Causal Effects of Affordance Change on Communication Behavior: Empirical Evidence from Organizational and Leadership Social Media Use*

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Abstract

This article provides empirical evidence for two hypotheses in the affordance literature. First, by leveraging a small affordance change — Twitter increasing its character limit from 140 to 280 on November 7, 2017, employing an instrumental variable approach, and examining 143,771 original tweets published by organizational and leadership accounts half a year before and after the intervention, we showed the direct causal relationship between affordances and communication behavior on digital media platforms. Second, by exploring what factors could explain the heterogeneity of causal effects, we showed that previous endogenous perceptions of communication constraint predicted later behavioral changes, despite the same exogenous intervention. These findings highlight the role of human agencies in the face of technological changes and provide empirical support for the affordance approach to information communication technologies (ICTs) as a reconciliation between technological determinism and social constructivism.

Keywords: Affordances, Digital Media, Communication Behavior, Causal Inference, Instrumental Variable, Twitter, Organizational Social Media Use

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1 Introduction

Much literature on how digital technology influences human communication has focused on one central concept: affordances (e.g., Halpern & Gibbs, 2013; Taipale, 2014). An affordance approach to digital media argues that interpersonal communication and computer-mediated communication differ in one significant way, that the latter requires inhuman objects to encode and decode messages through technical infrastructure and channels, and the characteristics of these technical infrastructures and channels afford and affect communication outcomes, including but not limited to the creation of media content, the management of organizational knowledge, and the emergence of social interactions (Park & Yang, 2017; Sun, Wang, & Jeyaraj, 2020; Treem & Leonardi, 2013). This affordance approach provided a theoretical lens for scholars to characterize different action possibilities on mediated channels and understand human-computer interactions in newly developed information communication technologies (ICTs) (e.g., Evans, Pearce, Vitak, & Treem, 2017; Kaptelinin & Nardi, 2012; Shin, 2017; Sundar, 2008).

Underlying this stream of research, the assumption lies that communication behavior on digital media platforms, such as social networking sites (SNSs), is closely related to and directly affected by affordances of these platforms. However, if we examine our knowledge critically, it becomes obvious that we do not actually have strong, rigorous, and documented evidence on the direct relationship between digital media affordances and human communication behavior. For example, we still do not know the degree to which a change in affordances can affect communication behavior in a causal manner. Further, in contrast to strong theoretical arguments that human agency affects how information technologies are used for communicative purposes (e.g., Nagy & Neff, 2015), we also lack empirical evidence on *whether* and *how* varying human perceptions affect digital media behavior.

This gap in the literature was indeed difficult to fill, because affordances in most cases stay the same across time on digital media platforms. In lab experiments, researchers can artificially change affordances but it threatens external validity. Most existing empirical research used a qualitative and comparative lens to study the effect of affordances on mediated communication (e.g., Fox & Warber, 2015; Halpern & Gibbs, 2013).

The current study tries to fill the knowledge gap by taking advantage of a recent event of affordance change to provide causal evidence on the relationship between affordances and communication behavior. Twitter, notorious for its restriction on text length, suddenly changed its character limit from 140 to 280 on November 7, 2017, which provided a great opportunity for causal identification on the effect of affordance change on communication behavior. Supplementing recent case studies on the event (e.g., Gligorić, Anderson, & West, 2018, 2019, 2020; Jaidka, Zhou, & Lelkes, 2019), we report statistical details on how the switch induces changes in content creation and underline the role of platform affordances in shaping user behavior in the digital world. Analyzing the exogenous intervention with an instrumental variable (IV) approach and using organizational settings (i.e., top organizations and leadership Twitter accounts) as the research context, we show how the change in affordances leads to various degrees of change in social media use, i.e., the use of language and interactive features on Twitter. Estimating user engagement level and perceptions of communication constraint with numeric proxies, we further explore what endogenous factors, if any, can explain the various degrees of behavioral change. The result highlights the role of human agency in the face of technological changes, and provides empirical augmentation to the affordance approach to ICTs as a reconciliation between techno-

logical determinism and social constructivism.

The paper is structured as follows. First, we review affordance theory and its application in literature to provide background on how the theoretical framework has developed and evolved in empirical studies. By doing so, we highlight how scholarly knowledge has assumed the direct connection between affordances and digital communication behavior without explicitly evaluating it. In the review, we also touch upon the debate between technological determinism and social constructivism to illustrate the value of rigorously evaluating human agencies during affordance change. Then, we introduce the case of Twitter character limit change, detail the empirical strategy for causal identification, justify the research context of organizational social media use, and present numeric variables and their respective hypotheses. After presenting results on behavioral changes, we discuss theoretical implications of the study as to how the affordance approach — recognizing agencies from both developers and users — helps researchers understand ICTs in society at large. We also discuss new ways forward to quantitatively and computationally analyze the role of digital media affordances in computer-mediated communication.

2 Literature Review

2.1 The Affordance Approach to Information Communication Technologies

James J. Gibson developed the theory of affordances in the field of ecological psychology to characterize the interactionist view of perceptions and actions, the gist being that affordances emerge from interactions between inhuman objects and human actors and support certain behavior in the physical world (Gibson, 1979; Greeno, 1994). This affordance perspective has been adapted into many fields, such as industrial design, human-computer interactions, and digital media, and provided scholars a theoretical framework to investigate relationships between actors and objects in our online and offline lives (e.g., Faraj & Azad, 2012; Lintern, 2000; Norman, 1988; Sundar, 2008).

Affordances, simply defined as action possibilities available in the environment, usually refer to properties of technology that enable and restrict users' certain digital behavior in the literature (Evans et al., 2017; McGrenere & Ho, 2000).

In empirical studies, the affordance framework has proved to be quite useful for scholars to theorize digital behavior. For example, a series of work has been conducted to compare communication behavior on popular social networking sites (SNSs), and many of them attributed their findings to the different affordances provided by those platforms (Fox & Holt, 2018). Oz, Zheng, and Chen (2018) compared user-generated political responses on Twitter and Facebook, and found that Twitter invited significantly more uncivil content from participants. They argued that Twitter's affordances, emphasizing weak-tie building and limiting post lengths, triggered more de-individuation compared to those on Facebook (Chen, 2011; Oz et al., 2018; Reicher, Spears, & Postmes, 1995). Halpern and Gibbs (2013) conducted a similar study and compared online deliberation on Facebook versus on YouTube. They also situated their findings in affordance theory and identified two affordances — identifiability and networked information access — as the root cause that makes YouTube a lesser place for political expression.

Insights from these comparative studies, along with some critical and qualitative work (e.g., Chan, 2018; McGuigan, 2019), have put affordances at the forefront of the ICTs literature and demonstrated how the affordance framework can contribute to theory building in digital media

research (see more examples such as [Fu & Zhang, 2019](#); [Jaidka, Guntuku, Buffone, Schwartz, & Ungar, 2018](#); [Kim, Chun, Kwak, & Nam, 2014](#)). However, if we examine the existing literature critically, it becomes clear that the direct link between affordances and communication behavior has not been carefully investigated. Most studies attributed their findings to different affordances across platforms, but we actually lack documented causal evidence that shows affordances can change communication behavior.

