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Business value of big data analytics: A systems-theoretic approach and empirical test

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A R T I C L E I N F O

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A B S T R A C T

Although big data analytics have been widely considered a key driver of marketing and innovation processes, whether and how big data analytics create business value has not been fully understood and empirically validated at a large scale. Taking social media analytics as an example, this paper is among the first attempts to theoretically explain and empirically test the market performance impact of big data analytics. Drawing on the systems theory, we explain how and why social media analytics create super-additive value through the synergies in functional complementarity between social media diversity for gathering big data from diverse social media channels and big data analytics for analyzing the gathered big data. Furthermore, we deepen our theorizing by considering the difference between small and medium enterprises (SMEs) and large firms in the required integration effort that enables the synergies of social media diversity and big data analytics. In line with this theorizing, we empirically test the synergistic effect of social media diversity and big data analytics by using a recent large-scale survey data set from 18,816 firms in Italy. We find that social media diversity and big data analytics have a positive interaction effect on market performance, which is more salient for SMEs than for large firms.

1. Introduction

Big data are increasingly driving the changes of decision-making and innovation in firms [1]. Owing to the advance in database management techniques, social media channels, and mobile devices, abundant information about customers is increasingly accumulated in firms [2]. In particular, social media — a group of Internet-based applications that build on the ideological foundations of Web 2.0, allowing user-generated content to be created and exchanged [3] — is turning consumers into an incessant generator of both traditional, structured, demographical, and transactional data as well as more contemporary, unstructured, socio-graphical, behavioral data [4].

Big data analytics are specific applications for managing, prioritizing, and analyzing big data for business purposes [2]. To efficiently manage and use big data from social media for decision-making and innovation, firms need to use big data analytics to handle the information with unprecedented volume, velocity, variety, veracity, and value [5] and take a completely new way of understanding consumer behavior and devising innovation and marketing strategies [6]. By doing so, firms can better understand their customers' profiles and leverage customer involvement for improving their market performance [7]. In other words, big data analytics potentially translate the raw data from social media into useful insight into customers and help search for hidden patterns of consumer behavior in the marketplace [4].

Although big data analytics have been widely recognized to be important for building firm competitiveness, a recent survey by Deloitte showed that big data analytics have not become widespread in many countries and regions [8]. It is therefore a timely inquiry on whether and how big data analytics create business value in the marketplace and thus to encourage firms' usage. The current literature on big data analytics is dominated by technical solutions for analyzing big data (see [2,5,9] and [10] for an overview) and lacks empirical investigation assessing the business value of big data analytics [11]. Until recently, a paucity of studies about the performance impact of big data analytics has been conducted in specific contexts such as supply chain management [12], marketing [4,13,14], or both [15,16]. However, these studies examined big data analytics alone and ignored the potential complementarity between big data analytics and other complementary technologies in value creation. This is a surprising gap because, in

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practice, the value of big data analytics can be expected to depend on the use of other technologies that gather big data with high volume, velocity, variety, veracity, and value in the first place.

The broader literature on the business value of information technology (IT) has documented that synergies from IT and complementary organizational resources are a key source of business value (e.g., [17–22]). However, little is known about how the complementarity between different technologies contributes to value creation. To the best of our knowledge, there is only one study considering big data analytics as a combination of different resources [23]. However, Gupta and George [23] still looked at the synergies between big data analytics and other organizational resources (e.g., human and intangible resources), rather than the complementarity between big data analytics and other technologies. Whether and how big data analytics and other complementary technologies jointly create business value remains unclear and needs systematic theorizing and empirical validation.

Big data technologies can be categorized into three generations: business intelligence, social media analytics, and mobile analytics [2]. Although it is suggested that these three generations of big data analytics create value in different ways [2], how their value creation mechanisms are different is unclear in the literature, as prior work often examined big data analytics in a generic manner [24]. To fill this important gap in the literature, it requires granular investigation on a specific type of big data analytics such as social media analytics. The purpose of this study is therefore to provide a more in-depth understanding of value creation mechanisms of social media analytics. We focus on social media analytics and draw on the systems theory to extend our understanding about whether and how big data analytics create value in combination with social media channels.

