Journal of Organizational and End User Computing
Volume 30 • Issue 1 • January-March 2018

Running with the Pack:
The Impact of Middle-Status Conformity on the Post-Adoption Organizational Use of Twitter

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ABSTRACT

Prior literature has utilized many theories to explain an organization's post-adoption technology use of social media platforms, but none of the common models include status as either a primary or a moderating variable. This is a significant gap in the literature because status is a structural enabler and inhibitor that determines acceptable and unacceptable behavior in a given setting. In an empirical study of Twitter and the cultural norm of retweeting for a sample of US colleges and universities, the authors demonstrate the following: (1) middle-status institutions had a higher likelihood of following the retweeting cultural norm relative to their high- and low-status counterparts, (2) middle- and low-status institutions who followed the retweeting cultural norm in a manner consistent with their status experienced greater post-adoption success relative to those institutions who did not, but the reverse was evident for high-status institutions (who appear to be rewarded for deviation from this cultural norm), and (3) the negative effect of deviating from retweeting cultural norms on post-adoption success is more pronounced with decreasing status.

KEYWORDS

Cultural Norms, Post-Adoption, Retweet, Social Media, Status, Theory of Middle-Status Conformity, Twitter

INTRODUCTION

Popular external social media platforms give organizations the ability to disseminate information, to collaborate with others, to enhance worker productivity, and to build relationships with stakeholders who may have previously been unreachable (Aggarwal, Gopal, Sankaranarayanan, & Vir Singh, 2012; Aral, Dellarocas, & Godes, 2013; Hemsley & Mason, 2013; Kane, Alavi, Labianca, & Borgatti, 2014). Consequently, it is now common practice for organizations in all types of industries to have a social media presence on external social media platforms (Kiron, Palmer, Phillips, & Kruschwitz, 2012; Qualman, 2013). However, many organizations have yet to tap the full potential of these platforms even though they have been widely adopted (Kane et al., 2014). This may be the case because simply choosing to adopt a social media platform is only a small step toward extracting value from the platform. The larger value for the organization is determined post-adoption whereby value is co-created through the continuous engagement by the organization and its followers (Culnan, McHugh, & Zubillaga, 2010; Prahalad & Krishnan, 2008; Stieglitz, Dang-Xuan, Burns, & Neuberger, 2014).

Similar to other technologies, each social media platform may have different cultural norms that form around features embedded in and the people using the technology (DeSanctis & Poole, 1994; Germonprez & Hovorka, 2013). Cultural norms are explicit or implicit guidelines that designate

DOI: 10.4018/JOEUC.2018010102

acceptable conduct within the framework of a particular group of people (Triandis, 1994). In the context of social media platforms, for instance, the following are all cultural norms: (1) how often to retweet content posted by others on Twitter, (2) when to re-pin pictures and videos on Pinterest, and (3) how frequently and when to like content on Facebook (Al-Debei, Al-Lozi, & Papazafeiropoulou, 2013; boyd, Golder, & Lotan, 2010; Hall & Zarro, 2013). Although cultural norms may form around a technical feature, the explicit and implicit guidelines for how and when the feature is used (i.e., the cultural norm) are determined by the users who are appropriating the feature (Germonprez & Hovorka, 2013).

Social media platforms are used in the public, which means that how one organization chooses to use the social media platform is influenced by how others are using the platform (boyd et al., 2010). For example, how often an organization conforms to the cultural norm of re-pinning content on Pinterest is, in part, determined based on how frequently similar organizations are conforming to the cultural norm of re-pinning. Yet, some companies knowingly or unknowingly do not follow the platform's cultural norms and following the cultural norms is not always indicative of an organization's successful or unsuccessful post-adoption use of a given social media platform. Anecdotally, it is easy to find examples of organizations across multiple industries where following the social media platform's cultural norms leads to a successful adoption of the platform and an unsuccessful adoption for others. The purpose of our paper is to theoretically and empirically investigate whether and how often organizations follow the cultural norms associated with a social media platform and whether following those cultural norms leads to greater post-adoption success.

We argue that an organization's status (i.e., hierarchical ranking of similar organizations) impacts how frequently it will follow the social media platform's cultural norms, because an organization's status helps determine what acceptable and unacceptable behavior is in a given context (Phillips & Zuckerman, 2001). We specifically hypothesize that middle-status organizations will have a higher likelihood of following the social media platform's cultural norms, because middle-status organizations have equal amounts of upside potential and downside risk and following the norms is the safest course of action (Durand & Kremp, 2016; Phillips & Zuckerman, 2001). We finally assert that organizations following the cultural norms in line with normative expectations will be more successful (ceteris paribus) relative to those who do not, because conforming to norms minimizes negative sanctions and maximizes positive rewards (Axelrod, 1986). However, we further theorize that the negative impact of deviating from the cultural norms will be greatest for low-status organizations, because it is more socially acceptable for higher status organizations to deviate from social and cultural norms (Phillips & Zuckerman, 2001; Podolny, 2005). We provide empirical evidence supporting these theorized relationships using the Twitter platform for a sample of US colleges and universities.

SOCIAL MEDIA PLATFORMS

Consistent with prior literature (Ellison & boyd, 2013; Kane et al., 2014), we define a social media platform as having four defining characteristics: (1) the ability for users to create a unique profile, (2) the ability of users to search for digital content within the platform, (3) the ability to create relationships with others on the platform, and (4) the ability to view their connections and the connections made by others. Based on these defining characteristics, Twitter, Facebook, Weibo, and LinkedIn are all social media platforms (boyd & Ellison, 2007).

Twitter, which is the empirical context of our study, is a micro-blogging social media platform where members post short 140 character tweets (messages), reply to tweets posted by other members, reply to other members more generally, retweet (repost) content previously posted by other Twitter users, and/or follow other members. Nodes (Twitter account holders) on the Twitter platform are both information producers and information consumers (Jansen, Zhang, Sobel, & Chowdury, 2009; Shi, Rui, & Whinston, 2014). Organizations typically use the Twitter platform to advertise their products and services (information production) and to listen to (metaphorically speaking) conversations that are happening on the platform related to their product or service offerings (information consumption) (Shi et al., 2014).[1]

The retweet has been referred to as the lifeblood of Twitter and it represents the core cultural norm associated with the platform (boyd et al., 2010; Murthy, 2013). In 2007, retweeting informally emerged without a technical feature as a cultural norm through social interactions between early Twitter adopters who were looking for unique ways to share and communicate on the Twitter platform (Helmond, 2013; Stone, 2009). A feature to support this cultural norm wasn't implemented until 2009. Retweeting is a normative expectation for Twitter users, which means users are expected to regularly find content to retweet to its followers (boyd et al., 2010; Murthy, 2013).