The examination of causality between affordances and communication behavior is indeed difficult, since most digital media platforms do not regularly change their affordances. Even when they do, their A/B testings are usually conducted and analyzed in house, without public data accessible for scholarly research. Some scholars tried to establish the causality using lab experiments, but many of them are comparative in nature and lack external validity (e.g., [Oz et al., 2018](#)). A few studies have taken advantage of a public event of affordance change — Twitter increasing its character limit from 140 to 280 — and provided some evidence on the link between affordances and communication in terms of engagement outcomes and linguistics ([Gligorić et al., 2018, 2019, 2020](#); [Jaidka et al., 2019](#)). The current study contributed to this growing trend of quantitative analyses of affordance theory by examining the same case but focusing on the explicit change of communication behavior, such as the use of interactive features and the compliance of treatment. By showing how platforms affordances changed human behavior, the study tries to underline the role of affordances in our digital lives. The overarching research question is:

RQ1: How did affordance change causally affect communication behavior, in the case of Twitter character limit increase?

2.2 Human Agency in Technological Affordances

It should be noted that affordance is closely related to other terms used in digital media literature such as “attribute” and “feature,” but some nuances exist ([Eveland, 2003](#); [Faraj & Azad, 2012](#)). While objects’ features are existent regardless of human presence and constant to all human actors, affordances are inherently relational, as human actors might perceive affordances and react to affordance change differently ([Ellison, Gibbs, & Weber, 2015](#); [Fulk & Yuan, 2013](#); [Gibbs, Rozaidi, & Eisenberg, 2013](#); [Shin, 2019](#)). Although ambiguity exists in affordance’s contemporary conceptualization and debates have not been settled on its ontology, such as whether or not affordances exist independently of human perceptions, most scholars agree that research should consider the role of human actors to better understand the affordance approach to the use of communication technologies (see [Boyle & Cook, 2004](#); [Burlamaqui & Dong, 2015](#); [Dohn, 2009](#); [Fayard & Weeks, 2014](#); [Jones, 2003](#); [Parchoma, 2014](#); [Sanders, 1997](#)). Some recent theoretical developments by conceptual articles, such as “perceived affordances” and “imagined affordances” ([Fox & Holt, 2018](#); [Nagy & Neff, 2015](#); [Zhao, Liu, Tang, & Zhu, 2013](#)), and empirical examinations of newly developed information technologies, such as blockchains and virtual reality ([Shin, 2017](#); [Shin & Hwang, 2020](#)), have further foregrounded the necessity to consider human agency in affordance studies.

This relational view of affordances contends that human agency, taking forms such as perceptions and interpretations, exerts influences on how affordances are eventually perceived and utilized by users for their digital behavior. It has become even more important to recognize the role of human agencies in affordances, considering the rise of “black box” technologies such

as algorithm which does not provide an interface for users to directly engage but nonetheless manifests its action possibilities through affordances (e.g., [Shin & Park, 2019](#); [Shin, Zhong, & Biocca, 2020](#)). In this sense, the call to emphasize human agency in affordance research can also be seen as a response to the sociological debate on technological determinism versus social constructivism.

In their scholarly exchange on the relationship between technological artifacts and human practices, [Hutchby \(2001, 2003\)](#) and [Rappert \(2003\)](#) reintroduced the technology-as-text metaphor in earlier writing ([Grint & Woolgar, 1997](#)), which argued that the meaning of technology (text) emerges from the dynamic interaction between the developer's intentions (the writer's composition) and the user's interpretation (the reader's understanding). Overemphasis on the developer's intentions falls into the camp of technological determinism, while overemphasis on the user's interpretation falls into the camp of social constructivism, neither of which accurately represents the social reality of technology. This predicament, therefore, calls for a "third way" to understand technology in society that can reconcile these two sides, and [Hutchby \(2001\)](#) suggested the affordance approach as a possible answer. The definition he provides — affordances constrain the ways that technological artifacts could possibly be interpreted — incorporates both schools' theoretical arguments and gives scholars a way out from the "unpalatable choice between undersocialized and oversocialized conceptions of technology" ([Bloomfield, Latham, & Vurdubakis, 2010](#), p. 416). The concept of affordances has thus taken a transdisciplinary journey, transforming from a term in ecological psychology to a new yet ambivalent way to understand technology by sociologists.

In the era of mediated communication, scholars such as [Neff, Jordan, McVeigh-Schultz, and Gillespie \(2012\)](#) have argued that it is still relevant and important to recognize the tension between technological determinism and social constructivism as the backdrop for the increasing use of "affordances" in empirical research on digital media. In contrast to broad claims such as "technological determinism is dead" ([Wyatt, 2008](#)), [Neff et al. \(2012\)](#) cautioned against scholars' overcorrection in the direction of human power and advocated for the affordance approach which gives credit to both developers' and users' agencies. Applying this thinking to the case analyzed here, we would hypothesize that Twitter's character limit change might have affected its users in a nuanced way, rather than what would be simply suggested by either technological determinism or social constructivism. In other words, instead of the user population making uniform behavioral changes as intended by developers (a result expected by technological determinists) or the user population exerting agencies to resist exogenous changes (a result expected by social constructivists), we should see a mix of the two (a result suggested by the affordance approach to digital media). That is, we hypothesize that Twitter users have generally complied with the affordance change and exhibit some significant behavioral changes at the population level, but at the same time, there also exist some enormous between-subject variances driven by individual agencies.

What bears theoretical interests here is the question of why users might have changed their communication patterns to different degrees and what factors can explain those variances. Since the direct causal relationship between affordances and communication behavior is under-examined, there is limited empirical evidence to consult here, but we can make some informed speculations by extrapolating relevant research. For example, studies on community feedback and social influence have suggested that engagement indicators, such as retweets and likes, can serve as a positive or negative cue to alter users' psychological well-being and future behavior on social networking sites (e.g., [Burrow & Rainone, 2017](#); [Cheng, 2014](#); [Kross et al., 2013](#); [Muchnik,](#)

175 Aral, & Taylor, 2013). Frequent interactions with followers could thus contribute to a positive
feedback loop and motivate them to use social media more (Bell, Cassarly, & Dunbar, 2018; Utz,
Tanis, & Vermeulen, 2012; Walther et al., 2011). Therefore, it is reasonable to suspect that the de-
gree of behavioral change might be associated with users’ prior experiences on the studied social
media platform. Another factor that might come into play concerns the presence and absence of
180 communication constraint discussed in some literature on censorship and repression (e.g., Hobbs
& Roberts, 2018; Pan & Siegel, 2020; Roberts, 2020), since Twitter extending the character limit
can be understood as the platform lifting a restriction imposed by its developers earlier. The
prior experiences users had with the communication constraint might consequently influence
how they adapted to the new affordance when it was implemented (Boudreau & Robey, 2005;
185 Leonardi, 2011).

These two speculations both highlight the role of user agencies in affordances, in that
Twitter users’ various experiences prior to November 7, 2017 might have given them various
incentives to comply with the affordance change. More details on these hypotheses will be artic-
ulated in the next section, but our second research question is clear:

190 **RQ2:** What factors, if any, can explain the various degrees to which affordance change
affects communication behavior?