The systems theory is particularly suitable for theorizing the business value of IT, thus suggesting that a super-additive value can be created from synergies of resources, and the degree to which potential synergies can be realized depends on two enablers: 1) complementarity and 2) integration effort [19,25]. In this study, we explain why the functional *complementarity* between social media diversity (that is, the use of diverse social media channels) and analytics enables synergies that generate super-additive value. Our central argument is that firms using diverse social media channels are likely to gather big data with a larger scale, and the combination with big data analytics allows it to analyze the gathered data and derive market knowledge, which could be more beneficial for developing superior market performance. Furthermore, we consider the difference between small and medium enterprises (SMEs) and large firms in the required *integration effort* that enables synergies and explain why SMEs are more likely to more efficiently realize the synergies of social media diversity and big data analytics than large firms. We empirically test the interaction effect between social media diversity and big data analytics on market performance in SMEs and large firms based on a large-scale survey data set from 18,816 Italian firms in 2014.

The remainder of the paper is organized as follows. We present our theoretical foundation from the systems theory, followed by hypotheses development. We then describe the empirical methods and report the results. Finally, we conclude the paper by discussing the implications for theory and practice as well as the limitations from this study and the directions for future studies.

2. Theoretical foundation

Big data analytics have attracted tremendous scholarly attention in recent years [5,24,26]. Chen et al. [2] categorized big data technologies into three generations: business intelligence from database management that is widely used, social media analytics that are increasingly important, and mobile analytics that are emerging. As a particular type of big data analytics, social media analytics allow firms to effectively differentiate themselves from their competitors in the marketplace by improving the quality of decision-making and optimizing marketing strategies based on insight on customers [27,28]. It is therefore important for firms to embrace social media analytics to seize the market opportunities and create business value [24,29,30], but our understanding about how social media analytics create business value is quite limited. Systematic theorizing about the value creation mechanism of social media analytics is needed [17,21].

The systems theory suggests that all systems are composite things that have interacting components [31,32]. Accordingly, a system should possess properties that are derived from the interactions among its components [33,34]. A key concept that is central to the systems theory is the notion of synergies, which describes the phenomenon of super-additive value or sub-additive cost resulting from the interactions among components of a system [35]. Simply speaking, super-additive value is created if the combinative value of two components is greater than the sum of each component's individual value, i.e., Value (A + B) > Value (A) + Value (B). On the other hand, sub-additive cost occurs if the combinative cost is smaller than the sum of individual cost, i.e., Cost (A + B) < Cost (A) + Cost (B) [36,37].

In the IS literature, Bharadwaj [17] was among the first who discussed the synergies between IT resources and other organizational resources as a key aspect of IT capabilities. Tanriverdi [21] examined the IT relatedness of a firm's business units, which enhances cross-unit knowledge management capability and in turn, firm performance. In the same vein, Tanriverdi [22] studied the cross-unit IT synergies across multiple business units and found that super-additive value from cross-unit IT resources, rather than sub-additive cost, is the mechanism improving firm performance. Nevo and Wade [19] theorized the synergies between IT resources and other organizational resources and proposed the enablers to realize potential synergies of IT and complementary resources as 1) complementarity and 2) integration effort. Following this theorizing, Nevo and Wade [20] empirically validated their theoretical framework from Nevo and Wade [19] and found that complementarity and integration effort are indeed key drivers of the synergies between IT and complementary organizational resources. In the past research, however, how complementary technologies *within* IT resources may have synergies and create super-additive value is ignored, which will be examined by this study in the big data context.

In this study, we take a system theoretic approach to explain the value creation mechanism of social media analytics as super-additive value arising from the synergies between a firm's complementary use of diverse social media channels and big data analytics. However, we argue that gathering abundant information from diverse social media channels provides only the potential synergies. Handling the vast amount of information is a different matter [38], relying on the use of big data analytics. Thus, from a system theoretic perspective, the business value of social media analytics stems from the functional complementarity of social media channels for gathering big data and big data analytics for analyzing the big data gathered from social media. Next, we develop testable hypotheses based on the systems theory.

3. Hypotheses development

3.1. The synergies between social media diversity and big data analytics

Based on the systems theory, we argue that the use of social media channels and big data analytics is complementary in functions because the use of diverse social media channels allows a firm to gather more data from user-generated content, while the use of big data analytics allows it to effectively and efficiently analyze the data and derive insight on customers. Social media channels have become part of the evolving digital infrastructure presently [39,40], which allows customers to constantly share opinions and provide feedback about their user experience of products and services [41–43]. The user-generated content and firm-user interaction on social media channels accumulate a vast amount of digitized data containing market knowledge about how the preference of current customers looks like and changes [5,24]. To gather big data that contain market knowledge, firms need to use a variety of social media channels such as social networks (e.g., Facebook and LinkedIn), blogs or micro blogs (e.g., Twitter), multimedia platforms (e.g., YouTube), and Wiki communities (e.g., Wikipedia).