POST ADOPTION USE OF TECHNOLOGY AND SOCIAL MEDIA PLATFORMS

Previous research on social media platforms has primarily investigated adoption patterns (who adopted, when was it adopted, and why was it adopted) associated with these technologies at both the individual and the organizational levels (Aggarwal et al., 2012; Chau & Xu, 2012; Kane & Fichman, 2009; Koch, Gonzalez, & Leidner, 2012; Majchrzak, Wagner, & Yates, 2013; Parameswaran & Whinston, 2007; Wamba & Carter, 2014). Much has been learned from this adoption research but just adopting a social media platform is a very small component of the value proposition for organizations. It is not enough for an organization to simply have a Twitter or Facebook account. In fact, having an account on these platforms may even be detrimental for the organization if the account is not maintained and used appropriately, because value on these platforms is co-created through the continuous engagement by the organization and its followers (Culnan et al., 2010; Prahalad & Krishnan, 2008; Stieglitz et al., 2014).

Post-adoption use refers to the use practices after a technology has been adopted and implemented (Fichman & Kemerer, 1999; Zhu & Kraemer, 2005). Many theories have been used to explain the post-adoption use of a specific technology by organizations such as structuration theory (Orlikowski, 2000), adaptive structuration theory (DeSanctis & Poole, 1994), technology acceptance model (Venkatesh & Davis, 2000), expectation-confirmation theory (Bhattacherjee, 2001), institutional theory (King et al., 1994), and the resource-based view of the firm (Wade & Hulland, 2004). Across all of these theories, however, one factor that has received minimal attention is an organization's status (i.e., hierarchical ranking of similar organizations), which is an important omission because status is an organizational resource that may be leveraged to generate future returns (DiPrete & Eirich, 2006; Gould, 2002). Interestingly, in one of the original studies on adoption patterns, Rogers (1995) argued that organizational laggards or non-adopters may lose status and economic viability, which creates a contextual pressure to adopt a specific technology in order to protect its status and legitimacy. However, the post-adoption literature has largely not investigated status as a structural enabler or inhibitor in terms of how a technology (social media platforms in this case) is used post-adoption. Yet, an organization's status helps determine what acceptable and unacceptable behavior is in a given context (Phillips & Zuckerman, 2001), which may impact post-adoption use particularly on public social media platforms.

STATUS AND THE THEORY OF MIDDLE-STATUS CONFORMITY

Status is generally defined in one of two ways in the literature: (1) a social rank ordering of actors or (2) economic class distinctions between different groups (Berger, Fisek, Norman, & Zelditch Jr., 1977; Washington & Zajac, 2005). In our paper, we follow the former by defining status as the "prominence of an actor's relative position within a population of actors" (Wejnert, 2002, p. 304). In this manner, status refers to a hierarchical relationship among actors within a particular social setting (Piazza & Castellucci, 2014; Skvoretz & Fararo, 1996). Furthermore, those actors in high-status positions are awarded benefits and behavioral liberties not typically available to those actors in low-status positions (DiPrete & Eirich, 2006; Gould, 2002).

Hierarchies may be formally defined (i.e., authoritative or official rankings of law firms, colleges and universities, and hospitals) or informally defined (i.e., networks or clusters of firms with informal linkages) (Washington & Zajac, 2005; Wejnert, 2002). In this paper, we are theoretically interested in status within formal hierarchies, because these hierarchies are published by authoritative sources within an industry and are widely known by a variety of institutional stakeholders across industries (Washington & Zajac, 2005). It is important to note, however, that an organization's formal status may or may not be determined based on prior performance or the quality of the institution (George, Dahlander, Graffin, & Sim, 2016; Jensen & Roy, 2008; Washington & Zajac, 2005). In the field of academia, for instance, a college may have a reputation as being a diploma mill but have a relatively high formal status.

The theory of middle-status conformity postulates that there is an inverted U-shaped relationship between status and the likelihood of following social, cultural, and societal norms (Blau, 1960; Dittes & Kelley, 1956; Phillips & Zuckerman, 2001). This means that middle-status actors are expected to follow norms more than their high- and low-status counterparts, because middle-status actors have a degree of uncertainty in terms of possibly moving up or down within the social order, which makes following the norms the safest course of action (Blau, 1960). Contrarily, low-status and high-status actors have less pressure to conform to norms due to their structural position within the social hierarchy (Dittes & Kelley, 1956). Low-status actors have less at stake to conform to norms because actors in this status group are typically excluded regardless of whether they conform to or deviate from behavioral expectations (Durand & Kremp, 2016; Phillips & Zuckerman, 2001). High-status actors are typically comfortable in their position in the social hierarchy, so they feel more at ease deviating from the norms (Hollander, 1958). We assert that the theory of middle-status conformity is applicable to the post-adoption use of social media platforms, because the social penalties for non-conformity in terms of creating negative viral messages or simply being ignored can be particularly severe on large social media platforms such as Twitter and Facebook (boyd & Ellison, 2007). Moreover, the theory of middle-status conformity offers a parsimonious and effective explanation for when and why certain organizations conform to or deviate from norms in a variety of settings based on the presumed risk tolerance of firms in relation to status reduction (Durand & Kremp, 2016).

RESEARCH HYPOTHESES

There is a tension between attempting to establish distinctiveness by acting differently versus conforming to the practices of others (Durand & Kremp, 2016; Navis & Glynn, 2011). On the one hand, organizations have a desire to act similarly in order to establish legitimacy with peers and competitors, which protects them from being negatively perceived in the marketplace (Durand & Kremp, 2016; Phillips & Zuckerman, 2001; Scott, 2008). On the other hand, however, differentiation (or legitimate distinctiveness among peers and competitors) is one potentially important source of competitive advantage that cannot come from conforming to the practices of others (Durand & Kremp, 2016; Navis & Glynn, 2011). We propose that this tension coupled with an organization's status in the marketplace is an important factor in determining whether an organization will conform to the norms on a social media platform, because low-, middle-, and high-status organizations have different presumed risk profiles associated with non-conformity.

We argue that high-status organizations have less of a need to follow the cultural norms associated with the social media platform (i.e., retweeting on Twitter, liking on Facebook, re-pinning on Pinterest, and so on), because high-status organizations can withstand external criticism if they are perceived to be appropriating the platform in a non-normative manner (Hollander, 1958). For example, in the field of academia, a high-status institution such as Harvard or Yale bears minimal risk of losing status as a result of being criticized for not abiding by the cultural norms associated with the social media platform. New York University (NYU), for instance, received criticism for being a late adopter of social media and for not following the cultural norms associated with the social media platforms that they did adopt (Taylor, 2008). Yet, NYU did not have any noticeable reduction in their status.

