Conference on Information Systems, 2012, pp. 1–10 (Geelong, Australia).
[38] R.R. McCrae, P.T. Costa Jr., A five-factor theory of personality, Handbook of Personality: Theory and Research, 2 1999, pp. 139–153.
[39] P. Melville, V. Sindhwani, R. Lawrence, Social media analytics: channeling the power of the blogosphere for marketing insight, Proceedings of the 2009 1st Workshop on Information in Networks (WIN 2009). Manhattan, NY, USA. 2009.
[40] Merriam-Webster, Insight, Retrieved from, 2016. http://www.merriam-webster.com/dictionary/insight, .
[41] G. Morgan, P.J. Frost, L.R. Pondy, Organizational symbolism, Organizational Symbolism, 1983, pp. 3–35.
[42] F. Morstatter, J. Pfeffer, H. Liu, K.M. Carley, Is the sample good enough? Comparing data from twitter's streaming API with twitter's firehose, Proceedings of the Seventh International Conference on Weblogs and Social Media (ICWSM-13), 2013, pp. 400–408 (Cambridge, Massachusetts).
[43] S.A. Neslin, S. Gupta, W. Kamakura, J. Lu, C.H. Mason, Defection detection: measuring and understanding the predictive accuracy of customer churn models, Journal of Marketing Research 43 (2) (2006) 204–211.
[44] D.E. Pournarakis, D.N. Sotiropoulos, G.M. Giaglis, A computational model for mining consumer perceptions in social media, Decision Support Systems 93 (2017) 98–110.
[45] K. Regan, 10 amazing social media growth stats from 2015, Retrieved from, 2015. http://www.socialmediatoday.com/social-networks/kadie-regan/2015-08-10/10-amazing-social-media-growth-stats-2015, .
[46] P.S. Ring, G.P. Rands, Sensemaking, Understanding, and Committing: Emergent Interpersonal Transaction Processes in the Evolution of 3M's Microgravity Research Program, Research on the Management of Innovation: The Minnesota Studies, 1989, pp. 337–366.
[47] H. Simon, The New Science of Management Decision (rev. ed.), Prentice–Hall, NJ, 1977.
[48] V. Sinha, K.S. Subramanian, S. Bhattacharya, K. Chaudhary, The contemporary framework on social media analytics as an emerging tool for behavior informatics, HR analytics and business process, Journal of Contemporary Management Issues 17 (2) (2012) 65–84.
[49] J.J. Stapleton, Executive's Guide to Knowledge Management: The Last Competi tive Advantage, John Wiley & Sons, 2003.
[50] D.M. Steiger, Enhancing user understanding in a decision support system: a theoretical basis and framework, Journal of Management Information Systems 15 (2) (1998) 199–220.
[51] J. Sterne, Social Media Metrics: How to Measure and Optimize your Marketing Investment, John Wiley & Sons, 2010.
[52] S. Stieglitz, L. Dang-Xuan, Social media and political communication: a social me dia analytics framework, Social Network Analysis and Mining (2012) 1–15, http://dx.doi.org/10.1007/s13278-012-0079-3.
[53] S. Stieglitz, L. Dang-Xuan, A. Bruns, C. Neuberger, Social media analytics: an interdisciplinary approach and its implications for information systems, Business & Information Systems Engineering 6 (2) (2014) 89–96.
[54] D.J. Teece, G. Pisano, A. Shuen, Dynamic capabilities and strategic management, Strategic Management Journal 18 (7) (1997) 509–533.
[55] K.E. Weick, The collapse of sensemaking in organizations: the Mann gulch disaster, Administrative Science Quarterly (1993) 628–652.
[56] K.E. Weick, K.M. Sutcliffe, D. Obstfeld, Organizing and the process of sensemaking, Organization Science 16 (4) (2005) 409–421.
[57] M. Yang, M. Kiang, Y. Ku, C. Chiu, Y. Li, Social media analytics for radical opinion mining in hate group web forums, Journal of Homeland Security and Emergency Management 8 (1) (2011).
[58] K. Zhang, S. Bhattacharyya, S. Ram, Large-scale network analysis for online social brand advertising, MIS Quarterly 40 (4) (2016) 849–868.
[59] D. Zeng, H. Chen, R. Lusch, S.-H. Li, Social media analytics and intelligence, IEEE Intelligent Systems 25 (6) (2010) 13–16.
[60] Y.-Q. Zhu, H.-G. Chen, Social media and human need satisfaction: implications for social media marketing, Business Horizons 58 (3) (2015) 335–345.

