. Table 8 shows the different dimensions associated with LSM and immediacy.

Table 8

Dimension Abbreviations

Measurement	Abbreviation	Examples of Measurement
Auxiliary Verbs[M]	Aux	Am, have
Articles[I]	Art	A, an, the
Common Adverbs[M]	Can	Hardly, often
Conjunctions[M]	NJ	And, but
Indefinite Pronouns[M, I]	Ipn	It, those
Negations[M]	Ngn	Not, never
Personal Pronouns[M, I]	Ppn	I, they, we
Prepositions[M]	Prp	For, after, with
Present tense verbs[I]	Pst	Go, speak, write
Quantifiers[M]	Qnt	Many, few
Short words[I]	Srt	Length of word less than six letters

Note. [I] signifies aspects calculated within immediacy, while [M] signifies aspects calculated within LSM. Dimensions can be included in both immediacy and LSM measures.

As mentioned above, a set of equations was used to compare the values reported by the LIWC between the organization's post and the average of all scores of note for comments to the original post. For LSM, the following values were identified by Gonzales, Hancock, and Pennebacker (2010) as predictors of LSM. Measures were compared between the original post and the average of all subsequent comments: auxiliary verbs, common adverbs, conjunctions, indefinite pronouns, negations, personal pronouns, prepositions, and quantifiers. For immediacy, the following values were compared: articles, indefinite pronouns, personal pronouns, present tense verbs, and short words (Goode & Robinson, 2013). This comparison, through the use of equations as shown by Gonzales, Hancock, and Pennebacker (2010) can be explained as "the cumulative differences between speakers divided by the total level of accommodation per category measure (p. 9)". As this study measured the level of accommodation between one speaker specifically (MiLB team, through the original post) and the collective of all commenters to that one speaker (all comments on that particular MiLB team post), not all commenter posts were compared amongst themselves. The equation sequence was as follows:

For auxiliary verbs: $SOAUX_{Total=}CmprSO_{1}AUX_{A}= 1-(|SO_{1AUX}-AUX_{A}|)/(SO_{1AUX}+AUX_{A})$

$TRAUX_{total}=CmprTR_{1}AUX_{A}= 1-(|TR_{1AUX}-AUX_{A}|)/(TR_{1AUX}+AUX_{A})$

$NLAUX_{total}=CmprNL1AUXA= 1-(|NR_{1AUX}-AUX_{A}|)/(NR_{1AUX}+AUX_{A})$

For articles: $SOART_{total}=CmprSO1ARTA= 1-(|SO_{1ART}-ART_{A}|)/(SO_{1ART}+ART_{A})$

$TRART_{total}=CmprTR_{1}ART_{A}= 1-(|TR_{1\ ART}-ART_{A}|)/(TR_{1ART}+ART_{A})$

$NLART_{total}=CmprNL_{1}ART_{A}= 1-(|NR_{1\ ART}-ART_{A}|)/(NR_{1\ ART}+ART_{A})$

For Common Adverbs: $SOCMN_{total}=CmprSO_{1}CMN_{A}= 1-(|SO_{1CMN}-CMN_{A}|)/(SO_{1\ CMN}+CMN_{A})$

$TRCMN_{total}=CmprTR_{1}CMN_{A}= 1-(|TR_{1\ CMN}-CMN_{A}|)/(TR_{1\ CMN}+CMN_{A})$

$NLCMN_{total}=CmprNL_{1}CMN_{A}= 1-(|NR_{1\ CMN}-CMN_{A}|)/(NR_{1\ CMN}+CMN_{A})$

For Conjunctions: $SOCNJ_{total}=CmprSO_1CNJ_A= 1-(|SO_{1CNJ}-CNJ_A|)/(SO_{1\ CNJ}+CNJ_A)$

$TRCNJ_{total}=CmprTR_1CNJ_A= 1-(|TR_{1\ CNJ}-CNJ_A|)/(TR_{1\ CNJ}+CNJ_A)$

$NLCNJ_{total}=CmprNL_1CNJ_A= 1-(|NR_{1\ CNJ}-CNJ_A|)/(NR_{1\ CNJ}+CNJ_A)$

For Indefinite Pronouns: $SOIPN_{total}=CmprSO_1IPN_A= 1-(|SO_{1IPN}-IPN_A|)/(SO_{1\ IPN}+IPN_A)$

$TRIPN_{total}=CmprTR_1IPN_A= 1-(|TR_{1\ IPN}-IPN_A|)/(TR_{1\ IPN}+IPN_A)$

$NLIPN_{total}=CmprNL_1IPN_A= 1-(|NR_{1\ IPN}-IPN_A|)/(NR_{1\ IPN}+IPN_A)$

For Negations: $SONGN_{total}=CmprSO_1NGN_A= 1-(|SO_{1NGN}-NGN_A|)/(SO_{1\ NGN}+NGN_A)$

$TRNGN_{total}=CmprTR_1NGN_A= 1-(|TR_{1\ NGN}-NGN_A|)/(TR_{1\ NGN}+NGN_A)$

$NLNGN_{total}=CmprNL_1NGN_A= 1-(|NR_{1\ NGN}-NGN_A|)/(NR_{1\ NGN}+NGN_A)$

For Personal Pronouns: $SOPPN_{total}=CmprSO_1PPN_A= 1-(|SO_{1PPN}-PPN_A|)/(SO_{1\ PPN}+PPN_A)$

$TRPPN_{total}=CmprTR_1PPN_A= 1-(|TR_{1\ PPN}-PPN_A|)/(TR_{1\ PPN}+PPN_A)$

$NLPPN_{total}=CmprNL_1PPN_A= 1-(|NR_{1\ PPN}-PPN_A|)/(NR_{1\ PPN}+PPN_A)$

For Prepositions: $SOPRP_{total}=CmprSO_1PRP_A= 1-(|SO_{1PRP}-PRP_A|)/(SO_{1\ PRP}+PRP_A)$

$TRPRP_{total}=CmprTR_1PRP_A= 1-(|TR_{1\ PRP}-PRP_A|)/(TR_{1\ PRP}+PRP_A)$

$NLPRP_{total}=CmprNL_1PRP_A= 1-(|NR_{1\ PRP}-PRP_A|)/(NR_{1\ PRP}+PRP_A)$

For Present Tense Verbs: $SOPST_{total}=CmprSO_1PST_A= 1-(|SO_{1PST}-PST_A|)/(SO_{1\ PST}+PST_A)$

$TRPST_{total}=CmprTR_1PST_A= 1-(|TR_{1\ PST}-PST_A|)/(TR_{1\ PST}+PST_A)$

$NLPST_{total}=CmprNL_1PST_A= 1-(|NR_{1\ PST}-PST_A|)/(NR_{1\ PST}+PST_A)$

For Quantifiers: $SOQNT_{total}=CmprSO_1QNT_A= 1-(|SO_{1QNT}-QNT_A|)/(SO_{1\ QNT}+QNT_A)$

$TRQNT_{total}=CmprTR_1QNT_A= 1-(|TR_{1\ QNT}-QNT_A|)/(TR_{1\ QNT}+QNT_A)$

$NLQNT_{total}=CmprNL_1QNT_A= 1-(|NR_{1\ QNT}-QNT_A|)/(NR_{1\ QNT}+QNT_A)$

For Short Words: $SOSRT_{total}$=$CmprSO_1SRT_A$= 1-(|SO_{1SRT}-SRT_A|)/($SO_{1\ SRT}$+SRT_A)

$TRSRT_{total}$=$CmprTR_1SRT_A$= 1-(|$TR_{1\ SRT}$-SRT_A|)/($TR_{1\ SRT}$+SRT_A)

$NLSRT_{total}$=$CmprNL_1SRT_A$= 1-(|$NR_{1\ SRT}$-SRT_A|)/($NR_{1\ SRT}$+SRT_A)

To complete the measure for the LSM score, the following equation was used:

$$LSM_1= (AUX_{total}+ CMN_{total}+CNJ_{total}+IPN_{total}+NGN_{total}+PPN_{total}+PRP_{total}+QNT_{total}+SRT_{total})/9$$

In this equation, the subscript number next to "LSM" signifies which status number was being measured. This number could range anywhere from 1-90. Any measure with the subscript "total" next to it signified the individual measure score of LSM examined between the original post and all comments on that post. Again, according to Gonzales, Hancock, and Pennebaker, (2010), function words are to be used as measures of LSM, which included auxiliary verbs, articles, common adverbs, personal pronouns, indefinite pronouns, prepositions, negations, conjunctions, and quantifiers. The average of all totals generated a score between 0-1 with scores closer to one showing high levels of linguistic style matching.

The following equation were used to measure the immediacy score:

$$Immediacy_1=ART_{total}+IPN_{total}+PPN_{total}+PST_{total}SRT_{total}/5$$

In this equation, the subscript number next to "Immediacy" referred to the status number being measured. This number could range anywhere from 1-90. Any measure with the subscript "total" next to it signified the individual measure score of immediacy between the original post and all comments on that post. According to Goode and Robinson (2013) immediacy can be measured from the average of articles, indefinite pronouns, personal pronouns, and present tense verbs. The result of this calculation will result in a score between 0-1, with scores closer to one showing high levels of immediacy. Both of these measures were not averaged together as there may be other factors that have not yet been identified as measures of language accommodation. Both

LSM and immediacy were measured for each post selected. This process will answer the first RQ.

To answer the second research question, the finalized scores for LSM and immediacy found through the first research question were used in tandem with the reported *likes* and number of comments. A regression analysis was then utilized using the software package R to see if there was a correlation between accommodation measures (LSM, Immediacy) and Facebook metrics (*likes,* number of comments). The second research question asked what the correlations would be between different posting types, accommodation, and *likes* and/or number of comments. These correlations illustrated the relationship between the number of *likes* and number of comments on a Facebook post, and accommodation measures (LSM, Immediacy).

RQ3: Across all teams, what is the relationship between coded posts (neoliberal, team related, social, open code), language accommodation measures (LSM, immediacy), and *likes* and/or number of comments? To answer the third research question, which asks if there are different correlations across the deduced themes, R again will be used in a regression analysis. To be clear, this question required that a graphic representation be produced for all posts per theme for all three teams. Next, the primary investigator created a similar regression analysis per team per theme (accompanied with a graph). In this manner, the differences between each team's posting style and commenter response were observed. In other words, regression analyses were made in this study as follows: neoliberal regression for all teams' posts, social regression for all teams' posts, team related regression for all teams' posts, neoliberal regression for Charleston Riverdogs' posts, social regression for Charleston Riverdogs' posts, team related regression for Charleston Riverdogs' posts, neoliberal regression for Columbia Fireflies' posts, social regression for Columbia Fireflies' posts, team regression graph for Columbia Fireflies' posts, neoliberal regression for Greenville Drives' posts, social regression for Greenville Drives' posts, and a team related regression for Greenville Drives' posts. The results provided preliminary evidence of the success of different types of Facebook posts.

Data Collection and Sample Rationale- Study B

The primary investigator for Study B wanted to examine the differences in levels of accommodation and *likes* and number of comments between Single-A Minor League Baseball teams that have the highest number of page likes and the lowest number of page likes on Facebook. On February 1, 2017, the two teams were selected for this analysis. First, the primary investigator obtained a list of all MiLB teams at the Single-A level. This list came from MiLB.com (2015). These teams were listed as "Class A" on the website. "Class A Short" and "Class A Advanced" teams were excluded from this study so that the season for the sample teams would be similar (minus playoff appearances). Class A short and advanced teams have different lifespans than Class A teams. The overall sample pool for the Class A teams included the following teams: Asheville Tourists (27,759 page likes), Augusta Green Jackets (12,954 page likes), Beloit Snappers (7,285 page likes), Bowling Green Hot Rods (25,369 page likes), Burlington Bees (8,030 page likes), Cedar Rapids Kernels (16,566 page likes), Charleston Riverdogs (44,656 page likes), Clinton LumberKings (6,422 page likes), Columbia Fireflies (19,703 page likes), Dayton Dragons (40,522 page likes), Delmarva Shorebirds (30,822 page likes), Fort Wayne TinCaps (54,324 page likes), Great Lakes Loons (30,266 page likes), Greensboro Grasshoppers (55,940 page likes), Greenville Drive (38,767 page likes), Hagerstown Suns (9,750 page likes), Hickory Crawdads (17,661 page likes), Kane County Cougars (43,228 page likes), Kannapolis Intimidators (13,902 page likes), Lake County Captains (21,514 page likes), Lakewood BlueClaws (27,765 page likes), Lansing Lugnuts (57,705 page likes), Lexington Legends (31,159 page likes), Peoria Chiefs (27,416 page likes), Quad Cities River Bandits (23,211 page likes), Rome Braves (26,402 page likes), South Bend Cubs (47,451 page likes), West Michigan Whitecaps (60,831 page likes), West Virginia Power (14,727 page likes), and the Wisconsin Timber Rattlers (42,288 page likes). The teams selected from this sample were based on the number of page likes. The page with the highest amount of page likes was the West Michigan Whitecaps (60,831 page likes), while the page with the least amount of page likes was the Clinton LumberKings (6,422 page likes). Table 9 below shows the abbreviations used during the analysis.

Table 9

Team Abbreviations

Team	Abbreviation
West Michigan Whitecaps	WM
Clinton LumberKings	CL

After the two teams were selected, all Facebook posts and comments between the timeframe of September 10, 2015-September 10, 2016 were collected using the NVivo software package. After this collection, each post, starting on September 10, 2015, was given a number per team. A random number generator then selected 80 posts per team to observe. A baseline of 80 posts were chosen as Goode and Robinson's (2013) analysis examined blog posts and responses to 80 different posts. Again, the purpose of Study B was to compare team performance via a regression analysis between accommodation measures (LSM, immediacy) and Facebook metrics (*likes,* number of comments). In this manner, a team with over one million page likes and a team with just over 20,000 likes can be compared as the comparison measures performance on a more comprehensive scale than simply *likes* and number of comments. This measure examined the levels of accommodation between the original post and the subsequent comments. Next, the accommodation scores and *likes* and number of comments are run through a regression analysis.

Methodology- Study B

RQ1: What levels of language accommodation exist between the Single-A MiLB team with the highest number of page likes and the Single-A MiLB team with the lowest level of page likes? To answer the first research question, the primary investigator observed what the accommodation levels are for the two teams selected for this analysis based on immediacy and LSM. Within communications studies, immediacy has been a measure of the relationship between communicators and liking of the communications taking place (McCroskey & Richmond, 2000; Mehrabian, 1966). Further, immediacy refered to the ways in which a communicator explicitly communicates via “affective, evaluative, and/or preferential attitude(s) toward the objects, events, or people about which he communicates” (Mehrabian, 1966, p.26). Previous CAT studies have shown that the closer communications converge upon each other, the more positive the conversation is perceived by conversation participants (de Siqueira & Herring, 2009; Gasiorek & Giles, 2015; Gonzales, Hancock, & Pennebaker, 2009; Giles, Coupland, & Coupland, 1991; Giles, 2008; Ludwig et al., 2013). LSM was a measure that calculated how similar or different sentence structures were between conversation participants (Gonzales, Hancock, & Pennebaker, 2009; Wang, Reitter, & Yen, 2014).

LSM and immediacy were calculated through a combination of the LIWC software and a comparison between each element within both measures (Gonzales, Hancock, & Pennebaker, 2009; Goode & Robinson, 2013). The first part of this process began by gathering all Facebook posts through the qualitative gathering and analysis software package, NVivo. NVivo was used solely for gathering the dataset. Next, each post and subsequent comments were saved into individual Microsoft Excel files. This was done so that the LIWC software package could process each document, which represented a unique post and all comments for that particular post. The file names were saved as "1", "2", etc.… in separate team folders.

Next, each post was run through the LIWC software separately. The LIWC generated a results sheet which measured all components of a written conversation. The LIWC's results were represented in percentages. Each measure (LSM, Immediacy) was compared between the original team post on Facebook and an average of all comments in terms of the post components. To clarify, this means that all components within a post (personal pronouns, articles, etc.) and all comment results that were in response to the original post were averaged and compared between the average of all comments and the original post. Measures for immediacy (articles, indefinite pronouns, personal pronouns, present tense verbs, and short words) and LSM (auxiliary verbs, common adverbs, conjunctions, indefinite pronouns, negations, personal pronouns, prepositions, and quantifiers) were compared between the original post and an average of all subsequent comments (Gonzales, Hancock, & Pennebacker, 2010; Goode & Robinson, 2013). This comparison can be explained as the difference between two speakers, on one dimension, divided by the sum of the same dimension total (Gonzales, Hancock, & Pennebacker, 2010, p. 9). For example, when measuring two speakers' use of indefinite pronouns, a percentage was taken from each speaker's passage (number of indefinite pronouns used divided by the sentence total). Each speaker's passage underwent this analysis. The result gave a percentage, which was subtracted out between the first and second speaker with the absolute value of this total being reported. Finally, this difference was divided by the sum of percentages between the two speakers in terms of indefinite pronouns.

The first research question's purpose was to find the levels of accommodation (LSM, Immediacy) between the original post and comments left on the original post. Accommodation levels were not calculated between the commenters. To do this, the following sequence of equations were used to measure the levels of accommodation (LSM, Immediacy) between the original post and the comments:

For auxiliary verbs: $Wauto_{ma=}CmprWM_1AUX_A = 1-(|WM_{1AUX}-AUX_A|)/(WM_{1AUX}+AUX_A)$

$CLAUX_{total}=CmprCL_1AUX_A = 1-(|CL_{1AUX}-AUX_A|)/(CL_{1AUX}+AUX_A)$

For articles: $WMART_{total}=CmprWM1ARTA = 1-(|WM_{1ART}-ART_A|)/(WM_{1ART}+ART_A)$

$CLART_{total}=CmprCL_1ART_A = 1-(|CL_{1\ ART}-ART_A|)/(CL_{1ART}+ART_A)$

For Common Adverbs: $WMCMN_{total}=CmprWM_1CMN_A = 1-(|WM_{1CMN}-CMN_A|)/(WM_{1\ CMN}+CMN_A)$

$CLCMN_{total}=CmprCL_1CMN_A = 1-(|CL_{1\ CMN}-CMN_A|)/(CL_{1\ CMN}+CMN_A)$

For Conjunctions: $WMCNJ_{total}=CmprWM_1CNJ_A = 1-(|WM_{1CNJ}-CNJ_A|)/(WM_{1\ CNJ}+CNJ_A)$

$CLCNJ_{total}=CmprCL_1CNJ_A = 1-(|CL_{1\ CNJ}-CNJ_A|)/(CL_{1\ CNJ}+CNJ_A)$

For Indefinite Pronouns: $WMIPN_{total}=CmprWM_1IPN_A = 1-(|WM_{1IPN}-IPN_A|)/(WM_{1\ IPN}+IPN_A)$

$CLIPN_{total}=CmprCL_1IPN_A = 1-(|CL_{1\ IPN}-IPN_A|)/(CL_{1\ IPN}+IPN_A)$

For Negations: $WMNGN_{total}=CmprWM_1NGN_A = 1-(|WM_{1NGN}-NGN_A|)/(WM_{1\ NGN}+NGN_A)$

$CLNGN_{total}=CmprCL_1NGN_A = 1-(|CL_{1\ NGN}-NGN_A|)/(CL_{1\ NGN}+NGN_A)$

For PerWMnal Pronouns: $WMPPN_{total}=CmprWM_1PPN_A = 1-(|WM_{1PPN}-PPN_A|)/(WM_{1\ PPN}+PPN_A)$

$CLPPN_{total}=CmprCL_1PPN_A = 1-(|CL_{1\ PPN}-PPN_A|)/(CL_{1\ PPN}+PPN_A)$

For Prepositions: $WMPRP_{total}=CmprWM_1PRP_A = 1-(|WM_{1PRP}-PRP_A|)/(WM_{1\ PRP}+PRP_A)$

$CLPRP_{total}=CmprCL_1PRP_A = 1-(|CL_{1\ PRP}-PRP_A|)/(CL_{1\ PRP}+PRP_A)$

For Present Tense Verbs: $WMPST_{total}=CmprWM_1PST_A = 1-(|WM_{1PST}-PST_A|)/(WM_{1\ PST}+PST_A)$

$$CLPST_{total}=CmprCL_1PST_A= 1-(|CL_{1\ PST}-PST_A|)/(CL_{1\ PST}+PST_A)$$

For Quantifiers: $WMQNT_{total}=CmprWM_1QNT_A= 1-(|WM_{1QNT}-QNT_A|)/(WM_{1\ QNT}+QNT_A)$

$$CLQNT_{total}=CmprCL_1QNT_A= 1-(|CL_{1\ QNT}-QNT_A|)/(CL_{1\ QNT}+QNT_A)$$

For Short Words: $WMSRT_{total}=CmprWM_1SRT_A= 1-(|WM_{1SRT}-SRT_A|)/(WM_{1\ SRT}+SRT_A)$

$$CLSRT_{total}=CmprCL_1SRT_A= 1-(|CL_{1\ SRT}-SRT_A|)/(CL_{1\ SRT}+SRT_A)$$

To complete the measure for the LSM score, the following equation was used:

$$LSM_1= AUX_{total}+ CMN_{total}+CNJ_{total}+IPN_{total}+NGN_{total}+PPN_{total}+PRP_{total}+QNT_{total}+SRT_{total}/9$$

In this equation, the subscript number next to "LSM" signifies which status number was being measured. This number could range anywhere from 1-80. Any measure with the subscript "total" next to it signified the individual measure score of LSM examined between the original post and all comments on that post. The average of all totals generated a score between 0-1, with scores closer to one showing high levels of linguistic style matching, a measure of accommodation.