We also expect low-status organizations to have a reduced likelihood of following the cultural norms associated with the social media platform but for different reasons. Low-status organizations have minimal downside risk because they are already at the bottom of the social hierarchy (Phillips & Zuckerman, 2001). In the field of academia, for example, for-profit schools are generally ranked at the bottom or excluded by many ranking institutions. Yet, it is important for these institutions to establish legitimacy within the field of academia, because employers are seeking graduates from legitimate academic institutions (Wellen, 2006) and being considered illegitimate for an extended period of time will hurt their chances of survival (Durand & Kremp, 2016). One way for a low-status institution to establish legitimacy within the field of academia is by being distinct and the reduced downside risk enables low-status firms to engage in distinctive actions. On Twitter, for example, it is not uncommon for these institutions to not engage in or to minimally engage in the typical interactive norms of mentioning and retweeting content posted by others.

Middle-status organizations, however, are unique in the sense that they are mired in the middle. Therefore, we argue that these organizations will have a higher likelihood of following the cultural norms associated with the social media platform, because these organizations have to balance the risk of losing status with potentially gaining status (Blau, 1960; Dittes & Kelley, 1956; Phillips & Zuckerman, 2001). In researching this potential relationship, we informally spoke to the social media staff at a middle-status bank and a middle-status US university. Both of these organizations were very concerned about using Twitter and Facebook in a manner that could potentially exclude them from possibly becoming grouped with higher status peers.[2] The downside risk due to non-conformity was more important to both of these organizations than attempting to use the platform in a distinctive manner. Therefore, we hypothesize the following curvilinear relationship:

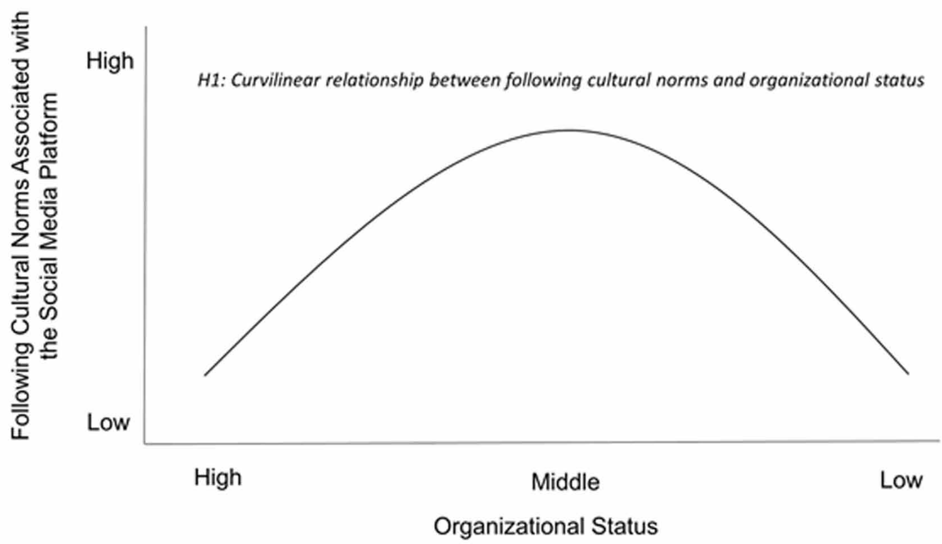
H1: Middle-status organizations will follow the cultural norms associated with the social media platform more than their high- and low-status counterparts (see Figure 1).

Whether following the cultural norms is a more or less productive strategy depends, in part, on whether the enforcement of the cultural norms by the community leads to better or worse outcomes. For example, if the Facebook community rewards organizations who adhere to the normative use of the “Like” cultural norm with greater attention and punishes organizations that do not conform to the normative use of the ‘Like’ cultural norm with less attention, then organizations will have a higher likelihood of adhering to the “Like” cultural norm. This is consistent with rational choice theory, which suggests compliance with social and cultural norms is a utility maximizing strategy because organizations will not knowingly engage in behaviors that attract punishments (Rommetveit, 1968; Thibaut & Kelley, 1986). In this manner, conforming to social and cultural norms minimizes negative sanctions and maximizes positive rewards (Axelrod, 1986). On Twitter, for instance, if an organization is not retweeting content in line with normative expectations, then one sanction is that the community will not retweet the organization’s tweets or mention the organization in future posts (i.e., it will be less successful at having its content ‘trend’). As such, we hypothesize the following:

H2: Ceteris paribus, organizations who follow the social media platform’s cultural norms in line with normative expectations will have greater post-adoption success relative to those organizations who do not.

However, this effect may not be consistent for high-, middle-, and low-status organizations. Status hierarchies tend to be stable at the higher end of the social structure, which means that high-status

Figure 1. Hypothesis 1



organizations have more freedom to deviate from behavioral norms without fear of decreasing in status (Dittes & Kelley, 1956; Phillips & Zuckerman, 2001). In many industries, high-status firms maintain their place in the hierarchy by being distinct and are typically rewarded by exhibiting this type of legitimate distinctiveness, but this is often not the case for middle- and low-status institutions (Durand & Kremp, 2016; Navis & Glynn, 2011; Podolny, 1993). Additionally, communities may be looking for reasons to criticize lower status institutions (Phillips & Zuckerman, 2001). For example, in the field of academia higher status not-for-profit institutions rarely pass up an opportunity to criticize their lower status for-profit counterparts. As such, we hypothesize the following moderating relationship:

H3: Ceteris paribus, the negative impact of deviations from the social media platform's cultural norms on post-adoption success will be more pronounced with decreasing status.

RESEARCH DESIGN AND METHODS

We empirically tested our hypotheses using a sample of tweets and re-tweets on the Twitter platform in calendar year 2012 for a sample of US colleges and universities. We investigated US colleges and universities and the Twitter platform for several reasons. First, retweeting as a cultural norm has been well established within the Twitter platform prior to 2012 (boyd et al., 2010; Murthy, 2013). Second, irrespective of the status of the institution, US colleges and universities are both information consumers as well as information producers on the Twitter platform. Third, US colleges and universities regularly retweet content posted by other Twitter users on a variety of topics and their tweets are regularly retweeted by others, so these institutions and their followers are active participants related to the cultural norm of retweeting. Finally, using a single context in a single country allows us to control for differences in audience preferences between institutions. The followers of different US colleges and universities on Twitter are similar in the sense that they are typically students, employees, alumni, or other institutional stakeholders. Although differences may exist between institutions, we have no reason to believe the followers of, for instance, Michigan State University are significantly different from the followers of the University of North Carolina.