3 Case, Context, and Hypotheses

In light of the lack of empirical evidence on the causal relationship between affordances
and communication behavior, the current study seeks to fill the gap in scholarly knowledge by
195 analyzing a major event of affordance change in recent years with publicly available data sets.

The case analyzed here is Twitter increasing its character limit from 140 to 280 on Novem-
ber 7, 2017. According to corporate press releases, Twitter started beta-testing the extended type
box in September the same year, giving some eligible users early access to the new feature, and
then publicly rolled out the feature to all Twitter users two months later (Rosen & Ihara, 2017).
200 Twitter’s initial intention is to provide users with different language preferences the same po-
tential to express themselves on the platform, and in the meantime improve user experiences by
reducing the time spent editing tweets in the composer (Rosen, 2017; Rosen & Ihara, 2017).

This sudden intervention created a great quasi-natural experiment setting that makes the
identification of causal effects possible, the intuition being that Twitter users might exhibit dif-
205 ferent communication patterns after the affordance change. However, the “experiment” did not
come with random assignment and did not create a clear control group, since all Twitter users en-
tered the new 280-character era at the same time. Time-series analysis is reasonable but might still
suffer spuriousness due to history threats. Therefore, in this paper, we opted to use instrumental
variable analyses — widely used in econometrics (e.g., Angrist & Pischke, 2009) and recently gain-
210 ing steam in management literature (e.g., Chintrakarn, Treepongkaruna, Jiraporn, & Lee, 2020;
Shoham, Almor, Lee, & Ahammad, 2017) — by analyzing tweets published by temporally stable
users suggested by previous literature.

More specifically, we analyzed the intervention with a randomized encouragement de-
sign, by treating tweets published by Twitter users as randomly assigned to being drafted either
215 before or after November 7, 2017. That is, tweets that were drafted after the switch date were
encouraged to use the newly expanded bandwidth, despite not all of them complying with the
treatment by tweeting more than 140 characters in the end. In fact, this encouragement design

well corresponds to the contemporary understanding of the affordance theory, as it “refutes the dichotomy between agency and determinism” (Fayard & Weeks, 2014, p. 239). In our case, Twitter developers do not and cannot determine the behavior of their users by simply setting a new character limit, but in the meantime, it is difficult for users to exert their absolute agency to resist the technological change because their online environment has indeed changed. In other words, the relational view of technological affordances promotes the idea that technological changes encourage or nudge certain online behavior (Lee, Lee, & Hwang, 2014; Shin et al., 2020), which the current design captures through an instrumental variable approach using a two-stage least square regression model.

However, research employing instrumental variables requires several identification assumptions, the critical one being the ignorability assumption (see Angrist, Imbens, & Rubin, 1996; Sovey & Green, 2011), which states that the instrument (Z , in our case, a dummy indicating whether a tweet was published before or after the affordance change) should have no direct effect on the outcome (Y , in our case, indicators on communication behavior), other than through its effect on the treatment assignment variable (T , in our case, a dummy indicating whether a tweet used more than 140 characters). In other words, if the treatment did not happen, after the switch date, digital media users should have been tweeting in the same fashion as what they had been doing before November 7, 2017. This requirement motivated us to examine organizations’ social media use as the research context.

Organizational social media use has long been criticized by business and public relations scholars for being organization-centric and irresponsible to exogenous factors. Except few notable corporate accounts with distinct personalities such as Wendy’s Twitter presence, most organizational accounts do not fully utilize social media’s potentials as an interactive and two-way channel to communicate with key stakeholders. Instead, they merely broadcast corporate press releases, share news and blog links, and advertise products and promotions on social media, as evidenced by numerous studies (e.g., Ao & Huang, 2020; Kim et al., 2014; Lovejoy & Saxton, 2012; Qu, 2020; Waters & Williams, 2011; Wirtz & Zimbres, 2018; Yue, Thelen, Robinson, & Men, 2019). Apart from the lack of human resources for organizational social media management and the persistence of information control in corporate culture, it could also be argued that, to a certain degree, affordances of Twitter as a text-based social media platform are not encouraging organizations’ personnel to create relevant content for their followers or to initiate meaningful interactions with external stakeholders (Lovejoy & Saxton, 2012; Zhou & Xu, 2020). The insensitivity of organizational social media use to exogenous changes helped the current study fulfill the ignorability assumption. Moreover, major organizations happen to tweet a lot, which provides us a sufficient sample size for a reasonable estimation of the treatment effect.

To answer the second research question and explore why examined accounts might change their communication behavior to different degrees, two variables — user engagement level and perception of communication constraint — were created and proxied numerically to test two sets of hypotheses, in correspondence to the two speculations articulated in the literature review section.

Social media users enjoy vastly different levels of content engagement, even when they have similar numbers of followers on the platform. Some accounts, maintained by a team of social media professionals, are much better received by Twitter users than others. By engaging stakeholders and followers with genuine conversations and generating relatable content that oftentimes goes viral, some Twitter accounts in our sample will garner higher numbers of retweets

and likes compared to others. These high-frequency interactions with followers might give organizations and the leadership more incentive to take advantage of the increased character limit and continue improving their social media content creation to build relationships with their audiences. Therefore, it is hypothesized that active and well managed accounts with high engagement outcomes before the affordance change would use the newly extended type box more (H1.1) and increase their multimedia creation (H1.2) after the treatment. The user engagement level was numerically proxied as the median of the number of retweets and likes received by the account's pre-treatment tweets, divided by its number of followers. Medians are used to estimate average user engagement levels since the distribution of engagement indicators (i.e., retweets and likes) is highly skewed. The hypothesis is:

H1: Accounts with higher pre-treatment user engagement levels will use the newly afforded type box more often in their post-treatment tweets (H1.1) with more multimedia features (H1.2).

On the other hand, in line with Twitter's initial rationale (Rosen, 2017), it is also reasonable to expect that accounts who experienced more communication constraint pre-treatment would utilize the newly extended type box more often (H2.1) and increase their multimedia creation (H2.2). In other words, those who regularly posted tweets close to 140 characters before the affordance change might have had a hard time revising tweets over and over again to make sure their tweets did not exceed the 140 character limit. Consequently, when the constraint was released, they might take the lead to use the newly afforded feature. Perceptions of communication constraint were thus numerically proxied as the median number of characters used by the account's pre-treatment tweets. The closer the variable is to 140, the higher communication constraint is thought to be perceived by the account. The hypothesis is:

H2: Accounts that perceived higher pre-treatment communication constraint will use the newly afforded type box more often in their post-treatment tweets (H2.1) with more multimedia features (H2.2).

4 Method

We selected 100 major corporations and non-profit organizations and 84 leadership accounts for the current study. Four lists were consulted and combined, including the top 50 Fortune 500 companies and the top 50 largest U.S. charities, compiled by Fortune and Forbes in 2018,¹² and leadership accounts compiled by Yue et al. (2019) and Afshar (2013). Table 1 shows the Twitter handles of those examined accounts. Aligning ourselves with principles of open science and data transparency, we have deposited the dataset, scripts, and relevant files on Open Science Framework (OSF) for replication purposes. We recognize the fact that the literature on digital media effects has been mostly focusing on its influence on communication behavior and user experiences on the personal level (e.g., Shin, 2017; Sun et al., 2020), despite the advantage of using organizational social media accounts for causal identification. Therefore, to provide additional evidence, we also combined these leadership accounts, representing Fortune 500 companies, startups, and political organizations, into our data collection process.

