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Acceptance of Text-Mining Systems: The Signaling Role of Information Quality

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Abstract

The popularity of the big data domain has boosted corporate interest in collecting and storing tremendous amounts of consumers' textual information. However, decision makers are often overwhelmed by the abundance of information, and the usage of text mining (TM) tools is still at its infancy. This study validates an extended technology acceptance model integrating information quality (IQ) and top management support. Results confirm that IQ influences behavioral intentions and TM tools usage, through perceptions of external control, perceived ease of use, and perceived usefulness; top management support also has a key role in determining the usage of TM tools.

Keywords: technology acceptance model (TAM); text mining; big data; information quality; top management support

1. Introduction

The expansion of the Internet and its multiplication of customer touchpoints have generated an abundance of customer data, often referred to as *big data*. Customers who engage through multiple communication channels and share their opinions on various online (social media) platforms create substantial (*volume*), rapidly expanding (*velocity*), and varied types of data that provide both structured and unstructured (linguistic, video, image, and audio) cues (*variety*) [1]. According to IBM, 80% of all of that data is unstructured, which creates a vast challenge that some companies might not even realize they face [2]. Information systems (IS) literature in turn seeks to suggest many successful approaches to analyze large volumes of unstructured, textual customer data using text mining (TM), defined as the process of analyzing and summarizing a large body of textual data to extract useful, previously unknown information [3]. Extant TM approaches include [4] web mining [5], classification [6], clustering [7], natural language processing (NLP) [8], concept extraction [9,10], information extraction [11], and information retrieval [8,12].

In particular, IS managers highlight their struggle to convert textual customer data into relevant information. The unstructured consumer data generally are not readily available from transactional databases; therefore, additional data collection efforts are needed [13], but IS managers worry about the quality of the input data obtained from interactions with clients, social media platforms, or (n)ethnography-based research, such that they hesitate to use or analyze them [14]. Further challenges also arise [13], due to the lack of readily available in-house analytical competences and insufficient company frameworks to integrate the outputs of TM tools into existing analytical methods and reporting systems. In this sense, IS managers are not confident about output quality. Finally, industry TM tools are unpopular, perhaps because of the substantial monetary investments and approval from top management that are required to purchase the software. The complex software programs demand that users gain extensive experience before they can analyze or interpret textual data effectively, which may limit the scope of useful information available to marketing departments [15].

To contribute to this literature stream, we investigate drivers of TM adoption by companies that seek to analyze textual customer information. From a broader perspective, prior literature considers the adoption of big data technology and its value creation potential [16,17], but specific questions about what drives the adoption of TM systems (TMS) remain unanswered. A related study in the big data field [18] investigates the adoption of data mining systems, yet data mining differs methodologically from TM. Instead of structured, quantitative data, TM deals with unstructured, textual data. The input data differ, and the insights gained from these mining tools also are different in nature. Moreover, TM is less mature than data mining as a methodology; therefore, insights that are specific to adoption tendencies for TMS remain necessary. We address in particular what drives organizations to adopt TMS. Modern customers have vast opportunities to share their evaluations through channels such as email, company websites, blogs, and social media. Companies therefore must take advantage of these textual data if they hope to improve customer experiences and create better long-term relationships [19].

Accordingly, this study contributes to IS literature in three main ways. First, we contribute to technology adoption literature by investigating underlying drivers of TM adoption, using the well-studied technology adoption model (TAM). Second, whereas several studies investigate information quality (IQ) with a system-design orientation [e.g., 11], conceptualize IQ [20], or provide measurement instruments [21], very few include IQ as a determinant of system usage [22]. Noting the relevance of input data quality and output IQ for TMS though, we investigate this link as an antecedent in the TAM. Third, prior IS literature highlights the influential role of top management for determining the strategic potential of IS [23], but not its impact on the adoption of big data. We answer calls for such research [24] and investigate how management support, in the form of monetary investments, might encourage TMS adoption. In so doing, we clarify the link between behavioral intentions and TMS usage behavior.

In the next section, we review research from the TAM and IQ traditions. After we outline the research model and hypotheses, we describe the research methodology. Section 5 contains the findings of our field test. Finally, we discuss the results, theoretical and managerial implications, and some limitations and directions for further research.

2. Conceptual Background

2.1. Technology Acceptance Models

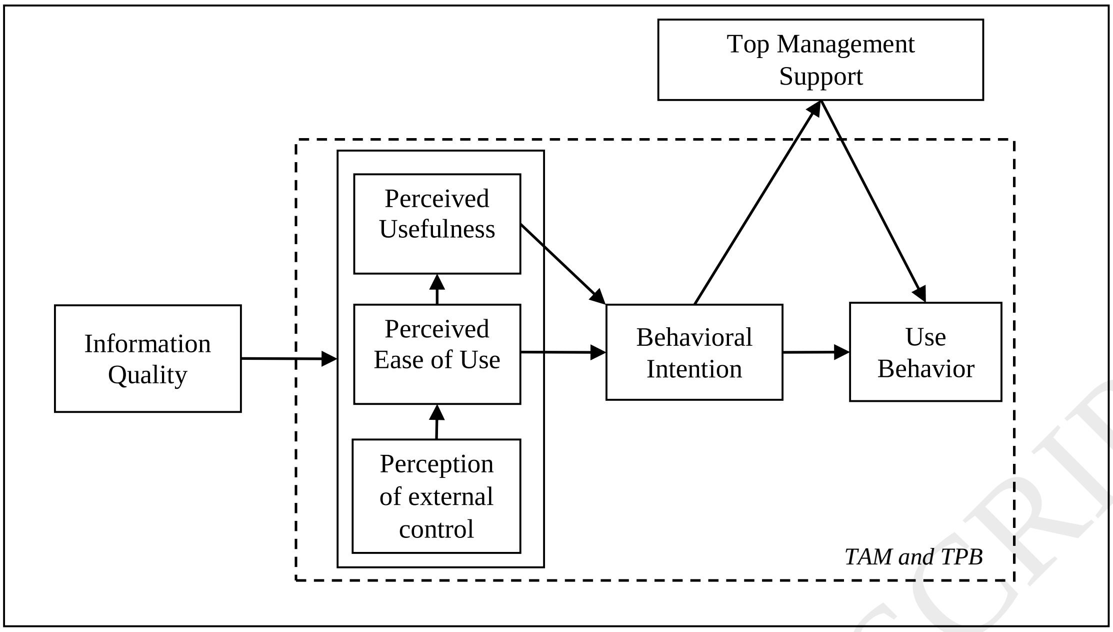
Several theories offer explanations for users' adoption of information technologies (IT). Theories that highlight motivational factors that underlie the use or acceptance of IT include the theory of reasoned action (TRA) [25], theory of planned behavior (TPB) [26,27], TAM [28], TAM2 [29], and TAM3 [24], as well as the unified theory of the acceptance and use of technology (UTAUT) [30]. According to the TRA [25], which is a behavioral theory that models attitude–behavior links, people use IT if they anticipate positive outcomes associated with its use. The TPB [26,27] succeeded the TRA and introduced another determinant of intention, namely, perceived behavioral control, that is, perceptions of internal and external resource constraints on performing a behavior. The TAM also is based on the TRA [25]; it specifies determinants of individual technology acceptance, such as perceived usefulness and perceived ease of use, such that it serves to predict individual adoption behaviors [31].