In order to determine our sample and the 'formal' status of US colleges and universities, we used the 2012 US News and World Report rankings. Although many different published rankings exist, the US News and World Report publication is considered the authoritative source, the one that most typically appears in general marketing materials, is relatively stable from year to year, and has been referred to as the "granddaddy of college rankings" (Chisolm, 2010, p. para 1). However, many US colleges and universities vehemently complain that the rankings are biased. Notwithstanding these complaints, whether this ranking is based on prior performance, institutional quality, institutional age, enrollments, or endowment size is not relevant to our study, because we are not theoretically interested in the source of an institution's formal status. This list provides an authoritative source in terms of the hierarchal ranking of one college relative to another college using a consistent methodology (irrespective of any systematic biases). Furthermore, institutions are acutely aware of their standing on this list.

The US News and World Report publishes many different categories of rankings. In our study, we used the general national ranking category, which lists US colleges and universities who offer a full collection of undergraduate majors, master's degrees, and Ph.D. programs. We used one category within the US News and World Report's list in order to get a ranking of schools using the same ratings criteria for each institution. Of the 281 schools in the published rankings in the general national ranking category in 2012, 8 were removed because they did not adopt Twitter in calendar year 2012. For the remaining 273 schools, we went to each institution's home webpage and found their primary Twitter account.

We have two dependent variables in our study: (1) how frequently an institution retweets content posted by other Twitter users (H1) and (2) how frequently an institution's tweets are retweeted by others plus how frequently an institution is mentioned by others (H2 and H3). Prior literature has established the retweet as a core cultural norm (since 2007) associated with Twitter whereby there is a normative expectation that Twitter users will retweet previously posted content (boyd et al., 2010; Murthy, 2013). Using the Twitter API, we counted the number of tweets that were retweets that each US college or university had in calendar year 2012. Given that some institutions adopted the platform during 2012, we standardized these counts by the number of months that an institution was active in order to facilitate comparisons.

The second dependent variable is a proxy for post-adoption success. Success on Twitter is determined by active engagement of its followers (Culnan et al., 2010; Hemsley & Mason, 2013; Prahalad & Krishnan, 2008), which is determined based on how many times a user's tweets get retweeted and how many times a user is mentioned by others (Bruns & Stieglitz, 2013). Together, these two measures determine how much buzz an organization is creating on the platform. Mentions capture how frequently the community is discussing the account (the organization) and retweets capture the spread of a specific tweet (the content). These two are inter-related and success or buzz on the platform is a function of both metrics. Using the Twitter API, we counted the number of times that a tweet posted by a US college or university was retweeted by another Twitter user and how many times each institution was mentioned by another Twitter user in calendar year 2012. We then standardized these values based on institutional followership due to significant follower differences between institutions.

Hypothesized Independent Variables

The status of each institution was determined using the aforementioned published 2012 rankings. We then grouped institutions into status clusters of 25. US News and World Report only publishes the continuous rankings of the top 200 institutions in the general national ranking category. The remaining institutions are clustered into either a “ranked not published” or “unranked” cluster of schools, making the use of continuous scale not feasible. Clustering in groups of 25 was chosen as opposed to, say, groups of 20 or 30, because of the significance and prevalence of the ‘top 25’ marketing tactic used in admission’s advertising in the field of academia. Using this approach, the relative ranking of the ‘ranked not published’ group is number 9 and the unranked cluster of schools is status group 10.[3] Using these ten status groups, status groups 4 (75-100), 5 (101-125), and 6 (126-150) are mathematically and conceptually in the middle relative to the other institutions in our sample. We then mean centered the ten status groups in order to reduce the variance inflation factors associated with testing the squared term.

To measure how far an institution deviated from the retweeting cultural norm based on the status of the institution, we first estimated the number of times an institution in each status group was expected to retweet content posted by other Twitter users. To do this, we used the model that was used to estimate the frequency of retweeting (see Model 3 in Table 4 in the results section) using the group means for each control variable and the reference posting platform for each status group. We then did a simple subtraction between each institution’s actual number of retweets per month active and the calculated baseline for each status group.[4] This difference may be negative (retweeting less than expectations for their status group), positive (retweeting more than expectations for their status group), or zero (retweeting in line with expectations for their status group). We, however, are only hypothesizing about how far an institution deviates from normative expectations. Whether the institution is over- or under-following cultural norms is not relevant to our hypotheses, so we took the absolute value of the difference. Table 1 displays the descriptive statistics for all hypothesized independent and dependent variables.

Context Specific Control Variables

We control for the following possible alternative explanations: (1) number of tweets per day, (2) average number of hashtags used per tweet[5], (3) number of followers[6], (4) number of Twitter users an institution is following, (5) the primary platform each institution used to post its tweets, (6) the size of the institution, (7) reciprocity, and (8) tweet content. The first five control variables were determined using data elements from the Twitter API. Firm size was determined by the published 2012 enrollment figures. For reciprocity, we conservatively assume that all retweeting activity is the result of reciprocal behavior, because we do not have the Twitter handles for all of the retweets in our sample. To do this, we calculated a ratio of the number of retweets and the number of tweets that were retweeted by others. For example, if an institution retweeted 50 posts and had 100 of its tweets retweeted by others, then we assume that 50% of all retweeting behaviors is the result of reciprocity, which is obviously an overstatement.

Determining tweet content involved two steps. We first identified tweet topics and then counted the frequency of tweets in each topic. In order to identify tweet topics, we sampled the most popular tweets from 30 schools (three from each status group) and conducted an iterative content analysis involving multiple researchers grouping logically related tweets. The result was five topical categories (see Table 2).

We then coded the top 5 tweets that were retweeted by other Twitter users for each institution against these five topical categories.[7] We coded 50 of these tweets together to refine the process and then independently coded a sample of the same 100 tweets to assess inter-rater reliability, which resulted in a simple Cohen’s Kappa value of 0.85. The remaining tweets were divided between two coders. After the coding was completed, we counted the number of tweets in each category for each institution. Table 2 displays the category counts and Table 3 displays the descriptive statistics for all other control variables.

Table 1. Descriptive Statistics for Hypothesized Independent Variables & Dependent Variables