sion Support Systems 61 (2014) 115–125.
[15] A. Ghose, P.A. Ipeirotis, B. Li, Examining the impact of ranking on consumer behavior and search engine revenue, Management Science 60 (7) (2014) 1632–1654.
[16] L.R. Goldberg, The structure of phenotypic personality traits, American Psychologist 48 (1) (1993) 26.
[17] D.A. Grégoire, P.S. Barr, D.A. Shepherd, Cognitive processes of opportunity recognition: the role of structural alignment, Organization Science 21 (2) (2010) 413–431.
[18] V. Grubmüller, K. Götsch, B. Krieger, Social media analytics for future oriented policy making, European Journal of Futures Research 1 (1) (2013) 20.
[19] V. Grubmüller, B. Krieger, K. Götsch, Social media analytics for government in the light of legal and ethical challenges, Proceedings of the 2013 International Conference for E-Democracy and Open Government 2013, 2013, p. 185 (Krems an der Donau, Austria).
[20] W. He, H. Wu, G. Yan, V. Akula, J. Shen, A novel social media competitive analytics framework with sentiment benchmarks, Information Management 52 (7) (2015) 801–812.
[21] D.D.L.D.L. Hoffman, M. Fodor, Can you measure the ROI of your social media marketing? MIT Sloan Management Review 52 (1) (2010) 41–49.
[22] L.D. Hollebeek, M.S. Glynn, R.J. Brodie, Consumer brand engagement in social media: conceptualization, scale, development and validation, Journal of Interactive Marketing 28 (2) (2014) 149–165.
[23] C. Holsapple, S.-H. Hsiao, R. Pakath, Business social media analytics: definition, benefits, and challenges, Proceedings of the 20th Americas Conference on Information Systems (AMCIS), 2014.
[24] L. Horwitz, L. Aberle, S. Robinson, Social media monitoring long on promise, hort on results, TechTarget Report, 2016 SearchContentManagement.TechTarget.com.
[25] V.S. Jacob, R. Pakath, The roles of computerised support systems: a decision sub rocess- based analysis, Behaviour & Information Technology 10 (2) (1991) 231–252 (Erratum: 10(6), 545).
[26] F. Kaske, M. Kugler, S. Smolnik, Return on investment in social media—does the hype pay off? Towards an assessment of the profitability of social media in organizations, System Science (HICSS), 2012 45th Hawaii International Conference on (pp. 3898–3907). IEEE, 2012.
[27] J.H. Kietzmann, K. Hermkens, I.P. McCarthy, B.S. Silvestre, Social media? Get serious! Understanding the functional building blocks of social media, Business Horizons 54 (3) (2011) 241–251.
[28] G. Klein, R. Pliske, B. Crandall, D.D. Woods, Problem detection, Cognition, Technology & Work 7 (1) (2005) 14–28.
[29] K. Kurniawati, G. Shanks, N. Bekmamedova, The business impact of social media analytics, Proceedings of the European Conference on Information Systems (p. 48), 2013 (Utrecht, The Netherlands).
[30] R.Y.K. Lau, S.S.Y. Liao, K.F. Womg, D.K.W. Chiu, Web 2.0 environmental scan ning and adaptive decision support for business mergers and acquisitions, MIS Quarterly 36 (4) (2012) 1239–1268.
[31] M.G. Lazano, J. Schreiber, J. Brynielsson, Tracking geographical locations using a geo-aware topic model for analyzing social media data, Decision Support Systems 99 (2017) 18–29.
[32] W. Li, H. Chen, J.F. Nunamaker, Identifying and profiling key sellers in cyber carding community: AZSecure text mining system, Journal of Management Information Systems 33 (4) (2016) 1059–1086.
[33] Bing Liu, Sentiment Analysis and Opinion Mining, Morgan & Claypool, CA, 2012.
[34] S. Ludwig, K.D. Ruyter, M. Friedman, E.C. Bruggen, M. Wetzels, G. Pfann, More than words: the influence of affective content and linguistic style matches in online reviews on conversion rates, Journal of Marketing 77 (1) (2013) 87–103.
[35] R. Ma, Y.-C. Huang, O. Shenkar, Social networks and opportunity recognition: a cultural comparison between Taiwan and the United States, Strategic Management Journal 32 (2011) 1183–1205.
[36] W.G. Mangold, D.J. Faulds, Social media: the new hybrid element of the promotion mix, Business Horizons 52 (4) (2009) 357–365.
[37] M. Mayeh, R. Scheepers, M. Valos, Understanding the role of social media moni toring in generating external intelligence, Proceedings of the 2012 23rd Australasian

in different ways. First, as we have done in Section 4, one may use the framework (in diagrammatic or tabular form) to organize a suitable review of SMA literature to help better-comprehend past work.

Second, such an exercise could help one catalog hots spots and hollow spots in prior work. Third, one may use the results of such a catalog to understand why research/practice attention is lacking where it is or to help determine where to devote future attention. Fourth, one may use the framework as a project management tool, to track progress in an ongoing SMA-based endeavor. Fifth, one may use the framework as a means to benchmark oneself against others. Finally, one may use the framework as one basis to judge whether or not SMA project goals are being realized in terms of evaluation metrics like those exemplified. In corporate settings, the business metrics and post-Intelligence foci mentioned in boxes 5B and 8, respectively, take on added import.