Although the TAM has the same parsimoniousness as the TRA and TPB [32], it is easier to use than the TPB, and it provides a quick way to gather individual perceptions. In a meta-analysis [33], the TAM emerged as a valid and robust model. The UTAUT then provided a way to combine the TAM, TRA, and TPB. It includes four antecedents of behavioral intentions: performance expectancy, effort expectancy, social influence, and facilitating conditions. The TAM3 offers a conceptual improvement over the TAM2; relative to the UTAUT, it also predicts that individual differences, system characteristics, social influence, and facilitating conditions represent antecedents of perceived usefulness and perceived ease of use. Accordingly, TAM3 is one of the most widely used models to predict the acceptance and use of IT [33]. It recently has been applied to data mining adoption [18]. Indeed, [18] investigate the adoption of data mining by replicating the TAM3 while adding response time and format, two antecedents of perceived usefulness. Thus, our study differs from [18] by considering IQ dimensions as determinants of perceived ease of use and perceived usefulness instead of antecedents proposed by TAM3.

As depicted in Figure 1, our model incorporates the key variables from the TAM. Similar to TAM, we consider perceived usefulness and perceived ease of use as determinants of behavioral intention. We also integrates a key construct of TPB [26,27] i.e., perception of external control (which is considered in TAM3). To provide actionable guidance, we consider IQ dimensions as determinants of perceived usefulness and ease of use as well as perception of external control. We also consider top management support to better understand the relationship between behavioral intention and use behavior.

Figure 1

Theoretical framework



2.2. *Information Quality*

Researchers who use IQ as a determinant of system use and user satisfaction note that instead of the performance of the system, the measure of its success should be the quality of the information that it provides [22]. Managers make decisions based on system outputs; therefore, information has value only if it enhances the decision maker's performance [20]. Many studies investigate IQ with a system-design orientation [20], specifying its definition, dimensions, and measurement [21,34].

In particular, IQ emerges as a multidimensional concept. Wang's well-known classification [34] contains four IQ categories: intrinsic, accessibility, contextual, and representational IQ. Lee et al. [21] provide a synthesis of these IQ categories and their dimensions, along with measurement instruments for the different dimensions, as depicted in Table 1. Specifically, *intrinsic IQ* indicates that information has quality in its own right; it comprises dimensions such as accuracy, reliability, correctness, and completeness. *Contextual IQ* instead refers to the consideration of the information within the overall context of the task at hand, such that its dimensions are relevancy, usefulness, and currency. Both *representational* and *accessibility IQ* emphasize the access that the system provides to information that is well presented and easy to interpret. Whereas representational quality includes interpretability, ease of understanding, consistency, and conciseness, accessibility quality encompasses dimensions such as accessibility and security [20,21,34].

Several studies use these frameworks to investigate acceptance of various IS as well. For example, contextual and representational IQ dimensions appear important for determining end-user satisfaction with enterprise content management systems [35], and the perceived IQ dimensions (i.e., representational, accessibility, and intrinsic) of business intelligence systems increase users' information satisfaction [36]. Therefore, the conceptual framework of IQ appears appropriate for investigating the acceptance of IS and, more precisely, TMS.

2.3. Top Management Support

Top management support indicates the degree to which top managers understand the importance of TM adoption and are involved in TM implementation projects [37]. In a sense, top management support is a key requirement for the successful implementation of any system that could influence business relationships [23]. If top management enthusiastically supports a particular system, the firms and their employees are more proactive in their adoption of that system [38]. Consequently, we include management support as key variable explaining the link between intention and usage of TM.

3. Research Model and Hypotheses

In this section, we detail our conceptual model and research hypotheses, as depicted in Figure 2. We predict that the four categories of IQ affect perceptions of ease of use and usefulness, as well as the facilitating conditions. As shown in Table 1, for each category, we select important IQ factors related to TMS, that is, the dimensions that are the most representative of the category; we also add dimensions specific to TMS.