Status Group[1]	US News & World Report Rank		Sample Size	Expected Number of Retweets (Per Active Month)			Absolute Value Deviation From Cultural Norm[5]		Tweets that were Retweets		Months Active		Tweets that were retweets / Months Active		Tweets Retweeted by Other Twitter Users		Mentions		Number of Followers		Post-Adoption Success	
				Estimated Avg[2]	Alt Estimated Avg[3]	Simple Avg[4]	Avg	S.D.	Avg	S.D.	Avg	S.D.	Avg	S.D.	Avg	S.D.	Avg	S.D.	Avg	S.D.	Avg	S.D.
-4.8	1	25	26	13.5	16.0	17.6	15.4	15.7	187.8	227.1	10.8	2.3	18.5	21.2	5,316	6,046	880	607	35,858	46,444	21.2	12.8
-3.8	26	50	22	16.2	20.6	21.2	18.9	17.0	281.8	264.7	11.2	2.3	25.0	23.9	3,743	4,783	832	509	17,170	14,757	29.1	18.0
-2.8	51	75	25	18.7	24.5	21.4	15.2	13.1	167.1	189.7	11.1	2.7	16.9	19.8	5,713	13,035	569	527	20,321	16,546	24.5	18.5
-1.8	76	100	22	20.7	26.9	18.4	27.5	36.0	179.6	351.7	10.3	3.2	24.5	45.2	2,638	3,200	524	462	14,194	15,871	24.3	16.4
-0.8	101	125	29	22.0	27.3	20.4	24.3	32.4	245.2	258.2	9.7	3.5	30.9	39.8	2,633	3,117	688	620	12,993	11,511	29.1	18.1
0.2	126	150	18	22.5	25.5	21.5	30.1	33.4	252.8	212.3	8.9	3.9	37.7	42.4	3,173	5,608	738	574	12,778	12,531	30.6	22.5
1.2	151	175	27	22.1	22.1	19.5	19.2	17.2	166.6	195.4	10.9	1.8	18.0	25.3	1,987	2,418	557	559	8,980	8,558	27.6	21.7
2.2	176	200	26	20.8	17.6	18.6	15.1	6.6	149.1	173.6	11.4	1.8	12.8	14.3	1,090	1,056	297	323	5,858	3,883	25.8	21.3
3.2	Ranked Not Published		66	18.9	13.0	23.3	15.1	21.2	142.1	140.1	10.6	3.0	16.0	25.7	1,345	1,581	342	401	5,003	3,684	31.3	20.5
4.2	Unranked		12	16.4	8.8	8.6	12.2	4.3	53.6	73.6	9.7	3.0	5.7	6.4	455	840	440	554	3,702	4,952	26.4	24.6

[1]The status group was grand mean centered for the status groupings (1 to 10) of all 273 institutions in the sample. That is why the status group variable is not a simple count from 1 (high-status) to 10 (low-status).
[2]We used the results from Model 3 inTable 4 using the group means for all control variables and the reference group platform in order to estimate the expected average.
[3]This alternative estimate was calculated using the status only model (Model 2 inTable 4).
[4]For each status group, we took the average of each institution's actual retweets per month active instead of using the results from Models 2 or 3.
[5]This column is based on the first estimated average values column in this table.

Table 2. Frequency of Content Category by Status Group

	Mean Centered Status										
	-4.8	-3.8	-2.8	-1.8	-0.8	0.2	1.2	2.2	3.2	4.2	Total
Sports	25	33	32	31	51	16	40	43	80	1	352
Community Activities	10	20	22	16	16	14	18	16	59	25	216
Campus Life	39	26	24	19	37	28	42	42	103	10	370
Administrative	11	6	23	19	17	17	18	14	56	9	190
Academia & Scholarship	45	25	24	25	24	15	17	15	23	11	224

Table 3. Descriptive Statistics for the Control Variables by Status Group

Mean Centered Status	Followers[¥]		Following[¥]		Tweets Per Day		Hashtag Use Per Tweet		Enrollment[¥]		Reciprocity		# of Institutions whose Primary Posting Platform is		
	Avg	S.D.	Avg	S.D.	Avg	S.D.	Avg	S.D.	Avg	S.D.	Avg	S.D.	Twitter	Prof Mgt Apps	Other
-4.8	35,858	46,444	1,128	1,505	3.79	1.72	0.44	0.39	17,213	9,593	0.07	0.09	9	17	0
-3.8	17,170	14,757	2,093	2,463	3.49	1.61	0.49	0.26	22,190	15,186	0.15	0.15	16	6	0
-2.8	20,321	16,546	1,946	2,993	2.93	1.56	0.46	0.45	29,213	15,214	0.06	0.09	12	12	1
-1.8	14,194	15,871	1,008	2,375	2.40	2.28	0.76	1.33	18,637	12,085	0.13	0.19	15	5	2
-0.8	12,993	11,511	1,105	1,539	2.87	1.59	0.66	0.44	18,997	10,476	0.16	0.16	15	12	2
0.2	12,778	12,531	1,861	3,330	3.11	1.49	0.43	0.32	23,352	15,228	0.17	0.16	8	8	2
1.2	8,980	8,558	2,290	4,402	2.94	2.00	0.37	0.28	18,973	12,498	0.15	0.19	13	13	1
2.2	5,858	3,883	1,016	2,363	2.38	1.53	0.48	0.39	16,662	8,709	0.18	0.22	12	10	4
3.2	5,003	3,684	870	1,374	2.24	1.55	0.39	0.30	16,659	9,901	0.20	0.23	32	26	8
4.2	3,702	4,952	671	644	1.75	1.74	0.53	0.40	41,643	82,927	0.35	0.33	5	4	3

[¥]In the data models, we took the natural log of these values due to excessive deviations from normality.

RESULTS

We used negative binomial regression models to analyze our non-negative count dependent variables, because a negative binomial is particularly appropriate when count data are over- or under-dispersed and do not contain an excessive number of zeroes (Cameron & Trivedi, 2013), which is the case with both of our dependent variables. In each reported model, the negative binomial dispersion parameter was estimated by maximum likelihood using a log link function. For the hypothesized independent variables, all variance inflation factors (VIFs) were below 2. The content type control variables had VIFs between 10.0 and 20.4, but all other control variables were below 3.5. Therefore, we ran all models with and without the content type control variables and the results were not materially different, so these variables were included in the final analyses. An outlier analysis revealed no data points had undue influence on the results.

Following Cultural Norm of Retweeting Models

The model used to test Hypothesis 1 is the following:

$$Y = \exp\left(\beta_0 + \beta_1(\text{Mean Centered Status}) + \beta_2(\text{Mean Centered Status})*(\text{Mean Centered Status}) + \beta_c\mathbf{X}_c\right)$$

where Y is the standardized count of the number of tweets that were retweets and $\mathbf{X}_c$ is the vector of control variables. The results for these models are reported in Table 4.

Model 1 tests a linear relationship between the status of the institution and the frequency that an institution retweeted content previously posted by other users of the platform. In this model, the linear status coefficient is significant and negative, which suggests that higher-status institutions have a higher likelihood of retweeting content relative to their middle- and low-status counterparts. However, Model 2 tests a curvilinear relationship between the status of the institution and the frequency that an institution retweeted content previously posted by other users of the platform. Model 2 is a better fit than the linear model (Model 1) and the mean centered status squared term is highly significant. As shown in Table 5, the inverted-U in Model 2 peaks at institutions rated 101 to 125 and in Model 3 peaks at institutions rated 126 to 150 (assuming average values for all control variables), which are the middle-status institutions in our sample. Therefore, the proposed H1 curvilinear relationship is supported.