Acknowledgments

(1) We list author names alphabetically. (2) We thank the anonymous reviewers for their comments and suggestions.

Appendix A. Supplementary bibliography

A Supplementary bibliography for this article can be found online at https://doi.org/10.1016/j.dss.2018.03.004.

References

[1] A.S. Abrahams, W. Fan, G.A. Wang, Z.J. Zhang, J. Jiao, An integrated text analytic framework for product defect discovery, Production and Operations Management 24 (6) (2015) 975–990.

[2] R. Bandari, S. Asur, B.A. Huberman, The pulse of news in social media: forecasting popularity, Proceedings of the Sixth International AAAI Conference on Weblogs and Social Media (ICWSM-12), Dublin, Ireland, 2012, p. 26.

[3] N. Bansal, N. Koudas, BlogScope: a system for online analysis of high volume text streams, Proceedings of the 33rd International Conference on Very Large Data Bases (VLDB '07), 2007, p. 1410 (Vienna, Austria).

[4] H. Bao, Q. Li, S.S. Liao, S. Song, H. Gao, A new temporal and social PMF-based method to predict users' interests in micro-blogging, Decision Support Systems 55 (3) (2013) 698–709.

[5] R.A. Barron, M.D. Ensley, Opportunity recognition as the detection of meaningful patterns: evidence from comparison of novice and experienced entrepreneurs, Management Science 52 (9) (2006) 1331–1344.

[6] D.M. Blei, Probabilistic topic models, Communications of the ACM 55 (4) (2012) 77–84.

[7] S.P. Borgatti, A. Mehra, D.J. Brass, G. Labianca, Network analysis in the social sciences, Science 323 (5916) (2009) 892–895.

[8] BusinessDictionary.com, Insight (Retrieved from),, 2016. http://www. businessdictionary.com/definition/insight.html, .

[9] L. Chen, C.W. Holsapple, S.-H. Hsiao, Z. Ke, J.-Y. Oh, Z. Yang, Knowledge-dissemination channels: analytics of stature evaluation, Journal of the Association for Information Science and Technology 68 (4) (2017) 911–930.

[10] R. Colbaugh, K. Glass, Detecting emerging topics and trends via social media analytics, Proceedings of the 2011 IADIS International Conference e-Commerce, 2011, p. 51 (Rome, Italy).

[11] T. Cooper, Enhancing insight discovery by balancing the focus of analytics between strategic and tactical levels, The Journal of Database Marketing & Customer Strategy Management 13 (4) (2006) 261–270.

[12] J.N. Cummings, B.S. Butler, R. Kraut, The quality of online social relationships, Communications of the ACM 45 (7) (2002) 103–108.

[13] H.J. Einhorn, R.M. Hogarth, Behavioral decision theory: processes of judgment and choice, Journal of Accounting Research (1981) 1–31.

[14] M.S. Gerber, Predicting crime using twitter and kernel density estimation, Deci-

Validation Publications	Lau et al. [30]	Bao et al. [4]	Zhang, et al. [58]	Lazano, et al. [31]	Li et al. [32]	Pournarakis et al. [44]
	Adaptive DSS in other domains (e.g., financial risk assessment, bankruptcy prediction, portfolio management).	algorithm; Drawing upon user retweeting and commenting behavior to enhance model performance; Use as a product/service recommender system and an advertising/promotion decision support tool.	Increasing revenue/profits through better user targeting; Customer segmentation using brand communities; Audience targeting based on brand-specific user sentiments.		between price or reputation and seller quality; Studying buyer ads besides seller ads; Generalizing the system to other languages (notably, Russian).	corporate image along different dimensions; including non-text (e.g., activity) data; Performing what-if analysis using different numbers of clusters/topics.
(7) Further acquisition & design						
(7A) Sense making	Structuring business relation network; Ranking top 10 M&A targets; Understanding business-business connections.	Structuring user-topic & user-user networks; Ranking topics; Understanding user-topic & user-user connections.	Structuring brand-brand and brand user networks; Identifying brand communities; Ranking brands.	None reported.	Identifying the best 3 and worst 3 sellers in the top 3 underground forums.	None reported.
(7C) Insight generation	Besides target rankings and business relationships: Subjects asked to explain the rationale for Top 10 M&A candidate choices; Identifying sociocultural and economic-political characteristics of ranked M&A targets.	None besides topic rankings and user-topic/user-user connections.	None besides brand rankings, brand communities, and brand-brand/brand-user connections.	The SLDA model: has similar location prediction but a higher time prediction accuracy as the baseline keyword-based model; better than the keyword-based model at discovering topics.	Besides seller ranking: Generating Seller profiles by characterizing sellers using three topical groups.	Average of 2500 tweets daily; Moderately negative brand sentiment; Tweet volume varies by topic; All topics elicit negative sentiment except free ride codes. Particularly negative about service, support, expanding women employees, & innovation.
(8) Further evaluation						
(8B) Analysis focus	Not evident.	Not evident.	Not evident.	Not evident.	Not evident.	Not evident.
(8A) Analyses outputs	N/A	N/A	N/A	N/A	N/A	N/A
(9) Further choice &	N/A	N/A	N/A	N/A	N/A	N/A
(10) Feedback, review, learning & behavior modification	System-level and individual-level adaptation by the DSS over time.	Not explicit.	Not explicit.	Disappointing USE2016 corpus results; analysis was redone using USTwiNews corpus to obtain useful results.	Not explicit.	Not explicit.