[Insert Table 1 Here]

¹<https://fortune.com/fortune500/2018/>

²<https://www.forbes.com/top-charities/list/>

Table 1: Examined Organizational and Leadership Twitter Handles

Corporations				
walmart	exxonmobil	UnitedHealthGrp	McKesson	CVSHealth
amazon	ATT	GM	Ford	Healthcare_ABC
Chevron	cardinalhealth	verizon	kroger	generalelectric
Walgreens	Chase	FannieMae	Google	HomeDepot
BankofAmerica	ExpressScripts	WellsFargo	Boeing	Phillips66Co
AnthemInc	Microsoft	ValeroEnergy	Citi	comcast
IBM	Dell	StateFarm	JNJCares	FreddieMac
Target	Lowes	MarathonPetroCo	ProcterGamble	MetLife
UPS	pepsi	intel	DowDuPontCo	ADMupdates
Aetna	FedEx	UTC	Prudential	Albertsons
Non-Profit Organizations				
UnitedWay	FeedingAmerica	Americares	TFGH	SalvationArmyUS
StJude	DirectRelief	Habitat_org	BGCA_Clubs	ymca
FoodForThePoor	compassion	CCharitiesUSA	GoodwillIntl	SamaritansPurse
LutheranSvcs	AmericanCancer	WorldVision	StepUp4Students	nature_org
RedCross	American_Heart	mapintl	CMMBTweets	operationbless
crutweets	PPFA	PAN_Foundation	UNICEFUSA	MountSinaiNYC
SavetheChildren	CatholicRelief	MayoClinic	feedthechildren	CARE
MSF_USA	DanaFarber	CarterCenter	Good360	nyphospital
HealthWellOrg	MakeAWish	shrinershosp	sloan_kettering	EIFoundation
Rotary	TheJDC	PSImpact	KidneyFund	ACLU
Leadership				
bkrunner	BruceDBroussard	ChuckRobbins	IndraNooyi	JeffBezos
JonasPrising	KentThiry	SYFMKeane	MarkVHurd	mtbert
mtbarra	CEOMikeJackson	RobertIger	satyanadella	SteveCollis_ABC
SteveEasterbrk	tim_cook	LadyAshBorg	SchambachSays	ramiessaid
valgui1	ytechdata	ashoddd	merongribetz	JoSchneier
AmirRubin	bjurgs	etaibeck	cjpedregal	Louel
bgrey	jasonaramburu	DanReich	seanduffy	SameerPatel
Benioff	richardbranson	Bill_Gross	chrisbrogan	briansolis
Jon_Ferrara	mcuban	garyvee	jack	levie
SteveCase	rwang0	RomanStanek	petecashmore	SteveForbesCEO
timoreilly	elonmusk	bhalligan	charleneli	realDonaldTrump
MichaelDell	PeterAceto	AndrewGrill	WendySLea	BillGates
shervin	MickyArison	markfidelman	marissamayer	rupertmurdoch
aneelb	kevinrose	bryankramer	dens	dickc
davemorin	ManpowerGroupJJ	MichelleRhee	invoker	davidkarp
drewhouston	jeffweiner	jeremys	eldsjal	NPRGaryKnell
AmFamJack	peretti	andrewmason	WesternUnionCEO	

4.1 Data Collection and Variables

We collected one year of Twitter data from the 184 accounts identified above. The tweets' publishing times range from six months before to six months after November 7, 2017 when the new character limit took effect. A web crawler in Python was used to scrape tweet IDs from

the advanced Twitter search page, which eliminated the sampling issues caused by Twitter API’s data mining rate limit and returned a complete collection of tweets published by these examined accounts. Tweets were then rehydrated to retrieve metadata for further analyses. We only used tweets with original content creation, with retweets and reply tweets — starting with “@” and identified by examining the “in-reply-to” metadata — discarded. In total, 151,780 original tweets were published by these 184 accounts between May 7, 2017 and May 7, 2018. Upon further examination detailed in Appendix S1, several accounts were removed due to small numbers of published tweets and being beta testers with early access. The final data set thus contains 143,771 tweets from 135 accounts.

Variables analyzed in this study include a tweet’s number of characters, text characters, media, URLs, hashtags, and mentions and its publication time, all provided by the Twitter API metadata. We also constructed the number of features as the sum of numbers of media, URLs, hashtags, and mentions, to proxy the level of interactive multimedia use of a single tweet. At the account level, the number of followers was extracted from the metadata, along with two variables created to proxy the account’s engagement level with Twitter users and the account’s perception of communication constraint. These two variables were created to explore why these examined accounts exhibited different communication behaviors after the affordance change, the rationale of which has been detailed in the previous section.

4.2 Empirical Models

As discussed earlier, it is challenging to establish the causal relationship between the treatment of whether a tweet contains more than 140 characters (T) and the outcome variable of communication behavior indicators (Y), because the relationship, when conventionally estimated, might suffer spuriousness and omitted variable bias due to potential confounders, such as industry types, number of followers, and corporate culture. To deal with this endogeneity issue, the study uses the instrumental variable approach. The design is summarized in Figure 1, with the two stage least squares (2SLS) regression models shown below.

$$Y_{it} = b_2 + A_i + \beta_3 \hat{T}_{it} + \beta_4 \hat{T}_{it} A_i + \epsilon$$

$$T_{it} = b_1 + A_i + \beta_1 Z_{it} + \beta_2 Z_{it} A_i + \epsilon$$

[Insert Figure 1 Here]

At the first stage, T_{it} is a dummy that evaluates whether account i ’s tweet t utilized the extended bandwidth afforded by the technological change. Tweets with more than 140 characters are labeled as 1, and those with less than 140 characters are labeled as 0. A_i are Twitter account fixed effects, included to construct a model that accounts for all individual differences among accounts (e.g., tenure, gender, and revenues), so that we can examine within-subject behavioral changes. Z_{it} is a dummy instrument that indicates whether the publication time of account i ’s tweet t is earlier (coded as 0) or later (coded as 1) than November 7, 2017. As we hypothesized earlier that the degrees to which examined accounts complied with the encouragement might differ from each other, we added the interaction of the instrument variable (Z_{it}) and the fixed effects (A_i). Constant and error term are b and ϵ . Therefore, the first stage model can be described as: The intervention of affordance change exogenously increased the chance that a Twitter account used more than 140 characters in its tweets. This intervention might have consequently led to

Figure 1: Research Design

changes in communication behavior as the outcome variable (Y_{it}) modeled at the second stage.

At the second stage, we estimate how the propensity of being treated ($\hat{T}_{it}$), instrumented and predicted at the first stage, affected the actual communication indicators in a single tweet. A_i are still fixed effects, and the interaction of the predicted compliance ($\hat{T}_{it}$) and the fixed effects (A_i) is added to allow Twitter accounts to exhibit various degrees of behavioral change. We examined multiple dependent variables (Y_{it}), with more details provided in the online Appendix.