The user-generated content that a firm gathers from a variety of social media channels is often highly unstructured. For example, social network websites provide network data, blog and Wiki tools are dominated by texts and images, and multimedia platforms contain audios and videos. To derive market knowledge from such data with high volume, velocity, variety, veracity, and value, big data analytics must be used to efficiently organize and effectively analyze very unstructured web content [2]. Specifically, big data analytics enable firms to analyze and interpret very unstructured web content for tracking and evaluating customer sentiments, key trends, and issues and understanding how their products, services, and brand image are discussed by customers [2,4,44,45]. Such market knowledge can optimize firms' innovation and marketing strategies [27,28,46], thus allowing them to provide better service for customers in the marketplace. For example, social network analysis can derive insight from social network websites, text mining and opinion mining are capable of handling blogs and comments, and web analytics are functional in analyzing image and video data from multimedia platforms.

The use of big data analytics can also mitigate information overload in processing the abundant information from social media, thus improving the quality of decision-making that is limited by scarce managerial attention [41,47,48]. Big data analytics can prioritize and categorize the selection ranking of customer preferences and marketing means by solving the "paradox of choice" — that is, too much information is as problematic as too little information in decision-making [49].

The systems theory suggests that complementarity of resources is an enabler of synergies [50,51], which generates super-additive value because the joint value of complementary resources is greater than the sum of their individual values [35,52]. Given the complementarity between the use of social media channels and big data analytics, we argue that the value creation mechanism of social media analytics resides in the synergies of social media diversity and big data analytics because different social media channels accumulate big data for big data analytics to transform the raw data into market knowledge that benefits firm performance in the marketplace (i.e., sales). In the same line, recent studies show that IT-driven market knowledge can enhance firms' market competitiveness by better understanding customer preferences to make innovation decisions and marketing strategies [4,15,53]. As a result, the synergies of social media diversity and big data analytics generate super-additive value to increase sales with better innovation decisions and marketing strategies, which is manifested by a positive interaction effect on market performance. It leads to the following hypothesis:

H1. Social media diversity and big data analytics have a positive interaction effect on market performance.

3.2. The difference in realizing synergies between SMEs and large firms

It has been documented that SMEs and large firms are different in deriving value from various technologies [54–57], thus guiding us to further compare the value creation of social media analytics for SMEs and large firms. The technology adoption literature has documented that SMEs and large firms are different in the use of technologies such as Internet [58], e-commerce [59], and electronic data interchange [60]. SMEs and large firms encounter a lot of different challenges in the marketplace. For example, SMEs have resource constraints with limited capital, labor, and marketing channels [61]. Because of the resource constraints, they are known by high barriers of technology adoption [62,63]. Compared with large firms, most SMEs perceived the adoption of new technologies for facilitating innovation and marketing processes as expensive, risky, and complex tasks [64]. A key issue of SMEs is therefore the use of out-of-date technologies in market operations [65].

However, SMEs might act faster, more flexibly and efficiently for the immediate problems in the marketplace if they have used valuable technologies such as social media analytics because it is easier for SMEs to adapt the decision-making and marketing strategies [61,66,67]. Although Corte-Real et al. [15] depicted that all companies can invest in dynamic capabilities such as organizational agility to be more adaptable, the small scale and hierarchy of SMEs make them more flexible than large firms [57]. As a result, unlike large firms with relatively higher organizational rigidity in decision-making and marketing strategies, social media analytics may be a more powerful means for SMEs to improve the quality of decision-making and optimize their marketing strategies. In contrast, large firms have larger scale and multiple product lines and even serve different industries. Their use of various social media channels gathers user-generated content from various market segments with a more complex structure; hence, the required effort of integrating social media diversity and big data analytics, therefore, is higher than that of SMEs.