Validation Publications	Lau et al. [30]	Bao et al. [4]	Zhang, et al. [58]	Lazano, et al. [31]	Li et al. [32]	Pournarakis et al. [44]
(4G) Sentiment analysis	Yes: detect positive/negative sentiment in financial documents.	No.	Yes: analyze user sentiments about brands.	No.	Yes: quantify customer reviews of sellers.	Yes: classify tweets as positive or negative.
(4H) Text classification	No.	No.	No.	No.	Yes: classify seller ads.	No.
(4I) Social network analysis	No.	Yes: analyze user-topic and user-user network structures).	Yes: analysis involves Facebook data.	No.	No.	No.
(4J) Activity analysis	No.	No.	Yes: analyze brand administrator and user posts (e.g., comments, likes).	No.	No.	No.
(4K) Other procedures	Emotion analysis: assess the degree of affects implied in stakeholder/investor comments); business relation mining (to assess the competitiveness of an M&A target).	None.	None.	None.	None.	Genetic Cluster Analysis (GCA): group semantically similar documents; k-Means cluster analysis: as a benchmark for GCA.
(5) Evaluation						
(5A) Statistical metrics	Precision; recall; F-Measure; accuracy; precision in top 10; *p*-value.	Precision in top n.	Weighted node degree; weighted Eigenvector centrality.	Accuracy; box plots; confidence; deviation.	Precision; recall; F-Measure; sentiment score; perplexity; p-value.	None.
(5B) Business metrics	Various financial metrics (ROE; ROA; cash flow to debt ratio; net assets ratio; EBITDAR, debt to equity ratio, etc.).	Computation cost per iteration.	Conversion; lift; engagement (implicit); data source costs (implicit).	Computation speedup (through parallel processing of streaming data).	None.	Brand awareness metrics (tweet volume/period; tweet volume/topic/period); brand name metrics (sentiment classification/period; sentiment/topic/period).
(5C) Analyses outputs	Reports; visuals.	Reports; visuals.	Reports; visuals.	Reports; visuals.	Reports.	Reports; visuals.
(6) Choice & implementation						
(6A) Problem recognition	Not reported.	Reported results are sensitive to input parameter settings.	Need to: demonstrate that selected users will actually click on focal brand ads; Ensure that increased user activity on focal brand is not due to other causes (e.g., brand promotions, referrals).	Tweet length limits text to about headline size, impeding unsupervised co-occurrence learning; USE2016 corpus had poor text quality and content relevance; SLDA model is unable to keep similar clusters assigned to the same topic on large time scales; The need to pre-define the desired number of topics; Disambiguation of locations with the same name.	The authenticity of customer reviews not established (i.e., possible feedback manipulation).	Analyses based on a single social media channel (Twitter) and text data; the number of topics/clusters pre-defined (10).
(6B) Opportunity detection	Potential for: Including companies beyond those in the Forbes 2000 list; Applying	Potential for: Automated input parameter tuning using a Markov Chain Monte Carlo	Potential for: Increasing user engagement with and loyalty to a focal brand;	Not reported.	Potential for: Distinguishing customer review authenticity; Investigating correlation	Potential for: Using insights to drive future actions/decisions toward enhancing positive

Table 4
Business SMA framework validation.