3.1. Information Quality

3.1.1. Contextual Output Quality

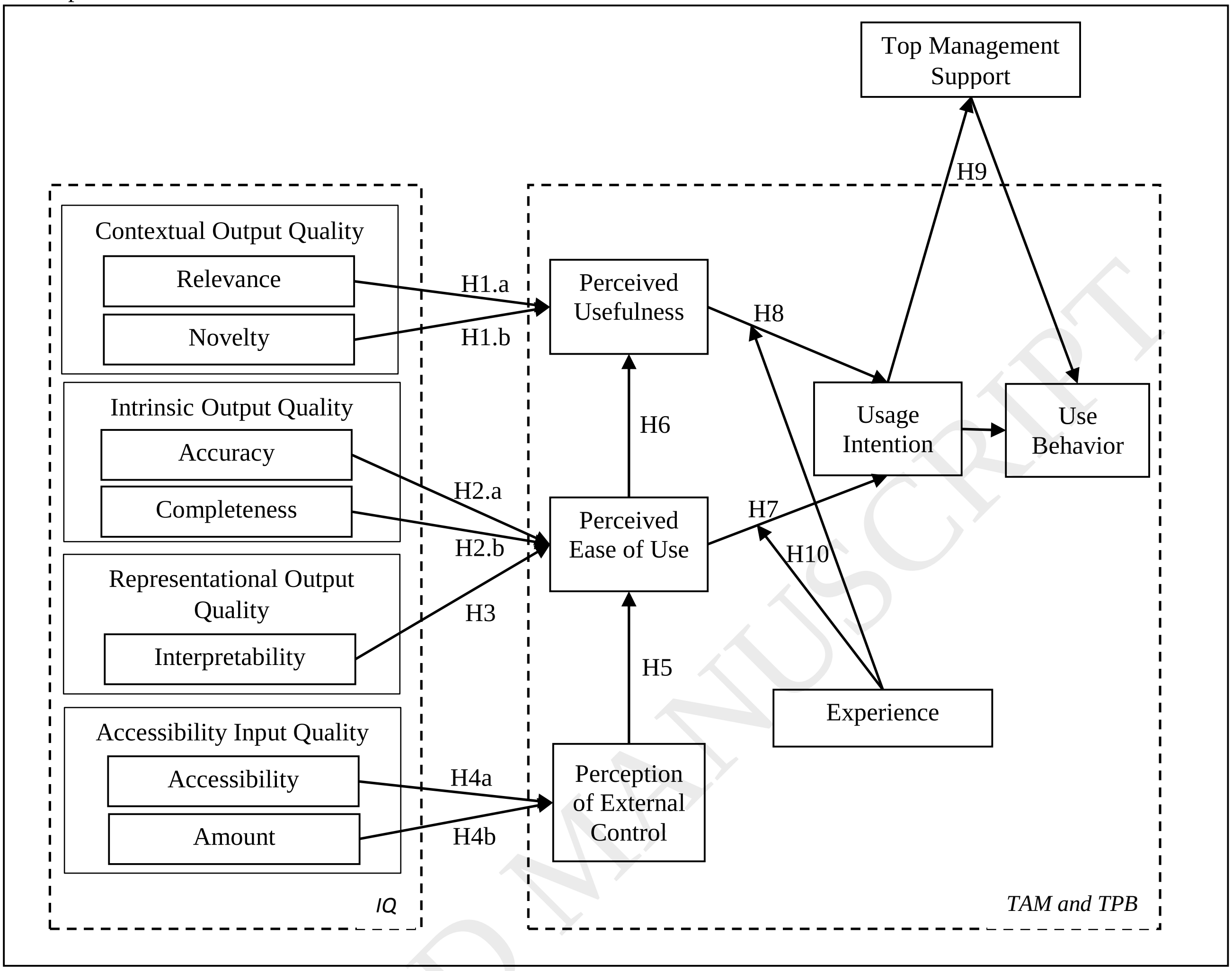
The two important dimensions of contextual IQ, which we consider as potential determinants of perceived usefulness, are *output relevance* and *output novelty*. People form perceptions of

Table 1

Four categories of IQ and their dimensions (inspired by [21])

	Intrinsic IQ	Contextual IQ	Representational IQ	Accessibility IQ
[20,34]	**Accuracy**, believability, reputation, objectivity	Value-added, **relevance**, completeness, timeliness, appropriate amount	Understandability, **interpretability**, concise and consistent representation	**Accessibility**, ease of operations, security
[39]	**Accurate**, factual	Quantity, reliable/timely	Arrangement, readable, reasonable	
[40]	Believability, **accuracy**, credibility, consistency, **completeness**	**Relevance**, usage, timeliness, source currency, data warehouse, currency, nonvolatility,	**Interpretability**, syntax, version control, semantics, aliases, origin	**Accessibility**, system availability, transaction availability, privileges
[22]	**Accuracy**, precision, reliability, freedom from bias	Importance, **relevance**, usefulness, informativeness, content, sufficiency, completeness, currency, timeliness	Understandability, readability, clarity, format, appearance, conciseness, uniqueness, comparability	**Accessibility**, usableness, **quantitativeness,**
[41]	**Accuracy**, precision, reliability, freedom from bias	Currency, level of detail	Compatibility, meaning, presentation, lack of confusion	**Accessibility**, assistance, ease of use, locability
[42]	**Accuracy**, consistency	Completeness, timeliness		
[20]	Correctness, unambiguous	Completeness	Meaningfulness	
[21]	**Accuracy**, Concise representation, consistent representation	**Relevant,** timely, completeness, appropriate amount, add value	**Interpretability**, understandability, easy to manipulate, conciseness, consistency	**Accessibility,** security
[43]		Topicality, scope, reliability, **novelty**, understandability		
This study	**Output accuracy and completeness**	**Output relevance and novelty**	**Output interpretability**	**Input accessibility and amount**

Figure 2
Conceptual model



usefulness on the basis of their cognitive instrumental processes, that is, “by cognitively comparing what a system is capable of doing with what they need to get done in their job” [29]. They evaluate the match between important work goals and the consequences of performing their job tasks by using a system. The latter serves as a basis for perceptions of the usefulness of a system. Similar to Venkatesh and Davis [29], we draw on behavioral decision theory, such as image theory [44], to justify these antecedents of perceived usefulness. This theory highlights two key concepts [44]: trajectory and strategic images. The trajectory image is a mental representation of individual goals; the strategic image is a mental representation of alternative actions that people must undertake to achieve their goals, which they have identified through the trajectory image. When people choose among action sequences and make adoption decisions, they pass through two steps. First, they use a compatibility test to choose those options that are most compatible with their decision standards or outputs that are most relevant to the decision at hand. Second, with a profitability test, they compare the selected options to choose the best one, such that users may value outputs that are the most novel compared with what they already know. Accordingly, we predict two cognitive instrumental determinants of perceived usefulness: *output relevance* and *output novelty*.

First, *output relevance* is a judgment of the strength of the relationship between the needs of the decision maker in a specific situation and the information provided by the system [45]. Thus, we define it as the degree to which information provided by the TMS is applicable and helpful for the decision at hand [46]. Decision makers often have knowledge about decision contexts, which enables them to decide which decisions to make by using a system [47,48]. According to image theory, during the compatibility test, managers evaluate systems and select those that are compatible with their decision-making tasks. More precisely, they choose systems that provide information relevant to the decisions to be made. Therefore, output that is relevant to the decision should affect perceived usefulness positively.

H1a: Output relevance has a positive effect on TMS' perceived usefulness.

Second, *output novelty* is the degree to which the output of the TM system is new to the user and different from what the user has known before [43]. According to image theory, during the profitability test, decision makers choose the best option among a choice set of systems that are relevant to their decision-making. They choose the one with the highest added value, that is, the one that offers unique, new information relative to what they already know. According to [49], information corresponding to something already known cannot be useful, because it will not produce any cognitive change. Past research affirms that the most useful information is novel and unique [50]. Therefore, we predict a positive effect of output novelty on perceived usefulness.

H1b: Output novelty has a positive effect on TMS' perceived usefulness.