The systems theory suggests that the degree to which the potential synergies of resources can be realized depends on two enablers: 1) complementarity and 2) integration effort [19]. The integration effort of complementary resources not only determines the degree of realized synergies but may also increase the complementarity of resources [20]. Although the use of diverse social media channels and big data analytics is complementary in functions, we argue that the required integration effort to realize the synergies of social media diversity and big data analytics differs between SMEs and large firms. As SMEs have a smaller scale and limited scope of target market, the complexity of integrating the use of social media channels and big data analytics is relatively lower than large firms [68–70]. SMEs are more likely to make a sufficient integration effort and realize a higher degree of synergies than large firms, thus generating super-additive value to improve sales in the marketplace through better innovation decisions and marketing strategies [71]. We therefore propose that the positive interaction effect of social media diversity and big data analytics on market performance is stronger for SMEs than for large firms. It leads to the following hypothesis:

H2. The positive interaction effect of social media diversity and big data analytics on market performance is stronger for SMEs than for large firms.

4. Methods

4.1. Data

To test our hypotheses, we use a large-scale data set from the 2014 Italian Survey on Information and Communication Technology (ICT) Usage in Enterprise. The Italian National Institute of Statistics (Istat) has conducted this survey on an annual basis since 2001 based on a representative sample of firms with at least 10 employees from all industries in Italy, including manufacturing, energy and utility, construction, transportation, technical services, information services and communication, scientific services, and business services. The purpose of this survey is to gather indicators on the information society in Italy with regard to firms' usage of the Internet (e.g., website, social media, and cloud computing) and connection (e.g., fixed and mobile broadband), e-business (e.g., enterprise systems and e-commerce applications), and ICT skills, etc. Istat uses a probabilistic sampling strategy by randomly stratifying a sample of firms with probability equal for units belonging to the same layer defined by industries. In 2014, a total of 30,312 firms were sampled, and 18,953 of them provided valid responses, leading to a high response rate of 62.53%. By excluding those observations with missing data, it resulted in a final sample of 18,816 firms. Istat systematically checks and cross-validates the data and thus confirms the high quality of the data.

There are several advantages of using this data set for our study. First, this survey is a part of the European Community statistics on the information society following the Commission Regulation (No. 808/2004), which established the legal basis to guarantee the high response rate in data collection. Second, a representative large sample of Italian firms was surveyed, thus allowing us to derive generalizable findings. Finally, our data were recently collected, in 2014, providing timely assessment of the business value of social media analytics.

4.2. Measures

4.2.1. Market performance

We measure market performance by using a survey question asking a firm's total sales in the marketplace, which has been widely used in prior IS, management, and marketing literature as a performance measure (e.g., [72–74]). As this dependent variable is very skewed, we take the natural logarithm to normalize it [75].

4.2.2. Social media diversity

We measure a firm's social media diversity based on a set of survey questions asking whether the firm uses social networks (e.g., Facebook), blogs or micro blogs (e.g., Twitter), multimedia platforms (e.g., YouTube), and Wiki communities (e.g., Wikipedia). The response to each of these questions is binary: 1 if a firm uses a specific social media channel and 0 otherwise. To aggregate these measurement items into a single variable that can reflect the diversity of social media channels used by a firm, we create a summative index by summing up the four items. The summative index therefore has a 5-point scale ranging from 0 to 4. Higher values on the summative index indicate that a firm uses more different social media channels. Summative index method has been used to capture different IT constructs based on a set of binary variables in the IS literature, although the theoretical lenses and measurement items are different across studies. Some notable examples that use summative index method to measure key IT constructs include Banker et al. [76], Joshi et al. [77], and Saldanha et al. [7]. We apply this method to create a summative index about the use of different social media channels because our construct of interest is the diversity of social media channels used by a firm.

4.2.3. Big data analytics

Similar to the questions asking whether a firm uses a specific social media channel, we rely on a survey question asking whether a firm uses big data analytics for deriving insight on customers. The response to this question is binary: 1 if a firm uses big data analytics for this purpose and 0 otherwise.

4.2.4. SMEs vs. large firms

In the survey, firm size is measured by the number of employees in four classes, with a value of 1 for 10–49 employees, 2 for 50–249 employees, 3 for 250–499 employees, and 4 for 500 or more employees. As prior literature has widely defined SMEs as enterprises with no more than 500 employees (e.g., [78,79]), we use 500 employees as the cutoff to distinguish SMEs and large firms to divide our sample into 16,475 SMEs with no more than 500 employees and 2341 large firms with 500 or more employees.