Therefore, in the two equations, β_1 and β_3 indicate population-level changes, as to how the newly afforded bandwidth encouraged the population of examined Twitter accounts to publish tweets that comply with the developers' intent (β_1) and exhibit different communication patterns (β_3). The interaction terms β_2 and β_4 , in the meantime, represent the individual agency of each Twitter account. That is to say, despite the same encouragement and the universal population-level change, examined social media accounts could respond to the affordance change in different ways: First, the degree to which these accounts started to use more than 140 characters might vary, indicated by the coefficient β_2 ; Then, controlling the tendency to use more than 140 characters ($\hat{T}_{it}$), the degree of behavioral change might still vary, indicated by the coefficient β_4 .

Before presenting the results, it should be noted that the instrumental variable design makes two other assumptions, both of which were fulfilled by the current study. First, the instrument (Z) should have a strong causal effect on the treatment assignment variable (T) with a rule of thumb of $F > 10$. In the current data set, $F = 46,185$ which indicates that Z is a very strong instrument. Second, there should be no unmeasured confounders for the assignment of treatment. In our study, the treatment is assigned to the whole population, and every account since November 7, 2017 has the ability to publish tweets with more than 140 characters. Similar to previous studies, the threshold determining whether or not a tweet utilized the newly afforded feature was set to 145 characters due to HTML encoding issues (Jaidka et al., 2019).

5 Findings

Table 2 shows the 2SLS regression result on how the affordance change affected communication behavior of the examined population of Twitter accounts. On average, the treatment of extending the character limit from 140 to 280 significantly increased the length of published tweets by 47.558 characters ($p < .001$). In other words, controlling the degree to which these

Table 2: 2SLS Regression Results

	First Stage		Second Stage					
	Treatment T	Characters	Text	Mentions	Hashtags	URLs	Media	Features
Publication Time Z	0.700*** (0.092)							
Instrumented Treatment $\hat{T}$		47.558*** (18.194)	29.338 (17.961)	-0.039 (0.355)	-0.260 (0.447)	0.351* (0.196)	0.442** (0.185)	0.494 (0.635)
Observations	143,771	143,771	143,771	143,771	143,771	143,771	143,771	143,771
R ²	0.426	0.373	0.377	0.263	0.362	0.206	0.319	0.413
Adjusted R ²	0.425	0.371	0.376	0.261	0.361	0.204	0.318	0.412
Residual Std. Error (df = 143501)	0.291	40.274	39.758	0.786	0.990	0.434	0.411	1.406
F Statistic (df = 269; 143501)	396.604***	316.748***	323.203***	190.240***	303.192***	138.197***	249.797***	374.840***

Note:

*p<0.1; **p<0.05; ***p<0.01

examined accounts adopted the new type box, tweets published after November 7, 2017 were significantly longer than those published before November 7, 2017.

[Insert Table 2 Here]

Those extra characters were used mainly for three purposes. First, the treatment increased the length of textual information by 29.338 characters ($p = .102$), defined as the number of characters used by plain text, hashtags, and mentions that bear linguistic meanings. The direction of change is in line with hypothesized expectations but not statistically significant according to conventions. Second, the treatment increased the use of external links, such as corporate websites and news articles, by 0.351 more URLs per tweet ($p = .074$). This effect is marginally significant. Third, the treatment increased the use of media, such as images and videos, by 0.442 extra unit per tweet ($p = .017$). In summary, around two thirds of the extra 48 characters induced by affordance change were devoted to textual information, providing more linguistic clarity, while around one third of the upward change occurred because examined accounts infused their tweets with more information-rich multimedia content. The intervention brought no significant change to the population's use of mentions, hashtags, and interactive features overall.

It should be pointed out that the treatment effects on the use of characters and media reflect communication behavioral changes at different levels. While the increased number of characters might be a direct effect, as these examined accounts tried to fill the extended type box with more textual content, which was not possible before, the increased number of media cannot be explained by the same argument. As detailed in the online Appendix, characters needed to hyperlink media content did *not* and still do not count toward a tweet's character allowance. In other words, the ability to add media content to tweets has never been restricted, and the feature of adding images and videos to tweets received no change whatsoever on November 7, 2017. Twitter accounts were able to hyperlink media content on top of a maxed-out tweet throughout the studied period. The significant increase of media content suggests that the examined population of Twitter accounts have altered their online communication protocols after the affordance change, and started to avoid publishing plain-text tweets without multimedia content.

Therefore, the examined case of affordance change did alter communication patterns at the population level. This uniform upward shift suggests that a well-implemented technological change can induce behavioral change as originally intended. However, as detailed below, human agencies still played an important role in how these external forces were interpreted and

Table 3: Regressions on How User Engagement Level and Communication Constraint Pre Treatment Predict Between-Subject Variances of Using More Than 140 Characters Post Treatment

	Interaction Coefficient β_2		
	Model 1	Model 2	Model 3
User Engagement Level	-16.224 (22.350)		9.032 (15.583)
Communication Constraint		0.008*** (0.001)	0.008*** (0.001)
Observations	134	134	134
R ²	0.004	0.527	0.528
Adjusted R ²	-0.004	0.523	0.521
Residual Std. Error	0.208 (df = 132)	0.143 (df = 132)	0.143 (df = 131)
F Statistic	0.527 (df = 1; 132)	147.029*** (df = 1; 132)	73.312*** (df = 2; 131)

Note:

*p<0.1; **p<0.05; ***p<0.01

incorporated.

A closer look at between-subject differences shows that the effect of affordance change on communication behavior vastly varies across examined accounts. For instance, indicated by the interaction coefficient β_4 with more details shown in Appendix Figure 2, the effect of affordance change on the number of characters used by organizational and leadership tweets showed huge variances. Pepsi, after the character limit change, posted more concise tweets instead ($\beta_4 = -338.831, p < .001$), while the positive effect of affordance change on the number of characters was more prominent for Target ($\beta_4 = 176.788, p < .01$). The finding stays true for other kinds of feature use, for example the use of media shown in Appendix Figure 3.

To answer the second research question, the study continued to explore what factors mainly contributed to the various effect sizes of affordance change on social media use. Regressing interaction coefficients β_2 on the two hypothesized contributing factors, Table 3 shows that between-subject variances were explained mostly by the previous endogenous perception of communication constraint ($\beta = .008, p < .001$). The effect of social expectation, proxied as the user engagement level before the treatment, is not statistically significant. Hypotheses H1.1 is thus not supported, while H2.1 is supported. Noticeable is the fact that the previous perception of communication constraint has a huge explanation power ($R^2 = 0.527$), indicating that the between-subject variances among examined Twitter accounts can be well explained by their previous perceptions. In other words, accounts that perceived more communication constraint — those whose pre-treatment tweets constantly hit close to the 140 character threshold — were more affected by the affordance change and more likely to use the extended type box post-treatment. This finding is also illustrated in Figure 2, which plots the instrumented treatment compliance variable $\hat{T}_i$ against the communication constraint proxy variable.