3.1.2. Intrinsic and Representational Output Quality

[29] identifies determinants of perceived ease of use, classified into two categories: anchor and adjustment variables. Anchor variables are general beliefs about systems and systems usage; adjustment variables are beliefs shaped by direct experience with the target system [51]. Yet TAM3 does not include variables reflecting users' evaluations of the system experience, other than perceived enjoyment. Rather, TAM3 considers system usability, measured objectively, which cannot represent the overall user evaluation. We argue that user perceptions of the system output constitute an adjustment variable that likely determines the perceived ease of use. Previous research has demonstrated that system characteristics, such as

functionality, response, format, and response time, affect the perceived ease of use [18,52,53]. Consequently, we consider two IQ categories, intrinsic and representational output quality, as determinants.

First, *intrinsic output quality* is the degree to which the system provides sound information, with good quality in its own right [21]. It includes completeness, accuracy, conciseness, and consistent representations [21], but we focus on accuracy and completeness as the two main dimensions of intrinsic quality of TMS output. *Accuracy* refers to the probability of preventing errors or failures [21,54] and can be described as correctness [55]. *Completeness* is the extent to which the output has sufficient breath, depth, and scope to facilitate the task at hand [20]. A set of data is complete if all necessary values are included [56] and the system represents every meaningful state of the represented real-world system [20]. We hypothesize that TMS that provide information conforming to specifications, such that it is free of error and complete, are likely to be perceived as easy to use by users.

H2a: Output accuracy has a positive effect on TMS' perceived ease of use.

H2b: Output completeness has a positive effect on TMS' perceived ease of use.

Second, *representational output quality* is the degree to which information is usable, spanning output interpretability, ease of understanding, and ease of manipulation [21]. We consider the *interpretability* of a TMS output as the focal dimension and define it as the degree to which data are presented appropriately, in language and units, with clear data definitions [20,21]. Decision makers may perceive a TMS as easier to use if its outputs are interpretable. Furthermore, both intrinsic and representational output quality represent adjustment variables, evaluated through direct experience with the system, that likely affect the perceived ease of use of TMS.

H3: Output interpretability has a positive effect on TMS' perceived ease of use.

3.1.3. Accessibility Input Quality

One of the resources necessary to use TMS is a large amount of accessible textual data, which provides the input to be analyzed by the TM software. For example, letters from customers, customer complains through email, transcripts of telephone calls, and customers' posts on social networks all can be summarized by TMS [19]. Instead of measuring IQ, we account for data quality, because our focus is the accessibility of TMS input data rather than the TMS output. Thus, we consider accessibility input quality as an antecedent of perceptions of external control. Accessibility input quality reflects the accessibility, availability, and convenience of access to the input text data [20–22,40,41]. Two key dimensions of accessibility input quality are accessibility and amount: accessibility is the degree to which textual data are available or easily and quickly retrievable [20], and amount is the extent to which the quantity or volume of available input text data are appropriate [20]. We expect:

H4a: Input accessibility has a positive effect on perceptions of external control.
H4b: Input amount has a positive effect on perceptions of external control.

3.2. Perception of External Control, Perceived Usefulness, and Perceived Ease of Use

A perception of external control is an anchor variable that determines the perceived ease of use [24]. Control perceptions stem from situational constraints or enablers of behavior [26], reflecting people's notions of the availability of resources and knowledge about a particular behavior. This important construct was added to the TRA [57], to build on the TPB [26]. Control also has been incorporated into the TAM3, in terms of perceptions of external control [51], or individual control beliefs about the availability of organizational resources and support structures that can facilitate system use [24]. Perceptions of external control positively influence ease of use perceptions [24,51]. Therefore, we hypothesize:
H5: Perceptions of external control have a positive effect on perceived ease of use.

Prior research provides substantial evidence in support of the TAM, namely, that behavioral intentions to use a system are determined by perceived usefulness and perceived ease of use, and perceived usefulness also is influenced by perceived ease of use [24,33,51,58–60]. We test these TAM-proposed relationships in the context of TMS, with the hypothesis that
H6: Perceived ease of use has a positive effect on perceived usefulness.
H7: Perceived ease of use has a positive effect on usage intentions.
H8: Perceived usefulness has a positive effect on usage intentions.

3.3. Top Management Support

Previous studies emphasize how top management support can increase the incorporation of technology into business processes, which facilitates system adoption and usage [37,61–64]. Furthermore, top management support has a critical influence on market orientations [65,66], such that it can highlight the importance of being responsive to customers' needs. Managers in the company need to encourage employees to share market intelligence and respond to market needs [67]; top managers' emphasis on a market orientation thus should lead to market intelligence generation, dissemination across departments, and responsiveness by the organization, such that it can use relevant market intelligence to develop and execute plans [66,68]. In this sense, TMS are useful tools for generating customer intelligence, by extracting and identifying useful information and gaining knowledge from large databases [69]. Top management support even may turn managers' intentions to use TMS into actual usage behavior, by strengthening beliefs that market intelligence and knowledge created through TM lead to customer value creation and by encouraging investments in TM software. Therefore, we hypothesize:

H9: Usage intentions have a positive effect on TM system usage behavior, through top management support.

3.4. Moderating Effect of Experience with TMS

Prior research [30,69,70] has conceptualized experience as an opportunity to use a system and operationalized it as the passage of time since the initial use of a system by a user [24]. Past studies [24] investigate its moderating effect on the relationship between perceived ease of use and behavioral intentions, showing that perceived ease of use is an important determinant of systems usage, even after users gain substantial hands-on experience with the technology. Because TMS are complex to use, the effect of perceived ease of use even may be stronger when users have accumulated experience, in line with learning curve theory [71,72]. That is, users must familiarize themselves with the systems, understand how to use them, and determine how to interpret the outputs. In the early implementation stage, perceived ease of use likely is low, particularly for complex systems. But once users have learned the main functions of the system, they may make more progress in learning how to use minor system functions. As experience with the TMS increases, the effort required to use it likely decreases, which should enhance perceived ease of use and its effect on usage intentions.

With more experience, the effect of perceived usefulness on usage intentions may decrease though. Repetitive usage of TMS helps users accumulate knowledge, and the system outputs likely grow less novel relative to what they learned previously while using the system. Thus, system outputs may add less value to the accumulated knowledge of users with substantial experience with the TMS, so the effect of perceived usefulness on usage intentions may be weaker.

H10: The experience with TMS moderates the relationship between perceived ease of use and usage intention, through perceived usefulness, by moderating the effect of perceived usefulness on behavioral intentions and the effect of perceived ease of use on behavioral intentions, such that experience increases the effect of perceived ease of use on behavioral intentions.