4.2.5. Control variables

We control a number of variables that may influence market performance. First, we control a binary variable from a survey question asking whether a firm uses *interorganizational systems (IOS)*, which may play an important role in supply chain integration between a focal firm and its business partners and therefore may influence the focal firm's market performance [80]. Second, we control another binary variable from a survey question asking whether a firm uses *enterprise resource planning (ERP) systems*, which reflects company-wide digital integration that may influence a firm's market performance [81]. Third, we control for a firm's *IT intensity* based on a survey question about the percentage of employees using computers, which is a genetic indicator of a firm's total IT resources [82]. Fourth, we control for *firm size* by the number of employees in four classes mentioned earlier in full sample analysis, although it is not possible to do so in split sample analysis for SMEs and large firms because of no variation in the single class of employment for large firms. Finally, we add *industry dummies* to control for the fixed effects of industry sectors. Table 1 reports the descriptive statistics and correlations of our variables.

5. Results

5.1. Hypotheses testing

As all our measures have a single measurement item except social media diversity, which has been aggregated by calculating a summative index, there is no need to estimate a separate measurement model in structural equation modeling (SEM). We use ordinary least squares (OLS) regression to test our hypotheses, which is essentially equivalent to estimating a structural model with a single measurement item in SEM. Table 2 reports the regression results. We first estimated a control model and found that all variables had a statistically significant effect on market performance. As expected, IOS and ERP were positively associated with market performance. Consistent with prior findings on the business value of IT [72], firms with high IT intensity and large size have better market performance.

We then added social media diversity into the model and found that it had a statistically significant and positive effect on market performance. Next, we further added big data analytics into the model and found that it also had a statistically significant and positive effect on market performance. Finally, we included the interaction term of social media diversity and big data analytics in the model. Interestingly, we found that both social media diversity and big data analytics did not demonstrate any main effects on market performance in the full model. However, the interaction term of social media diversity and big data analytics had a statistically significant and positive effect on market performance ($\beta = 0.050, p < 0.001$).[1] These results suggest that social media diversity and big data analytics jointly have a synergistic effect on market performance, as a greater value of one variable can reinforce the effect of another variable. Thus, H1 was supported.

To test H2, it is possible to employ either a three-way interaction term or a split sample analysis. Recent methodology literature suggests that when 1) the primary interest is in testing group differences rather than testing individual differences and 2) the multicollinearity problem is a serious concern, a split sample analysis is perfectly acceptable and statistically equivalent to a three-way interaction term [83]. In this case, split sample analysis is preferred because it is more parsimonious and easier to interpret than a three-way interaction term. We therefore use split sample analysis to test H2 because it allows us to better examine the group differences between SMEs and large firms and to avoid multicollinearity when using a three-way interaction term. To test the three-way interaction effect, we also need to add three two-way interaction terms into the model, which increases the maximum variance inflation factor (VIF) from 4.01 to 9.61 — close to the threshold 10, thus indicating a serious multicollinearity problem. The only disadvantage of split sample analysis is the smaller size of split samples than the size of the full sample, which, however, is not a problem for our study. After splitting the sample, we still have 16,475 SMEs and

[1] Note that a small unstandardized coefficient alone does not imply that the effect is small. Although the unstandardized coefficient is small due to different scales between our independent and dependent variables, the standard error is much smaller making the effect highly significant.

Table 1
Descriptive Statistics and Correlations.

	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)
(1) Market performance	15.127	1.701						
(2) Social media diversity	0.630	1.000	0.253					
(3) Big data analytics	0.349	0.477	0.219	0.243				
(4) IOS	0.194	0.395	0.217	0.156	0.175			
(5) ERP	0.464	0.499	0.425	0.203	0.399	0.202		
(6) IT intensity	0.488	0.335	0.228	0.280	0.245	**0.128**	0.273	
(7) Size	1.677	1.080	0.749	0.246	0.159	0.173	0.345	**0.047**

Note: All correlations are significant at $p < 0.001$. The correlations in bold are used as the proxy of common method variance.

Table 2
OLS Regression Results.