Control Variables (for H1)

The statistical significance of the control variables reveals some interesting effects. First, institutions posting tweets directly on the Twitter platform instead of via other social media platforms such as Facebook or professional social media management applications such as Sprout Social or Hoot Suite have an increased likelihood of following the cultural norm of retweeting. The use of professional social media management applications may distance organizations from directly interacting with participants on the social media platform, which may impede understanding and appropriately following of the platform's cultural norms. Second, the more hashtags that an institution uses per tweet decreases the likelihood that an institution will follow the cultural norm of retweeting. This may be the case because an institution may be focused on finding and re-using hashtags instead of finding previously posted content to retweet. Third, the more followers an institution had and the more times an institution's tweets were retweeted by others (reciprocity), the more likely that the institution was to follow the norm of retweeting.

Robustness Check on H1 Conclusions

We ran all negative binomial models testing H1 clustering the US colleges and universities in groups of 20 (Models 7-9) and groups of 30 (Models 4-6) in order to ensure that our results were not due to our decision to group the institutions in status groups of 25. In all instances, the curvilinear models were the best fit using the AIC measure of model fit, the apex of each curve peaked between institutions ranked from 101 to 125 or from 126 to 150, and the direction (sign) and statistical significance of all coefficients were the same. Therefore, the curvilinear relationship is not due to how we clustered the institutions in our sample.

Deviations from Cultural Norms and Successful Post-Adoption Models

The model used to test H2 and H3 is the following:

$$Y = \exp(\beta_0 + \beta_1(\text{Deviation From Cultural Norm}) + \beta_2(\text{Mean Centered Status}) + \beta_3(\text{Deviation From Cultural Norm})*(\text{Mean Centered Status}) + \beta_c X_c)$$

where Y is the standardized count of the number of tweets retweeted by other Twitter users plus the number of mentions by other Twitter users and X_c is a vector of control variables. The results for these models are reported in Table 6.

The main effects model (Model 10) shows evidence supporting the conjecture that greater deviations from normative expectations leads to decreased post-adoption success. However, Model 11 reveals that the effect is qualified by organizational status (see Table 7). The effect of greater

Table 4. Models Testing the Following Cultural Norms Hypothesis

	Status Groups of 25			Status Groups of 30¥			Status Groups of 20¥		
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**
Intercept	2.99***	3.26***	0.61	2.99***	3.26***	0.58	2.99***	3.26***	0.69
Status[1]	-0.06**	-0.09***	0.02	-0.07**	-0.09***	0.02	-0.05**	-0.07***	0.01
Status*Status[2]		-0.04***	-0.03***		-0.05***	-0.03***		-0.02***	-0.02***
Platform (Twitter Reference Group)									
Other			-1.15***			-1.13***			-1.15***
Professional			-0.35***			-0.35***			-0.36***
Tweets Per Day			0.26***			0.26***			0.27***
Avg. Hashtags Per Tweet			-0.36**			-0.35**			-0.36**
ln(Followers)			0.28***			0.28***			0.28***
ln(Following)			0.06			0.06			0.06
ln(Enrollment)			0.04			0.04			0.03
Reciprocity			3.07***			3.08***			3.08***
Number of Tweets about:									
Sports			-0.34*			-0.34*			-0.34*
Community Activities			-0.28			-0.28			-0.28
Campus Life			-0.44**			-0.44**			-0.44**
Administrative			-0.34*			-0.35*			-0.35*
Academia & Scholarship			-0.26			-0.27			-0.26
Dispersion[3]	1.40	1.35	0.83	1.40	1.35	0.83	1.40	1.35	0.83
Model Details[4]									
Scaled Deviance	311.73	310.34	290.30	311.68	310.30	290.35	311.77	310.36	290.34
Degrees of Freedom (DFs)	271	270	257	271	270	257	271	270	257
(Scale Deviance) / (DFs)	1.15	1.15	1.13	1.15	1.15	1.13	1.15	1.15	1.13
AIC	2180	2172	2046	2180	2171	2047	2180	2172	2047

* Significant at 0.1, ** Significant at 0.05, ***Significant at 0.01

¥Clustering in status groups of 5, 10, and 15 yield the same pattern of results as the three status groups reported in this table.

[1]We mean centered the status variable in all models. That is why the status group variable is not a count from 1 (high-status) to 10 (low-status).

[2]The squared term is the mean centered status variable squared.

[3]The negative binomial dispersion parameter was estimated by maximum likelihood for each model.

[4]All models were specified using a negative binomial distribution and a log link function.

deviations from following the cultural norm of retweeting is positive for institutions ranked 1 to 25, 26 to 50, and 51 to 75, which means that high-status institutions are rewarded with greater follower engagement by not retweeting content in line with normative expectations. This effect is reversed for institutions ranked greater than 75 whereby greater deviations from following the cultural norm of retweeting results in less follower engagement. Therefore, the main effect proposed in H2 is only supported for middle- and low-status institutions.

The effect of deviations from following the cultural norm of retweeting is greater for low-status firms relative to high- and middle-status firms (see 'difference row' in Table 7). The community is punishing low-status institutions with fewer retweets and mentions for not following the cultural norm of retweeting in line with expectations more than the community is punishing high- and middle-status firms. The effect of status is greater for larger deviations from following the cultural

Table 5. Expected Retweeting Frequency By Firm Status (Models 2 and 3)

	Mean Centered Status									
	1 to 25	26 to 50	51 to 75	76 to 100	101 to 125	126 to 150	151 to 175	176 to 200	Ranked not published	Unranked
	-4.8	-3.8	-2.8	-1.8	-0.8	0.2	1.2	2.2	3.2	4.2
Expected Retweeting Frequency Model 2	16.0	20.6	24.5	26.9	27.3	25.5	22.1	17.6	13.0	8.8
Expected Retweeting Frequency Model 3[¥]										
Twitter Platform	13.5	16.2	18.7	20.7	22.0	22.5	22.1	20.8	18.9	16.4
Other Platform	4.4	5.8	7.2	8.4	9.3	9.6	9.4	8.7	7.5	6.2
Professional Management Applications	9.7	12.8	16.0	18.7	20.6	21.4	21.0	19.3	16.8	13.7

[¥]These values were derived using the averages across the entire sample for each control variable.

norm of retweeting relative to smaller deviations (see 'difference column' in Table 7). Along with the statistically significant interaction effect in Model 11, Model 11 is a better fit than Model 10, which supports H3.

Control Variables (for H2 & H3)

Institutions posting more tweets about sports, campus life, and general administrative topics were more likely to have those tweets retweeted by others. Interestingly, institutions posting tweets via professional social media management applications had no effect on the likelihood of having its tweets retweeted on the platform. This is interesting because many of these platforms have proprietary algorithms that are supposed to increase the likelihood of those tweets being retweeted by others, but this does not appear to be the case with our data. The more hashtags that an institution uses per tweet on average results in an increased likelihood of having its tweets retweeted by others. This makes logical sense because the use of hashtags makes the tweets more findable by others on the platform.