4. Research Methodology

4.1. Questionnaire Development

The questionnaire includes two sections. The first includes questions about analytical software experience (years), TM usage (numbers of hours each week), and TM software experience (years). We also measured several concepts with 7-point Likert scales, such as perceptions of TM software, top management support, and data quality. The items to measure intentions to use TM software (3 items), perceived usefulness (4 items), perceived ease of use (3 items), and perceptions of external control (3 items) were adapted from Venkatesh and Bala [24]. For the data input accessibility (4 items), input amount (3 items), output interpretability (3 items), output completeness (4 items), output accuracy (3 items), and output relevance (3 items) measures, we adapted scales from Lee et al. [21]. Finally, output novelty (2 items) came from Xu and Chen [43]. The scales are in Table 3.

The second section includes questions about the respondents' profiles, such as the industry and size of their company, as well as their function in the company, age, gender, level of education, and working experience. This questionnaire was pretested among academics and managers, and we reworded a few questions to improve their clarity.

4.2. Data Collection and Participants

We collected data with a web-based survey of marketing decision analysts in the United States and Europe, supported by a U.S. marketing research firm that works with *Fortune* 500 companies and specializes in the implementation and use of text analytics software in various industries. Through a company newsletter, we invited the company's clients to participate in the survey. To expand the sample, we also collaborated with a European association of marketing analysts who had expressed interest in TM and big data–related fields. Among the 177 respondents to the survey, 9 offered incomplete responses and were eliminated. The final sample thus includes 168 respondents, 51.1% of whom are based in the United States, and 29.2% of whom are women. The average age of participants is 41.92 years (SD = 11.46), their average working experience is 18.65 years (SD = 11.09 years), and their average experience with analytical software has lasted 14.74 years (SD = 9.92 years). We summarize the key characteristics of the sample in Table 2.

Table 2

Sample description

Industry		Company Size	
Information and communication	26.2 %	Less than 9 employees	10.8 %
Technology	13.7 %	10 to 19 employees	19.6 %
Education	10.1 %	20 to 99 employees	16.7 %
Financial and insurance	8.9 %	100 to 499 employees	39.9 %
Industry manufacturing	4.8 %	500 employees or more	13.1 %
Wholesale and retail trade	2.4 %		
Other	33.9 %		

Job		Gender	
Research and market research	56.5 %	Male	70.8 %
Marketing	14.9 %	Female	29.2 %
Administration, CEO, management	4.8 %		
Sales	4.2 %	**Education**	
Customer service	4.2 %	College	21.4 %
Other	15.0 %	Bachelor's degree	56.0 %
		Master's degree	21.4 %
		Ph.D. or higher	1.2 %

5. Results

We analyzed the data using SmartPLS 3 [73] in two stages, reflecting the measurement model and the structural model. These partial least squares (PLS) regressions can simultaneously test multiple relationships among several dependent and independent variables. The SmartPLS program provides path coefficients, t-values, and *p*-values for each relationship, obtained from bootstrapping with resampling (5000 resamples). In addition, SmartPLS indicates the R-squared values for any endogenous variable in the model. The PLS method is appropriate method for validating exploratory multipath models with latent variables [74]. Moreover, it provides the capacity to use smaller data samples without requiring a normal distribution of the data; the sample size (N = 168) for our study meets the common standards for PLS modeling [75].

5.1. Measurement Model

We performed validity and reliability analyses for each measure in the structural model (Table 3). The two dimensions of intrinsic output quality, accuracy and completeness, correlated strongly ($r = 0.636$; $p < 0.01$), indicating that they actually form a single

Table 3

Standard loadings, composite reliability (CR), and average variance extracted (AVE)

Constructs and Measured Items	Loadings
Accessibility (Cronbach's α = 0.947; CR = 0.961; AVE = 0.861)	
Text-based data would be easily retrievable.	0.922
Text-based data would be easily accessible.	0.925
Text-based data would be easily obtainable.	0.939
Text-based data would be quickly accessible when needed.	0.926
Amount (Cronbach's α = 0.763; CR = 0.838; AVE = 0.619)	
The text-based data available would be of sufficient volume to use in text-mining software.	0.897
The amount of text-based data available would not match the amount required for use in text-mining software. (Reversed)	0.714
The amount of text-based data available would not be sufficient to use in text-mining software. (Reversed)	0.736
Interpretability (Cronbach's α = 0.862; CR = 0.915; AVE = 0.782)	
It would be easy to interpret what text-mining outputs mean.	0.895
Text-mining outputs would be easily interpretable.	0.914
The measurement units for text-mining outputs would be clear.	0.842
Intrinsic Output Quality (Cronbach's α = 0.917; CR = 0.934; AVE = 0.670)	
The text-mining outputs would include all necessary values.	0.713
The text-mining outputs would be sufficiently complete for our needs.	0.868
The text-mining outputs would cover the needs of our task.	0.873
The text-mining outputs would have sufficient breadth and depth for our task.	0.877
Text-mining outputs would be correct.	0.798
Text-mining outputs would be accurate.	0.796
Text-mining outputs would be reliable.	0.793
Novelty (Cronbach's α = 0.770; CR = 0.895; AVE = 0.810)	
In the output of text-mining software, the amount of insights that are new to me would be small/substantial.	0.928
The output of text-mining software would be a small amount of/a substantial amount of unique information that I am coming across for the first time.	0.871
Relevance (Cronbach's α = 0.828; CR = 0.899; AVE = 0.749)	
The output of text-mining software could be used to solve problems at hand.	0.739
When making a decision in my job, I would really apply the knowledge learned from the output of text-mining software.	0.929
When making a decision in my job, I would take action according to what is suggested by the output of text-mining software.	0.915
Perception of External Control (Cronbach's α = 0.79; CR = 0.875; AVE = 0.701)	
I would have control over using text-mining software.	0.803
I would have the resources necessary to use text-mining software.	0.862
Given the resources, opportunities, and knowledge it takes to use text-mining software, it would be easy for me to use the text mining software.	0.846
Perceived Ease of Use (Cronbach's α = 0.839; CR = .901; AVE = 00.753)	
My interaction with text-mining software would be clear and understandable.	0.865
I would find text-mining software easy to use.	0.853
I would find it easy to get text- mining software to do what I want it to do.	0.884

Table 3 (Con't)

Standard loadings, composite reliability (CR), and average variance extracted (AVE)