	(1) Full sample	(2)	(3)	(4)	(5) SMEs	(6) Large firms
Social media diversity		0.019*	0.017*	−0.009	0.060***	0.058*
		(0.008)	(0.008)	(0.012)	(0.016)	(0.024)
Big data analytics			0.037*	0.001	−0.014	0.026
			(0.018)	(0.021)	(0.028)	(0.054)
Social media diversity × Big data analytics				0.050***	0.075***	0.052
				(0.016)	(0.022)	(0.031)
IOS	0.230***	0.227***	0.223***	0.223***	0.263***	0.304***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.027)	(0.041)
ERP	0.431***	0.429***	0.417***	0.421***	0.763***	0.409***
	(0.017)	(0.017)	(0.018)	(0.018)	(0.023)	(0.054)
IT intensity	0.798***	0.785***	0.780***	0.780***	0.619***	0.728***
	(0.025)	(0.026)	(0.026)	(0.026)	(0.035)	(0.060)
Size	1.066***	1.063***	1.063***	1.061***		
	(0.008)	(0.008)	(0.008)	(0.008)		
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	13.205***	13.210***	13.207***	13.220***	14.582***	17.145***
	(0.032)	(0.032)	(0.032)	(0.033)	(0.040)	(0.132)
R^2	0.6278	0.6279	0.6280	0.6282	0.1885	0.2598
Adj. R^2	0.6276	0.6277	0.6278	0.6280	0.1880	0.2569
F	4531.460***	3966.650***	3527.010***	3176.880***	424.920***	90.910***
n	18,816	18,816	18,816	18,816	16,475	2341

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors are in parentheses. Dependent variable is market performance.

2341 large firms, which could be deemed as large samples with sufficient statistical power.

We therefore estimated our full model again, without firm size as a control (no variation in the class of employment for large firms), for SMEs and large firms, respectively. Social media diversity demonstrated a statistically significant and positive effect on market performance for both SMEs and large firms, whereas big data analytics did not. We found a statistically significant and positive interaction effect of social media diversity and big data analytics on market performance for SMEs ($\beta = 0.041, p < 0.05$) but not for large firms ($\beta = 0.035, p > 0.05$). Because the regression coefficient for SMEs was significantly greater than zero whereas the regression coefficient for large firms was not significantly different from zero, our results indicate that the interaction effect of social media diversity and big data analytics is stronger for SMEs than for large firms. Thus, H2 was supported.

5.2. Robustness checks

5.2.1. Assessment of common method bias

A key concern for cross-sectional survey data is common method bias, as the same survey respondent answered all questions. We assessed common method bias by multiple methods. First, we conducted a Harman one-factor test by a principal component factor analysis. More than one factor with eigenvalue greater than 1 was extracted, and the first factor can only explain 37.24% of total variance. Second, we used the marker variable approach, which has been suggested as one of the most effective methods to assess common method bias in IS research [84]. We followed Lindell and Whitney [85] to use both the smallest correlation (i.e., 0.047) and, more conservatively, the second smallest correlation (i.e., 0.128) as the proxies of common method variance (CMV). We found that after partialling out CMV from the zero-order correlations between market performance and other variables, partial correlations remain statistically significant after decreases of up to 18% and 53% (see Table 3). Thus, we conclude that common method bias is not a serious concern in our data.

5.2.2. Endogeneity test

Our OLS results should be interpreted as association rather than causation because of the cross-sectional nature of our data. It is likely that endogeneity, from either reverse causality or simultaneity, makes the OLS results inconsistent. For example, firms with better market performance may have more financial resources to invest in social media channels and big data analytics, suggesting that the correlation can be driven by reverse causality. Omitted variables may also simultaneously affect social media diversity, big data analytics, and market performance, thus leading to an illusory correlation that we observed. To address these endogeneity issues, we followed Bharadwaj et al. [86] and Dong et al. [87] to estimate a two-stage Heckman model (see Table 4).

Specifically, we summed up our independent variables, namely, social media diversity and big data analytics, and then coded a dummy variable indicating whether a firm had a value greater than the mean of our sample. Past research has suggested that a firm's IT investment is influenced by its competitors' IT investment (e.g., [88,89]). In the first stage, we estimated a Probit model to predict the new dummy variable by the average level of competitors' social media diversity and big data

Table 3
Assessment of Common Method Bias.

Antecedents of market performance	Zero-order correlation	First smallest correlation as the proxy of CMV		Second smallest correlation as the proxy of CMV	
		Percentage of change (%)	Partial correlation	Percentage of change (%)	Partial correlation
Social media diversity	0.253***	14.56	0.216***	43.34	0.143***
Big data analytics	0.219***	17.59	0.180***	52.35	0.104***
IOS	0.217***	17.80	0.178***	52.97	0.102***
ERP	0.425***	6.67	0.397***	19.86	0.341***
IT intensity	0.228***	16.70	0.190***	49.70	0.115***
Size	0.749***	1.65	0.737***	4.92	0.712***

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 4
Heckman Model Results.