Validation Publications	Lau et al. [30]	Bao et al. [4]	Zhang, et al. [58]	Lazano, et al. [31]	Li et al. [32]	Pournarakis et al. [44]
Publication synopsis	Propose and evaluate a due diligence scorecard model-based adaptive DSS to enhance cross-border mergers and acquisitions (M&A) decision-making.	Propose and evaluate a temporal and social probabilistic matrix factorization (PMF) model to predict users' potential interests in microblogging.	Propose and evaluate an audience selection framework for online brand advertising.	Propose and evaluate a geo-aware streaming latent Dirichlet allocation (SLDA) model to track discussion topic evolution over time and location in social media.	Propose and evaluate a text mining system for identifying and profiling key sellers of credit accounts in the underground economy.	Propose and evaluate a model to help assess brand performance during brand equity appraisal by eliciting influential subjects from consumer perceptions in social media.
Business SMA framework phases						
(1) Analysis goals	Intelligence Gathering; Sense Making; Insight Generation; Decision Making.	Intelligence Gathering; Sense Making; Decision Making.	Intelligence Gathering; Sense Making; Insight Generation; Decision Making.	Intelligence Gathering; Insight Generation; Sense Making Decision Making.	Intelligence Gathering; Sense Making; Insight Generation; Decision Making.	Intelligence Gathering; Sense Making; Insight Generation; Decision Making.
(2) Social media	Hybrid (initiating company's corporate intranet; target company websites; online financial news sites; investors comments; stock exchange sites; Bloomberg; Reuters; etc.).	External (Sina-Weibo microblogging data).	External (Facebook customer data about multiple brands).	External (USE 2016 and USTwiNews Twitter corpora).	Hybrid (Seller ad data & customer reviews of sellers in eight underground forums).	External (Uber-related Twitter customer data).
(3) Attention & acquisition						
(3A) Data tracking	API; RSS; HTML Parsing.	API.	API.	API.	HTML Parsing.	API.
(3B) Stream analytics?	No.	No.	No.	Yes.	No.	No.
(4) Design						
(4A) Text data preprocessing	Remove: stop words; invalid abbreviations. Perform: Chinese word segmentation; part-of-speech tagging.	Remove: users with less than 16 posts.	Remove: non-English brand pages; low- activity & fake users; users with duplicate posts. Extract: top 2000 brands	Remove: stop words; punctuations; hashtags. Perform: text normalization and corpus vectorization	Remove: stop words; annotations. Perform: tokenization lemmatization.	Remove: stop words; non-letter characters; 1-character words, non-English tweets; URLs; mentions; re-tweet IDs. Perform: tokenization; stem extraction.
(4B) Network data preprocessing	No.	Construct: user-topic and user-user adjacency matrices.	Construct: brand-brand and brand-user adjacency matrices.	No.	No.	No.
(4C) Activity data preprocessing	No.	No.	Count: # comments and # like posts.	No.	No.	No.
(4E) Trend analysis	No.	Yes: to detect the impacts of a user's interest evolution and friendships on future interests.	No.	Yes: analyze location-based topic trends.	No.	No.
(4F) Topic modeling	No.	No.	No.	Yes: identify representative topics.	Yes: profile sellers based on ad characteristics.	Yes: identify prevailing topics.

jective of just staying informed, with further activity only triggered following problem/opportunity identification, as could happen in practice.

However, Table 4 does demonstrate that the Business SMA framework proposed in this paper is comprehensive enough to capture salient aspects of published academic Business SMA Research projects. Based on this evidence, we believe the framework to be a useful tool for researchers, students, and/or practitioners to better comprehend prior Business SMA endeavors and to guide ongoing/future endeavors. We also believe that the framework is flexible in allowing new SMA data acquisition, storage, and processing approaches through minor tweaks.

We articulate some possible uses of the framework by concerned stakeholders in the following section.

5. Concluding remarks

We were motivated to pursue this study by the paucity of research on Business SMA, particularly as it relates to articulating what Business SMA is and establishing a relatively comprehensive conceptual framework to help foster understanding, development, and work in the Business SMA field. Toward these ends, we furnish an organized, comparative review of existing literature that concentrates on SMA characterization – highlighting strengths and weaknesses of each view.

This leads to the adoption of an integrated, unifying Business SMA definition that is consistent with, and inclusive of, the diverse characterizations.

Furthermore, we have undertaken a thorough review of existing conceptual Business SMA frameworks. As with the characterizations, we highlight their respective strengths and weaknesses, adopt suitable facets from these frameworks, and integrate extensions to develop a more comprehensive Business SMA framework than has heretofore been available. We compare and contrast our framework with each of the preceding frameworks studied and demonstrate how SMA may be regarded as one means for Intelligence Gathering (via Social Monitoring) and to support other activities that may follow, i.e., Problem/Opportunity identification, Sense Making, Insight Generation, and Decision Making.

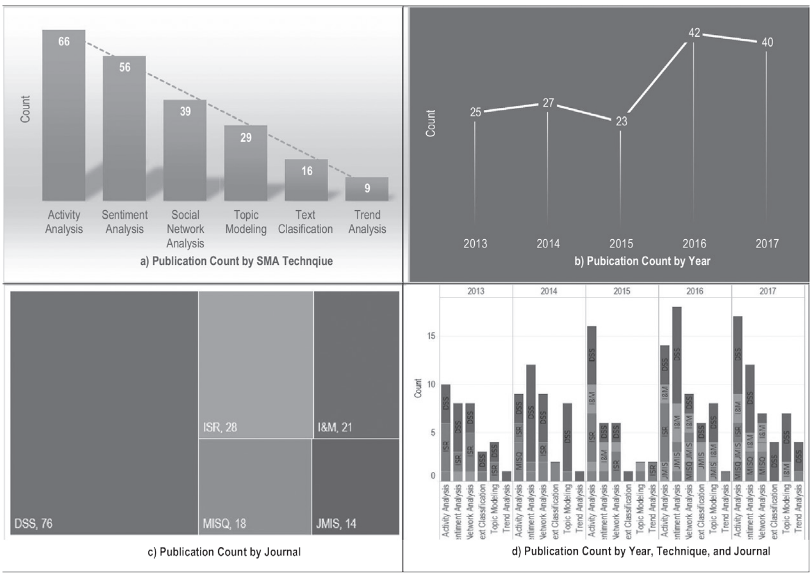
We conduct a review of recent academic SMA literature. Our literature survey indicates that (i) Trend Analysis and Text Classification have received the least research attention (in the forums and period surveyed), research output has witnessed a surge in the last two years, and that JMIS and MISQ together account for 20% of the total output with DSS dominating at 48%.