Constructs and Measured Items	Loadings
Perceived Usefulness (Cronbach's α = 0.911; CR = 0.937; AVE = 0.789)	
Using text-mining software would improve my performance in my job.	0.909
Using text-mining software in my job would increase my productivity.	0.854
Using text-mining software would enhance my effectiveness in my job.	0.893
I would find text-mining software to be useful in my job.	0.894
Top Management Support (Cronbach's α = 0.911; CR = 0.938; AVE = 0.790)	
The top management is greatly interested in using text-mining software.	0.868
The top management is aware of the benefits of text-mining software for future success.	0.906
The top management will allocate adequate financial and other resources to the development and operation of text-mining software.	0.883
The top management has a vision to project our company as the market leader in the use of text-mining software.	0.898
Usage Intention (Cronbach's α = 0.959; CR = .974; AVE = 0.925)	
Assuming I have access to text-mining software, I intend to use it in the next few months.	0.968
Assuming I have access to text- mining software, I predict that I will use it in the next few months.	0.972
I plan to use text-mining software in the next few months.	0.945

dimension, which we rename intrinsic output quality, to reflect that accuracy and completeness are two dimensions of intrinsic information quality [21]. The item loadings are satisfactory, with significant t-values; the composite reliabilities (CR) and alpha coefficients exceeded the recommended 0.7 level for each construct [76]. In support of convergent validity, the average variance extracted (AVE) is higher than 0.5 for all constructs. To assess discriminant validity among constructs, we used Fornell and Larcker's [76] criterion and the heterotrait–monotrait (HTMT) ratio [77]. All HTMT ratios are below 0.9, and the square root of the AVE for each latent variable is higher than its correlation with other variables, in support of good discriminant validity. Overall, the measures thus are reliable and valid. Table 4 provides descriptive statistics for each construct, as well as their correlations. Multicollinearity between the latent variables could have a small but significant impact that would bias the path coefficients [78]; therefore, we checked for such correlation across the independent variables by performing a collinearity test. The results showed minimal collinearity; the variance inflation factors of all constructs ranged between 1 and 1.43, well below the recommended threshold of 5–10 [74]. Thus, our results do not appear affected by multicollinearity. In addition, we also check the presence of the common method bias. We use Harman's single factor test [79]. Results show that the first factor accounts for 36.8% of the total variance explained which indicates that the data do not present any common method bias because the first component accounts for less than 50% of all the variables in the model.

Table 4

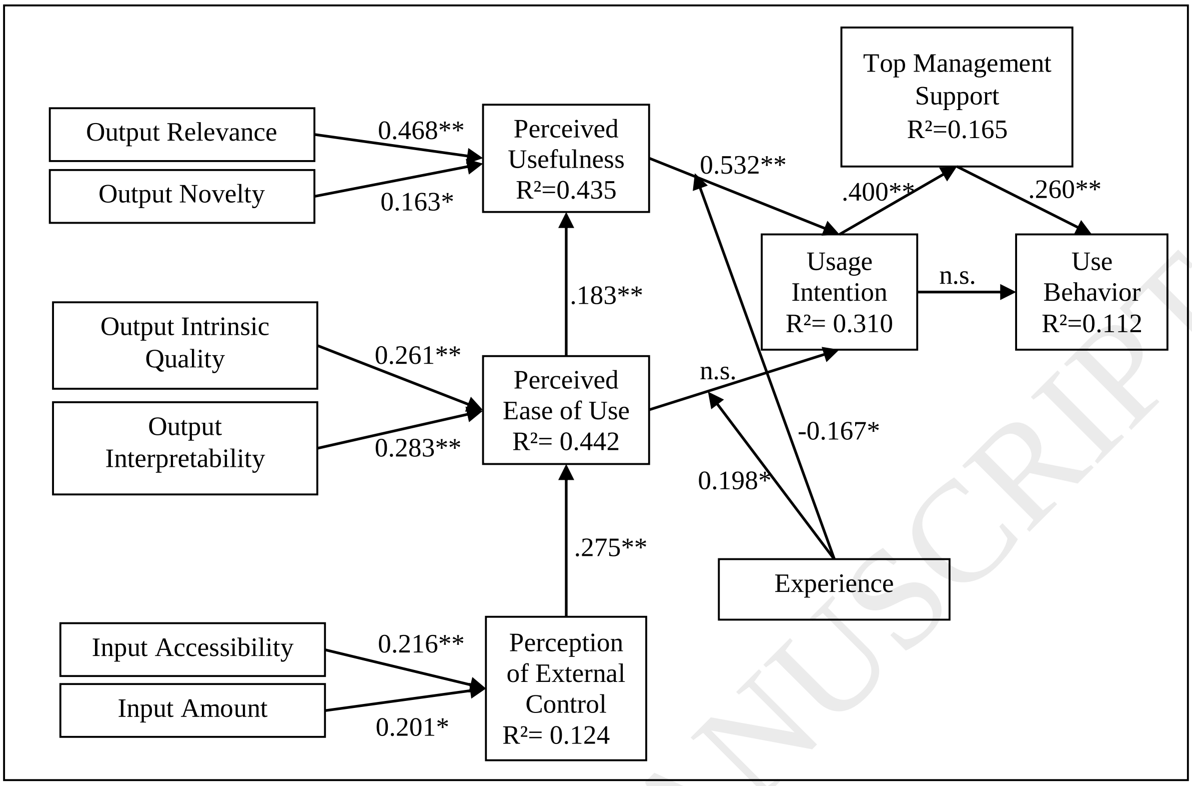
Descriptive statistics and latent variable correlation matrix: Discriminant validity (n = 168)

		Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Accessibility	4.613	1.413	**0.928**												
2	Amount	4.690	1.195	0.423	**0.787**											
3	Interpretability	4.387	1.236	0.407	0.148	**0.885**										
4	Novelty	4.455	1.264	0.163	0.252	0.315	**0.900**									
5	Intrinsic quality	4.381	1.124	0.365	0.268	0.614	0.459	**0.819**								
6	Relevance	4.706	1.269	0.330	0.353	0.380	0.536	0.560	**0.865**							
7	Perception of external control	5.006	1.204	0.301	0.293	0.351	0.335	0.509	0.445	**0.837**						
8	Perceived ease of use	4.014	1.343	0.261	0.128	0.540	0.235	0.575	0.371	0.507	**0.868**					
9	Perceived usefulness	5.452	1.197	0.215	0.267	0.304	0.455	0.406	0.622	0.332	0.391	**0.888**				
10	Experience	3.893	4.969	0.093	0.121	0.077	0.021	0.212	0.090	0.225	0.162	0.055	NA			
11	Top management support	4.185	1.597	0.197	0.221	0.234	0.374	0.366	0.551	0.472	0.373	0.469	0.120	**0.889**		
12	Usage intention	5.655	1.561	0.104	0.135	0.117	0.247	0.237	0.393	0.275	0.259	0.502	0.038	0.407	**0.962**	
13	Usage behavior	5.095	8.277	0.152	0.172	0.122	0.223	0.246	0.291	0.233	0.288	0.333	0.282	0.321	0.216	NA

Note: Bold numbers on the diagonal indicate the square root of the AVE.