	(1) First stage	(2) Second stage
Social media diversity		−0.010
		(0.012)
Big data analytics		−0.005
		(0.021)
Social media diversity × Big data analytics		0.057***
		(0.016)
Inverse Mills ratio		−0.856***
		(0.234)
Competitors' social media diversity	0.733***	
	(0.153)	
Competitors' big data analytics	−0.141	
	(0.454)	
IOS	0.290***	0.093*
	(0.026)	(0.041)
ERP	0.672***	0.076
	(0.022)	(0.096)
IT intensity	0.653***	0.459***
	(0.032)	(0.091)
Size	0.072***	1.028***
	(0.010)	(0.012)
Industry dummies	Yes	Yes
Constant	−1.072***	14.352***
	(0.075)	(0.312)
Pseudo R^2	0.1254	
Chi-square	3258.790***	
R^2		0.6284
Adj. R^2		0.6282
F		2891.180***
n	18,816	18,816

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors are in parentheses. Dependent variable in the first stage is a dummy variable indicating whether the sum of social media diversity and big data analytics is greater than the mean of our sample; dependent variable in the second stage is market performance.

analytics and other control variables. The Probit model demonstrated a good fit, as all predictors were statistically significant. We then calculated the inverse Mills ratio (IMR), which represents the propensity for social media diversity and big data analytics, which are endogenously determined.

In the second stage, we re-estimated the OLS model, with IMR as an additional control. We found that IMR was statistically significant, thus indicating that endogeneity exists. After controlling for the endogeneity, however, the results are still consistent with the OLS results. In particular, the interaction effect of social media diversity and big data analytics on market performance was still statistically significant and positive. Therefore, the endogeneity does not bias our conclusion, although social media diversity and big data analytics are endogenous.

6. Discussion

6.1. Theoretical implications

In this paper, we investigate the market performance impact of social media analytics rooted in the synergies between social media diversity and big data analytics, as well as the difference in this impact across SMEs and large firms. By doing so, we make several contributions to the research on big data analytics. First, drawing on the systems theory, we explain that the super-additive value arising from the synergies of the complementary use of social media channels and big data analytics is the value creation mechanism of social media analytics. This theoretical explanation contributes to our understanding about how big data analytics create value in conjunction with other technologies, which has long been ignored in past research. Our study departs from past research on the performance impact of big data analytics [4,12–16,23] by focusing on the synergies between big data analytics and other complementary technologies in value creation. We find that the super-additive value arising from the synergies between social media diversity and big data analytics is manifested by a positive interaction effect on market performance. To the best of our knowledge, no prior work has systematically demonstrated that the value of big data analytics is interdependent with other technologies such as social media.

Second, we deepen our theorizing by considering the difference between SMEs and large firms in the required integration effort to realize the synergies of social media diversity and big data analytics. We explain how firm size shapes the contingency of the value creation of social media analytics and find that SMEs are more likely to realize synergies of social media diversity and big data analytics, corroborating our arguments that SMEs face less required integration effort. Interestingly, we find that our sampled large firms on average may not meet the required effort to integrate the use of social media channels and big data analytics to realize their synergistic effect. To the best of our knowledge, the difference between SMEs and large firms in the value creation of social media analytics has not been studied in the literature. Recently, Huang et al. [90] have documented that, in other contexts, data-driven operation enables rapid growth of small startups in the marketplace. Our findings extend this implication to the big data context, thus suggesting that social media analytics is more valuable for SMEs.

Finally, our study contributes back to the systems theory in IS research by broadening past research from the synergies between IT and other complementary resources to the synergies between complementary technologies. Conventionally, the IT synergies literature focuses on the super-additive value or sub-additive cost of IT resources across multiple business units [21,35] or the synergies between IT resources and other organizational resources [19,20]. Compared to these studies, we broaden the idea of IT synergies by theorizing the synergies between different technologies *within* IT resources in the big data context.