We use a subset of the retrieved papers to help validate our framework. The validation exercise reveals academic research activity encompassing most of the phases of the Business SMA framework with the seeming exception of phases 8 and 9 to do with further evaluation and decision-making following sensed opportunity/insight identification. Also not prominently evident was activity relating to phase 10 (feedback, review, learning, and behavior modification). These findings may be an artifact of our focus on the premier, research-oriented, academic publication forums and the fact that we are not privy to firsthand insights into the analytics and decision-making processes of these researchers. A thorough validation using a more exhaustive set of research papers and comprehensive application case studies is a topic worthy of future research attention as also is validation using primary data.

Academics, students, and practitioners may use the framework we propose

Three selections were from DSS, two from MISQ, and one from JMIS. We then documented whether or not each paper reflected operationalization of a specific phase of the framework and the manner of operationalization. We present our findings in Table 4.

Fig. 2. a. Publication count by SMA technique. b. Publication count by year. c. Publication count by journal. d. Publication count by year, technique, and journal.



The table is largely self-explanatory. Between them, the six papers cover almost all of the phases and sub-phases of our framework with the exception being phases 8 and 9 (i.e., Further Evaluation and Further Choice & Implementation) and, to a lesser extent, phase 10 (Feedback, Review, Learning, & Behavior Modification). While phases 8 and 9 were not evident in any of the papers, phase 10 was clear in two of them. We believe that there could be two explanations for this. First, this may be due to the academic nature of the publication outlets surveyed – i.e., had we been examining comprehensive, real-world application case studies, we perhaps may have been able to find evidence relating to phases 8 and 9. Second, we are drawing inferences about what was accomplished by these researchers in terms of our framework phases in hindsight and without the benefit of real-time, first-hand information (e.g., through observation, ongoing interviews, and such). Real-time, first-hand information would allow us to, at least partly if not wholly, ascertain other aspects of the framework not visible in a published manuscript such as, flitting from phase-to-phase, backtracking-and-reiteration, and wheels-within-wheels (i.e., activities associated with phase 10), although we believe that all such behavior is very likely in academic research endeavors. Further, we had to infer what the goals of the SMA exercise were in each case also in retrospect; we do not know if the authors started out with these goals in mind or these evolved over the course of the research. What seems clear, however, is that none of these projects focuses solely on social monitoring with the obprior frameworks depicts data preprocessing steps. Mayeh et al. [37] make no mention of specific SMA processing steps and He et al. [20] are unconcerned with Social Network and Activity analyses. We explicitly depict the use of Statistical and Business Metrics during SMA. Ours is the only framework that emphasizes post-SMA processing involving, Sense Making, Insight Generation, and/or Decision Making (although we conjecture that "seizing" in Mayeh et al. [37] and the "recommendations and actions" cloud in He et al. [20] are concerned with such activities). Neither Mayeh et al. [37] nor Sinha et al. [48] depicts the packaging of analyses outputs. In He et al. [20], "reports" is the only packaging mentioned.

None of the other frameworks depicts possible re-cycling through prior analytics phases. Re-cycling here does not refer to the repetition of the analysis as and when fresh data become available as part of an ongoing process (such as with stream analytics) but to backtracking and redoing prior steps as necessary.

4. A brief survey and framework validation

Partly to document recent academic SMA research in the Management Information Systems (MIS) arena and partly with a view to validating our Business SMA framework, we did a literature search for articles published in the top-five MIS academic journals between January 2013 and December 2017. Several revealed-preference studies of stature among IS journals, under a variety of conditions, have consistently yielded the same set of journals (listed alphabetically) – Decision Support Systems (DSS), Information and Management (I&M), Information Systems Research (ISR), Journal of Management Information Systems (JMIS), and Management Information Systems Quarterly (MISQ) – as constituting the top five journals (e.g., [9]). We used AIS eLibrary (for MISQ), INFORMS PubsOnline (ISR), ScienceDirect.com Elsevier (DSS and I&M), and Taylor and Francis Online (JMIS), in conjunction with manual table-of-contents reviews to help locate relevant articles. The search yielded 157 unique publications (after weeding out papers that used surveys to gather data, review papers, and non-applied/conceptual pieces). A bibliography of our search results, organized by technique and year, is available as an online supplement to this paper. Because a specific paper may embody multiple techniques, it could appear under more than one technique in the bibliography.