The following equation was used to measure the immediacy score:

$$Immediacy_1=ART_{total}+IPN_{total}+PPN_{total}+PST_{total}SRT_{total}/5$$

In this equation, the subscript number next to "Immediacy" referred to the status number being measured. This number could range anywhere from 1-80. Any measure with the subscript "total" next to it signified the individual measure score of immediacy between the original post and all comments on that post. The result of this calculation resulted in a score between 0-1 with scores closer to one showing high levels of immediacy. Both of these measures were not averaged together as there may be other factors that have not yet been identified as measures of language accommodation. Both LSM and immediacy were measured for each post selected. This process answered the first RQ.

RQ2: For the Single-A MiLB teams with the highest and lowest number of page likes, what is the relationship between language accommodation measures (LSM, immediacy), and *likes* and/or number of comments? To answer the second research question, each measure of accommodation per post (LSM, Immediacy) was run through a regression analysis in R. This analysis measured Facebook metrics *(likes*, number of comments) against accommodation scores (LSM, immediacy) to see if these measures were correlated. The second research question asked if there would be a difference in correlations between the MiLB Facebook page with the most page likes and the MiLB Facebook page with the least page likes at the Single-A level. Different or no correlations may emerge when measuring each accommodation measure and traditional measures of Facebook post success.

Part of this dissertation's purpose was to establish a new method that social media managers can use to measure their posts' success. Smaller markets may not share the same success in terms of *likes* and number of comments as larger markets; thus, observing how well their social media posts were connecting with their fan base in terms of accommodation would be a valuable avenue for these teams to measure their posts' success. Part of this analysis, particularly the correlations, can be done without the use of expensive software.

CHAPTER 4

RESULTS

A total of 3,018 Facebook posts were collected across all teams for Study A and Study B. Facebook posts needed to have at least one comment to be included. Overall, the averages of the *likes* and number of comments for all posts collected had lower averages than the posts that were analyzed. Many of the posts taken out of these studies had zero comments and/or zero *likes*. Table 10 below compares the averages across all teams for posts, including average *likes*, number of comments for the posts included in these studies, and all posts originally collected.

Table 10

Simple Facebook Post Statistics

Team	Total Posts Collected	All Posts *Likes* Average	Selected Posts *Likes* Average	All Posts Comments Average	Selected Posts Comments Average
Drive	610	29.2193	60.1	1.2984	3.8111
Fireflies	421	76.8809	119.1556	4.7173	8.4778
Lumberkings	305	25.2679	34.7875	2.2393	3.65
Riverdogs	583	23.7055	37.4333	5.6381	7.7667
Whitecaps	1099	92.6427	156.4875	6.0173	9.625

The following results were found through the collection of *likes*, number of comments, calculation of accommodation scores, ANCOVA's, and regression models, where applicable. Negative scores on regression equations signified an inverse relationship between variables. For example, a regression equation such as $\widehat{LSM}$ = 0.4557 (s.e.= 0.0123) - 0.008 **Likes* (s.e.= 0.2134) signaled that for every additional *like*, LSM scores would decrease by 0.008 points.

Chapter 2 referred to Table 1 which showed the standardized scores presented in the LIWC manual (Pennebaker, Boyd, Jordan, & Blackburn, 2015). Standardized scores were not available for Facebook. Table 11 shows the standardized scores and the average scores found in this analysis. The scores from this analysis are labeled under the Facebook column.

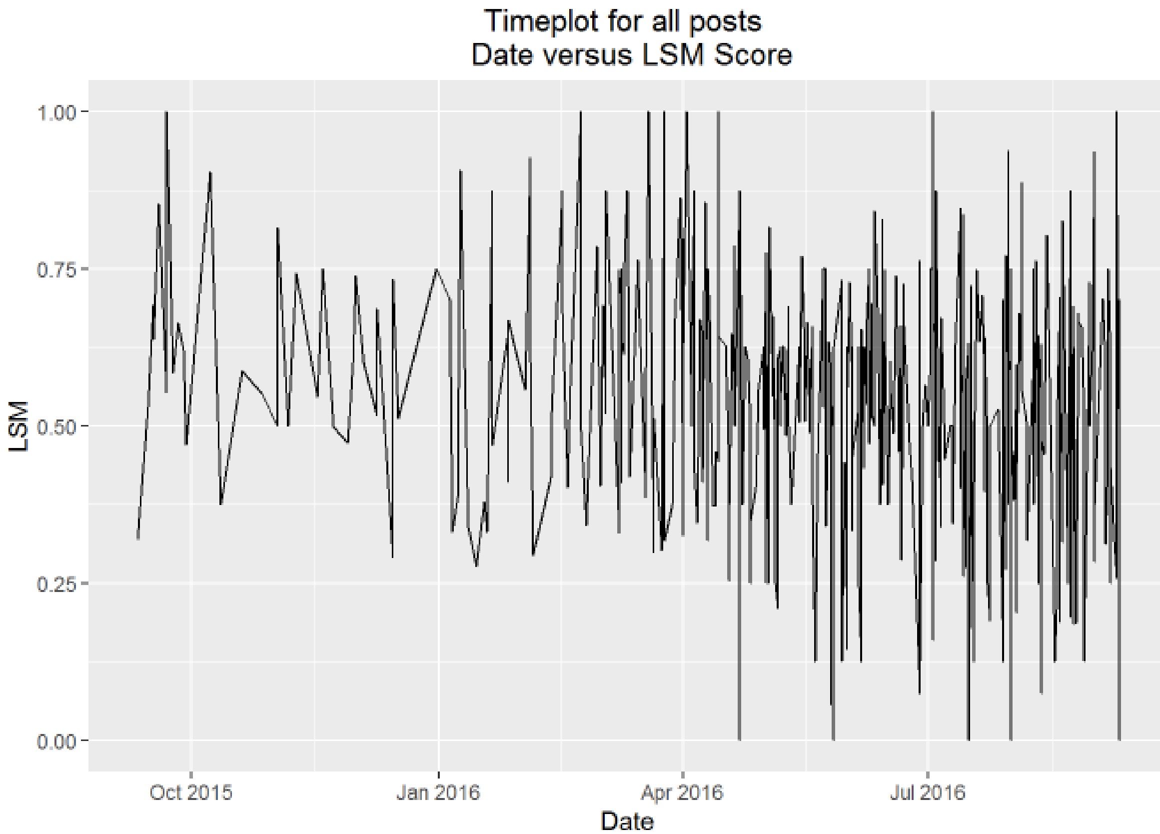
Table 11

Standardized Scores

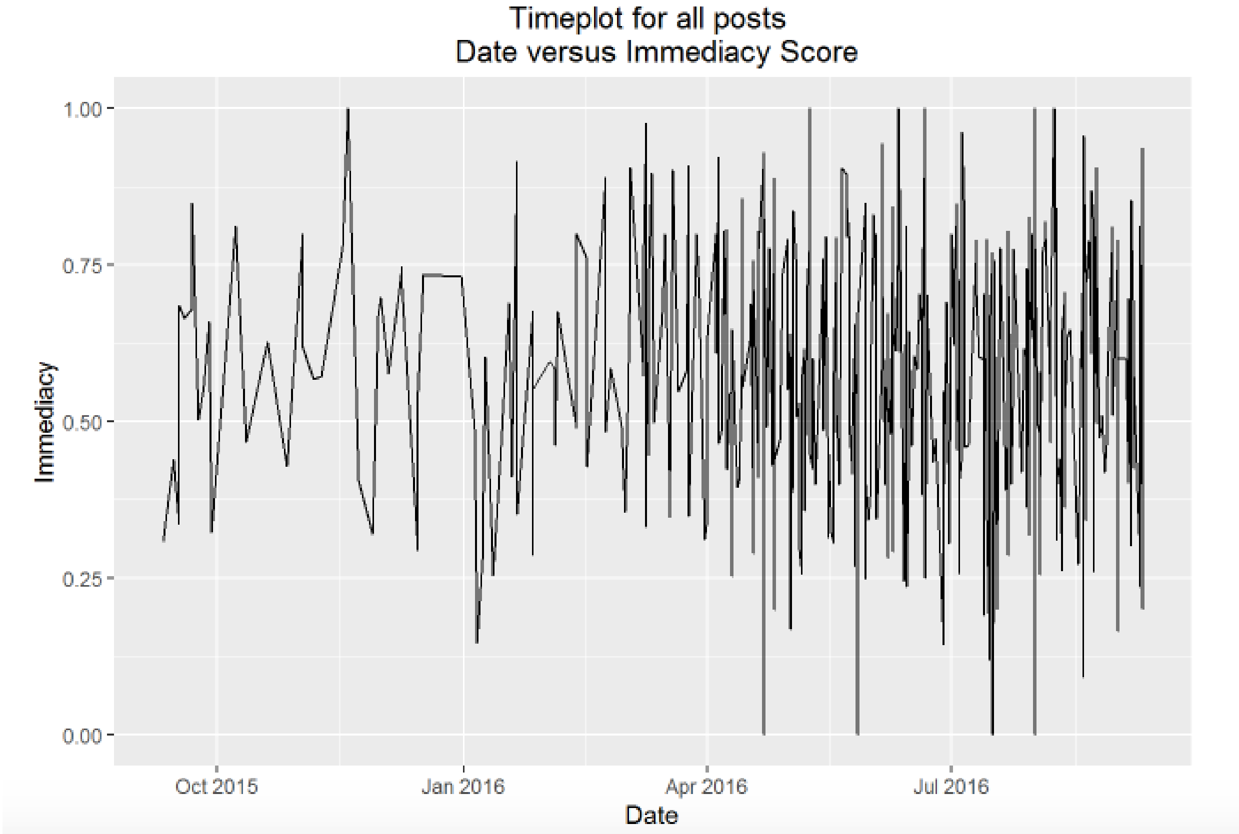
Measurement	Blogs	Twitter	Facebook
Auxiliary Verbs[M]	8.75	8.27	3.9049
Articles[I]	6.00	5.58	6.1447
Common Adverbs[M]	5.88	5.13	1.5363
Conjunctions[M]	6.43	4.19	2.5983
Indefinite Pronouns[M, I]	5.53	4.60	1.7932
Negations[M]	1.81	1.74	0.2801
Personal Pronouns[M, I]	10.66	9.02	3.8523
Prepositions[M]	12.60	11.88	12.9908
Present tense verbs[I]	17.03	16.33	8.7557
Quantifiers[M]	2.27	1.85	1.5395
Short words[I]	14.38	15.31	21.9959

Note. [I] signifies aspects calculated within immediacy, while [M] signifies aspects calculated within LSM. Dimensions can be included in both immediacy and LSM measures.

A distribution chart for all teams in Study A and Study B was created to see if LSM and/or immediacy scores were consistent throughout the analysis. In this manner, the accommodation measures could be analyzed to see if there were portions of time where Facebook users were responding to teams in a more converging or diverging manner. The first plot shows the dates of the Facebook posts analyzed and LSM scores.



This plot shows that LSM scores fluctuated more during the season (past April, 2016) than the offseason. In other words, the LSM scores tended to have a greater range during the regular season than the offseason. This plot also shows that the posts chosen were primarily posted during the regular season in 2016. Below is a time plot that shows immediacy scores and the date of the posts throughout this analysis.



This plot shows that immediacy scores tended to fluctuate more during the regular season (after April, 2016) than the offseason. In other words, the immediacy scores tended to have a greater range during the regular season than the offseason. This plot also shows that most of the posts chosen for this analysis were gathered from the regular season.

Results- Study A

Facebook posts were retroactively collected for the Riverdogs using NVivo from September 10, 2015, to September 10, 2016. A total of 584 posts were collected solely from the Riverdogs during this time frame, with 331 posts having one or more comments. Of the 331 posts available for analysis, there were 122 neoliberal posts, 110 social posts, 109 team related posts, and 0 other posting types. Thirty posts from each posting type were randomly selected from the website random.org. Appendix 1 shows all of the posting types, and affiliated figured, found for the Riverdogs' analysis. This appendix also portrays the LSM score, immediacy score, number of *likes*, and number of comments associated with each post.

Facebook posts were retroactively collected for the Fireflies using NVivo from September 10, 2015, to September 10, 2016. The Fireflies had 423 posts during this time frame, with 242 posts having one or more comments. Of the 242 posts available for analysis, there were 77 neoliberal posts, 74 social posts, 91 team related posts, and 0 other posting types. Thirty posts from each posting type were randomly selected from the website random.org. Appendix 2 shows all of the posting types, and affiliated numbers, used for the Riverdogs' analysis. This appendix also portrays the LSM score, immediacy score, number of *likes*, and number of comments associated with each post.

Facebook posts were retroactively collected for the Drive using NVivo from September 10, 2015, to September 10, 2016. The Drive had 611 posts during this time frame, with 222 posts having one or more comments. Of the 222 posts available for analysis, there were 59 neoliberal posts, 79 social posts, 84 team related posts, and 0 other posting types. Thirty posts from each posting type were randomly selected from the website random.org. Appendix 3 shows all of the posting types, and affiliated numbers, used for the Drive's analysis. This appendix also portrays the LSM score, immediacy score, number of *likes,* and number of comments for each post.

Research Question 1: What levels of accommodation (LSM, Immediacy) exist between user-generated comments and neoliberal, team related, social posts, or other open coded posts from South Carolina MiLB teams? The primary investigator used the LIWC software and equation combination mentioned in Chapters 2 and 3 to answer the first research question. *Likes* and number of comments were also collected. LSM scores for the Riverdogs' posts ranged from 0 (16 *likes*, 9 comments) to 1 (222 *likes*, 16 comments) with an average LSM score of

0.5116, while immediacy scores ranged from 0.1199 (1 *like*, 2 comments) to 1 (4 *likes*, 1 comment) with an average immediacy score of 0.5663. In this analysis, the post with the highest number of *likes* totaled at 775 *likes* (0.6419 LSM score, 0.4405 Immediacy score, 15 comments) with an average of 37.4333 *likes* per post, while the highest number of comments was 162 (0.3722 LSM score, 0.2245 Immediacy score, 89 *likes*) with 7.7666 comments per post on average. Neoliberal posts averaged an LSM score of 0.6028, immediacy score of 0.6153, 17.5 *likes* per post, and 17.8667 comments per post. Social posts averaged an LSM score of 0.5001, immediacy score of 0.5427, 68.2333 *likes* per post, and 2.8667 comments per post. Team related posts averaged an LSM score of 0.4321, immediacy score of 0.5409, 26.5667 *likes* per post, and 2.5667 comments per post.

LSM scores for the Fireflies' posts ranged from 0.190526 (19 *likes*, 3 comments) to 1 (515 *likes*, 36 comments) with an average LSM score of 0.5423, while immediacy scores ranged from 0.1672 (56 *likes*, 1 comment) to 0.9429 (280 *likes*, 5 comments) with an average immediacy score of 0.5634. In this analysis, the post with the highest number of *likes* totaled at 780 *likes* (0.4144 LSM score, 0.4729 Immediacy score, 14 comments) with an average of 119.1556 *likes* per post, while the highest number of comments was 64 (0.5351 LSM score, 0.5334 Immediacy score, 78 *likes*) with 8.4778 comments per post on average. Neoliberal posts averaged an LSM score of 0.5192, immediacy score of 0.5398, 108.3667 *likes* per post, and 9.4667 comments per post. Social posts averaged an LSM score of 0.5969, immediacy score of 0.5866, 160.5667 *likes* per post, and 9.967 comments per post. Team related posts averaged an LSM score of 0.5109, immediacy score of 0.5637, 88.5333 *likes* per post, and 6 comments per post.

To finish answering the first research question, the Drive's scores were then calculated. LSM scores for the Drive's posts ranged from 0 (5 *likes*, 1 comment) to 0.8464 (1,004 *likes*, 36 comments) with an average LSM score of 0.4955, while immediacy scores ranged from 0 (0 *likes*, 1 comment) to 1 (52 *likes*, 1 comments) with an average immediacy score of 0.5274. In this analysis, the post with the highest number of *likes* totaled at 1,127 *likes* (0.6692 LSM score, 0.4805 Immediacy score, 19 comments) with an average of 60.1 *likes* per post, while the highest number of comments was 36 (0.8464 LSM score, 0.5993 Immediacy score, 1004 *likes*) with 3.811 comments per post on average. Neoliberal posts averaged an LSM score of 0.4037, immediacy score of 0.5176, 34.1 *likes* per post, and 3.5 comments per post. Social posts averaged an LSM score of 0.5036, immediacy score of 0.4896, 111.9333 *likes* per post, and 4.9667 comments per post. Team related posts averaged an LSM score of 0.57925, immediacy score of 0.5749, 34.3 *likes* per post, and 2.9667 comments per post. Table 12 shows the average scores across all posting types and teams. In the table below, 'NL' stands for neoliberal posts, 'SO' stands for social posts, and 'TR' stands for team related posts.

Table 12

Team Averages and Totals

Team & Posting Type	Average LSM	Average Immediacy	Likes per Post	Comments per Post
Fireflies NL	0.5192	0.5398	108.3667	9.4667
Riverdogs NL	0.6028	0.6153	17.5	17.8667
Drive NL	0.4037	0.5176	34.1	3.5
Fireflies SO	0.5969	0.5866	160.5667	9.9667
Riverdogs SO	0.5001	0.5427	68.2333	2.8667
Drive SO	0.5036	0.4896	111.9333	4.9667
Fireflies TR	0.5109	0.5637	88.5333	6
Riverdogs TR	0.4321	0.5409	26.5667	2.5667
Drive TR	0.5793	0.5749	34.3	2.9667
Fireflies Overall	0.5423	0.5634	119.1556	8.4778
Riverdogs Overall	0.5116	0.5663	37.4333	7.7667
Drive Overall	0.4955	0.5274	60.1	3.8111

Research Question 2: What is the relationship between neoliberal, team related, social, and/or open coded posts, language accommodation measures (LSM, immediacy), and *likes* and/or number of comments? All model assumptions were met, and are available via email to the primary investigator. First, an analysis of covariance (ANCOVA) was calculated using LSM as the response variable to test the significance of the numeric and categorical variables as they related to LSM. The analysis of variance table below shows that *likes* was determined to be a significant factor (p= 0.0003) while comments was a significant factor at the $\alpha < 0.10$ level (p=

0.0682). This post analysis showed that the posting type (p= 0.8428) and the team (p= 0.7489) were not significant factors. Table 13 below summarizes these findings.

Table 13

Analysis of Variance (Response: LSM)

Factor	*df*	Sum. Sq.	Mean Sq.	F value	PR(>F)	Significant
Likes	1	0.5764	0.5764	13.6320	0.0003	***
Comments	1	0.1417	0.1418	3.3526	0.0682	*
Type	2	0.0145	0.0072	0.1711	0.8428	
Team	2	0.0245	0.0122	0.2894	0.7489	
Residuals	262	11.0775	0.0423			

Note: *** refers to findings that are significant at the $p < 0.00$ level, * refers to findings that are significant at the $p < 0.05$ level.

A multiple regression analysis was then used to see how all factors related to LSM. The equation $\widehat{LSM}$= 0.4645 + 0.0002*$Likes$ + 0.0019*Comments + 0.0189*Social + 0.0093*TeamRelated + 0.0238*Fireflies + 0.0113*Riverdogs was used, with the combination of neoliberal posts and posts for the Greenville Drive acting as the baseline for the model. This overall model produced a significant result (F(6, 262)= 2.984, p= 0.0078, R^2= 0.0639), with significant results for the variables *likes* (p= 0.0148) and number of comments at the $\alpha < 0.10$ level (p= 0.0719). Social (p= 0.5544) and team related (p= 0.7676) posting types were not significant, while the team designations of the Columbia Fireflies (p= 0.4475) and the Charleston Riverdogs (p= 0.7174) were not significant. The final model, after model reduction, used the following equation:

$$\widehat{LSM} = 0.4937 \text{ (s.e.= 0.0139)} + 0.0003*Likes \text{ (s.e.= 0.00009)}$$

Number of comments, as a factor, was close to significant at the $\alpha = 0.05$ level, but was not included in the equation as it was technically not a significant finding. The final model found a significant result between LSM and *likes* ($p = 0.00452$) and a non-significant result for comments ($p = 0.0666$), with an R^2 of 0.0476. Appendix 6, Appendix Table 1 shows the regression table for this analysis. This model showed that for every additional *like*, the LSM score would increase by 0.0003. This analysis revealed that 4.76% of the variability in LSM was explained by the regression model with *likes*. All other factors were deemed non-significant. The model summary for model 1 is presented below.