6.2. Managerial implications

Our study also offers important practical implications to managers for creating business value with social media analytics. Although big data are considered to be important for building firm competitiveness currently, the technologies have not become widespread — for example, 65% our sampled Italian firms had not adopted social media analytics by 2014. Our study reminds managers that it is not enough to simply adopt big data analytics without knowing that big data analytics need to be used in combination with other complementary technologies and require sufficient integration effort to realize the potential synergies, leading to super-additive value creation. Our study reveals that both social media diversity and big data analytics do not improve market performance separately but have synergies and jointly improve market performance. It provides timely guidance about how to create the business value of social media analytics by using diverse social media channels for gathering big data and adopting big data analytics to analyze the gathered big data. Our results demonstrate the function complementarity of social media channels and big data analytics, leading to synergies for super-additive value creation. Simply gathering unstructured data from social media channels does not provide any insight into benefit market strategies; similarly, only using big data analytics without sufficient market-facing data could not benefit market performance. Therefore, managers need to proactively integrate the complementary use of social media channels and big data analytics in their firms, which is critical for enhancing firm competitiveness in the marketplace.

In addition, we find that social media analytics are relatively more valuable for SMEs than for large firms. In our explanations, the degree to which the potential synergies between social media diversity and big data analytics can be realized relies on a firm's integration effort, and the required integration effort to realize the synergies is different across SMEs and large firms. For the managers of SMEs, they may be able to build the competitive advantage by better integrating social media channels and big data analytics and benefit from the synergies given that the required integration effort is easier to achieve. By doing so, SMEs may more efficiently realize the super-additive value from social media analytics and grow on steroids in the marketplace. On the other hand, we suggest the managers of large firms make a greater integration effort at the early stage to combine their complex use of social media channels and big data analytics if they want to utilize social media analytics to enhance their market performance because the required integration effort to realize the synergies of social media channels and big data analytics are relatively higher for large firms than for SMEs. Certainly, the managers of large firms can also realize the super-additive value from the complementary use of social media channels and big data analytics if sufficient integration effort is made.

6.3. Limitations and future studies

This study has some limitations. First, we consider market performance measured by a firm's total sales in the marketplace. While market performance is particularly suitable for our study because the business value of social media analytics resides in the market knowledge derived from user-generated content created by customers on social media, it does not fully capture the performance impact of social media analytics. Although it is beyond the scope of our study, future research may consider other performance indicators to explore the performance impact of social media analytics and enrich our understanding of the business value of social media analytics. Future research may also use alternative measures for market performance, such as market share (e.g., [53]), to test our findings. In addition, we consider big data analytics measured by a survey question asking whether a firm uses big data analytics for deriving insight on customers. Although this measure is aligned with our conceptualization of technology adoption as use or no use, it may oversimplify different levels of big data analytics use in practices. Future studies can improve it by considering the level of use or the effectiveness of use (e.g. [91,92]).

Second, although the data set that we used in this study was collected from a large-scale, cross-industry sample in a recent year, it has a cross-sectional design. To protect the confidentiality of participating firms, Istat does not provide us firm identifiers. This restricts us to merge multiple waves of survey and thus construct a panel data set. To avoid econometric issues related to repeated measures from the same firm, we decided to use the most recent available data from the survey in 2014 by the time of conducting this research. While our findings based on a large sample can reflect a generalizable value creation mechanism of social media analytics, we cannot fully test the causality underlying our hypothesized relationships. The cross-sectional design does not allow us to use advanced econometric techniques to address endogeneity, although we have tried to address the endogeneity issues in a robustness check. We also cannot examine the growth or decline in the market performance over time, while in a fast-changing market, the value creation mechanism of social media analytics may dynamically evolve. Thus, future research can move one step forward in extending our initial findings by using a longitudinal design.

Last but not least, caution should be exercised when generalizing our findings to countries other than Italy. Italy has been left behind in the digital economy compared to and thereby different from other European countries (European Union [93]). Firms in developing countries may also be different from Italian firms in the value creation mechanism of social media analytics. Future studies can collect data from firms in other countries to replicate our study and enrich the literature by providing more evidence on the business value of social media analytics in other national contexts.

7. Conclusion

Taking social media analytics as an example, this paper is among the first attempts to theoretically explain and empirically test the market performance impact of big data analytics. Drawing on the systems theory, we explain how and why social media analytics create super-additive value from the synergies between social media diversity and big data analytics. In addition, we consider the difference between SMEs and large firms in the required integration effort that enables the synergies of social media diversity and big data analytics. We empirically test the synergistic effect of social media diversity and big data analytics by using a recent survey data set from 18,816 firms in Italy and find that social media diversity and big data analytics have a positive interaction effect on market performance, which is more salient for SMEs than for large firms.

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