Figure 3

Path coefficients and R² values



* $p < 0.05$; ** $p < 0.01$.

5.2. Structural Model and Validation

To test our hypotheses, we measured the explained variance (R^2) of the dependent and mediating variables, the path coefficients (β), and their level of significance (t-values). Figure 3 contains the path coefficients and R^2 values, indicating the predictive ability of the independent variables.

As expected, output novelty and relevance, the two dimensions of contextual output quality, positively influence perceived usefulness (β = 0.163, $p < 0.05$; β = 0.468, $p < 0.01$, respectively), in support of H1a and H1b. In accordance with H2a, H2b, and H3, intrinsic output quality (accuracy and completeness) and representational output quality (i.e., interpretability) increase perceived ease of use (β = 0.261, $p < 0.01$; β = 0.283, $p < 0.01$, respectively). Input accessibility and amount also enhance perceptions of external control (β = 0.216, $p < 0.01$; β = 0.201, $p < 0.05$, respectively), which positively influences perceived ease of use (β = 0.275, $p < 0.01$), in support of H4a, H4b, and H5. Regarding the antecedents of behavioral intentions, the direct effect of perceived ease of use is not significant (β = 0.056, *n.s.*), but the relationship between perceived usefulness and behavioral intentions is (β = 0.532 $p < 0.01$). That is, perceived ease of use influences behavioral intentions through the influence of perceived usefulness. We find a significant total effect, demonstrating total mediation by perceived usefulness ($\beta = 0.153$, $p < 0.05$). These results support H6 and H8, but we cannot confirm H7. In addition, the moderating effect of users' experience with TMS must be considered; it moderates the relationships of perceived usefulness, perceived ease of use, and behavioral intentions, such that the effect of perceived usefulness on behavioral intentions decreases with greater user experience ($\beta = -0.167$, $p < 0.05$), whereas the effect of perceived ease of use on behavioral intentions increases with experience ($\beta = 0.198$ $p < 0.05$). That is, our results indicate a positive effect of ease of use on usage intentions with more experience. The positive effect of experience on the link between perceived ease of use and behavioral intentions also is stronger than its negative effect on the relationship between perceived usefulness and behavioral intentions. Thus, we find support for H10. Finally, behavioral intentions have no direct effects on usage behavior ($\beta = 0.102$, *n.s.*) but an indirect effect through top management support (total effect: $\beta = 0.206$, $p < 0.05$), in support of H9.

To judge overall model fit, we assessed the standardized root mean square residual (SRMR), which reflects the difference between the observed correlation and the predicted correlation, as well as the Q^2 (i.e., cross-validated redundancy) value, using the blindfolding procedure in SmartPLS3. The SRMR of the final model is good [80]; it is lower than 0.08 (SRMR = 0.063). The Q^2 values confirm the model's predictive relevance [81]. Specifically, the Q^2 values for perception of external control and top management support are small (i.e., lower than 0.15; perceived ease of use $Q^2 = 0.28$), but they are medium (i.e., 0.15–0.35) for all other dependent variables (behavioral usage $Q^2 = 0.16$; usage intentions $Q^2 = 0.28$; perceived ease of use $Q^2 = 0.32$; and perceived usefulness $Q^2 = 0.327$) [82].

6. Conclusion and implications

6.1. Discussion of findings

The digitalization of customer relationships enables companies to collect vast textual data, including customer evaluations of consumption and shopping experiences. Customers share their opinions through various channels (blogs, social media, company websites, email, and instant messaging), and analyzing these shared data is crucial for improving customer experiences and customer loyalty. However, usage of TMS remains minimal, and no studies investigate the factors that might influence TMS acceptance. Therefore, this study proposes and tests a model of TM adoption and use, which in turn identifies factors that influence TM acceptance. Our novel model integrates the TAM [28], TPB [26,27], and IQ theories [21,34]. The test of the model relies on a field study conducted in the United States and Europe, and the results confirm that IQ dimensions influence behavioral intentions and usage, through perceptions of external control, perceived ease of use, and perceived usefulness; top management support also has a key influence on the use of TM.

First, top management support is an important mediator between usage intentions and TMS use behavior. This finding is in line with prior studies that suggest that top management support is a key success factor for IT implementation in companies [23]. For a TMS adoption context, it is even more important, because top management support influences firms' market orientation [65,66]. By adopting TMS, firms can extract useful information from huge amounts of textual data, such that they can better understand customers' needs and become more customer oriented. Top management support is crucial, because it converts managers' intentions to adopt TMS into TMS usage.

Second, perceived ease of use influences behavioral intentions through the influence of perceived usefulness. Contrary to past research [18,24], our results fail to demonstrate that perceived ease of use has a direct effect on usage intention. However, the total effect is significant, indicating that the relationship between perceived ease of use and behavioral intention is fully mediated by perceived usefulness. Perceived usefulness provides an explanation of how perceived ease of use influences behavioral intentions. Moreover, experience with TMS moderates the relationships among perceived ease of use, perceived usefulness, and behavioral intentions. The effect of perceived ease of use on behavioral intentions increases with greater experience. Drawing from learning theory, we have theorized that because TMS are complex, users must accumulate experience with the systems before they can use them or interpret their outputs, which then increases usage intentions more. Our results also demonstrate that experience decreases the positive effect of perceived usefulness on behavioral intentions. With their greater experience with systems, users accumulate more knowledge from their analyses of text-based information, leaving less for them to learn from additional uses of TMS, which decreases the effect of perceived usefulness on behavioral intentions. Contrary to the argument that users stop relying on systems that are not easy to use [24], our results suggest that users stop using the TMS because it adds less value to their accumulated knowledge.

Third, we investigate antecedents of perceived usefulness, perceived ease of use, and perceptions of external control. We find that contextual output quality increases perceived usefulness; the extent to which output is perceived as relevant and novel enhances perceived usefulness. Consequently, TMS appear useful when the outputs fit with the needs of users who must make job-related decisions and also offer unique information, relative to what those users already know. The determinants of perceived ease of use include intrinsic and representational output quality, as well as perceptions of external control. We show that TMS users perceive the system as easy to use if it provides accurate, complete, and interpretable outputs. Therefore, successful TMS must provide information that addresses users' needs for the task at hand and that are reliable and clear to understand. Finally, perceptions of external control stem from the quality of the input available to be analyzed by the TMS. To produce high quality information, TMS require readily accessible data in sufficient amounts.