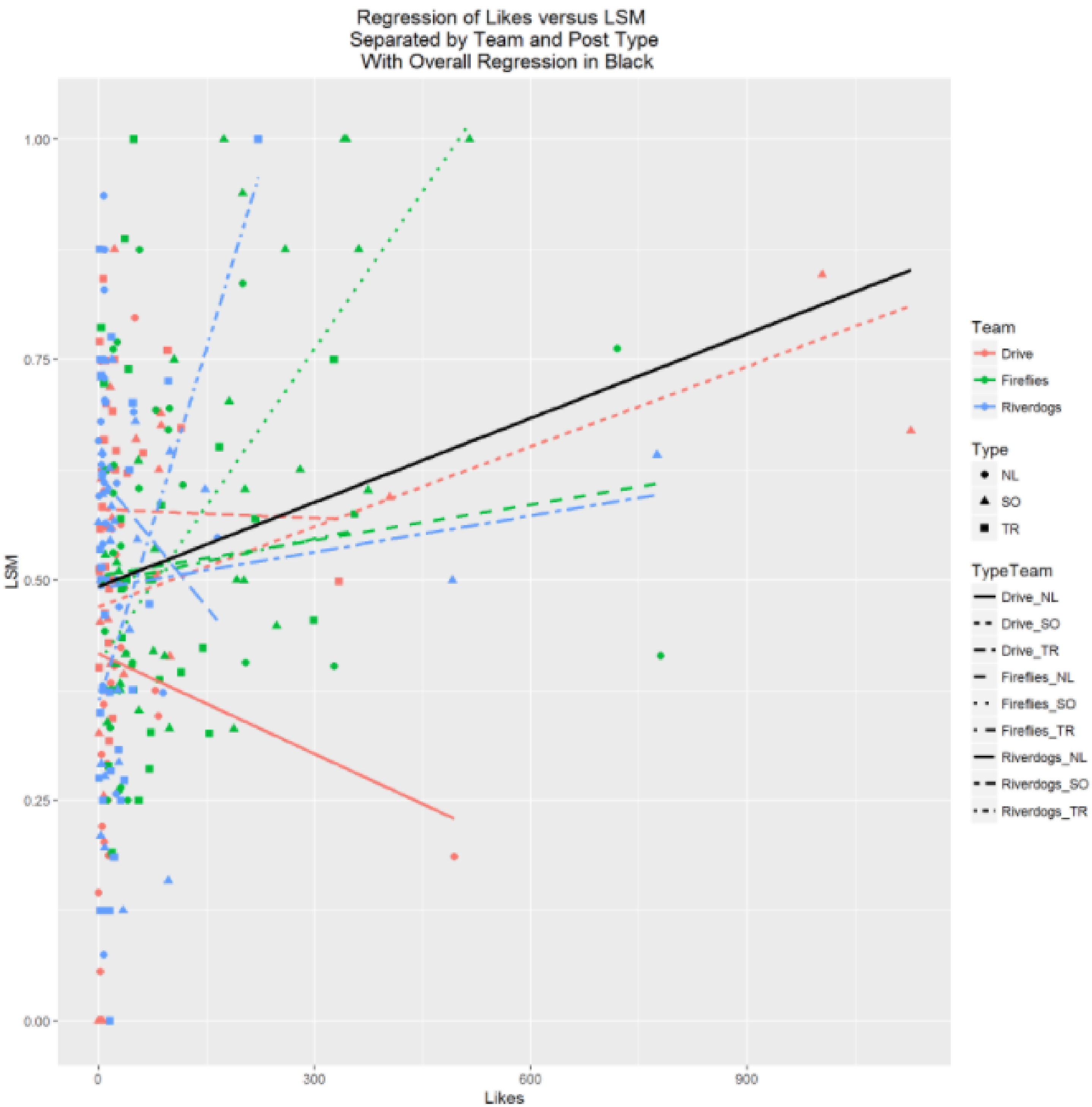
Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.25074	0.06287	0.04149	0.2058

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	0.04637	0.002896		16.008	$0.2e^{-15}$
	Likes	0.0002389	0.00009746	0.2183618	2.451	0.0149

Below is a graph that shows all regression lines associated with LSM, as well as the final model estimate.



Next, an analysis of variance was calculated for immediacy on the combined data. An ANCOVA was used to see the differences between numeric and categorical variables as they relate to immediacy. The analysis of covariance table below (Table 14) shows that no factors were considered significant.

Table 14

Analysis of Variance (Response: Immediacy)

Factor	Df	Sum. Sq.	Mean Sq.	F value	PR(>F)	Significant
Likes	1	0.0195	0.0195	0.4286	0.5133	
Comments	1	0.0009	0.0009	0.0197	0.8884	
Type	2	0.0295	0.0147	0.3236	0.7238	
Team	2	0.0795	0.3975	0.8726	0.4191	
Residuals	262	11.9346	0.0456			

Note: *** refers to findings that are significant at the $p < 0.00$ level, * refers to findings that are significant at the $p < 0.05$ level.

A multiple regression analysis was then used to see how all factors related to immediacy. The following equation was used:

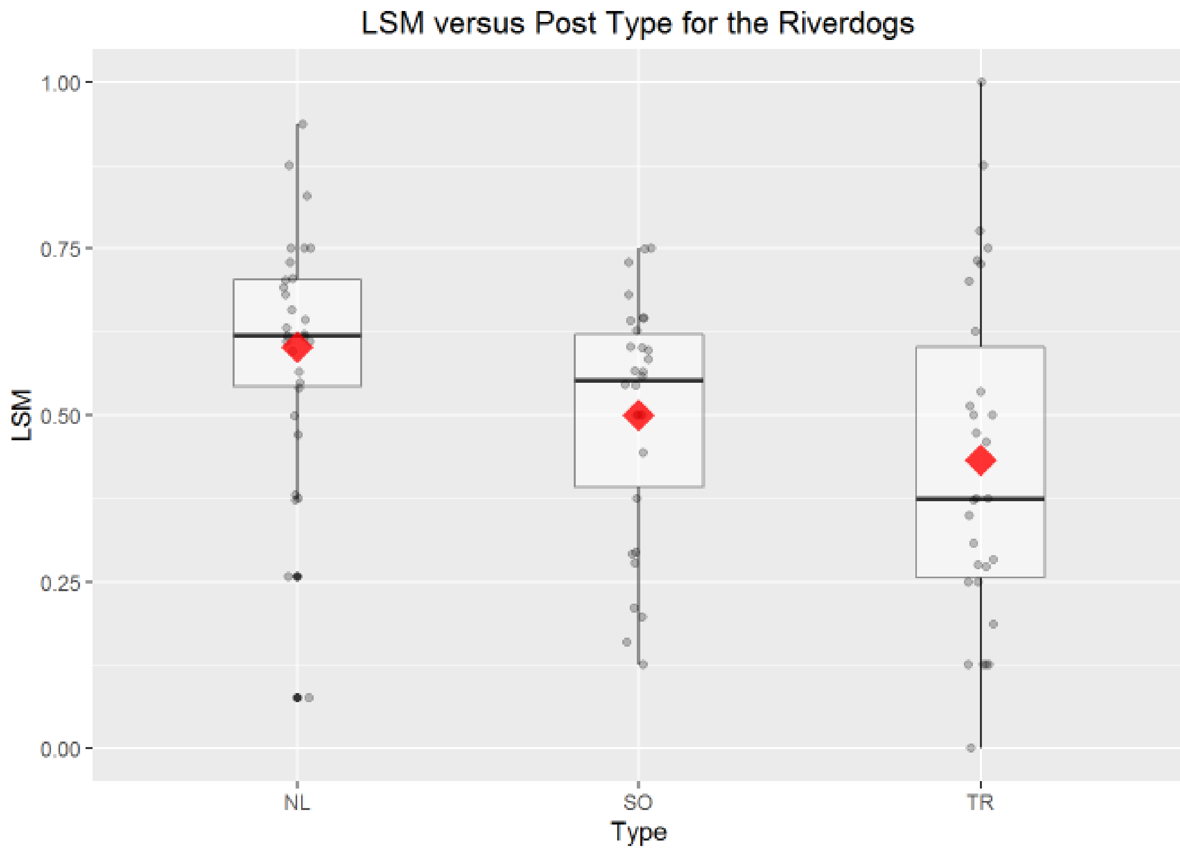
$$\widehat{Immediacy} = 0.5337 + 0.00009*Likes - 0.0005*\text{Comments} - 0.0252*\text{Social} - 0.0037*\text{TeamRelated} + 0.0332*\text{Fireflies} + 0.0397*\text{Riverdogs}$$

Neoliberal posts and the Greenville Drive’s posts were selected as this model’s baseline. The full model proved not to be significant ($F(6, 262)= 0.4735$, $p= 0.8278$, $R^2= 0.0107$), with no individual factors being significant. After model reduction, a simple ANOVA model was deemed appropriate. The ANOVA model was not significant; thus, it was deduced that traditional Facebook metrics were not helpful in predicting Facebook posts’ immediacy scores.

Research Question 3: Across all teams, what is the relationship between coded posts (neoliberal, team related, social, open code), language accommodation measures (LSM,

immediacy), and *likes* and/or number of comments? To answer the third research question, multiple regression analyses were performed for each team. Each team could have different significant relationships in regards to traditional Facebook metrics (*likes,* number of comments), posting types (neoliberal, social, team related), and accommodation scores (LSM, Immediacy). Each team's results will first be examined, with a table following this overview to show any significant findings. For all multiple regression analyses, R selected the first level in post type alphabetically as the baseline. This factor was neoliberal posts.

A multiple regression model was used to analyze the data for the Charleston Riverdogs. The equation $\widehat{LSM}$= 0.6039 + 0.0003*$Likes$ - 0.0003*Comments - 0.1212*Social - 0.1781*TeamRelated was used to test the relationship between LSM versus traditional Facebook metrics and posting type. Neoliberal posts were used as the baseline for this analysis. A significant result was found for the whole model ($F(4, 85)= 2.913$, $p= 0.2605$, $R^2= 0.1206$). Social posts ($t(89)= -2.050$, $p= 0.0435$) and team related posts ($t(89)= -3.094$, $p= 0.00267$) were the only factors with significant results. *Likes* ($t(89)= 1.169$, $p= 0.2456$) and number of comments ($t(89)= -0.241$, $p= 0.8194$) were not significant factors. Upon model reduction, a simple ANOVA was used to analyze the differences between post type with respect to LSM. Since the posting type wass significant, the primary investigator wanted to investigate the specific differences between the posting types. Pairwise comparisons were then completed to see the differences between neoliberal, social, and team related posting types. A Tukey's multiple comparisons of means test was used. Appendix 6, Appendix Table 8 portrays the ANOVA table, as well as the Tukey's multiple comparisons of means test. A significant result was detected when comparing team related posts to neoliberal posts ($p= 0.0055$), while social and neoliberal posts ($p= 0.1382$), and team related and social posts ($p= 0.4142$) were not significantly different from each other. This means that among all posting types, only team related and neoliberal posts were different when assessing which posting types have a relationship with LSM.



Next, a multiple regression analysis was completed to see the relationship between immediacy, traditional Facebook metrics, and posting type for the Riverdogs. The equation $\widehat{Immediacy}$= 0.6383 - 0.0001**Likes* - 0.0012*Comments - 0.0839*Social - 0.0912*TeamRelated was used to see this relationship, with neoliberal posts acting as the baseline. A non-significant result was detected for the whole model (F(4, 85)= 0.8231, *p*= 0.5141, R^2= 0.0373), with no factors being significant. Thus, it would seem as though there is no relationship between traditional Facebook metrics and/or posting types and immediacy scores for the Charleston Riverdogs.

The Columbia Fireflies' analysis began with a multiple regression model that included posting types and traditional Facebook metrics as predictors and LSM as the response. variable The constant variance test came back as significant. Further, the constant variance was of concern for this test, as the original Box-Cox test was centered at zero. The Box-Cox test suggested that the log of LSM be used to measure interactions with LSM for the Fireflies. The full model formula was $\widehat{LnLSM}$= -0.8198 + 0.0006*$Likes$ + 0.0039*Comments + 0.1024*Social + 0.0012*TeamRelated, with Neoliberal posts serving as the baseline. The model was found to be significant ($F(4, 85)= 3.212$, $p= 0.0166$, $R^2= 0.1313$), with *likes* being the only significant factor at the $\alpha < 0.10$ level ($t(89)= 1.816$, $p= 0.0729$). Number of comments ($t(89)= 1.043$, $p= 0.2998$), social posts ($t(89)= 1.081$, $p = 0.2827$), and team related posts ($t(89)= 0.013$, $p= 0.9899$) were all not significant. A reduced model was used to view the relationship between *likes*, social posts, team related posts, and the natural log of LSM. The following equation was used:

$$\widehat{LnLSM} = -0.7824 \text{ (s.e.= 0.0492)} + 0.0008*Likes \text{ (s.e.= 0.0003)}$$

The overall analysis resulted in a significant finding ($F(1, 88)= 10.38$, $p= 0.0018$, $R^2= 0.1055$). Appendix 6, Appendix Table 2, shows the regression table for this model. For every additional *like* to a Fireflies' post, the natural log of LSM scores were expected to increase by 0.0008. In this regression model, 10.55% of the variability in the natural log of LSM scores was explained by the regression with *likes*. The model summary and coefficients table for model 2 are shown below.

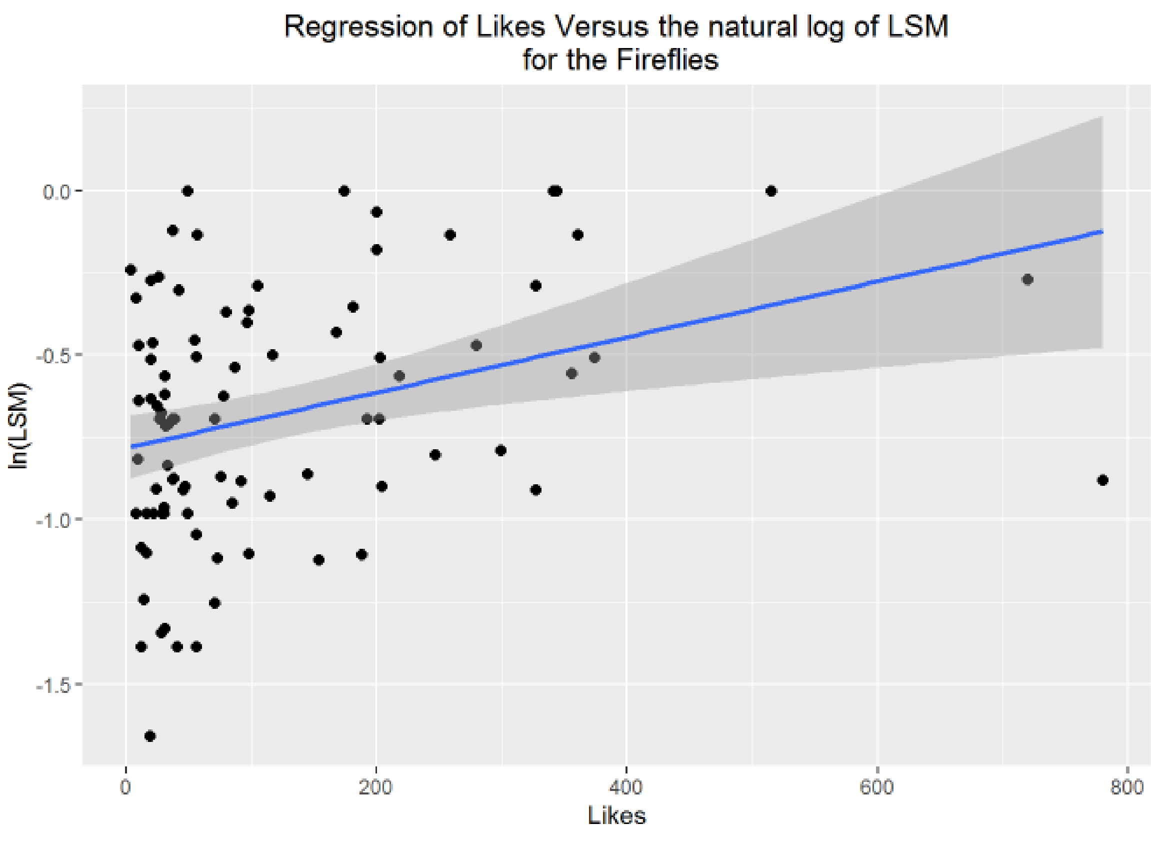
Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
2	0.32481	0.1055	0.0953	0.3605

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
2	(Constant)	-0.7824	0.0492		-15.903	$0.2e^{-15}$
	Likes	0.0008446	0.0002622	0.3247602	3.221	0.00179

The graph below shows this relationship.



A multiple regression analysis was used to determine the relationship between immediacy, and traditional Facebook metrics and posting types for the Fireflies. The equation $\widehat{Immediacy}$= 0.5188 + 0.0004**Likes* - 0.0019*Comments + 0.0286*Social + 0.0243*TeamRelated was used, with Neoliberal posts serving as the baseline for the analysis.

The overall result was not deemed significant ($F(4, 85) = 1.184$, $p = 0.3237$, $R^2 = 0.0528$), however *likes* was almost a significant factor in this analysis ($t(89)= 1.979$, $p = 0.051$). Non-significant factors included comments ($t(89)= -0.919$, $p= 0.360$), social posts ($t(89)= 0.528$, $p= 0.599$), and team related posts ($t(89)= 0.451$, $p= 0.653$). A simple regression model was then used to see if *likes* were a significant factor when considering the relationship with immediacy. The following equation was used:

$$\widehat{Immediacy} = 0.5301034 \text{ (s.e.= 0.0279)} + 0.0003{*}Likes \text{ (s.e.= 0.0001)}$$

A non-significant result was found ($F(1, 88)= 3.51$, $p= 0.06431$, $R^2= 0.0384$). Appendix 6, Appendix Table 3, features the regression table for this model. Although this finding was not statistically significant at the $\alpha < 0.05$ level, this finding was significant at the $\alpha < 0.10$ level. This would suggest that for every additional *like* for a Fireflies' Facebook post, the immediacy score for this post would increase by 0.0003. In this model, 3.84% of the variance in immediacy was explained by the regression with *likes*. The model summary and coefficients table for model 3 are shown below.

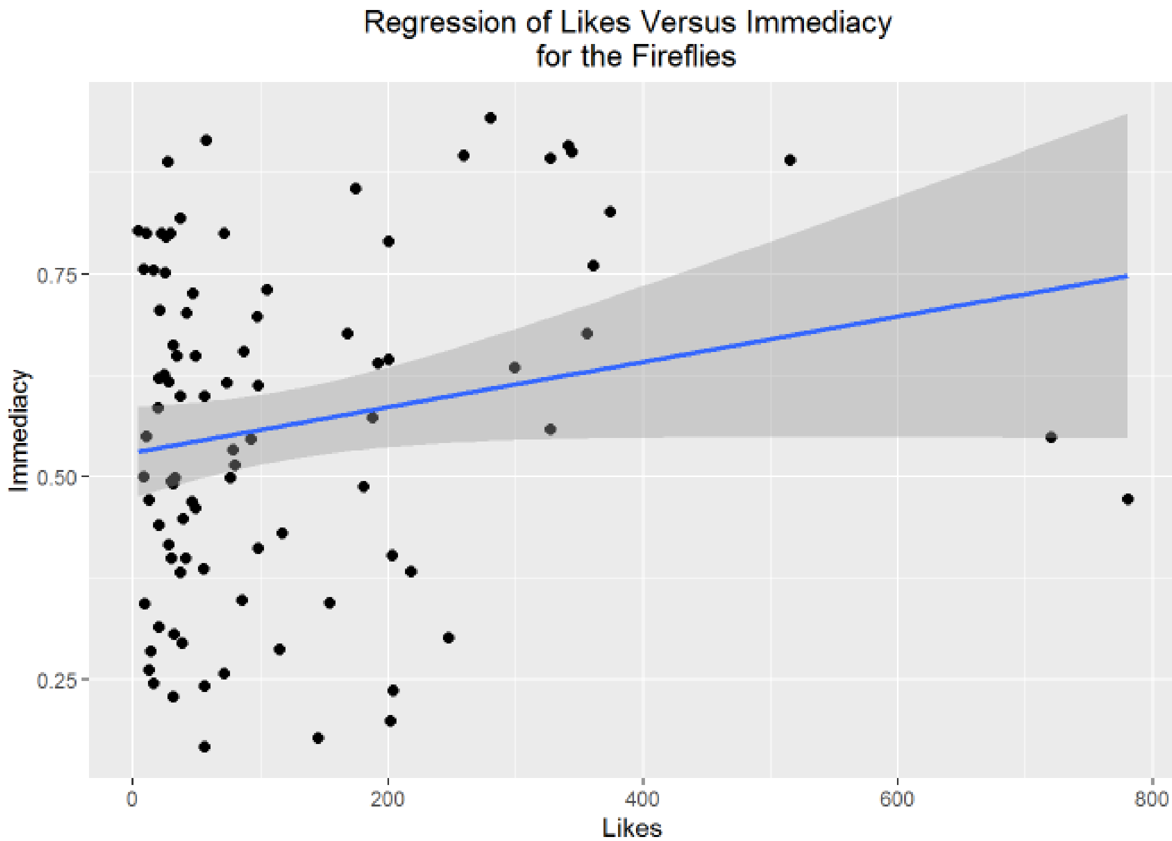
Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
3	0.195857	0.03836	0.02743	0.2049

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
3	(Constant)	0.5301034	0.0279658		18.955	$0.2e^{-15}$
	Likes	0.0002793	0.0001490	0.195854	1.874	0.0643

The graph of the reduced model is listed below.