Robustness Checks on H2 & H3 Conclusions

We made two study design decisions that may impact the results: (1) clustering institutions in status groups of 25 and (2) using the full models from the first set of negative binomials to determine normative expectations for retweeting content for each status group. As such, to test the robustness of our findings, we ran models using different methods for measuring deviations from the cultural norm of retweeting and different clusters of institutions. We calculated normative expectations using two alternative methods: (1) using the status only models (Model 2 in Table 4) instead of the full model (Model 3 in Table 4) and (2) using a simple average of the actual retweets per month active for each institution in each status group. Models using these two alternative definitions and clustering institutions in groups of 25 are reported as Models 12-15 in Table 6. All models yield the same pattern of results, but the interaction effect is only significant at the 0.1 level.

We then clustered institutions in groups of 20 and 30 and ran models using all three operational definitions of the deviations from following the cultural norm of retweeting variable for each clustering. These results are report as Models 16-21 in Table 6. In all cases, the primary operational definition yielded a highly significant interaction effect with the same sign as reported in clusters of 25. The results for the alternative operational definitions were the same in all models except in Model 17 (status clusters of 30 and using status only models to determine normative expectations) where the interaction effect dropped out of significance. Therefore, with the exception of one model, our results are robust to alternative operational definitions and different status clusters.

DISCUSSION AND CONCLUSION

Our data analysis yielded several important and interesting insights. First, middle-status institutions have a higher likelihood of following the cultural norm of retweeting content previously posted by others on Twitter relative to their high- and low-status counterparts. Second, following the cultural norms is a more productive strategy for middle- and low-status institutions but not for high-status institutions. The Twitter community is rewarding high-status institutions for deviating from the cultural norms rather than following the cultural norms. Finally, low-status institutions are punished by the Twitter community for not following the cultural norm of retweeting in line with expectations more than high- and middle-status institutions.

The main practical ramification of our study is that organizations should know their place in the formal hierarchy and act accordingly when using public social media platforms. Doing so may encourage an environment where its followers will be more likely to spread information (retweet content previously posted by the US college or university and/or mention the organization) throughout the network. As such, managers should understand the social positioning of their organization and the cultural norms associated with the specific social media platforms when interacting on these platforms. Acting appropriately based on the organization's formal status increases the chances of successful post-adoption usage. Knowing one's place in the formal social hierarchy is often easier said than done for organizations, because organizations are often delusional or in denial of their actual status in the formal hierarchy. For example, administrators of US colleges and universities consistently try to group themselves with higher ranked institutions instead of accepting their actual position and behaving accordingly. Our study suggests that managers need to recognize their actual placement in the formal hierarchy and not their idealized placement in the formal status hierarchy.

Additionally, we found that organizations who mostly used professional social media management applications (such as Hoot Suite and Sprout Social) were less likely to follow the cultural norm of retweeting (across all status groups) relative to organizations who posted their content directly on Twitter. In our Twitter dataset, US colleges and universities who used these professional social media management applications had no statistically significant impact on their post-adoption success, which was operationalized as having the organization's tweets retweeted by other Twitter users and an organization being mentioned by other Twitter users. Based on a sampling of marketing materials, professional social media management platforms proffer to increase the likelihood that a tweet will be retweeted based on their proprietary algorithms. In our sample, however, we do not find any statistically significant effect of using one of these platforms. This is contrary to the findings reported by Risius and Beck (2015) who demonstrate the positive effects of social media management tools. From a practical perspective, this means organizations should be cautious in terms of not over relying on these algorithms to manage each platform. While these services may provide other benefits besides getting messages to trend and spread throughout the social media platform, our data do not show any correlation between post-adoption success and the use of professional social media management applications. The use of professional social media management applications does, however, distance organizations from directly interacting with participants on the social media platform, which may impede understanding and appropriately following of the platform's cultural norms.

Our primary theoretical contribution is to demonstrate the importance of status to the post-adoption use of public social media platforms, specifically the applicability of the theory of middle-status conformity. Status is an important variable to include in the post-adoption literature for the following reasons: (1) status is a structural enabler and inhibitor (Phillips & Zuckerman, 2001; Podolny, 1993; Washington & Zajac, 2005), (2) status is an organizational resource that may be leveraged to generate future returns (DiPrete & Eirich, 2006; Gould, 2002), and (3) status helps determine acceptable and unacceptable behavior in a given social setting (Phillips & Zuckerman, 2001). Therefore, future research investigating the post-adoption of public social media platforms should, at a minimum, control for the effect of status.

Table 6. Models Testing Post-Adoption Success Hypotheses

	Status Groups of 25						Status Groups of 30¥			Status Groups of 20¥		
	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21
Intercept	1.72**	1.74**	1.71**	1.69**	1.71**	1.65**	1.73**	1.69**	1.76**	1.71**	1.68**	1.73**
Deviation From Cultural Norm:												
Estimated from Full Models[1]	-0.005***	-0.007***					-0.007***			-0.008***		
Estimated from Status Only Models[2]			-0.005***	-0.007***				-0.007***			-0.007***	
Average[3]					-0.005**	-0.006***			-0.008***			-0.008***
Status[4]	0.02	0.06***	0.02	0.05**	0.02	0.05**	0.07***	0.05**	0.09***	0.06***	0.05**	0.07***
(Deviation From Cultural Norm)*(Status)		-0.003***		-0.002*		-0.002*	-0.003**	-0.002	-0.004***	-0.002**	-0.002**	-0.003***
Tweets Per Day	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Average Hashtags Per Tweet	0.28**	0.30***	0.28**	0.29***	0.29**	0.30***	0.30***	0.29***	0.30***	0.30***	0.29***	0.31***
ln(Following)	0.03	0.02	0.02	0.02	0.03	0.02	0.02	0.02	0.01	0.02	0.02	0.009
ln(Enrollment)	0.03	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.03	0.04	0.02	0.03
Reciprocity	0.54**	0.46*	0.54**	0.50**	0.53**	0.49**	0.47*	0.49**	0.31	0.47**	0.47**	0.30
Platform (Twitter Reference Group)												
Other	-0.38**	-0.37**	-0.39**	-0.40**	-0.39**	-0.40**	-0.37**	-0.40**	-0.35**	-0.36**	-0.40**	-0.35**
Professional	0.11	0.12	0.11	0.10	0.10	0.10	0.11	0.10	0.12	0.11	0.11	0.12
Number of Tweets About:												
Sports	0.23**	0.23**	0.23**	0.24**	0.23**	0.25**	0.22*	0.25**	0.24**	0.21*	0.25**	0.23**
Community Activities	0.09	0.10	0.10	0.11	0.10	0.12	0.09	0.11	0.10	0.08	0.11	0.11
Campus Life	0.24**	0.26**	0.25**	0.27**	0.24**	0.27**	0.24**	0.27**	0.27**	0.23**	0.27**	0.28**
Administrative	0.23**	0.24**	0.23**	0.25**	0.23**	0.25**	0.23**	0.25**	0.25**	0.22*	0.25**	0.25**
Academia & Scholarship	0.12	0.14	0.13	0.14	0.13	0.14	0.13	0.15	0.15	0.12	0.15	0.15