6.2. Theoretical Implications

This study offers several contributions to academic literature on TM adoption, because it reveals drivers specific to a context involving the analysis of textual customer information. To the best of our knowledge, this study is the first to theoretically investigate and empirically test the determinants of TM adoption by integrating the TAM, IQ dimensions, and top management support in the same conceptual framework. First, using the TAM, we show that the underlying drivers of TM adoption are perceived usefulness, perceived ease of use, and perceptions of external control.

Second, in accordance with suggestions that IQ is a determinant of system use [22], we demonstrate that the multiple dimensions of IQ can be considered antecedents of perceived usefulness, ease of use, and external control. We introduce output relevance and novelty as determinants of perceived usefulness; intrinsic quality and interpretability as antecedents of perceived ease of use; and input accessibility and amount as factors that influence perceptions of external control.

Third, we contribute to extant literature by explaining the mechanism through which behavioral intentions influence usage behavior. Previous research mostly has considered the direct influence of top management support on intentions to adopt or use systems [37], as well as on the adoption of market-oriented strategies. We demonstrate further that top management support functions as a mediator in the relationship between intentions and use of the TMS. Support from top management is a necessary condition to convert intentions into use.

Fourth, similar to past research [24], we consider users' experience with TMS as a moderator in the relationship of perceived usefulness, perceived ease of use, and behavioral intentions. However, our results differ as well, in that prior research [24] implies that even if experience strengthens the effect of perceived ease of use on perceived usefulness, its direct effect on behavioral intentions weakens with more experience. In this study, based on the learning theory, we demonstrate that greater experience prompts a positive relationship between perceived ease of use and behavioral intentions.

6.3. Implications for Practice

This research has several important implications for managers and TM software designers, in that it can help them understand the factors and organizational conditions that influence TM usage. First, TM software developers may find it helpful to consider the determinants of TM acceptance. In particular, IQ dimensions such as novelty, relevance, accuracy, and interpretability of TM outputs can increase the perceived usefulness and ease of use of TM. Therefore, TM software designers must ensure that the insights provided by their TM tools are unique and new; facilitate users' decision making; are easy to interpret; and are complete and accurate. If TM software grants users new information that they can use to make decisions, its perceived usefulness will be higher, and users will make better decisions [83]. Furthermore, when the insights provided by TM software are easy to interpret, reliable, and comprehensive, the system is likely to be perceived as easy to use. Therefore, our results should encourage software designers to contextualize and co-create, with end users, the functionalities and look-and-feel of TM tools, to guarantee that the TM outputs are perceived as relevant, novel, accurate, and interpretable. Previous research shows that such co-creation efforts enhance future usage behavior [e.g., 84].

Second, training end users on how to deal with the outputs of the TM tool to support and complement their decision-making strategy would be beneficial. As previous research shows, training helps employees feel comfortable about tapping a new source of insights to inform their business decisions [e.g., 85].

Third, determinants of perceptions of external control, such as input amount and accessibility, have key roles. Managers must be granted easy access to necessary textual resources before they can rely on a TM strategy to improve their business decision-making. A cross-functional team of multiple stakeholders, including IT experts, data scientists, and business decision makers, might function to collect and grant access to accurate textual data that can support decision-making. Previous research in the field of big data analytics indicates that cross-functional teams greatly contribute to implementation success [86]. Furthermore, interplays and deep integration with the IT system to obtain necessary inputs are essential to boost perceived ease of use, through perceptions of external control, which also can lead to improved business performance [87].

Fourth, the results are in line with previous research in big data analytics that emphasizes the critical influence of top management support on the adoption of big data tools [24]. Encouraging TM adoption in an organization is a difficult task; it must be accompanied by a market orientation that drives the collection of customer-focused natural language data. In this sense, it is a strategic decision that must be embedded in the company's strategy and encouraged by the board. Employees with strong behavioral intentions tend to believe they will receive the support of their top managers, in terms of interest and financial and other needed resources, which converts their intentions to use TM into real use behavior.

6.4. Limitations

Although this study adds significantly to IS literature, several limitations in the current study suggest some paths for further research. First, similar to past research [88], we conducted a cross-sectional study in which we measured all the constructs at the same point in time, so we can only infer causality in the conceptual model. Further research could collect longitudinal data to determine these causal links more explicitly. Second, our convenience sample, drawn from North America and Europe, requires caution before generalizing the proposed model to other regions. This study accordingly could be replicated with samples from other parts of the globe.

6.5. Further Research

Our findings highlight the need for continued research into TMS adoption. First, beyond IQ, other factors—such as individual [58] and task [89] characteristics or organizational factors [90]—could affect TM adoption, so we hope additional studies test for these effects. Second, our results pertaining to the effect of experience do not consistently align with the findings of prior studies [24]. Continued research should investigate the moderating effect of users' experience in other contexts, to verify that our results hold even in other types of complex systems. Third, several TM technics and applications are available, but we do not differentiate among them and focus solely on business and marketing applications. It would be interesting to investigate whether our results hold for different types of TM and other applications, such as health care or governance [91]. Fourth, further research should integrate privacy and security issues related to analyses of textual data. As more digital textual data become available, misuses of TM threaten to undermine people's privacy. Fifth, by using TMS to analyze textual data, companies might be able to position themselves as customer-oriented; with their better understanding of their customers' needs, they can develop better offers and encourage long-lasting relationships. Therefore, we call for more research into how to increase the expected value of information derived from TMS.

6.6. Conclusions

Digitalization offers companies opportunities to collect big data; TMS enable them to transform those data into valuable information. No prior research has investigated the drivers of TMS adoption by organizations. This study contributes by identifying factors that determine TMS usage. Top management support in customer-oriented companies is a key driver; perceived usefulness and ease of use also have important influences on intentions to adopt TMS, and they in turn depend on IQ dimensions, such as TM output relevance, novelty, interpretability, and intrinsic quality, as well as perceptions of external control. The latter factor depends on the amount and accessibility of textual data. From a managerial perspective, we recommend that TMS designers should focus on the quality of the information provided. Business intelligence departments also must make sufficient amounts of textual data available and easily accessible. To expand on our findings, further research could evaluate the value that results from using TMS to make better decisions, gain a better understanding of customer experiences, and thus potentially achieve a competitive advantage.

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