The Greenville Drive's analysis began with a multiple regression model that included posting types, traditional Facebook metrics, and their relationship with LSM. The formula $\widehat{LSM}$= 0.3639 - 0.00005**Likes* + 0.0119*Comments + 0.08657*Social + 0.01819*TeamRelated was used to view the relationship between all of these factors, with Neoliberal post scores serving as the baseline for the model. The overall model was found to be significant (F(4, 85)= 4.723, *p*= 0.001723, R^2= 0.1819), with individual metrics varying in terms of significance. *Likes* were found to be not significant (t(89)= -0.273, *p*= 0.7857), as were social posts (t(89)=1.699, *p*= 0.0930) and number of comments (t(89)= 1.791, *p*= 0.0768). Team related posts were found to be significant (t(89)= 3.628, *p*= 0.0005). A condensed model was then used found to more simply explain the relationship between LSM and comments, social posts, and team related posts. Comments and social posts were included as these results were significant at $\alpha < 0.10$ level. The following equation was used:

$$\widehat{LSM} = 0.3671 \text{ (s.e.= 0.0379)} + 0.0105\text{*Comments (s.e.= 0.0041)} + 0.0844\text{*Social (s.e.= 0.0501)} + 0.1811\text{*TeamRelated (s.e.=0.0498)}$$

Neoliberal posts served as the baseline for this analysis. The overall model was significant (F(3, 86)= 6.341, p= 0.0006, R^2= 0.1811), with individual components such as comments (t(89)= 2.547, p= 0.0126) and team related posts (t(89)= 3.638, p= 0.0005) both being significant. Appendix 6, Appendix Table 4 shows the regression table for this final model. Again, social posts were deemed not significant (t(89)= 1.686, p= 0.0954). For the Drive, every time they posted a team related post, this post was expected to have an increase in LSM scores by 0.1811 points, while each additional comment was expected to generate 0.0105 points more for the LSM score. In this model, 18.11% of the variability in LSM was explained by the regression with team related posts and comments. The model summary and coefficients table for model 4 are shown below.

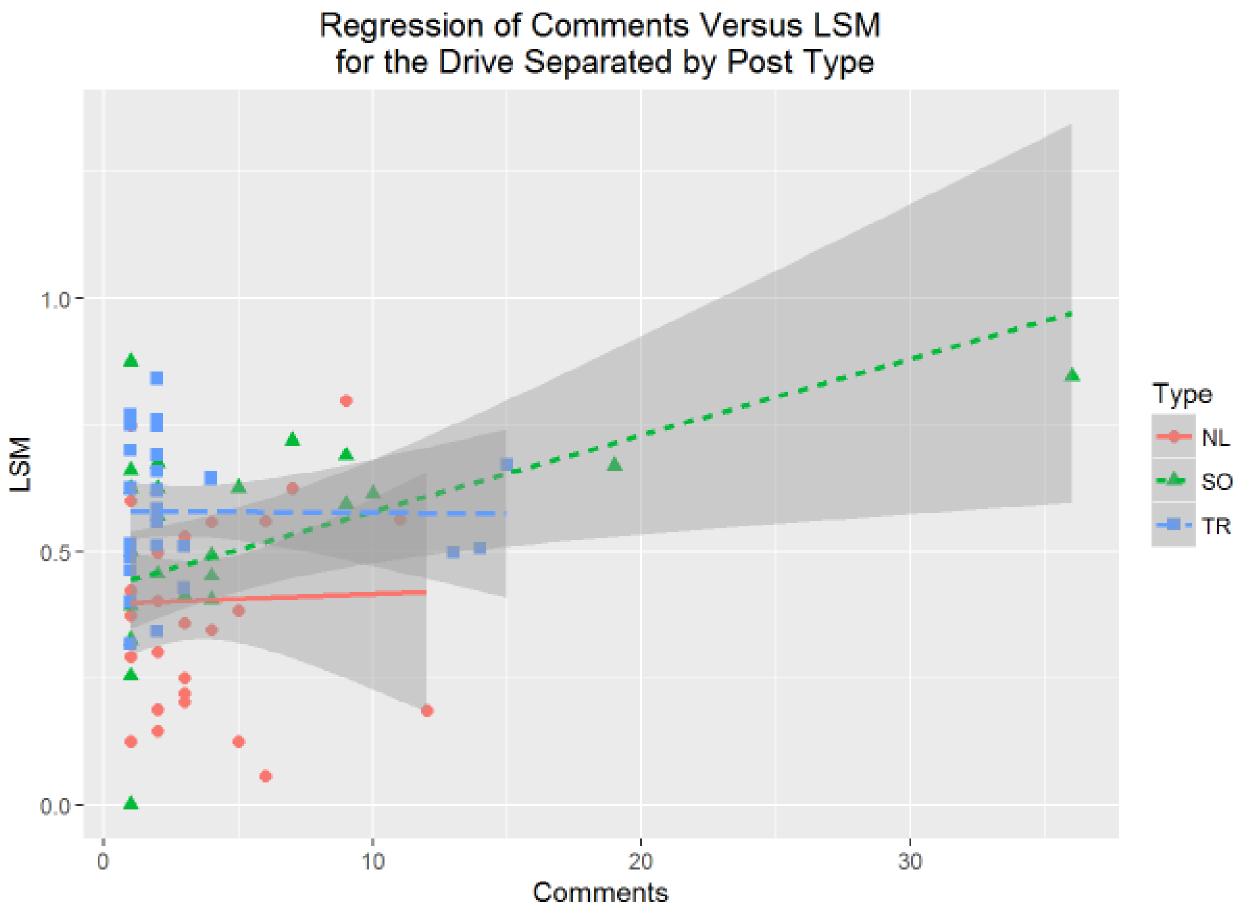
Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
4	0.425558	0.1811	0.1526	0.1926

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
	(Constant)	0.367051	0.037997		9.660	$2.23e^{-15}$
4	Comments	0.010483	0.004116	0.2521607	2.547	0.012644
	TypeSO	0.084444	0.050090		1.686	0.095453
	TypeTR	0.181100	0.049773		3.638	0.000467

The graph below illustrates these findings.



A multiple regression analysis was used to measure the relationship between immediacy, and traditional Facebook metrics (*likes*, number of comments) and posting types (neoliberal, social, and team related posts). The equation $\widehat{Immediacy}$= 0.05181 + 0.00001**Likes*- 0.0003*Comments - 0.0029*Social + 0.0057*TeamRelated was used to view this relationship. Neoliberal posts were used as the baseline for this analysis. The overall model produced a non-significant result ($F(4, 85)= 0.6389$, $p= 0.6362$, $R^2= 0.0292$) with all components rendering non-significant results. Thus, immediacy did not have any relationship with *likes* or number of comments. Table 15 summarizes all significant findings within Study A at the $\alpha < 0.05$ level.

Table 15

Significant Within-Team Factors

Team	LSM or Immediacy	Factor	Significant p-value
Charleston Riverdogs	LSM	Social Posts	p= 0.0435
Charleston Riverdogs	LSM	Team Related Posts	p= 0.00267
Columbia Fireflies	LSM	*Likes*	p= 0.0031
Greenville Drive	LSM	Number of Comments	p= 0.0126
Greenville Drive	LSM	Team Related Posts	p= 0.0005

Results- Study B

Facebook posts were retroactively collected for the Lumberkings using NVivo from September 10, 2015 to September 10, 2016. The LumberKings had 306 posts during this time frame, with 187 posts containing one or more comments. Eighty of the 187 posts were randomly selected for analysis. The website random.org was used to choose the posts used for this analysis. Appendix 4 shows all of the post numbers used for the Lumberkings' analysis, as well as the LSM score, immediacy score, number of *likes*, and number of comments associated with each post.

Facebook posts were also retroactively collected for the Whitecaps using Nvivo from September 10, 2015 to September 10, 2016. The Whitecaps had 1,100 posts during this time frame, with 855 posts having one or more comments. Eighty of the 855 posts with comments were randomly selected for analysis. The website random.org was used to choose the posts for this analysis. Appendix 5 shows all of the post numbers used for the Whitecaps' analysis, as well as the LSM score, immediacy score, number of *likes*, and number of comments associated with each post.

Research Question 1: What levels of language accommodation exist between the Single-A MiLB team with the highest number of page likes and the Single-A MiLB team with the lowest level of page likes? To answer the first research question, the primary investigator used the combination of LIWC and the set of algorithms explained in chapters 2 and 3. *Likes* and number of comments were also collected. LSM scores for the Lumberkings' posts ranged from 0.2993 (20 *likes*, 7 comments) to 0.9262 (42 *likes*, 10 comments) with an average LSM score of 0.5522, while immediacy scores ranged from 0.1461 (18 *likes*, 1 comment) to 1 (9 *likes*, 1 comment) with an average immediacy score of 0.6160. In this analysis, the post with the highest number of *likes* totaled at 172 *likes* (0.5545 LSM score, 0.7921 Immediacy score, 1 comment) with an average of 34.7875 *likes* per post, with the highest number of comments was 16 (0.4686 LSM score, 0.3514 Immediacy score, 8 *likes*) with 3.65 comments per post on average.

For the Whitecaps, LSM scores ranged from 0.0742 (22 *likes*, 1 comments) to 1 (4405 *likes*, 106 comments) with an average LSM score of 0.5413, while immediacy scores ranged from 0.2502 (20 *likes*, 4 comments) to 0.9623 (15 *likes*, 2 comments) with an average immediacy score of 0.5613. In this analysis, the post with the highest number of *likes* totaled at 4,405 *likes* (1 LSM score, 0.8483 Immediacy score, 106 comments) with an average of 156.4875 *likes* per post. This post also had the highest number of comments in the Whitecaps' analysis, while there were 9.625 comments per post on average. Table 16 shows a summary of these findings.

Table 16

Team Averages and Totals

Team & Posting Type	Average LSM	Average Immediacy	Likes per Post	Comments per Post
Clinton Lumberkings	0.5522	0.6160	34.7875	3.65
West Michigan Whitecaps	0.5413	0.5613	156.4875	9.625

Research Question 2: For the Single-A MiLB teams with the highest and lowest number of page likes, what is the relationship between language accommodation measures (LSM, immediacy), and *likes* and/or number of comments? The primary investigator also sought to see the relationship between accommodation scores (LSM, Immediacy), and *likes* and/or number of comments. This analysis started with the Lumberkings. All model assumptions were met, and are available via email to the primary investigator.

First, a multiple linear regression was calculated to explore the relationship between LSM score versus *likes* and number of comments for the Lumberkings. The equation $\widehat{LSM}$= 0.4989 + 0.0003**Likes* + 0.0122*Comments was first used to see the relationship between LSM score from *likes* and number of comments. The full model produced a statistically significant result ($F(2, 77)= 4.462$, $p= 0.0147$) with an R^2 of 0.0806. In this full model, the slope coefficient for comments produced a statistically significant value from zero ($t(79)= 2.626$, $p= 0.0104$), but the slope coefficient from *likes* was not significant from zero ($t(79)= 0.603$, $p= 0.5486$). A reduced model was deemed beneficial by removing *likes* from the model as that value was insignificant. This way, the degrees of freedom would be reduced. This would more simply describe the relationship between LSM and number of comments without interference from the number of *likes* detected.

The reduced model equation is as follows:

$$\widehat{LSM} = 0.5049 \text{ (s.e.= 0.022)} + 0.0129 * \text{Comments (s.e.= 0.0044)}.$$

A significant result was detected (F(1, 78)= 8.631, *p*= 0.0043) with an R^2 of 0.09963. Appendix 6, Appendix Table 5, portrays the regression table for this final model. Although a significant result was detected, the real world implications were weak as detected by the low R^2 value. This finding suggested that for every additional comment on a post for the Lumberkings, there would be an increase of 0.0129 points for LSM scores. In this model, 9.963% of the variability in LSM is explained by the regression with comments. The model summary and coefficients table for model 5 are shown below.

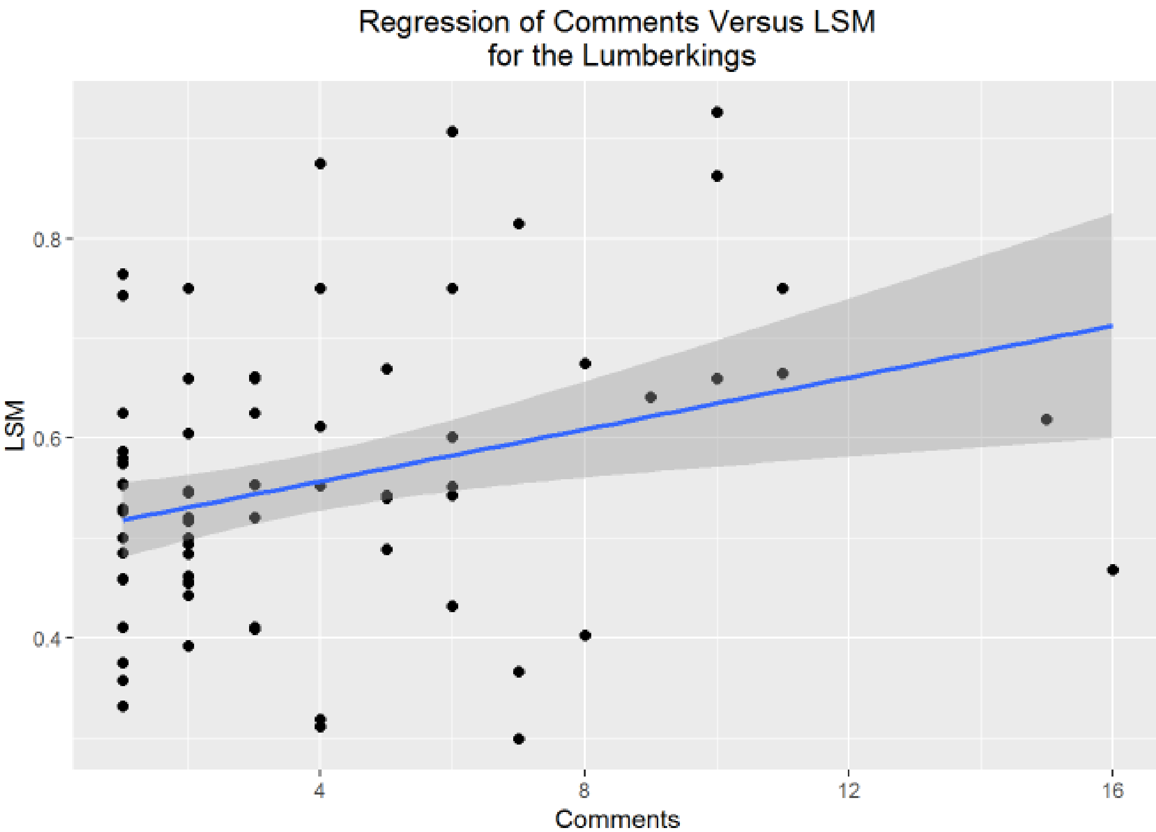
Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
5	0.31564	0.09963	0.08809	0.1315

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
5	(Constant)	0.504867	0.021826		23.132	$0.2e^{-15}$
	Comments	0.012981	0.004418	0.3156431	2.938	0.00434

The graph below illustrates these results.



Immediacy scores for the Lumberkings were then calculated. A multiple linear regression was calculated to explore the relationship between immediacy scores, and *likes* and number of comments. The equation $\widehat{Immediacy}$= 0.6211 + 0.0002**Likes* - 0.0035*Comments was first used to view the relationship between immediacy scores, and *likes* and number of comments. The full model did not produce a significant result (F(2, 77)= 0.1918, *p*= 0.8259, R^2= 0.0049), with neither the slope of the coefficient for *likes* (t(79)= 0.396, *p*= 0.396) or number of comments (t(79)= -0.571, *p*= 0.570). Thus, no relationship was detected between immediacy and the number of *likes* and number of comments a post received from the Lumberkings.

Next, regression models were used for the Whitecaps' dataset. A multiple linear regression model was used to determine the relationship between LSM, and *likes* and number of comments. The equation $\widehat{LSM}$= 0.4841 - 0.00002**Likes* + 0.0006*Comments was used to view the relationship between LSM, and *likes* and number of comments. The full model produced a significant result ($F(2, 77)= 10.37$, $p= 0.0001$, $R^2= 0.1917$) which suggested that one or both *likes* and/or number of comments had a significant relationship with LSM for the Whitecaps' Facebook posts. In this full model, the slope of the coefficient for *likes* ($t(79)= -0.257$, $p= 0.7979$) produced a non-significant result from zero, while number of comments ($t(79)= 3.074$, $p= 0.0029$) produced a significant result from zero. A simpler model was then used to examine the relationship between LSM and number of comments for the Whitecaps' Facebook posts.

The following simplified model equation was used to view the relationship between LSM and number of comments:

$$\widehat{LSM}= 0.4856 \text{ (s.e.= 0.0241)} + 0.0058\text{*Comments (s.e.= 0.0013)}$$

A significant result was detected ($F(1, 78)= 20.92$, $p= 0.00002$) with an R^2 of 0.2115. Appendix 6, Appendix Table 6 portrays the regression table for this final model. The number of comments that Facebook users leave on Whitecaps' Facebook posts seem to correspond to a higher LSM score. For every comment left on a post by the Whitecaps, the LSM score would increase by 0.0058 points. In this model, 21.15% of the variability in LSM was explained by the regression with comments. The model summary and coefficients table for model 6 are shown below.

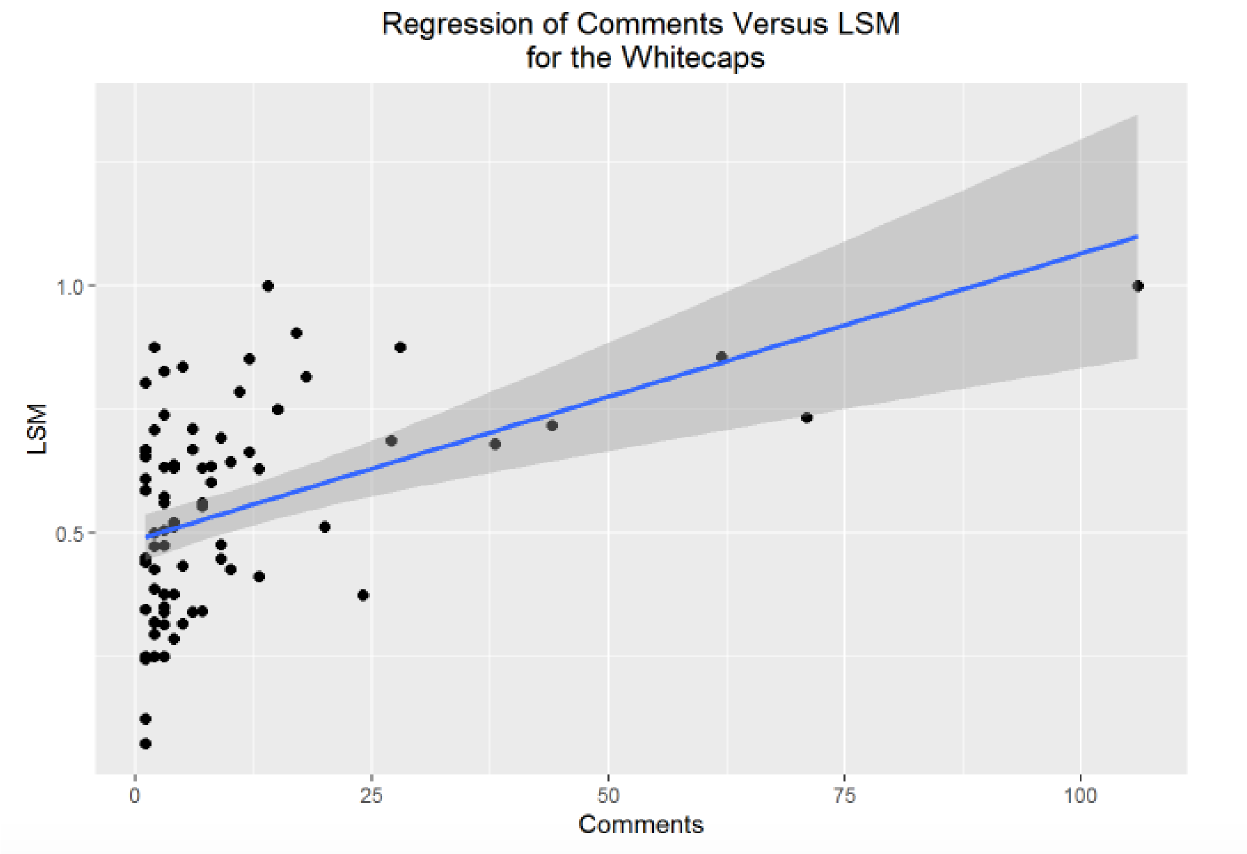
Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
6	0.45989	0.1861	0.2014	0.1861

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
6	(Constant)	0.485559	0.024117		20.133	$0.2e^{-15}$
	Comments	0.005794	0.001267	0.4598862	4.574	$1.77e^{-5}$

The graph below illustrates this relationship.



Next, a multiple linear regression model was used to determine the relationship between immediacy, and *likes* and number of comments for Facebook posts for the Whitecaps. The equation $\widehat{Immediacy}$= 0.5429 + 0.00002**Likes* + 0.0016*Comments was used to view the relationship between immediacy, and *likes* and number of comments. A non-significant result was detected ($F(2, 77)= 1.933$, $p= 0.1517$, $R^2= 0.0478$). The slope of the coefficient for *likes* produced non-significant results from zero ($t(79)= 0.353$, $p= 0.725$), as was the same for number of comments ($t(79)= 0.949$, $p= 0.345$). However, due to the p-value for *likes* being as high as it was, the primary investigator decided to examine the relationship between immediacy and number of comments in a simpler model.