Fig. 2a through d categorize these publications in insightful ways. From a techniques perspective (Fig. 2a), Activity Analysis, Sentiment Analysis, and Social Network Analysis were the dominant techniques utilized (in 42%, 36%, and 25% of the publications, respectively). From an average of 25 publications yearly through 2015, output has trended upward to the low 40s in '16 and '17 (Fig. 2b). Focusing on outlets (Fig. 2c), the vast majority (48%) appeared in DSS, followed by ISR (18%) and I&M (13%). Fig. 2d depicts a consolidated view using all three dimensions (i.e., technique, year, and publication outlet).

We selected five papers from this research pool as well as one particularly comprehensive piece from 2012 to help validate our framework.

The primary selection criteria used was to ensure that the pieces, between them, covered several of the different data source types (internal/external/hybrid; microblogs, forums, SNS), streaming and non-streaming analytics, and deployed at least two of the different SMA techniques in the framework.

going on?," Insight Generation on, "Why is it going on?," and Decision Making on, "What shall we do about it?," with all of these predicated on Intelligence Gathering. This decision may be a final decision or some intermediate decision, as decisions themselves have the potential for giving rise to other problems/ opportunities. As Simon [47] notes, backtracking and repeating prior phases is also often called for, whereby Choice & Implementation acts as a catalyst prompting further cycles of Intelligence Gathering, Problem/ Opportunity Detection, Sense Making, Insight Generation, and Decision Making. Box 10: Feedback & Review/Learning & Behavior Modification (i.e., phases "g" and "h") coupled with the dotted feedback arrows in Fig. 1 represents the potential for such cyclical behavior.

3.3. Comparison

The general, comprehensive Business SMA framework developed above is one that emphasizes the point that Social Media Analytics has a larger role to play within the context of corporate decision-making.

Table 3
Comparison of business SMA frameworks.

Framework characteristic	Business SMA frameworks				
	Mayeh et al. [37]	Sinha et al. [48]	Stieglitz et al. [53]	He et al. [20]	Comprehensive BSMA framework
1. Provides theoretical underpinnings	Yes: Dynamic capabilities [54].	Yes: Big five model/five factor model [16]/five factor theory [38].	No.	No.	Yes: Management decision science theory (Simon [48], Einhorn & Hogarth [13]).
2. Depicts SMA purpose(s)	No.	Yes.	Yes.	Yes.	Yes.
3. Depicts specific data source types					
Internal SM data	No.	Employees only.	No.	No.	Yes.
External SM data	Customers only.	Customers only.	No.	Competitors only.	Yes.
Hybrid SM data	No.	No.	No.	No.	Yes.
4. Depicts data tracking activities	No.	No.	Yes.	Yes.	Yes.
5. Depicts specific data type capture					
Text data	No.	No.	Weak yes[a].	Yes.	Yes.
Network data	No.	No.	Weak yes[a].	Weak yes[b].	Yes.
Activity data	No.	No.	Weak yes[a].	No.	Yes.
6. Depicts store-&-process vs streaming analytics	No.	No.	No.	No.	Yes.
7. Depicts pre-analytics processing activities					
Text data pre-processing	No.	No.	Weak yes[a].	Weak yes[b].	Yes.
Network data pre-processing	No.	No.	Weak yes[a].	Weak yes[b].	Yes.
Activity data pre-processing	No.	No.	Weak yes[a].	No.	Yes.
8. Depicts analytics processing activities					
Trend analysis	No.	Yes.	Yes.	Yes.	Yes.
Content analysis	No.	Yes.	Yes.	Yes.	Yes.
Sentiment analysis	No.	Yes.	Yes.	Yes.	Yes.
Social network analysis	No.	Yes	Yes.	No.	Yes.
Activity analysis	No.	Yes.	Yes.	No.	Yes.
9. Depicts evaluation metrics					
Statistical metrics	No.	No.	No[c].	No[c].	Yes.
Business metrics	No.	No.	No[c].	No[c].	Yes.
10. Depicts post-analytics processing activities					
Sense-making activities	Weak yes[d].	No.	No.	Weak yes[e].	Yes.
Insight-generation activities	Weak yes[d].	No.	No.	Weak yes[e].	Yes.
Decision-making activities	Weak yes[d].	No.	No.	Weak yes[e].	Yes.
Output packaging	No.	No.	Yes.	Yes (reports).	Yes.
11. Depicts possible *re*-cycling through prior analytics phases	No.	No.	No.	No.	Yes.

[a] Inferred based on analysis "approaches" shown in this framework.
[b] Inferred based on "text collection" data store shown in this framework.
[c] Associated remarks made elsewhere in the narrative.
[d] Inferred based on "seizing" shown in this framework.
[e] Inferred based on the "recommendations and actions" cloud shown in this framework.