[Insert Table 3 Here]

[Insert Figure 2 Here]

Regressing interaction coefficients β_4 on the two hypothesized contributing factors, the

Figure 2: Effects of Communication Constraint Perceptions on Later Behavioral Change

Note: The figure, corresponding to the first stage regression model (OLS) in Table 2, plots the predicted and instrumented treatment compliance rate $\hat{T}_i$ after November 7, 2017 against the median number of characters used by examined Twitter accounts prior to November 7, 2017. Dots represent observations of social media use, and dotted lines represent 95% confidence intervals of the solid linear regression line. The figure shows that perceptions of higher communication constraints prior to the intervention are associated with greater communication behavioral change after the intervention.

study finds that the degree to which affordance change affects Twitter feature use was generally not associated with either user engagement level or perceived communication constraint. More details can be found in Appendix Table 2. Hypotheses H1.2 and H2.2 were thus rejected.

In summary, the investigation shows that although the affordance change resulted in some population-level behavioral changes in major organizations and leadership's online communication, the effect hugely varied across Twitter accounts. Affordance change did not affect communicative agents uniformly, instead, previous endogenous factors moderate the degree to which communication behavior adapted to the exogenous change. The result highlights the role of human agencies in the face of technological changes, and provides empirical support for the affordances approach as a reconciliation between technological determinism and social construc-

tivism.

6 Discussion

By analyzing a major event of affordance change, the study documents evidence on the causal link between affordances and mediated communication patterns, and explicates how social media users adjusted their digital behavior in response to a technological change. Complementing works that examined social networking sites with an affordance approach (e.g., [Fox & Holt, 2018](#); [Nagy & Neff, 2015](#)) and theorized the role of user perceptions and experiences in media affordances (e.g., [Shin, 2019](#); [Zhao et al., 2013](#)), the results highlight the necessity of considering human agencies when studying communication behavior on digital channels. By showing that users' future behavior generally complies with developers' original intent but heavily deviates from each other due to previous perceptions and experiences, the findings demonstrate the value of using affordances as a third way to understand information communication technologies in society, which recognizes the relational dynamics between human behavior and technological artifacts and does not fall into the traps of technological determinism and social constructivism.

One contribution of this study is the direct assessment of the causal effect of affordance change on communication behavior. Despite the prevalence of the term "affordances" in digital media research, little attention has been paid to evaluate its direct connection with how users actually communicate on digital media platforms. Comparative, critical, and theoretical pieces (e.g., [Oz et al., 2018](#); [Schrock, 2015](#)) have long been contextualizing their empirical findings within the framework of affordances and claiming that social media affordances are the contributing factor that drives various communication behavior across popular networking sites. The hypothesis is intuitive, but as reviewed in earlier sections, empirical evidence on the connection remains elusive. The heavily publicized instance of affordance change, analyzed in the current study with 2SLS, was a rare case where the causal effect of affordance change on communication behavior can be precisely captured, examined, and quantified. By showing how a group of representative tweeters adjusted their communication patterns post-treatment, the paper serves as an important footnote on how affordance, as a central concept in the literature that theorizes the impact of digital technology, drives our digital behavior and influences our digital world, and how social media platforms have been designed and can be designed to invoke desired prosocial behavior ([Aakhus, 2007](#); [Gillespie, 2010](#)).

The second contribution of this study is the provision of robust evidence on the role of human agencies in the face of technological affordance changes. As demonstrated in the study, the affordance change does not affect users in a uniform way, instead, the effect varies across accounts and conditions upon their previous experiences on the social media platform. Their levels of perceived communication constraint influence their degrees of reaction, especially on the use of the extended type box. The finding on communication constraint highlights the importance of conceptualizing affordance as a product that is constantly influenced by human perceptions, in that users can perceive the same communication channel differently and can consequently have various experiences of the affordance change ([Fox & McEwan, 2017](#); [Graves, 2007](#)). This finding also connects with the emergent human-computer interaction literature that explored affordances of recent information communication technologies that cannot be investigated in conventional ways, one example being algorithm's affordances (e.g., [Shin & Park, 2019](#)). Uncertainties brought by this intangible technology further underline the fact that technology is more than mechanical

artifacts and “technical qualities such as prediction and accuracy” (Shin et al., 2020, p. 8), and that it is more critical than ever to advance a user-centric view of how humans interpret and process technological changes.

The third contribution of this study is its theoretical implication for the affordance approach to understanding technology (especially digital media platforms) in society. Evidence presented in the manuscript contributes to previous arguments on how researchers should understand affordances in digital media research, considering the long history of theoretical tension between technological determinism and social constructivism. For example, Nagy and Neff (2015) presented affordances as “a kind of middle ground between technological determinism and social construction” (p. 2), where the materiality of technology designed by developers and the interpretation of technology initiated by users interact and contest. Similarly, Hogan (2009) found both technological determinism and social constructivism to be polar understandings of technology use, and as shown by the current study, the affordance approach — taking a more neutral stand on the issue, giving both schools their deserved credit, and acknowledging both entities’ (i.e., developers’ and users’) agencies during the process — can better explain communication behavior on digital media platforms. Therefore, despite establishing the causal link between affordance change and communication behavioral change, this case study does not assert a deterministic view on the role of affordances in human communication. Instead, the clear evidence of causality only exists at the first stage of the 2SLS model, and it is indeed users’ various interpretations of how the technological change can be utilized for communicative purposes that are driving the behavioral indicators captured by our statistical models. For example, examined users did not consequently mention more people, use more hashtags, or even put in more textual information (see Table 2). The encouragement (nudge) administered by developers remains merely an encouragement (nudge) for users. In this sense, the analysis reported in this paper provides theoretical interesting and empirically sound evidence for the affordance approach to digital media, in that developers’ designs do not determine communication behavior and user agencies do not determine communication behavior either. It is the interaction between developer intent and user experiences that is shaping how digital communication takes shape on Twitter.

The fourth contribution of the study relates to the research context of organizational social media use. Existing literature has long been fixating on why organizations only use social media for one-way communication to serve their business purposes (e.g., Lovejoy & Saxton, 2012), despite the clear evidence of how interactive engagement can benefit them in situations such as corporate crises (e.g., Xu & Xiong, 2020; Xu & Zhou, 2020) and intercultural communication (e.g., Al-Kandari, Gaither, Alfahad, Dashti, & Alsaber, 2019). In other words, these previous studies attribute the blame to communicative agents in the process. But as the current study evinced, social media’s technological affordances could also play a huge role in determining what kinds of public communication emerges on these platforms. The different ways users — including organizations’ management teams and ordinary stakeholders — perceive affordances can thus affect the communication process that bears critical consequences for business success. In this sense, the current paper also echoes with some new management literature that examined external and internal communication challenges from the affordances perspective (e.g., Argyris & Monu, 2015; Ellmer & Reichel, 2020), and argues that scholars should consider incorporating affordance theory into their empirical inquiries to better understand why organizations behave in a certain way on social media. In fact, recent insights from Davies and Hobbs (2020) have found that digital media’s affordances can sometimes encourage or nudge social media influencers to engage

in propagandistic communication practice and violate the normative guidelines of ethical public relations (Kent & Li, 2020), without serious ramifications from regulatory entities. Though a discussion on how communication patterns invoked by digital media affordances could create negative consequences for the general society is far beyond the scope of our study, the current paper does highlight the fact that technological changes implemented by information technology companies can exert profound effects on organizations' and organizational personnel's communication behavior, and that affordance theory can be employed to produce new scholarly insights on this important topic.