The reduced model equation used to examine immediacy and number of comments is as follows:

$\widehat{Immediacy}$= 0.5413 (s.e.= 0.024) + 0.0021*Comments (s.e.= 0.0011).

A non-significant value was detected ($F(1, 78)$= 3.783, p= 0.0554, R^2= 0.0463) at the $\alpha < 0.05$ level. Appendix 6, Appendix Table 7, portrays the regression table for this final model. When interpreted at the $\alpha < 0.10$ level, these results suggested that every additional comment posted on a Whitecaps' Facebook post would lead to a 0.0021 point increase in immediacy scores. In this model, 4.63% of the variability in immediacy was explained by the regression with comments. The model summary and coefficients table for model 7 are shown below.

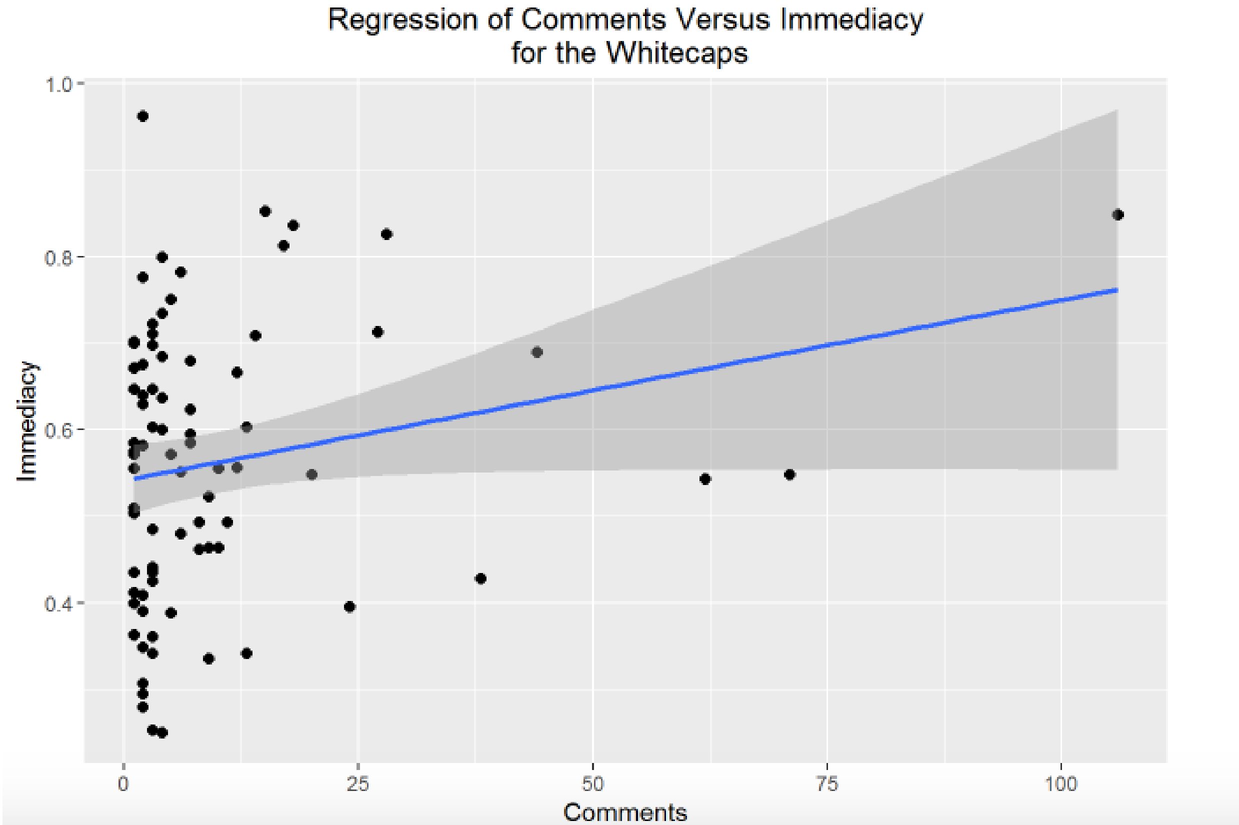
Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
7	0.2150814	0.04626	0.03403	0.1573

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
7	(Constant)	0.541256	0.020387		26.549	$0.2e^{-15}$
	Comments	0.002083	0.001071	0.2150707	1.945	0.0554

The graph below illustrates this relationship.



To recap the findings from Study B, number of comments was the only factor deemed significant when looking across accommodation measures between these two teams. Number of comments were not a significant factor when observing immediacy for the Clinton Lumberkings. These findings are represented in the table below.

Table 17

Significant Within-Team Factors

Team	LSM/Immediacy	Factor	Significance
Clinton Lumberkings	LSM	Number of Comments	*
West Michigan Whitecaps	LSM	Number of Comments	*
West Michigan Whitecaps	Immediacy	Number of Comments	**

Note: ** refers to findings that are significant at the $p < 0.10$ level, * refers to findings that are significant at the $p < 0.05$ level.

Post-Test: Study B

Following the initial analysis, the primary investigator wanted to observe if word count on Facebook posts originating from the MiLB franchise had any significant relationship with LSM and/or immediacy. One of the factors associated with CAT in determining the level of language convergence is utterance length, or the length of the phrase (Giles, Coupland, & Coupland, 1991). Thus, this factor was deemed important to test for its relationship in measuring accommodation measures, such as LSM and immediacy. This was completed for both the Lumberkings and the Whitecaps. Full models were made for this analysis, which also included *likes* and number of comments. In this manner, the primary investigator could see if word count had an effect on the accommodation measure given all factors included in this analysis. A third research question was added for Study B.

RQ 3: What is the relationship between accommodation scores (LSM, immediacy) and an organization's (Clinton Lumberkings, West Michigan Whitecaps) post's word count?

This analysis began with the Lumberkings LSM scores. When compared with word count, *likes*, and number of comments, the full model equation was $\widehat{LSM} = 0.5495 +$

0.0003*$Likes$ + 0.0106*Comments – 0.0014*Word Count. A significant interaction was found for the full model (F (3, 76)= 3.79, p=0.0137, R^2= 0.1301). with the only significant interaction coming by way of number of comments within the model (t(79)= 2.242, p= 0.0279). *Likes* (t(79)= 0.666, p= 0.5073) and word count (t(79)= -1.515, p= 0.1338) had non-significant results. The reduced model included word count again, $\widehat{LSM}$= 0.5551 + 0.0115*Comments – 0.0014*WordCount, which had a significant result for the full model (F(2, 77)= 5.503, p=0.0058, R^2= 0.1251), with number of comments producing a significant result (t(79)= 2.555, p=0.0126), while word count still produced a non-significant result (t(79)= -1.496, p= 0.1387). A reduced model was used to observe the relationship between number of comments and LSM for the Lumberkings. The following equation represented the final model:

$$\widehat{LSM} = 0.5049 \text{ (s.e.= 0.0218)} + 0.0129^{*}\text{Comments (s.e.= 0.0044)}$$

The full model produced a significant result (F(1, 78)= 8.631, p= 0.004, R^2= 0.0996). Appendix 6, Appendix Table 5 portrays the regression table for this final model. These results suggested that it was expected for every additional comment posted to a Facebook post for the Lumberkings than LSM scores would increase by 0.0129 points. Variability in LSM is explained by 9.96% of the regression with number of comments. The model summary and coefficients table for model 5 are shown below.

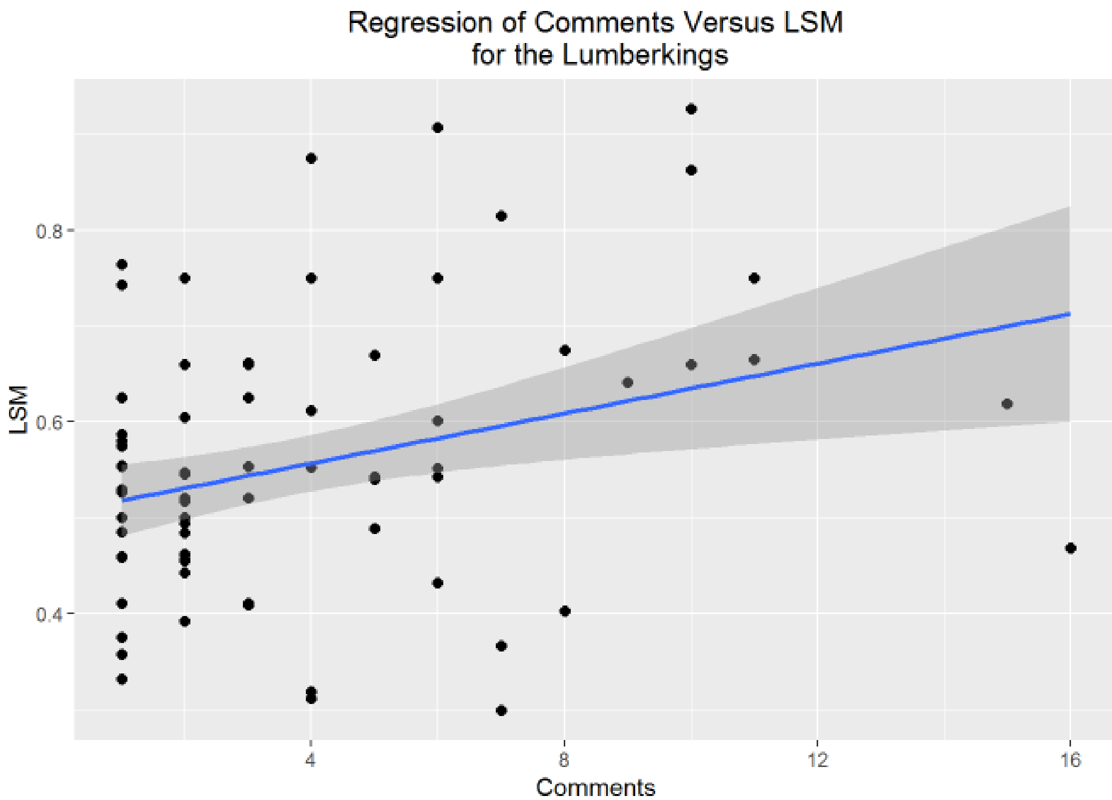
Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
5	0.31564	0.09963	0.08809	0.1315

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
5	(Constant)	0.504867	0.021826		23.132	$0.2e^{-15}$
	Comments	0.012981	0.004418	0.3156431	2.938	0.00434

Below is a graph that shows these results.



Next, immediacy scores for the Lumberkings were analyzed with word count, *likes*, and number of comments. The equation $\widehat{Immediacy}$= 0.6119 + 0.0002*$Likes$ – 0.0032*Comments + 0.0003*WordCount was used, but did not produce a significant result (F(3, 76)= 0.1407, *p*= 0.9353, R^2= 0.0055). Thus, no individual factors seemed to affect the final score for immediacy for the Lumberkings' Facebook posts.

The Whitecaps were then analyzed. First, LSM was measured through a multiple regression model, with *likes*, number of comments, and word count as factors. The full model equation $\widehat{LSM}$= 0.4614 – 0.00001*$Likes$ + 0.0063*Comments + 0.0009*WordCount produced a significant result (F(3, 76)= 6.899, *p*=0.0004, R^2= 0.214). Individually, number of comments (t(79)= 3.087, *p*= 0.00282) came back with a significant finding, while *likes* (t(79)= -0.234, *p*=

0.8154) and word count (t(79)= 0.424, *p*= 0.6728) came back with non-significant results. A reduced model was used to further explore the relationship between LSM, number of comments and word count. The equation $\widehat{LSM}$= 0.4621 + 0.0059*Comments + 0.0009*WordCount produced a significant result for the model (F(2, 77)= 10.45, *p*= 0.00009, R^2= 0.2135). Again, number of comments was a significant factor (t(79)= 4.509, *p*= 0.00002), while word count produced a non-significant result (t(79)= 0.439, *p*= 0.662). This model was again reduced to include only number of comments. The following final model equation was used:

$$\widehat{LSM} = 0.4856 \text{ (s.e.= 0.0241)} + 0.0058\text{*Comments (s.e.= 0.0013)}$$

The final model produced a significant result (F(1, 78)= 20.92, *p*=0.00002, R^2= 0.2115). Appendix 6, Appendix Table 6 portrays the regression table for this final model. For every additional comment for a Whitecaps' post, we would expect to see a 0.0058 point increase in LSM scores. In this model, 21.15% of the variance is explained by the regression with number of comments. The model summary and coefficients table for model 6 are shown below.

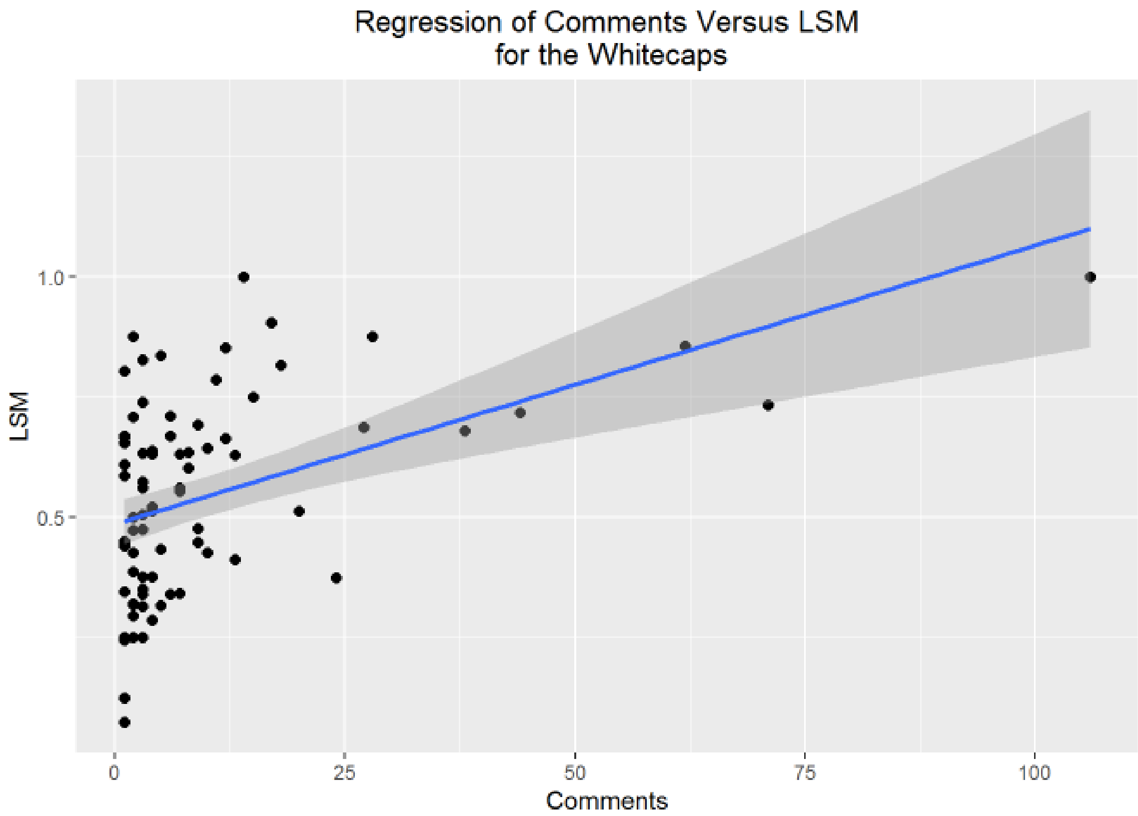
Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
6	0.45989	0.1861	0.2014	0.1861

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
6	(Constant)	0.485559	0.024117		20.133	$0.2e^{-15}$
	Comments	0.005794	0.001267	0.4598862	4.574	$1.77e^{-5}$

The graph below portrays this relationship.



Next, immediacy was used in a regression model with *likes*, number of comments, and word count. The equation $\widehat{Immediacy}$= 0.5451 + 0.00002**Likes* + 0.0016*Comments – 0.00009*WordCount produced a non-significant result (F(3, 76)= 1.272, p=0.2899, R^2=0.0478). No factors produced significant results. This model was reduced to include *likes* and number of comments, by the equation $\widehat{Immediacy}$= 0.5429 + 0.00002**Likes* + 0.0016*Comments again produced a non-significant result (F(2, 77)= 1.933, p= 0.1517, R^2= 0.0478). *Likes* (t(79)= 0.353, p= 0.725) and number of comments (t(79)= 0.949, p= 0.345) were found to be non-significant. The model was again reduced to only include immediacy and number of comments. The following equation represents the final model:

$$\widehat{Immediacy} = 0.5413 \text{ (s.e.= 0.0204)} + 0.0021 * \text{Comments (s.e.= 0.0011)}$$

The final model produced a significant finding at the $\alpha < 0.10$ level ($F(1, 78)= 3.783$, $p= 0.0554$, $R^2= 0.0463$), with comments being a significant factor ($t(79)= 1.945$, $p= 0.0554$). Appendix 6, Appendix Table 7, portrays the regression table for this final model. Thus, for every additional comment on a Whitecaps' Facebook post, it was expected that there would be a 0.0554 point increase in that post's immediacy score. In this model, 4.63% of the variability in immediacy was explained by the regression with comments. The model summary and coefficients table for model 7 are shown below.

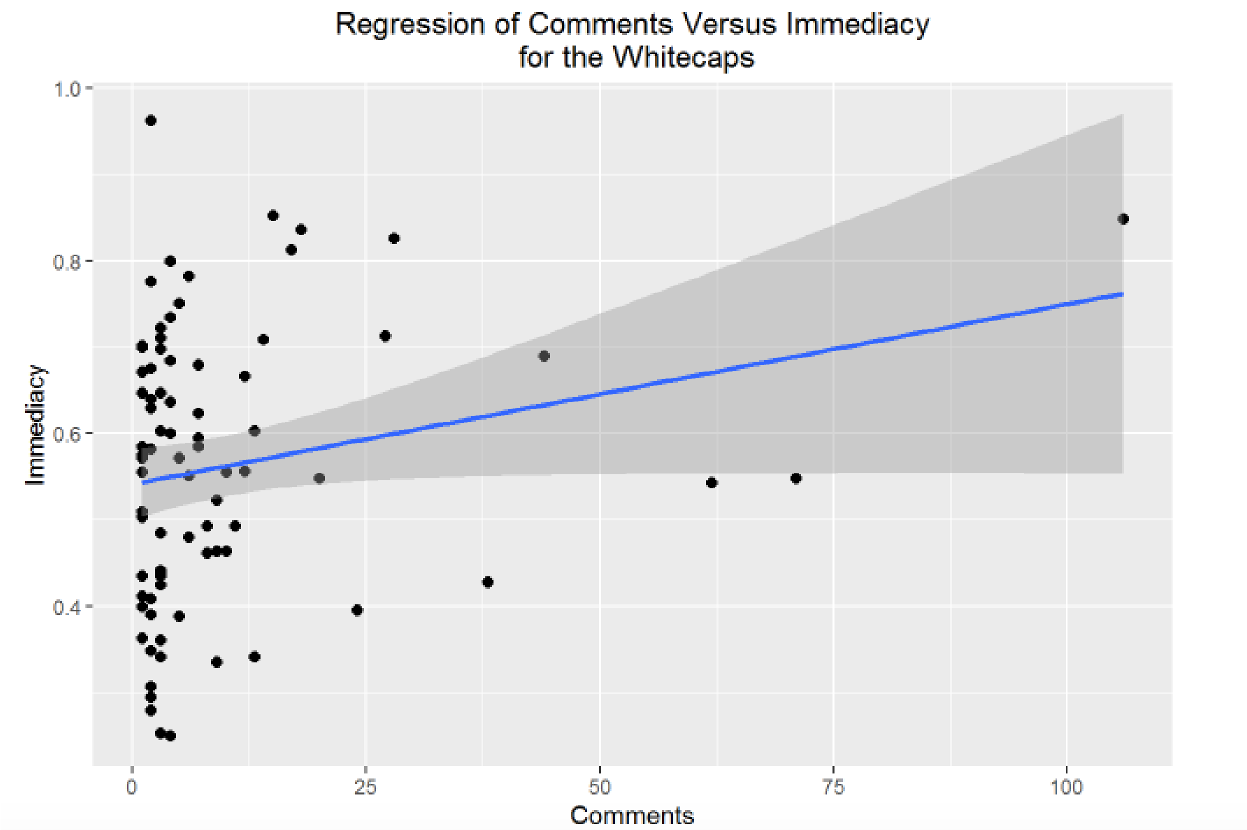
Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
7	0.2150814	0.04626	0.03403	0.1573

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
7	(Constant)	0.541256	0.020387		26.549	$0.2e^{-15}$
	Comments	0.002083	0.001071	0.2150707	1.945	0.0554

The graph below illustrates this finding.



Word count had no significant results with LSM or immediacy with either team's dataset throughout this analysis. Number of comments had significant results with both teams, while *likes* was significant when looking at LSM for the Whitecaps.

CHAPTER 5

DISCUSSION

General Discussion

The studies in this dissertation examined elements of communication accommodation theory (linguistic style matching and immediacy) in a social media and sport setting. These studies were the first to use the Language Inquiry and Word Count (LIWC) software in a Facebook setting, particularly in sports. Further, these studies were the first to solely examine Single-A Minor League Baseball teams on Facebook. Through the use of statistical analysis, these two studies explored the relationships between accommodation measures (linguistic style matching, immediacy), traditional Facebook metrics (*likes*, number of comments), posting types to an MiLB Facebook page (neoliberal, social, team related), and word count of a Facebook post. When significant results were detected, they did not fully explain the whole relationship between social media posts and their traditional metrics. These results were unexpected given previous literature on CAT; however, these findings could be a part of a bigger picture when evaluating social media posting strategies.