continued on following page

Table 6. Continued

	Status Groups of 25						Status Groups of 30¥			Status Groups of 20¥		
	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21
Dispersion[5]	0.40	0.39	0.40	0.40	0.40	0.40	0.39	0.40	0.39	0.39	0.39	0.38
Model Details[6]												
Scaled Deviance	297.60	296.21	297.56	296.54	297.62	296.59	296.45	296.68	296.13	296.23	296.29	295.97
Degrees of Freedom (DFs)	258	257	258	257	258	257	257	257	257	257	257	257
(Scaled Deviance) / (DFs)	1.15	1.15	1.15	1.15	1.15	1.15	1.15	1.15	1.15	1.15	1.15	1.15
AIC	2289	2284	2290	2288	2291	2289	2286	2288	2279	2283	2285	2277

* Significant at 0.1, ** Significant at 0.05, ***Significant at 0.01

¥Clustering in status groups of 5, 10, and 15 yielded the same pattern of results as the three status groups reported in this table (with the interaction effect significant at least at the 0.1 level). The main effects only models for status groups 20 and 30 are not reported in this table due to space limitations, but the interaction effect models all had better model fit statistics than the main effect only models.

[1]The baseline for each status group was calculated using the full models (Model 3 for status groups of 25, Model 6 for status groups of 30, and Model 9 for status groups of 20) using the group means for each control variable and the reference group platform.

[2]The baseline for these deviation from norm values were calculated using the status only models (Model 2 for status groups of 25, Model 5 for status groups of 30, and Model 8 for status groups of 20) instead of the full models with all of the control variables.

[3]The baseline for these deviation from norm values were calculated using a simple average of the actual retweets per month active for each institution in each status group.

[4]The status variable was mean centered in all models. That is why the status group variable is not a simple count from 1 (high-status) to 10 (low-status).

[5]The negative binomial dispersion parameter was estimated by maximum likelihood for each model.

[6]All models were specified using a negative binomial distribution and a log link function.

Table 7. Interaction Between Status & Deviation From Cultural Norm of Retweeting (Model 11)

Deviation From Norm	Mean Centered Status										
	1 to 25	26 to 50	51 to 75	76 to 100	101 to 125	126 to 150	151 to 175	176 to 200	Ranked not published	Unranked	Difference Column
	-4.8	-3.8	-2.8	-1.8	-0.8	0.2	1.2	2.2	3.2	4.2	
0	21.7	23.1	24.5	26.0	27.6	29.3	31.2	33.1	35.1	37.3	-15.6
10	23.4	24.1	24.9	25.6	26.4	27.2	28.0	28.9	29.8	30.7	-7.3
20	25.2	25.2	25.2	25.2	25.2	25.2	25.2	25.2	25.2	25.2	0.0
30	27.1	26.3	25.6	24.8	24.1	23.4	22.7	22.0	21.4	20.7	6.4
40	29.2	27.5	25.9	24.4	23.0	21.7	20.4	19.2	18.1	17.0	12.2
50	31.5	28.8	26.3	24.0	22.0	20.1	18.3	16.8	15.3	14.0	17.5
Difference Row	-9.8	-5.7	-1.8	2.0	5.6	9.2	12.9	16.3	19.8	23.3	

These estimates assume average values for all control variables and the reference platform as the primary posting platform.

Like all research, our research has its limitations. First, we only investigated a single industry within a single country, but previous research might suggest cultural differences in the use of social media platforms (specifically Twitter) (Pentina, Zhang, & Basmanova, 2013; Yin, Feng, & Wang, 2015). It might be possible that the cultural context of the institution mediates or moderates the relationships we reported in this paper. Several context extensions are necessary and provide interesting future lines of research in order to maximize (and to test) the generalizability of our findings. Second, our empirical investigation used the Twitter social media platform. Social media platforms have unique users, cultural norms, and different success metrics (Hughes, Rowe, Batey, & Lee, 2012), so future empirical work is necessary. We, however, are generalizing to theory not to a population (Lee & Baskerville, 2003) in our paper. Third, institutions may go through many different stages of post-adoption use of a social media platform and our study assumes all institutions are at more or less the same stage of use. Success, however, may be defined differently depending on the stage of post-adoption use. For example, initial post-adoption success on Twitter may be accumulating followers whereas a later measure of post-adoption success may be mentions and retweets. In our study, we control for this by standardizing mentions and retweets per followers, but an interesting future study may be to conduct a longitudinal analysis of tweeting based on different post-adoption stages with different metrics at each stage.

Fourth, we theoretically and empirically investigated formal status and not informal status. It is possible that informal status among colleges and universities has a complementary impact on following the cultural norms and post-adoption success. Therefore, an interesting future research project may add informal status to our research model or substitute formal status with informal status to investigate those effects. Finally, Shi and colleagues (2014) demonstrate that network ties impact the likelihood of retweeting content on the Twitter platform, but we did not have the data to test these effects in our models. Future research can investigate the network level effects in conjunction with the status effects on the likelihood of following cultural norms and post-adoption success.

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ENDNOTES

[1] Individuals may use these platforms for different purposes, but our focus is on how organizations use Twitter and other social media platforms.

[2] A cursory investigation of the tweets and Facebook activity of both institutions revealed a very similar pattern of re-tweeting and Facebook liking with several of their middle-status peer institutions.

[3] Each status group may not have an equal number of schools in it due to ties in the rankings and how US News & World Report lumps schools into the last two status groups. Therefore, the 'middle' in our sample is not simply 273/2. The middle is determined based on the relative ranking of the status groups. We ran several robustness checks to ensure that our results were not due to how we were clustering the schools (see robustness checks sub sections in the results section).

[4] We considered other options for measuring deviation from norms such as using the grand mean across all 10 status groups, but using the grand mean loses the fact that the normative expectations are different for each status group. We also considered further clustering the institutions into three groups (high-, medium-, and low-status groups), but we have no solid justification to group the institutions different for each part of the study and the three categorical groupings would be quite arbitrary.

[5] A hashtag is a metadata tag prefixed with a "#" in order to group related tweets.

[6] The number of followers is a component of the second dependent variable so this control is only used in the H1 models.

[7] These represented 107,878 out of the 120,397 total tweets that were retweeted in our sample.

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