7 Limitations and Future Directions

The identification of causal effects requires researchers to analyze a precise but small intervention. Therefore, the current study naturally lacks the external validity to illustrate how another kind of affordance change might affect communication behavior in the same causal manner. This limitation is baked into the study design, but it also creates new venues for future qualitative and mixed-method research to contextualize our results and provide more granular analyses on how affordance changes could induce communication behavioral changes. For example, our findings showed that, although the ability to add media content did not receive any immediate change due to the character expansion, examined accounts started posting more images and videos in response. It is likely that some organizations restructured their social media guidelines because of the affordance change, and there might be other mechanisms that are unknown to authors that produced the results uncovered by our computational analysis. Without interviewing these teams and personnels or conducting a content analysis of collected tweets, it is difficult to specify these mechanisms and substantiate these claims.

Another limitation of the current study is the lack of a sociological inquiry into our second research question. Social media users behave in an ecosystem where they constantly interact with each other, and their behavior is not completely bounded by their psychological perceptions of previous experiences or expectations as we hypothesized. Digital media creates digital organization-public relationships (Lock, 2019) that promote behavioral contagion that is not captured by the current study. In other words, the reason why these examined social media accounts exhibited behavioral changes might be that they were following suit and imitating other users, and the two proposed hypotheses — focusing on user engagement and constraint perceptions — failed to test this possibility. Future research can construct these accounts' ego networks (e.g., the concerned account's followings and followers), collect data on these accounts' posting histories, and examine whether intercorrelations exist among those connected users. Scholars can also inquire whether and how user attributes correlate with behavioral changes by labeling accounts with variables that have been found to affect organizational and leadership communication patterns, such as strategic purposes, gender, and prestige (e.g., Fu & Zhang, 2019; Sommerfeldt, Yang, & Taylor, 2019; Yue, Chung, Kelleher, Bradshaw, & Ferguson, 2020).

Last but not least, the current study signals a future direction for digital media literature to examine technical interventions from an affordance perspective. Although a lot of A/B testings executed by information technology companies either do not amount to a change of affordance (e.g., Matias, 2019) or are conducted in house without public datasets available as we previously discussed (e.g., Kramer, Guillory, & Hancock, 2014), it remains a fact that these digital trace data are becoming readily available due to the increasing use of computational tools developed for

570 social science researchers. By streaming data from platforms that provide public data access, such as Twitter and Reddit, monitoring minor technical changes implemented by the company, and analyzing logged user behavioral data with an instrumental variable approach demonstrated here, scholars can accumulate more empirical evidence on how affordances change communication behavior and our digital media ecology at large.

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1 Appendix

1.1 Data Description

The main text reads that the original data set is a complete collection of original tweets ($N = 151,780$) that were published by the top 50 Fortune 500 companies (according to the Forbes 2018 list), the top 50 largest U.S. charities (according to the Forbes 2018 list), and 84 social leadership accounts compiled by Yue, Thelen, Robinson, and Men (2019) and Afshar (2013) between May 7, 2017 and May 7, 2018. Among examined accounts, two are private (@SteveEasterbrk and @petecashmore) and five accounts didn't publish any content during the studied period (@andrewmason, @ManpowerGroupJJ, @MickyArison, @NPRGaryKnell, @rupertmurdoch). Table 1 shows the examined 177 accounts' Twitter handles, numbers of tweets, and numbers of followers (at the time of data collection).

Several organization and leadership accounts listed in Table 1 — @ADMupdates, @Aetna, @AmirRubin, @aneelb, @bgrey, @bjurjs, @bkrunner, @BruceDBroussard, @cjpedregal, @davidkarp, @DowDuPontCo, @drewhouston, @EIFoundation, @eldsjal, @etaibeck, @Ford, @IndraNooyi, @jasonaramburu, @JeffBezos, @jeremys, @JonasPrising, @KentThiry, @Louel, @marissamayer, @merongribetz, @MichelleRhee, @mtbarra, @mtbert, @peretti, @Phillips66Co, @ramiesaid, @RobertIger, @satyanadella, @seanduffy, @shervin, @SteveCollis_ABC, @SYFMKeane, @valguil, and @WesternUnionCEO — were removed before the final data analysis for better fixed-effect model performance due to their small numbers of tweets published in the studied period (<100 tweets).

Two organizations and one leadership account — @ACLU, @MetLife, and @briansolis — were also removed due to their early access to the 280 character limit before November 7, 2017, detailed in Section 1.2. Therefore, the final data set used for data analysis ($N = 143,771$) consists of 77,521 tweets from 92 organizations and 66,250 tweets from 43 leadership accounts.

1.2 Determine the Cutoff Time of Character Limit Change

To have a rigorous estimation of the appropriate cutoff time for the current study, Figure 1 is plotted, with X axis indicating the relative publishing time of the tweet and Y axis indicating the number of characters used by a tweet. Each dot corresponds to a tweet in the data set, while colors indicate different Twitter accounts. It should be noted that the goal is to determine a valid cutoff moment *for the current study*, instead of the exact moment Twitter switched its character limit from 140 to 280 on its server. The actual server time should be earlier than what the current study suggests.

Panel A shows that two organizations and one leadership accounts — @ACLU, @MetLife, and @briansolis — had early access to the 280 character limit beta-tested since September 2017 (Rosen, 2017). These accounts were thus removed from the main study and Panel B. Panel B shows a closer look at the tweets published 500000 seconds before and after November 7 2017, 00:00:00 GMT, which shows that the first tweet that used more than 140 characters was published by @dickc at November 7 2017, 22:17:17 GMT: <https://twitter.com/dickc/status/928023577416237056>

The cutoff time was thus determined as November 7 2017, 22:17:16 GMT.

Table 1: Data Description (N=177)