Study A examined the relationship between accommodation measures, traditional Facebook metrics, and posting types. The first research question asked what levels of accommodation exist between user-generated comments and posting types. Overall, the Columbia Fireflies had the highest overall score for linguistic style matching (0.5423) while the Charleston Riverdogs had the highest overall immediacy score (0.5663) of the three teams observed. Tamburrini, Cinnirella, Jansen, and Bryden (2015) suggested that, in a social media setting (Twitter), individuals would converge their language styles to that of a group they associate with. The greater the language style convergence, the more highly identified the groups' members were with the group itself. The LSM findings in Study A both affirm and contradict the findings of Tamburrini, Cinnirella, Jansen, and Bryden. Overall, the Fireflies had the highest LSM score, the highest number of *likes* per analyzed post (119.1556), as well as the highest number of *likes* in the overall data set (76.8809), when compared to the Charleston Riverdogs (37.4333, 23.7055) and the Greenville Drive (60.1, 29.2193). However, the Fireflies had the fewest page likes (18,703), and average game attendance totals (3,785 attendees per game) when compared with the Charleston Riverdogs (44,656 page likes, 4,311 attendees per game) and the Greenville Drive (38,767 page likes, 4,810 attendees per game). The later finding echoes the recommendation of Williams, Heiser, and Chinn (2012) in that a more active Facebook audience for MiLB teams may only be posting for personal gains, and not necessarily to portray fandom. These authors suggested that Facebook lurkers, or individuals who consume content by an organization without producing original content of their own, were more highly identified fans of an MiLB team. Thus, it could be that the Columbia Fireflies market has a high number of individuals who want to be associated with the hype of a new MiLB team, but may not want to commit to being a highly identified fan within the Fireflies' first season of playing. Furthermore, it is difficult to measure the amount of *likes* that a post will receive by the LSM score, and vice versa. This suggestion further stemmed from the regression results, described in the subsequent research questions.

The second research question asked what the relationship was between posting type, language accommodation measures, and traditional Facebook metrics. This analysis was performed across all posts from all teams included in this study. LSM and *likes* per Facebook post were the only significant results across all possible combinations, meaning that posting type and number of comments did not have significant interactions with LSM and/or immediacy. Although a significant interaction was found, the effect on the LSM score was very low (0.0003). In other words, for every *like* on a Facebook post, the LSM score would increase by 0.0003 points. Although previous research suggested that higher levels of LSM would lead towards conversation participants having positive feelings towards the conversation itself (Giles, 2008; Ireland, 2011), this doesn't necessarily translate into a person clicking on the *like* button in a Facebook mediated setting on a particular Facebook post. This finding somewhat supports the assertions by Burgoon, Dillman, & Stern (1995) in that conversations cannot fully be broken down to a state where they can be micro-analyzed. There are many complexities when breaking down a conversation that are unaccounted for. Other factors are involved in having a Facebook user *like* a post. Wakefield and Wakefield (2016) found that excitement alone was not a predictor of whether fans would engage in social media during a sporting event (i.e., NASCAR). Thus, a Facebook mediated conversation won't necessarily lead to more *likes* solely because a conversation has a high LSM and/or immediacy score.

The third research question asked how each individual team's accommodation scores interacted with posting types and traditional Facebook metrics. Team related posts, social posts, *likes* per post, and number of comments per post were found as significant factors on various teams when observing the relationship with LSM. Immediacy did not have any significant interaction with any factor for any team. Team related posts, or posts that discuss the personnel involved within the MiLB teams, trades, game recaps, etc., were a significant factor for both the Riverdogs and the Drive. For these teams, this finding would suggest that individuals would want to engage in a deeper conversation about the team related posts (Giles, 2008). The first principle of CAT suggested that individuals will accommodate their language gradually to those they are having a conversation with to form a stronger bond. The relationship between team related posts and LSM was positively correlated for the Drive, although the factors had very little actual effect on each other. This suggested that there would need to be a high number of comments posted from users to the organization’s post for there to be a noticeable increase in LSM scores. This could mean that, similar to the findings in the second research question, other factors may be involved in determining why individuals post to Facebook, or in this instance, post a comment in a more converging way. These conversations were highly complex (Burgoon, Dillman, & Stern, 1995). Further, the LSM and immediacy scores gathered from this analysis were not highly predictive of traditional Facebook metrics. This finding means that other factors are present when attempting to predict a post’s success, be that from an accommodation perspective or a traditional Facebook metrics’ perspective.

The first research question in Study B asked what levels of language accommodation exist between Single-A MiLB teams with the highest and lowest levels of page likes. For both LSM and immediacy, the Clinton Lumberkings had a higher average score than the West Michigan Whitecaps. This may be explained by the power structures that reside in both the areas of Clinton, Iowa, and Grand Rapids, Michigan. When comparing the two locations, Grand Rapids is a larger population (195,097 people) than Clinton (47,768 people). In Grand Rapids, the infrastructure has grown alongside of the location’s population, as the city offers tours, nightlife, recreational activities, and is touted as “Beer City, USA” (Experience Grand Rapids, n.d.). Clinton is more of a rural setting, as their main attractions are based on outdoor activities, such as hiking, fishing, and recreation (Visit Clinton Iowa, n.d.). In other words, the LumberKings have an advantage in their market as they have much less competition than Grand Rapids, although the Whitecaps have a bigger audience to draw from. This dynamic may explain why Clinton had higher totals for LSM and immediacy than West Michigan. Individuals have been known to converge their language structure to that of authority figures (Liao, Bazarova, & Yuan, 2016; Riordan, Markman, & Stewart, 2012). These findings suggest that in a small community, such as Clinton, Iowa, Minor League Sports may have a greater influence due to less competition and greater power over their community than those in larger markets, such as West Michigan. Further exploration is needed, but preliminary evidence based on this study and previous findings suggested that the LumberKings are seen as having a greater amount of power in their community than the Whitecaps.

The second research question asked what the relationship was between traditional Facebook metrics and accommodations measures. Number of comments and LSM scores were significant factors for both the Clinton LumberKings and the West Michigan Whitecaps, while number of comments was a significant factor in determining immediacy scores for the Whitecaps. These findings further those of Giles, Coupland, and Coupland (1991), that suggested language convergence may happen in terms of information density and expression of opinions. In other words, the more Facebook users' comments converge upon the organization's original post in terms of linguistic style matching, the more comments a social media manager would expect to see for that particular post. It should be noted that this finding has a very minimal effect, meaning that high LSM scores may only lead to one or two more comments for posts that already have a large amount of comments. These findings act as preliminary evidence that in a Facebook setting, linguistic style matching, can lead to a greater number of comments.

The post analysis inquiry, presented as the third research question in Chapter 4, asked if there was a relationship between accommodation scores and the word count of posts by MiLB organizations. Although word count was never a significant factor in either observation, the finding was significant to CAT literature. Word count was never identified as a significant factor in this analysis. This finding was surprising as utterance length, or the number of words spoken by a conversation participant, was identified as a factor within language convergence (Giles, Coupland, & Coupland, 1991). This finding may have been caused by a small sample size for each of the multiple regression models, but this phenomenon should be explored in other mediated communication settings. Another explanation may be that texts presented on online mediums are expected to have short passages, coming either from the interlocutor or subsequent comments.

Theoretical Implications

LSM and immediacy, as measures within the communication accommodation theory, may not have been the most effective avenue for measuring traditional Facebook metrics. Investigators are still attempting to tease out extraneous factors involved within the development of CAT as the theory has had many theoretical revisions since its inception (Galois, Ogay, & Giles, 2005). Other theories, such as social identity theory, may be used to help explain the relationship between Facebook conversations and traditional Facebook metrics. For example, measures of fan identification may further explain the relationship in Facebook post interactions, and their effect on traditional Facebook metrics. It should be noted that studies have had positive outcomes when measuring CAT in a mediated setting against a task. Yilmaz (2016) found that higher LSM totals were an indicator of team success when they were faced with a task (deciding how to deal with bribery). Specifically, teams that matched well on LSM totals were more successful in accomplishing the task. The studies presented in this dissertation add to CAT literature in an online setting as these observations were not a controlled experiment, as seen in Yimaz (2016), but were observations in the actual mediated setting. Further, these studies looked at CAT within the setting of Facebook, which showed that Facebook can be used as a medium for future academic inquiry. Although LSM and immediacy were not seen as effective in measuring the relationship between the organization’s posts, comments, and traditional Facebook metrics, these studies have shown how CAT can quantitatively be examined. Quantitative explorations in CAT can help reveal power structures within a community (Liao, Bazarova, & Yuan, 2016) through measuring immediacy and LSM scores. Further, if higher levels of language accommodation represent interest by all parties in a conversation (Giles, 2008), then organizations on Facebook may use accommodation measures to gauge audience response to a number of posts. Although accommodation measures have little effect on traditional Facebook metrics, the organization may benefit by understanding their online fanbase more in-depth. While CAT may not have been effective in predicting traditional Facebook metrics, there are other ways that CAT can be examined in a social media setting (see Goode & Robinson, 2013; Noble & Fernandez, 2015; Nguyen, Trieschnigg, & Cornips, 2015; Pavalanathan & Eisenstein, 2015; Tamburrini, Cinnirella, Jansen, & Bryden, 2015). By continuing to quantitatively examine CAT measurements in different settings, researchers can refine the theory and its measures.

Other studies have used CAT in mediated settings (Danescu-Niculescu-Mizil, Gamon, & Dumais, 2011; Goode & Robinson, 2013; He et al., 2016; Ludwig et al. 2013; Pavalanathan & Eisenstein 2015; Nguyen, Trieschnigg, & Cornips 2015; Tamburrini, Cinnirella, Jansen, & Bryden, 2015). These studies used CAT in a different way than was used for the studies in this dissertation. While these studies observed what was being said, the studies presented in this dissertation went a step further and assessed the effectiveness of measures within CAT (LSM, immediacy). Not only were interactions observed in a mediated setting, but they were assessed for their relationship with traditional Facebook metrics.

These studies were the first known attempt within CAT literature to apply accommodation measures, such as LSM and immediacy, to a sport in social media setting. Other studies have observed interactions surrounding television dramas on blogs (Goode & Robinson, 2013), geographically similar groups on Twitter (Pavalanathan & Eisenstein, 2015), interactions between various Dutch dialects on Twitter (Nguyen, Trieschnigg, & Cornips, 2015), group identity on Twitter (Tamburrini, Cinnirella, Jansen, & Bryden, 2015), and Wikipedia (Noble & Fernandez, 2015). These studies built on the works of Goode and Robinson (2013) by using LSM and immediacy measures. The studies presented here showed how researchers could use LSM and immediacy scores in regression models to determine their effect on other metrics. Furthermore, the studies presented here observed geographically similar teams (Pavalanathan & Eisenstein, 2015), and found that not only were their LSM scores different but the organizations' posting strategies were different. For example, the Columbia Fireflies would post about their employees, while the Charleston Riverdogs would post in creative ways to incorporate sponsors and sell products. Similar to Nguyen, Trieschnigg, and Cornips (2015), these studies found that local institutions from the community were discussed, as well as local events (particularly discussions based around the MiLB team or their sponsors). Posts from all of the observed teams helped to build the identity of the team (Tamburrini, Cinnirella, Jansen, & Bryden, 2015) through showing images from games or events, team artifacts, and showcasing various aspects of the organization. While other examinations have been performed on mediums such as Blogs (Goode & Robinson, 2013), Twiter (Nguyen, Trieschnigg, & Cornips, 2015; Pavalanathan & Eisenstein, 2015; Tamburrini, Cinnirella, Jansen, & Bryden, 2015), and Wikipedia (Noble & Fernandez, 2015), the studies in this dissertation examined CAT within the context of Facebook. This is significant as studies involving CAT on social media tend to revolve around sites such as Twitter. These studies expanded the reach of CAT, and showed that this theory can be applied to Facebook as well. These studies showed that LSM and immediacy scores could be used in regression, ANOVA, and ANCOVA methodologies. Quantitative research has been limited in

CAT research to date, but these studies showed how accommodation measures can be quantitatively analyzed. In short, these studies show that CAT can be applied to a greater variety of mediated settings while also using a variety of methodologies. Researchers should continue to use this theory in different settings.

These studies built on the work of Williams, Heiser, & Chinn (2012) by researching social media usage in Minor League Baseball. While these authors employed a survey methodology at MiLB games, the studies in this dissertation examined MiLB teams on Facebook while exploring the relationship between accommodation measures and traditional Facebook metrics. Study A showed that the MiLB teams selected for analysis posted in neoliberal, social, and team related ways during the regular season and offseason. MiLB franchises are staples in small communities across the United States as shown by over 38 million fans attending games across the league on an annual basis (Knight, n.d.). Areas such as the history of the MiLB (Land, Davis, & Blau, 1994), MiLB sustainability (Agha & Rhoads, 2016), attendance predictors (Gitter & Rhoads, 2010), promotions (Howell, Klenosky, & McEvoy, 2015; Paul & Weinbach, 2013), community relations (Lachowetz, Dees, Todd, & Ryan, 2009), and franchise naming (Dwyer, Le Crom, Tomasini, & Smith, 2011) have all been observed in the context of Minor League Baseball. With the limited marketing budget of MiLB franchises, social media activities are sometimes the only way a team can promote upcoming games and events. This provides social media researchers plenty of opportunities for observation and understanding of how Minor League Sports franchises communicate online. Social media researchers need to continue to observe Minor League Baseball through various mediums as these teams serve as entertainment hubs for hundreds of cities across North America.

These studies were the first to explore CAT within the context of social media in sport. Minor League Baseball has not been examined solely in a social media in sport setting to date, yet these examinations have shed light on the prominence of MiLB franchises in their community. Study B found preliminary evidence that MiLB franchises may have more community-based power in a smaller community than a larger community. Previous research suggested that communication accommodation theory could be used to identify power structures (see Liao, Bazarova, & Yuan, 2016; Riordan, Markman, & Stewart, 2012). The differences in LSM and immediacy scores between the West Michigan Whitecaps and the Clinton LumberKings suggested that the smaller market MiLB team (Clinton, Iowa) may have a greater influence over their local community than the West Michigan Whitecaps. As discussed previously, this may be due to the limited local entertainment competition in the Clinton area, whereas the Whitecaps have a lot more entertainment competition in the surrounding Grand Rapids area. The LSM and immediacy scores for the LumberKings were higher, which implied that the community was more likely to be influenced by the entity (Liao, Bazarova, & Yuan, 2016; Riordan, Markman, & Stewart, 2012). While the studies in this dissertation focused on sport organizations' use of Facebook as opposed to athletes' use of Twitter, there were instances where a small-scale issues would occur. For example, rain delays or bad weather could jeopardize an MiLB franchise from hosting a game, and thus they would miss out on a revenue stream. While Sanderson (2010) found that Facebook was used for athletes to counteract negative press, the studies in this dissertation revealed that the sport organization would also face, and resolve, negative issues through the Facebook. In response to the potential loss in revenue, some teams in this analysis would simply acknowledged the game cancellation, and its impact on scheduling while other posts instructed users on how ticket holders could redeem ticket vouchers for future games. In this scenario, organizations were able to use Facebook to handle negative issues such as game cancellations on Facebook through information dissemination. Thus, MiLB teams used Facebook to minimize their revenue losses for game cancellations due to weather. Teams did this by advertising the makeup game and allowing patrons to return to a future game (where the organization could sell concessions and/or merchandise to them). Although rained out games are understandable, these MiLB teams were able to offer customers an opportunity to come to a future game. These posts could state the make-up game time as well. Next, these studies revealed that MiLB franchises are using Facebook to disseminate plenty of information about their club, upcoming events, and the inner workings of their organization. This finding suggested that sports organizations were starting to use social media platforms to disseminate important information more frequently than the findings of Waters, Burke, Jackson, and Buning (2011). Teams in this analysis would show more of the inner workings of their organization through Facebook than the authors in the previous study suggested organizations would. This could mean that teams are becoming comfortable with using Facebook to convey important messages. Another explanation could be that the differences between MiLB and the NFL (the medium observed by the authors) would allow for the MiLB to be more inclusive to the social media community. MiLB franchises are not as popular as NFL franchises, and thus allowing the community to have more access to the inner workings of the franchise may be a way that MiLB franchises can increase, or retain, their fanbase. Allowing social media fans a behind the scenes look within an organization echoes the recommendations of Thompson, Martin, Gee, and Eagleman (2014) as they suggested sports organizations should have promotional strategies to give social media users insights into their organization.

Study A found that MiLB teams utilized the suggestions of O'Hallarn, Morehead, and Pribesh (2016). These authors suggested that organizations should follow the acronym STEAM, which stands for steal (or learn from other organizations' posts), team (post team updates, along with ticket sales updates), engagement (engaging with the fan base), analytics (use software to measure post effectiveness), and mavens (recruiting highly identified fans that can spread the word about an organization on social media). Study A suggested that teams were posting team related posts, engaging fans through social posts, and in some instances, using mavens. The Charleston Riverdogs are partially owned by actor and comedian Bill Murray, whom they used in some of their posts. Not every market will have a highly identifiable representative, but all teams should attempt to include prominent community members to aid in their social media campaigns.

Practical Implications

The primary investigator noticed a lack of second-screen experience posts throughout the analysis. Second-screen experiences are defined as "…a second electronic device used by audience members while watching a television program" (Cunningham & Eastin, 2015, p. 1). Second-screen experiences have become an additional staple to some shows, such as AMC's The Walking Dead. MLB-TV offers an extension for their package where consumers can watch any broadcasted MiLB game. Games can be broadcasted regionally while many television or internet broadcasts are handled by the MiLB team in-house. The primary investigator for these studies used to work on broadcast productions for the Greenville Drive, and although games were not usually broadcasted regionally, all games would be broadcasted through MLB-TV. Broadcasters should be aware of the second-screen experience and mimic second-screen experiences that their MLB counterparts are already partaking in. Graphics packages should include in-game hashtags so fans can interact with others and broadcasters during the game. Selfies taken with said hashtags could be featured in the broadcast through these graphics packages, which could also be sponsored; thus leading to more revenue for the MiLB team.

Interactions that are similar to second-screen experiences can be seen at sporting events as administrators will attempt to engage with their audience through mediated settings. These experiences, referred to here as first-screen experiences, can be defined as computer-mediated interactions revolving around and occurring during a real-life event, such as a baseball game. First-screen experiences may be a game hashtag, selfie postings, or other in-game tie-ins, that encourage spectators to engage via an online setting. These experiences add another element to sporting events. Most first-screen experiences in sports that occur during games, are “Tweet Your Seat” or “Selfie Shares”, where users post photos of their seats with some type of hashtag (Newman, Peck, Harris, & Wilhide, 2013). Organizations should attempt to further their customers’ first-screen experiences as consumers have been found to have a better perception of the team if they follow the team on social media while at a game (Walsh, Clavio, Lovell, & Blaszka, 2013). These first-screen experiences should occur on various mediums in various ways. For example, the “Tweet Your Seat” or similar posts should be contained to Twitter or Instagram, while longer, more in-depth posts could be contained to Facebook. The host organization should announce these contests over the PA system.

One way to enhance users first-screen experience at sporting events could be through a season long Facebook promotion, referred here as “item finds.” First, all home games would be used for this promotion. Next, sport administrators would place an item, highly identifiable with the sponsor for this promotion, in a location accessible to all patrons in a different spot per game. Administrators should ensure that this item cannot easily be moved after hiding it. Patrons participating in this promotion would need to take a selfie with said object, post the selfie to Facebook, and tag both the sponsor and the MiLB franchise. The user's post should also have the location of the upload to ensure users are not photoshopping themselves onto one night's item find. At the end of the season, prizes should be given for the patron who posted the most successful item finds, the most creative item finds, and the most in-depth video posts on how patrons found the item. In this manner, the MiLB organization will add another level of interest for patrons to attend games, as well as involve patrons with a sponsor in creative ways. For example, one of the Greenville Drive's current partners, Hubbell Lighting, may be a suitable fit for the item find. The item itself could be a green lightbulb, which would portray a connection to Greenville. This item would also be unique and easy to identify, but still could be hard to find as much of the Drive's stadium is green. PA reads could occur during pregame and an inning break early in the baseball game. A bottom of the eighth inning PA read could be used to encourage fans to participate next game. This read should also include the end of the year prizes. This PA could be accompanied by a graphic displayed on the organization's scoreboard with the Facebook post that found the item first. Finally, the most creative posts could be revisited throughout the offseason as a sponsor based throw back Thursday promotion.

Teams should actively investigate and use other franchises' in-game first-screen experiences through research on the competition's social media outlets (O'Hallarn, Morehead, & Pribesh, 2016). This principle also applies for general social media practices. Borrowing social media strategies from other teams can also be applied towards sponsorship posts (neoliberal posts), player updates as former players may move up or down in a farm system (team related posts), and survey posts surrounding game experiences (social posts).

The next significant finding was derived from the coding of all Facebook posts in Study A. When coding for social posts, one indicator included the use of team artifacts to create a conversation. Again, social posts were posts that attempted to garner a response from a team's Facebook audience. Many social posts incorporated the use of team artifacts, or objects related to the team. These could include structures, art, the field, scoreboards, scorecards, or any item that was related to the team. In the analysis, most of the artifact posts contributed by the Columbia Fireflies were brand new. These artifacts can be a rallying-point for users so long as the interpretation is guided (Dougherty, Kramer, Klatzke, & Rogers, 2009). When artifact type posts were used explanation of the artifact helped the organization's social media viewers interpret the post. Most of these posts may be straightforward but they could be taken the wrong way. For example, a post that depicts a stadium expansion for more seating may be taken as positive or negative. If an MiLB team expanded their stadium and posted pictures of said expansion, this may be interpreted as a misuse of taxpayer dollars if the team has not paid off their debts or was having an issue in repaying their debts. An explanation can be used with the post to guide users in their interpretation. If framed correctly, social posts that include team artifacts can enhance an MiLB team's social media presence.

One addition to the STEAM model for Minor League Baseball would be the incorporation of sponsors into the strategy. Many teams already include their sponsors into social media posts as part of their sponsorship agreement, but some teams don't incorporate sponsors in a creative way. For example, the Greenville Drive host a "Gabriel Builders Quality Start" to highlight outstanding pitching performances. These posts give an overview of the player's performance, followed by a paragraph description of Gabriel Builders, and a photo. Although this post mentions a business in the Greenville area and incorporates the on-field performance of a key player, there aren't any aspects of interactivity. These posts lend themselves to responses such as "Great game Drive! Keep it up ____________!" or "Let's Go Drive!" Sponsor posts should allow a variety of responses and entice different Facebook users to contribute. For example, the Gabriel Builders sponsorship could be altered to an interactive post such as "Kyle Hart takes the mound tonight against Delmarva! Tell us how many innings, strikeouts, and hits Hart allows tonight for a chance to win a home makeover after the regular season, compliments of Gabriel Builders!" The makeover prize should be negotiated, but with this combination, the Drive could plug-in Gabriel Builders every home game. This should lead users to be more engaged with the sponsor throughout the season.

One of the strategies employed by the Columbia Fireflies during this analysis was using Facebook to introduce their fans to employees within their organization. Fans of the Fireflies, or their MLB affiliate New York Mets, may know of some of the players that were playing in Columbia; however, in Minor League Baseball players can come and go frequently. Thus, the Fireflies introducing their staff through Facebook gave fans a more in-depth understanding of the inner-workings of the Fireflies organization. The organization recognized its employees for their efforts and hard work in a positive manner, thus investing in them. This strategy should be employed by all sports organizations, especially with the ticketing department. Giving the ticket department a more human element than an over-the-phone voice persona can create a personal connection which may lead to greater customer service reviews, and potentially greater ticket sales revenue. Front line employees, such as ticket takers, concessionaires, merchandise sales employees, and ushers should also be introduced to the community through social media so that customers can have a greater connection with the employees they would most likely come in contact with. In short, sports organizations that invest in their employees through posts to social media will empower their employees, and provide greater context for their customers on the employees that serve them.

The last practical implication worth noting involved the timing of each organizations' posts throughout the year. The time plots presented before the individual results sections suggest that MiLB organizations are posting with greater frequency during the season that the offseason. This would make sense, as many social media managers either relocate to different jobs or take time off from work during the offseason. The primary investigator noticed that the most successful team in terms of page likes was West Michigan Whitecaps, an organization that kept their audience engaged during the offseason by posting throughout the offseason. MiLB teams can benefit from posting during the offseason, including the major holidays and posts such as throw back Thursdays. Posting on social media during the offseason can further engage a fan base (Thompson, Martin, Gee, & Eagleman, 2014). Posts during the offseason can include updates on alumni players, other farm teams or the MLB team associated with the MiLB team, or community events. Social media managers should take advantage of this time as a means of community engagement and interactivity.

Social media managers should continue to focus on monetizing social media through sponsorships and clicks off of their Facebook page (Parganas & Anagnostopoulos, 2015). A cohesive social media strategy should begin with creative posts for sponsors. Next, organizations should post throughout the year (Thompson, Martin, Gee, & Eagleman, 2014) to keep their social media fanbase engaged. Additionally, social media managers should consider creating graphics for a second-screen experience for online broadcasts that brings social media users into the broadcast conversation. This social media strategy should work to incorporate first-screen strategies to further engage fans attending games. Next, posts that discuss artifacts should include a description from the MiLB organization (Dougherty, Kramer, Klatzke, & Rogers, 2009). Last, MiLB social media managers should continually research and improve social media posts through analyzing current posts from other teams (even across other sports). If social media managers keep these suggestions in mind, they may be able to increase their overall reach, and potentially bolster their team's bottom line.

Directions for Future Research

Moving forward, scholars can research various aspects when studying social media in sport within CAT. First, researchers can measure how LSM and immediacy scores may change throughout the season against a team's win-loss record at the time. This could be done with a specific number of teams as a longitudinal study. Gitter and Rhoads (2010) suggested that a Minor League Baseball team's record will influence attendance figures. Will this hold true for communication accommodation on social media? Further, CAT on social media can be used as a means of identifying power structures of organizations within a community. Facebook posts can be gathered from businesses and/or sports teams in an area during a certain period of time. LSM and immediacy totals should be compared across all businesses, while accounting for the profit margins, number of employees, and lifetime in the community when calculating this effect. Social media management tools need to be used by social media managers to continue to grow a social media campaign's reach (Benthaus, Risius, & Beck, 2016; Funk, 2013; O'Hallarn, Morehead, & Pribesh, 2016). Current social media management and analytics tools also need to include an audience response variable outside of traditional social media metrics (such as *likes*, retweets, favorites). In other words, a more qualitative approach should be taken when analyzing audience responses. Academic investigators can help in this process by using various measures to see their effect between a post's responses and traditional social media metrics. The studies in this dissertation began this process by looking at two measures of communication accommodation: linguistic style matching and immediacy. Further, posting type and word count were also examined. These pieces begin to tell a small portion of the overall model that should be used to analyze social media. Measures found within different theories should also be used to explain responses to a post and how well the post performs. In this manner, social media managers could tailor their posts to their target audiences. Measures within other theories, such as social identity theory, parasocial interaction, and figurational theory, may better explain how responses to a Facebook post may affect the number of *likes* for said post. Finally, researchers may want to investigate the relationship between the time of a Facebook post and the accommodation scores for MiLB teams. Are accommodation scores higher on weekends as opposed to weekdays? This inquiry could be taken a step further as actual attendance figures per game could be compared with accommodation scores, as well as variables such as time and day. Other variables, such as promotions and fireworks, would also need to be accounted for.

Conclusion

These analyses began to bridge the gap in social media in sport research by introducing the communication accommodation theory into this realm of inquiry. Further, these studies were the first to primarily investigate Single-A Minor League Baseball teams in a social media setting. Single-A baseball teams account for over 30 different communities. Social media research can reveal details about these communities including power structures, community influencers including corporations or mavens, and local trends. There are over 200 teams in Minor League Baseball that serve small to large communities and cities throughout the United States. Some of these communities, such as Clinton, Iowa, host an MiLB franchise as their only source of professional sports. These teams allow researchers the opportunity to investigate communities beyond major markets, as well as the communication strategies of smaller markets on social media. Within social media in sport research, investigators have the opportunity to view communications in a wide variety of contexts. These studies found that MiLB teams had different accommodation scores across teams, and posting types. Various measures including accommodation scores, traditional Facebook metrics, posting type, and word count, were not all found to be related throughout the analysis. Further, significant results varied in terms of accounting for variance, as well as the estimated relationship between the factors.

Mixed results were found across these analyses. While some of the findings back the assertions of Burgoon, Dillman, and Stern (1995) that CAT cannot fully account for all of the nuances of a conversation, language accommodations scores may have hinted at the power structures of MiLB teams in different communities (Liao, Bazarova, & Yuan, 2016; Riordan, Markman, & Stewart, 2012). It's suggested that language accommodation accounted for a small portion of how traditional Facebook metrics (*likes*, number of comments) were affected by interactions between a host organization's Facebook posts and subsequent comments from Facebook users. The highest accommodation scores found in Study B suggested that teams in smaller populaces may have a greater amount of power within their community than teams in larger areas (Liao, Bazarova, & Yuan, 2016; Riordan, Markman, & Stewart, 2012). This finding should be further examined in subsequent inquiries, and can further explain how sport entities fit into a community.

Social media managers need to continue to post in a variety of ways, and work to further integrate the live, in-person audience into the social media setting while at the game. Previous research suggested that fans who use social media related to the host team at sporting events have better perceptions of the sporting brand than those who do not (Walsh, Clavio, Lovell, &

Blaszka, 2013). One of the first-screen experiences could be the item find which would give patrons another activity during an MiLB game. This would also increase the visibility of a sponsor as the patron would need to tag the sponsor in their post to participate in the item find. Further, social media managers should work to post in many creative ways for their sponsors. A greater response to posts involving sponsors may entice sponsors to re-sign for the following season, or for new potential sponsors to seek a partnership. In this manner, social media managers can further monetize their campaigns, and more importantly, justify their jobs. Social media managers can also do this through clicks off of Facebook, as well as bringing in or retaining sponsors.

To conclude, Minor League Baseball franchises offer a plethora of opportunities for researchers to investigate different fan bases than those of Major League Baseball clubs. MiLB teams serve as an affordable avenue of entertainment for many families in communities across North America, and their audiences may provide greater insights to a more rural dataset than could be observed in other professional sports. Understanding communication in sport across all levels can help researchers and practitioners identify new social media strategies, responses to social media campaigns across all sports, and develop new strategies and techniques to enhance other teams' social media campaigns. Social media scholars have scratched the surface on MiLB research, which can be observed in a variety of ways. Researchers can employ different measures to analyze responses and interactions between MiLB franchises and their online audience, such as using content analyses on Facebook for posts originating from MiLB franchises, or using social identity theory to observe responses from rival MiLB franchises during a rivalry series. Social media practitioners and academics can both work towards creating an analytical tool that takes measures from various theories to understand the relationship between a Facebook audience. These measures may give better insight into their relation to traditional Facebook metrics. In this manner, social media managers can craft quality Facebook posts time and time again.

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Appendices

Appendix 1- Riverdogs' Totals

Post Number	Date	LSM	Immediacy	Likes	Comments
NL1	9/10/2016	0.372197	0.224519	89	162
NL2	9/9/2016	0.257781	0.284711	24	7
NL3	9/9/2016	0.609815	0.418419	25	2
NL7	9/4/2016	0.701857	0.600757	10	2
NL10	9/1/2016	0.936015	0.7898	7	22
NL11	9/1/2016	0.375	0.4	5	1
NL13	8/31/2016	0.618964	0.64589	6	35
NL20	8/24/2016	0.691156	0.905849	49	4
NL21	8/23/2016	0.875	0.804651	9	21
NL29	8/19/2016	0.704521	0.765754	9	24
NL32	8/9/2016	0.610362	0.310736	8	9
NL33	8/9/2016	0.75	0.839823	8	20
NL38	8/7/2016	0.498053	0.5329	5	4
NL43	8/4/2016	0.680021	0.771416	3	15
NL49	7/31/2016	0.540911	0.705458	6	30
NL56	7/16/2016	0.630786	0.770204	4	25
NL58	7/14/2016	0.595203	0.659376	1	18
NL61	7/3/2016	0.75	0.84727	3	21
NL62	7/2/2016	0.621777	0.622574	5	18
NL65	6/30/2016	0.564765	0.304984	10	14
NL69	6/28/2016	0.074972	0.144128	7	1
NL75	6/14/2016	0.829199	0.811652	8	1
NL79	6/9/2016	0.75	0.843102	6	16
NL82	6/2/2016	0.729457	0.830692	8	19
NL84	5/27/2016	0.548079	0.528874	165	3
NL92	5/19/2016	0.657985	0.794093	0	10
NL93	5/19/2016	0.617244	0.481213	5	5
NL111	4/8/2016	0.643256	0.806799	6	20
NL115	1/18/2016	0.380397	0.688773	6	1
NL121	9/29/2016	0.469925	0.323926	28	6
SO3	9/9/2016	0.644987	0.478627	5	2
SO4	9/9/2016	0.293174	0.235576	28	6
SO9	9/1/2016	0.641904	0.440472	775	15
SO11	8/30/2016	0.729167	0.8111111	4	1
SO13	8/30/2016	0.5	0.509527	7	2

SO16	8/26/2016	0.679927	0.495967	51	4
SO21	8/23/2016	0.54439	0.717202	16	1
SO22	8/23/2016	0.196231	0.259367	9	1
SO24	8/23/2016	0.565234	0.706258	0	2
SO36	8/5/2016	0.566424	0.795012	22	2
SO41	8/3/2016	0.597565	0.479983	6	1
SO43	8/1/2016	0.583333	0.569048	18	3
SO48	7/16/2016	0.5	0.680008	24	1
SO51	7/4/2016	0.64583	0.476063	99	4
SO52	7/3/2016	0.159074	0.454518	97	2
SO55	6/17/2016	0.602581	0.599132	148	2
SO56	6/15/2016	0.748639	0.49139	8	1
SO62	5/24/2016	0.75	0.773474	19	4
SO63	5/20/2016	0.125	0.4	34	1
SO66	5/8/2016	0.626964	0.717289	15	1
SO67	5/6/2016	0.209787	0.257157	3	1
SO70	4/20/2016	0.558162	0.410596	17	3
SO72	4/14/2016	0.44365	0.627397	43	2
SO78	4/8/2016	0.499676	0.42544	491	14
SO87	1/15/2016	0.277107	0.460507	9	3
SO95	12/15/2015	0.291314	0.295435	4	1
SO99	11/30/2015	0.600784	0.668693	11	3
SO100	11/17/2015	0.546045	0.779577	54	1
SO102	11/2/2015	0.5	0.8	3	1
SO105	10/12/2015	0.375	0.467459	27	1
TR1	9/10/2016	0	0.2	16	9
TR2	9/10/2016	0.460013	0.936022	9	1
TR3	9/10/2016	0.700876	0.568763	48	8
TR7	9/9/2016	1	0.812759	222	16
TR8	9/9/2016	0.5	0.689287	11	1
TR9	9/9/2016	0.307482	0.551718	28	1
TR11	9/1/2016	0.283447	0.16557	17	2
TR12	9/1/2016	0.513943	0.547707	4	1
TR19	8/24/2016	0.18546	0.496736	22	1
TR20	8/22/2016	0.25	0.608686	6	1
TR25	8/17/2016	0.125	0.271998	16	1
TR31	8/8/2016	0.5	1	4	1
TR36	8/3/2016	0.349112	0.255705	3	1
TR37	8/1/2016	0.25	0.6	31	1
TR38	8/1/2016	0.75	1	3	1

TR41	7/30/2016	0.272739	0.31898	36	2
TR42	7/29/2016	0.125	0.6	3	1
TR44	7/18/2016	0.125	0.2	4	1
TR45	7/17/2016	0.534698	0.533327	3	3
TR47	7/15/2016	0.274964	0.119894	1	2
TR57	6/22/2016	0.7257	0.701555	97	5
TR63	6/6/2016	0.125	0.4	5	1
TR67	5/30/2016	0.732317	0.848753	4	3
TR68	5/30/2016	0.375	0.248663	6	1
TR87	5/14/2016	0.625	0.76	43	3
TR92	5/2/2016	0.775628	0.64	18	3
TR95	4/23/2016	0.375	0.490925	48	1
TR96	4/22/2016	0.875	0.929029	2	1
TR98	4/13/2016	0.372553	0.411831	16	1
TR107	11/28/2016	0.472849	0.319834	71	3

Appendix 2- Fireflies' Totals

Post Number	Dates	LSM	Immediacy	Likes	Comments
NL2	9/9/2016	0.603943	0.241617	56	11
NL5	8/12/2016	0.63015	0.705557	21	3
NL6	8/11/2016	0.25	0.262055	12	1
NL9	8/10/2016	0.762017	0.4408	20	2
NL19	7/16/2016	0.264581	0.228474	31	1
NL20	7/14/2016	0.260693	0.617108	28	1
NL21	7/14/2016	0.836805	0.790513	200	11
NL24	7/6/2016	0.375	0.8	29	1
NL25	7/4/2016	0.406683	0.726419	47	1
NL30	6/28/2016	0.762974	0.548409	720	62
NL33	6/25/2016	0.414361	0.472978	780	14
NL39	6/14/2016	0.406624	0.23612	204	32
NL40	6/13/2016	0.375	0.244894	16	1
NL41	6/10/2016	0.695117	0.613194	98	4
NL44	6/5/2016	0.531215	0.622247	20	3
NL46	6/3/2016	0.538773	0.662037	31	1
NL47	6/3/2016	0.332679	0.755606	16	2
NL49	5/31/2016	0.441794	0.343488	9	5
NL54	5/16/2016	0.598988	0.314987	20	1
NL55	5/15/2016	0.769961	0.7956	26	2
NL57	5/2/2016	0.25	0.4	41	1
NL61	4/28/2016	0.402286	0.469967	46	4
NL63	4/26/2016	0.5	0.888892	27	3
NL64	4/25/2016	0.607758	0.43124	117	21
NL66	4/20/2016	0.5	0.6	37	1
NL67	4/18/2016	0.417054	0.295031	38	2
NL70	3/29/2016	0.670614	0.698112	97	25
NL72	3/2/2016	0.69269	0.51462	80	17
NL74	2/18/2016	0.402602	0.559277	327	50
NL76	1/21/2016	0.875	0.915486	57	1
SO3	9/6/2016	0.447886	0.301823	247	17
SO4	9/6/2016	0.404349	0.625849	24	3
SO5	9/5/2016	0.60286	0.402828	203	11
SO8	8/9/2016	0.375	0.4	30	1
SO10	8/2/2016	0.382334	0.494341	30	3
SO11	8/1/2016	0.635395	0.386626	55	5
SO12	7/31/2016	0.938556	0.644944	200	27

SO13	7/30/2016	0.601729	0.826712	374	13
SO18	7/15/2016	0.413535	0.546597	92	4
SO19	7/14/2016	0.415497	0.382197	37	2
SO21	7/6/2016	0.338249	0.471387	12	10
SO27	6/20/2016	0.5	0.639981	192	1
SO30	6/8/2016	0.535071	0.533402	78	64
SO31	6/5/2016	0.625	0.942865	280	5
SO34	5/25/2016	0.509983	0.415973	28	1
SO37	5/2/2016	0.351627	0.167239	56	1
SO40	4/26/2016	0.499304	0.19882	202	8
SO45	4/14/2016	1	0.855306	174	7
SO48	4/10/2016	0.528197	0.549835	10	1
SO52	3/25/2016	1	0.908779	341	16
SO54	3/19/2016	1	0.901278	344	18
SO56	3/12/2016	0.419241	0.498866	76	4
SO57	3/11/2016	0.875	0.897017	259	8
SO59	3/8/2016	0.330893	0.572892	188	1
SO62	3/3/2016	0.519725	0.751538	25	2
SO64	2/23/2016	1	0.890549	515	36
SO65	2/16/2016	0.875	0.760529	361	18
SO70	1/19/2016	0.33152	0.411745	98	1
SO73	1/5/2016	0.702515	0.488183	181	5
SO74	12/31/2015	0.75	0.731034	105	6
TR1	8/13/2016	0.454238	0.63492	299	6
TR2	8/11/2016	0.25	0.6	56	1
TR7	8/5/2016	0.886813	0.8189	37	1
TR10	7/31/2016	0.375	0.8	22	1
TR13	7/28/2016	0.32682	0.616373	73	2
TR15	7/24/2016	0.190526	0.585041	19	3
TR16	7/22/2016	0.569339	0.491697	31	3
TR17	7/22/2016	0.395151	0.286984	115	13
TR20	7/17/2016	0.722858	0.756573	8	1
TR21	7/17/2016	0.491846	0.649213	34	2
TR31	7/6/2016	0.375	0.500008	8	1
TR34	7/5/2016	0.5	0.448615	39	2
TR35	7/4/2016	0.285665	0.257079	71	2
TR36	7/3/2016	1	0.649719	49	9
TR46	6/20/2016	0.569699	0.382855	218	5
TR47	6/19/2016	0.739093	0.70277	42	3
TR51	6/16/2016	0.375	0.462055	49	1

TR55	6/11/2016	0.5	0.8	71	1
TR58	6/9/2016	0.574918	0.676603	356	13
TR59	6/7/2016	0.434196	0.499579	33	1
TR61	6/3/2016	0.625	0.8	10	1
TR67	5/27/2016	0.288827	0.285659	14	2
TR68	5/27/2016	0.422928	0.17765	145	14
TR70	5/26/2016	0.584741	0.655266	87	36
TR72	5/23/2016	0.75	0.893579	327	8
TR75	5/18/2016	0.489566	0.305805	32	2
TR80	4/20/2016	0.786082	0.8035	4	1
TR82	4/1/2016	0.325673	0.345125	154	16
TR84	3/18/2016	0.386862	0.347839	85	13
TR89	1/27/2016	0.650843	0.676745	168	16