Twitter Handles	No. of Followers	No. of Tweets	Twitter Handles	No. of Followers	No. of Tweets	Twitter Handles	No. of Followers	No. of Tweets
ACLU	1594861	4130	etaibeck	344	55	mtbert	16478	8
ADMupdates	4586	44	ExpressScripts	22211	380	nature_org	929635	1881
Aetna	50551	65	exxonmobil	299785	326	nyphospital	38414	2369
Albertsons	29477	121	FannieMae	50297	737	operationbless	590672	1435
amazon	2985035	649	FedEx	276632	386	PAN_Foundation	4438	161
American_Heart	267899	2183	FeedingAmerica	459658	726	pepsi	3010565	303
AmericanCancer	1148001	372	feedthechildren	22069	367	peretti	78970	44
Americares	71657	2524	FoodForThePoor	95007	918	PeterAceto	29961	675
AmFamJack	11793	1326	Ford	1169614	79	Phillips66Co	8776	66
AmirRubin	555	2	FreddieMac	68383	451	PPFA	261874	703
AndrewGrill	18060	957	garyvee	2204334	4487	ProcterGamble	199284	428
aneelb	23076	10	generalelectric	455686	362	Prudential	153346	419
AnthemInc	34693	379	GM	687677	409	PSImpact	38237	1051
ashoddd	729	110	Good360	16021	534	ramiessaid	3281	31
ATT	870301	512	GoodwillIntl	31784	244	realDonaldTrump	86432161	2274
BankofAmerica	521966	252	Google	21010574	967	RedCross	5338339	447
Benioff	1035726	901	Habitat_org	1082053	703	richardbranson	12621404	3461
BGCA_Clubs	44303	425	Healthcare_ABC	4121	471	RobertIger	211378	45
bgrey	1298	66	HealthWellOrg	1805	245	RomanStanek	12318	232
bhalligan	77727	275	HomeDepot	380907	305	Rotary	328152	1278
Bill_Gross	244365	448	IBM	520978	917	rwang0	128758	10044
BillGates	52078446	294	IndraNooyi	84908	40	SalvationArmyUS	65094	471
bjurjs	611	56	intel	4794263	500	SamaritansPurse	1021785	1566
bkrunner	18582	86	invoker	51960	253	SameerPatel	14267	548
Boeing	527532	231	jack	4786406	368	satyanadella	2320844	76
briansolis	280067	2055	jasonaramburu	2034	1	SavetheChildren	2849455	1518
BruceDBroussard	6358	18	JeffBezos	1716318	58	SchambachSays	1880	119
bryankramer	191227	3144	jeffweiner	602673	156	seanduffy	4918	7
cardinalhealth	14757	380	jeremys	215911	71	shervin	98904	82
CARE	1275433	571	JNJCares	101792	1007	shrinershosp	21666	1564
CarterCenter	67814	1040	Jon_Ferrara	26862	3986	sloan_kettering	68548	1514
CatholicRelief	75711	2081	JonasPrising	7471	52	StateFarm	99881	181
CCharitiesUSA	33416	657	JoSchneier	986	130	StepUp4Students	2661	648
CEOMikeJackson	15015	125	KentThiry	3415	88	SteveCase	735655	1415
charleneli	104961	109	kevinrose	1591406	175	SteveCollis_ABC	456	13
Chase	364661	427	KidneyFund	14659	941	SteveForbesCEO	231577	1894
Chevron	358449	213	kroger	144616	384	StJude	436179	378
chrisbrogan	334108	4942	LadyAshBorg	13196	257	SYFMKeane	2142	7
ChuckRobbins	54734	234	levie	2422903	134	Target	1934264	228
Citi	912235	1253	Louel	1251	7	TFGH	2644	170
cjpedregal	466	10	Lowes	267178	693	TheJDC	13875	132
CMMBTweets	23730	777	LutheranSvcs	945	454	tim_cook	12179895	184
comcast	175114	200	MakeAWish	220355	2150	timoreilly	1764546	833
compassion	213258	878	mapintl	2756	396	UNICEFUSA	422709	2560
crutweets	16762	1862	MarathonPetroCo	6095	197	UnitedHealthGrp	16742	252
CVSHealth	44518	1182	marissamayer	1601132	11	UnitedWay	199821	937
DanaFarber	88496	1793	markfidelman	85474	17495	UPS	208939	470
DanReich	2404	112	MarkVHurd	154731	127	UTC	41725	315
davemorin	416940	267	MayoClinic	1900162	4696	ValeroEnergy	7536	198
davidkarp	38579	43	McKesson	19906	1019	valgui1	266	36
Dell	709133	900	mcuban	7977564	151	verizon	1662368	332
dens	84417	1786	merongribetz	2451	13	Walgreens	885004	226
dicke	1562103	144	MetLife	53173	302	Walmart	965347	663
DirectRelief	90435	403	MichaelDell	657257	280	WellsFargo	304561	234
DowDuPontCo	4278	31	MichelleRhee	73765	10	WendySLea	10356	839
drewhouston	280373	13	Microsoft	8553405	587	WesternUnionCEO	15150	57
EIFoundation	2312	22	MountSinaiNYC	72237	4754	WorldVision	1157165	1308
eldsjal	146048	29	MSF_USA	901557	846	ymca	38763	744
elonmusk	39040874	340	mtbarra	52225	70	ytechdata	1463	219

1.3 Variables

The numbers of characters, URLs, media, hashtags, and mentions were provided by Twitter API. Internal URLs (i.e., retweet with comments by quoting tweets as URLs) do not contribute to the tweet's character count. Characters needed to hyperlink media content also do not count toward a tweet's character allowance. For example, before the character limit change, users were allowed to post a tweet with 140 text characters along with an image.

Considering the fact that external URLs take up large numbers of characters that do not

convey any textual meaning, the number of text characters was created as the number of total characters minus the number of characters taken by external URLs. Users' external URLs are shortened by Twitter's in-house URL shortener to 23 character per item when posted on the platform.

Therefore, in the main text, the number of text characters (*Text*) refers to the number of characters used by textual information, including plain text, hashtags, and mentions. The numeric variable is obtained by subtracting the number of characters used by external URLs from the total number of characters.

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Figure 1: Determine Cutoff Time

Figure 2: Differential Treatment Effects (β_4) of Affordance Change on Number of Characters

Note: Despite population-level changes, the effect of affordance change on examined Twitter accounts' communication behavior still varies. Shown in the figure is the estimates of the interaction coefficients (β_4) for the use of total characters. @Albertsons is the reference level. Red indicates statistical significance at the 0.05 level.

Figure 3: Differential Treatment Effects (β_4) of Affordance Change on Number of Media

Note: Despite population-level changes, the effect of affordance change on examined Twitter accounts' communication behavior still varies. Shown in the figure is the estimates of the interaction coefficients (β_4) for the use of media. @Albertsons is the reference level. Red indicates statistical significance at the 0.05 level.

Table 2: Regression Results on Between-Subject Variances of Feature Use

	Interaction Coefficient β_4													
	Characters		Text		Mentions		Hashtags		URLs		Media		Features	
User Engagement Level	10,435.280*		-115.798		-552.478***		-1.996		544.449***		-85.706		-95.731	
	(6,073.917)		(5,958.531)		(63.740)		(108.298)		(83.095)		(55.028)		(151.737)	
Communication Constraint		-0.070		0.126		0.005		-0.003		-0.008**		-0.0001		-0.006
		(0.247)		(0.239)		(0.003)		(0.004)		(0.004)		(0.002)		(0.006)
Observations	134	134	134	134	134	134	134	134	134	134	134	134	134	134
R ²	0.022	0.001	0.00000	0.002	0.363	0.020	0.00000	0.004	0.245	0.036	0.018	0.00001	0.003	0.008
Adjusted R ²	0.014	-0.007	-0.008	-0.005	0.358	0.012	-0.008	-0.004	0.240	0.029	0.011	-0.008	-0.005	0.001
Residual Std. Error (df = 132)	56.424	57.035	55.352	55.295	0.592	0.734	1.006	1.004	0.772	0.872	0.511	0.516	1.410	1.406
F Statistic (df = 1; 132)	2.952*	0.079	0.0004	0.277	75.130***	2.642	0.0003	0.476	42.930***	4.955**	2.426	0.002	0.398	1.082

Note:

*p<0.1; **p<0.05; ***p<0.01