Appendix 3- Drive Totals

Post Number	Date	LSM	Immediacy	Likes	Comments
NL4	8/25/2016	0.186052	0.474663	494	12
NL6	8/19/2016	0.187774	0.092056	14	2
NL9	8/18/2016	0.25	0.6	13	3
NL11	8/11/2016	0.383444	0.446734	17	5
NL13	8/3/2016	0.202551	0.579636	8	3
NL14	8/3/2016	0.220857	0.304068	5	3
NL16	7/19/2016	0.74854	0.77662	2	1
NL19	6/28/2016	0.125	0.4	8	1
NL23	6/1/2016	0.145343	0.4	0	2
NL25	5/30/2016	0.125	0.4	12	5
NL27	5/26/2016	0.056239	0.26832	2	6
NL28	5/24/2016	0.358732	0.573972	7	3
NL30	5/19/2016	0.375	0.511139	10	1
NL31	5/18/2016	0.5598	0.579548	11	6
NL33	5/11/2016	0.375	0.4	79	1
NL35	4/26/2016	0.291667	0.44	12	1
NL36	4/20/2016	0.75	0.694334	8	1
NL37	4/18/2016	0.402338	0.757457	22	2
NL38	4/17/2016	0.625	0.637692	5	7
NL40	4/6/2016	0.345686	0.483756	83	4
NL41	4/1/2016	0.797472	0.627638	50	9
NL44	3/24/2016	0.302232	0.578805	4	2
NL46	3/16/2016	0.625	0.8	4	1
NL49	2/19/2016	0.563198	0.628792	31	11
NL51	2/12/2016	0.423608	0.490532	31	1
NL52	2/2/2016	0.558144	0.59553	19	4
NL53	12/4/2015	0.600706	0.576424	7	1
NL56	11/23/2015	0.498361	0.404737	35	2
NL57	11/6/2015	0.500496	0.567343	6	2
NL59	9/15/2015	0.528999	0.439446	24	3
SO4	8/24/2016	0.625	0.714793	8	2
SO5	8/22/2016	0.455356	0.869285	13	2
SO9	8/1/2016	0	0	3	1
SO14	7/17/2016	0.325894	0.457538	1	1
SO16	7/16/2016	0	0	0	1
SO18	7/15/2016	0.392857	0.483109	35	1
SO19	7/13/2016	0.846376	0.599295	1004	36

SO25	6/22/2016	0.689189	0.611628	86	9
SO26	6/21/2016	0.659714	1	52	1
SO28	6/15/2016	0.675077	0.440278	87	2
SO29	6/12/2016	0.689189	0.611628	86	9
SO31	6/11/2016	0.689189	0.611628	86	9
SO34	6/8/2016	0.669171	0.480516	1127	19
SO36	6/7/2016	0.625301	0.282235	8	5
SO37	6/3/2016	0.452082	0.345035	2	4
SO40	6/1/2016	0.625	0.616685	20	1
SO43	5/27/2016	0	0	6	1
SO50	5/7/2016	0.625	0.616076	8	1
SO52	5/3/2016	0.718678	0.8225	16	7
SO54	4/22/2016	0.413314	0.428491	99	3
SO55	4/22/2016	0	0	5	1
SO58	4/18/2016	0.254417	0.289943	7	1
SO61	4/11/2016	0.625	0.50003	84	1
SO62	4/11/2016	0.570299	0.496403	19	2
SO64	4/4/2016	0.5	0.8	13	1
SO67	3/18/2016	0.59376	0.421116	404	9
SO69	3/10/2016	0.61441	0.446379	4	10
SO71	3/3/2016	0.875	0.904785	22	1
SO72	3/1/2016	0.404877	0.356332	17	4
SO73	2/23/2016	0.492652	0.48257	36	4
TR6	8/28/2016	0.511972	0.483953	1	2
TR7	8/27/2016	0.658795	0.419833	8	2
TR12	8/11/2016	0.643707	0.564265	62	4
TR14	8/7/2016	0.48991	0.465681	15	1
TR18	7/30/2016	0.770482	0.661777	2	1
TR19	7/29/2016	0.34282	0.395756	20	2
TR20	7/29/2016	0.700012	0.598291	11	1
TR24	7/17/2016	0.50939	0.604378	2	3
TR26	7/14/2016	0.461788	0.342591	9	1
TR27	7/13/2016	0.400532	0.190265	1	1
TR29	7/9/2016	0.5	0.68273	13	1
TR31	7/6/2016	0.67215	0.45914	115	15
TR35	7/1/2016	0.5	0.8	20	1
TR36	6/29/2016	0.5	0.690909	37	1
TR41	6/11/2016	0.841713	1	7	2
TR42	6/10/2016	0.514606	0.648203	10	1
TR43	6/7/2016	0.625	0.672818	24	1

TR44	6/1/2016	0.58312	0.536515	5	2
TR46	5/27/2016	0.625	0.674123	8	1
TR51	5/16/2016	0.506334	0.448626	80	14
TR54	5/10/2016	0.691346	0.424842	20	2
TR57	5/5/2016	0.428419	0.529984	14	3
TR59	4/29/2016	0.557848	0.735856	3	2
TR66	4/19/2016	0.646743	0.573858	25	4
TR69	4/10/2016	0.317372	0.252059	15	1
TR74	3/10/2016	0.760571	0.744005	96	2
TR75	3/8/2016	0.748556	0.698197	10	2
TR77	1/27/2016	0.498248	0.286584	334	13
TR80	11/19/2015	0.75	1	22	1
TR83	9/28/2015	0.62107	0.660262	40	2

Appendix 4- LumberKings' Totals

Post Number	Date	LSM	Immediacy	Likes	Comments	Word Count
1	9/9/2016	0.5403436	0.3931567	51	5	46
4	9/7/2016	0.60106469	0.61429098	92	6	29
6	9/5/2016	0.31162609	0.69609029	61	4	67
14	8/23/2016	0.46174785	0.57582112	64	2	46
16	8/21/2016	0.52081511	0.78779144	52	2	50
20	8/19/2016	0.52082118	0.95643564	62	3	30
21	8/18/2016	0.54292455	0.58458318	52	5	54
28	8/12/2016	0.36659154	0.59102866	53	7	43
34	8/7/2016	0.31823876	0.68337146	61	4	39
37	8/5/2016	0.55447542	0.7920539	172	1	37
38	7/31/2016	0.60506147	0.66505545	22	2	52
39	7/29/2016	0.39177667	0.3630514	25	2	68
40	7/29/2016	0.5	0.74462646	5	1	26
42	7/27/2016	0.5267929	0.41927893	9	1	30
43	7/24/2016	0.5	0.77559291	25	1	19
44	7/23/2016	0.45472413	0.51953759	27	2	31
45	7/22/2016	0.40238226	0.80428751	85	8	43
46	7/22/2016	0.64072478	0.70076382	36	9	30
53	7/15/2016	0.575	0.66926077	13	1	48
56	7/13/2016	0.66980587	0.7040062	7	5	65
57	7/13/2016	0.55292446	0.48404424	33	3	32
58	7/10/2016	0.5	0.79	13	2	39
60	7/5/2016	0.44304412	0.69046721	24	2	41
61	7/5/2016	0.6187765	0.73317943	42	15	36
62	7/4/2016	0.54502176	0.43603013	15	2	34
64	7/3/2016	0.66171021	0.55199647	20	3	40
65	7/2/2016	0.75	0.74333251	13	2	39
71	6/22/2016	0.65995923	0.64920186	7	2	40
72	6/20/2016	0.4583125	0.66663333	17	1	15
73	6/18/2016	0.48900913	0.58380151	104	5	35
75	6/17/2016	0.55278548	0.60465199	8	4	39
76	6/15/2016	0.61190369	0.64423668	28	4	13
81	6/9/2016	0.48500204	0.29278202	7	1	41
84	6/7/2016	0.625	0.49868391	55	1	38
89	5/26/2016	0.5	0.57647059	13	1	32
90	5/24/2016	0.375	0.58787879	5	1	32
91	5/23/2016	0.52977959	0.79431402	93	1	26

93	5/23/2016	0.75	0.84	40	6	8
94	5/21/2016	0.45642606	0.90444606	21	2	39
97	5/17/2016	0.6647199	0.3224761	166	11	41
102	5/10/2016	0.5	0.6	2	2	30
103	5/9/2016	0.5	0.8	8	1	44
104	5/9/2016	0.5	1	9	1	25
105	5/9/2016	0.48396895	0.44815187	11	2	8
106	5/7/2016	0.5	0.44653941	11	2	33
107	5/7/2016	0.55324199	0.35764019	7	1	12
108	5/6/2016	0.5	0.44934751	13	1	41
109	5/5/2016	0.54241815	0.52860794	17	6	24
110	5/4/2016	0.54738828	0.73267802	9	2	35
111	5/4/2016	0.6749584	0.50756605	2	8	6
113	5/3/2016	0.35714286	0.39365079	58	1	10
114	5/1/2016	0.625	0.79130435	11	1	45
115	5/1/2016	0.49388127	0.55096292	19	2	43
118	4/24/2016	0.625	0.77627119	35	3	37
121	4/20/2016	0.5	0.7755102	14	2	46
123	4/17/2016	0.57958265	0.68733224	5	1	45
125	4/14/2016	0.5	0.57714286	1	1	33
126	4/13/2016	0.45910167	0.46782491	18	1	40
127	4/10/2016	0.75	0.64615385	20	4	8
129	4/8/2016	0.41070281	0.58551634	2	3	30
130	4/8/2016	0.43192032	0.42320171	9	6	31
134	4/7/2016	0.65965394	0.80369903	73	10	24
135	4/5/2016	0.875	0.92195122	85	4	2
137	4/4/2016	0.65964577	0.609204	36	3	14
141	3/31/2016	0.86253019	0.31132839	30	10	4
142	3/28/2016	0.375	0.8	7	1	24
146	3/21/2016	0.29926716	0.56932196	20	7	35
148	3/15/2016	0.76426011	0.67257909	20	1	36
149	3/9/2016	0.75	0.97606838	10	11	10
150	3/9/2016	0.40909339	0.3314725	78	3	9
159	2/4/2016	0.92620377	0.58382515	42	10	9
160	1/27/2016	0.41067755	0.62854204	6	1	18
162	1/21/2016	0.46859432	0.35141895	8	16	22
168	1/9/2016	0.90683158	0.60346915	57	6	8
169	1/6/2016	0.33143783	0.14605164	18	1	23
171	12/9/2015	0.51691644	0.7470663	24	2	21
181	11/9/2015	0.74310603	0.57221392	17	1	97

182	11/2/2015	0.81442714	0.61877715	154	7	33
183	10/27/2015	0.55160968	0.42984058	109	6	20
185	10/20/2015	0.5869317	0.62685414	10	1	43

Appendix 5- Whitecaps' Totals

Post Number	Date	LSM	Immediacy	Likes	Comments	Word Count
3	9/10/2016	0.573835664	0.438396194	79	3	30
9	9/9/2016	0.836349466	0.750944292	18	5	25
12	9/8/2016	0.3158284	0.38816404	49	5	31
20	9/7/2016	0.25	0.42549933	29	3	22
21	9/7/2016	0.43320506	0.57199745	29	5	15
24	9/6/2016	0.75	0.85245902	107	15	3
39	9/1/2016	0.375	0.6	27	4	27
48	8/28/2016	0.125	0.57142857	93	1	13
50	8/26/2016	0.66671071	0.50979879	22	1	36
70	8/20/2016	0.42679822	0.62914581	11	2	29
72	8/20/2016	0.31500767	0.34137142	10	3	16
73	8/20/2016	0.71690148	0.68925658	53	44	16
75	8/20/2016	0.82655556	0.72167878	10	3	18
90	8/14/2016	0.80323189	0.64705918	1	1	30
96	8/12/2016	0.0741544	0.43483341	22	1	16
101	8/12/2016	0.44981919	0.36332039	3	1	30
105	8/12/2016	0.47580864	0.52227009	48	9	33
108	8/11/2016	0.560325	0.64734981	36	3	40
126	8/3/2016	0.44118997	0.4117863	24	1	13
132	8/1/2016	0.5	0.77647059	23	2	24
159	7/23/2016	0.25	0.4	10	1	14
166	7/21/2016	0.70799939	0.39066543	92	2	23
173	7/20/2016	0.63346429	0.60296733	110	3	16
180	7/18/2016	0.41097566	0.34111032	66	13	17
197	7/11/2016	0.62954171	0.60273542	41	13	18
199	7/10/2016	0.34434211	0.70204726	55	1	43
211	7/7/2016	0.44737429	0.46320037	4	9	32
226	7/5/2016	0.5	0.96226415	15	2	24
232	7/4/2016	0.875	0.40852307	29	2	17
266	6/24/2016	0.47410379	0.43523037	6	3	24
273	6/21/2016	0.28615309	0.25015792	20	4	21
302	6/9/2016	0.47231765	0.64008056	83	2	15
313	6/6/2016	0.65385503	0.5555623	105	1	15
315	6/5/2016	0.24384978	0.69979597	16	1	31
328	6/1/2016	0.56086552	0.62324319	368	7	29
344	5/25/2016	0.63400332	0.49347204	56	8	26
346	5/24/2016	0.34007861	0.47989875	49	6	21

370	5/14/2016	0.50501872	0.48553063	7	3	13
396	5/6/2016	0.60886342	0.57419355	8	1	29
398	5/5/2016	0.375	0.36088383	105	3	12
401	5/5/2016	0.25	0.29473684	206	2	7
408	5/3/2016	0.25	0.58181818	135	2	21
409	5/3/2016	0.81698873	0.83649635	117	18	9
425	4/26/2016	0.25	0.58461538	89	1	25
426	4/26/2016	0.35067397	0.44084854	46	3	37
434	4/22/2016	0.875	0.82554517	121	28	5
452	4/18/2016	0.375	0.711111111	109	3	7
458	4/14/2016	0.64291222	0.5552508	37	10	15
464	4/12/2016	0.37328097	0.39544079	186	24	20
482	4/9/2016	0.85530214	0.54352409	2335	62	15
505	4/7/2016	0.66949052	0.67111917	8	1	38
522	4/5/2016	0.42664642	0.46402448	70	10	36
530	4/2/2016	1	0.70932706	488	14	14
531	4/1/2016	0.63189329	0.63670103	26	4	52
550	3/25/2016	0.31831765	0.34892699	29	2	13
558	3/21/2016	0.51225434	0.54777945	58	20	33
579	3/9/2016	0.63130327	0.59542713	133	7	21
583	3/8/2016	0.71067946	0.78227559	77	6	28
591	2/29/2016	0.78587451	0.49344976	342	11	12
593	2/25/2016	0.34164115	0.58510743	36	7	36
614	2/16/2016	0.6792821	0.42788637	135	38	32
619	2/12/2016	0.52221274	0.7999952	88	4	16
631	2/5/2016	0.29502176	0.67577696	10	2	17
632	2/4/2016	0.60190867	0.46127323	17	8	25
645	1/27/2016	0.66821357	0.55158921	87	6	21
666	1/12/2016	0.33920864	0.25342349	5	3	37
670	1/8/2016	0.38631407	0.27924299	132	2	24
687	12/17/2015	0.51249588	0.73427912	50	4	22
689	12/15/2015	0.73294727	0.54817043	115	71	14
694	12/9/2015	0.686144	0.71293395	242	27	23
705	12/1/2015	0.73917249	0.69820094	78	3	21
751	10/8/2015	0.90349033	0.81256048	165	17	34
767	9/26/2015	0.6641225	0.55633889	50	12	13
773	9/24/2015	0.58527075	0.50310164	53	1	37
778	9/22/2015	0.55296336	0.67976971	109	7	41
786	9/22/2015	1	0.84831625	4405	106	8
806	9/19/2015	0.85285028	0.66573645	74	12	31

810	9/17/2015	0.69183303	0.3354699	20	9	33
811	9/17/2015	0.63744365	0.68436464	23	4	44
849	9/11/2015	0.31964126	0.30746684	74	2	34

Appendix 6- Regression Tables

Appendix Table 1: Regression of *Likes* versus LSM separated by team and post type

```
Call:
lm(formula = LSM ~ Likes + Comments + Type + Team, data = Comb.dat)


Residuals:
      Min       1Q   Median       3Q      Max
 -0.51055 -0.13754  0.00878  0.14304  0.47176


 Coefficients:
                Estimate Std. Error t value Pr(>|t|)
 (Intercept)   4.637e-01  2.896e-02  16.008   <2e-16 ***
 Likes         2.389e-04  9.746e-05   2.451   0.0149 *
 Comments      1.905e-03  1.060e-03   1.797   0.0736 .
 TypeSO        1.882e-02  3.188e-02   0.591   0.5553
 TypeTR        1.191e-02  3.140e-02   0.379   0.7047
 TeamFireflies 2.383e-02  3.127e-02   0.762   0.4467
 TeamRiverdogs 1.402e-02  3.114e-02   0.450   0.6531
 ---
 Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


 Residual standard error: 0.2058 on 263 degrees of freedom
 Multiple R-squared:  0.06287,    Adjusted R-squared:  0.04149
 F-statistic: 2.941 on 6 and 263 DF,  p-value: 0.008551
```

Appendix Table 2: Regression of *Likes* versus the natural log of LSM for the Fireflies

```
Call:
lm(formula = LSM_L ~ Likes, data = Fireflies.dat)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.89166 -0.22806  0.03242  0.28090  0.74097 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.7823532  0.0491950 -15.903  < 2e-16 ***
Likes        0.0008446  0.0002622   3.221  0.00179 ** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3605 on 88 degrees of freedom
Multiple R-squared:  0.1055, Adjusted R-squared:  0.0953 
F-statistic: 10.38 on 1 and 88 DF,  p-value: 0.00179
```

Appendix Table 3: Regression of *Likes* versus Immediacy for the Fireflies

```
Call:
lm(formula = Immediacy ~ Likes, data = Fireflies.dat)

Residuals:
     Min       1Q   Median       3Q      Max
-0.39295 -0.15869  0.00387  0.17110  0.36947

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.5301034  0.0279658  18.955   <2e-16 ***
Likes       0.0002793  0.0001490   1.874   0.0643 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2049 on 88 degrees of freedom
Multiple R-squared:  0.03836,    Adjusted R-squared:  0.02743
F-statistic:  3.51 on 1 and 88 DF,  p-value: 0.06431
```

Appendix Table 4: Regression of Comments versus LSM for the Drive separated by Post Type

```
Call:
lm(formula = LSM ~ Comments + Type, data = Drive.dat)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.46198 -0.08788  0.01416  0.14286  0.41302 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 0.367051   0.037997   9.660 2.23e-15 ***
Comments    0.010483   0.004116   2.547 0.012644 *  
TypeSO      0.084444   0.050090   1.686 0.095453 .  
TypeTR      0.181100   0.049773   3.638 0.000467 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1926 on 86 degrees of freedom
Multiple R-squared:  0.1811, Adjusted R-squared:  0.1526 
F-statistic: 6.341 on 3 and 86 DF,  p-value: 0.0006178
```

Appendix Table 5: Regression of Comments versus LSM for the Lumberkings

```
Call:
lm(formula = LSM ~ Comments, data = Lumberkings.dat)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.29647 -0.07041 -0.01785  0.06695  0.32408 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 0.504867   0.021826  23.132  < 2e-16 ***
Comments    0.012981   0.004418   2.938  0.00434 ** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1315 on 78 degrees of freedom
Multiple R-squared:  0.09963,    Adjusted R-squared:  0.08809 
F-statistic: 8.631 on 1 and 78 DF,  p-value: 0.004344
```

Appendix Table 6: Regression of Comments versus LSM for the Whitecaps

```
Call:
lm(formula = LSM ~ Comments, data = Whitecaps.dat)

Residuals:
     Min       1Q   Median       3Q      Max
-0.41720 -0.15050  0.00246  0.12916  0.43332

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.485559   0.024117  20.133  < 2e-16 ***
Comments    0.005794   0.001267   4.574 1.77e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1861 on 78 degrees of freedom
Multiple R-squared:  0.2115, Adjusted R-squared:  0.2014
F-statistic: 20.92 on 1 and 78 DF,  p-value: 1.774e-05
```

Appendix Table 7: Regression of Comments versus Immediacy for the Whitecaps

```
Call:
lm(formula = Immediacy ~ Comments, data = Whitecaps.dat)

Residuals:
     Min       1Q   Median       3Q      Max
-0.29943 -0.12322  0.01628  0.11757  0.41684

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.541256   0.020387  26.549   <2e-16 ***
Comments    0.002083   0.001071   1.945   0.0554 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1573 on 78 degrees of freedom
Multiple R-squared:  0.04626,    Adjusted R-squared:  0.03403
F-statistic: 3.783 on 1 and 78 DF,  p-value: 0.05538
```

Appendix Table 8: LSM versus Post Type for the Riverdogs

```
Call:
lm(formula = LSM ~ Type, data = Riverdogs.dat)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.52785 -0.14468  0.02345  0.12063  0.56794 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.60282    0.03777  15.958  < 2e-16 ***
TypeSO      -0.10276    0.05342  -1.924  0.05768 .  
TypeTR      -0.17076    0.05342  -3.197  0.00194 ** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2069 on 87 degrees of freedom
Multiple R-squared:  0.1064, Adjusted R-squared:  0.08586 
F-statistic: 5.179 on 2 and 87 DF,  p-value: 0.007494

  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = myfit1.red1)

$Type
            diff        lwr         upr     p adj
SO-NL -0.1027583 -0.2301407  0.02462406 0.1381608
TR-NL -0.1707639 -0.2981463 -0.04338154 0.0054539
TR-SO -0.0680056 -0.1953880  0.05937676 0.4141810
```