Table 3 provides a comparison of the five frameworks discussed above on several attributes that we summarize with the following takeaways: Ours is the only framework grounded in seminal decision-making theory. We allow for internal, external, and hybrid data sources without restrictions. We explicitly depict data tracking (as do [20,53]). Unlike all other frameworks, we explicitly illustrate the capture of Text, Network, and/or Activity data and distinguish between store-and-process and streaming analysis. None of the become concerned that events may be taking an unexpected and undesirable direction that potentially requires action." Prior research has viewed Opportunity Detection from different perspectives. Barron and Ensley [5], view Opportunity Detection as a pattern recognition task where experience-based cognitive frameworks (e.g., prototypes), "provide individuals with a basis for noticing connections between seemingly independent events or trends (e.g., advances in technology, shifts in markets, changes in government policies, etc.), and for detecting meaningful patterns in these connections."

Grégoire et al. [17], on the other hand, view Opportunity Detection as, "a cognitive process of structural alignment," and one, "where different kinds of mental connections play different roles in the process of recognizing opportunities, with different consequences."

Prior researchers have studied both phenomena in the context of SMA: for example, [1], address Problem Recognition and [35], examine Opportunity Identification.

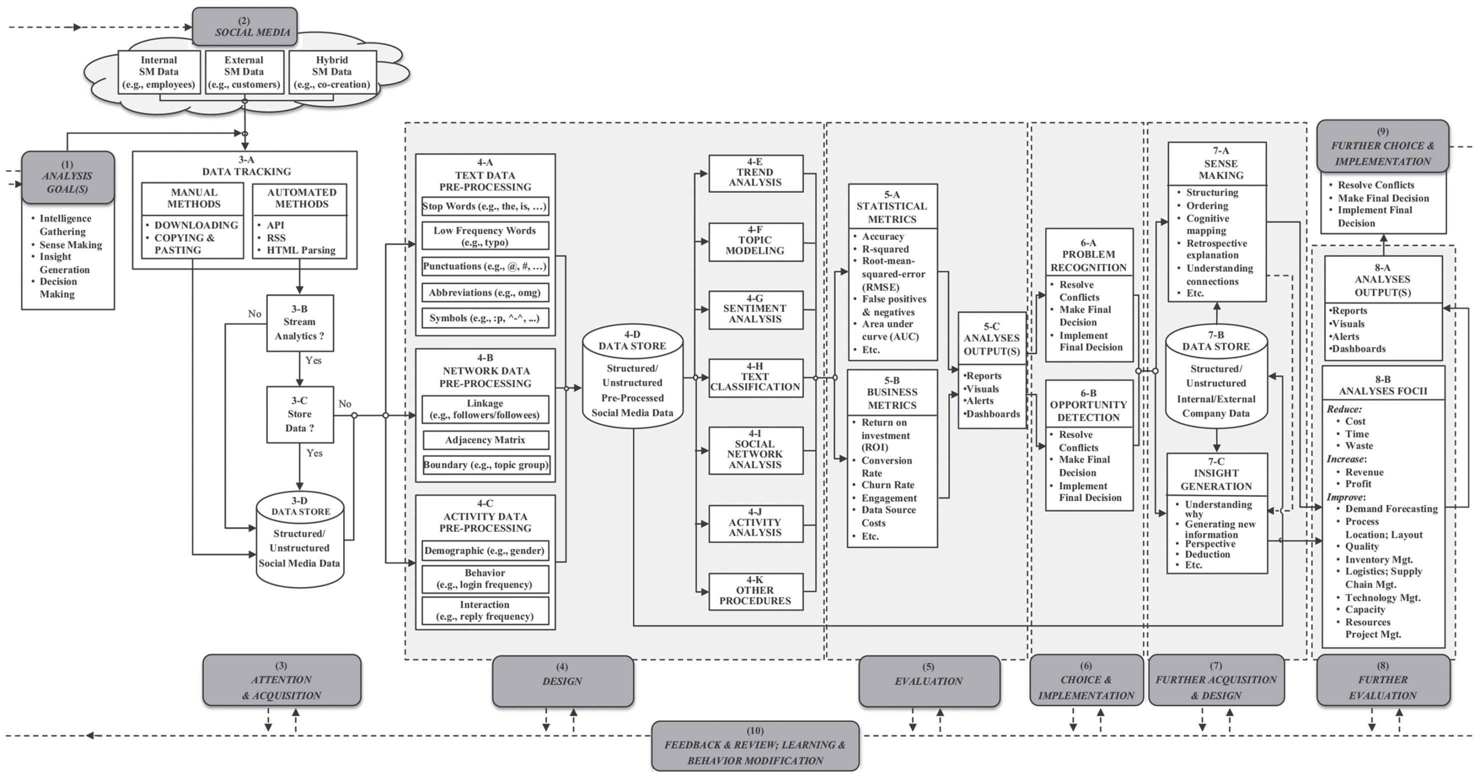
Box 7: Further Acquisition & Design depicts the process of attempts made at problem solving/opportunity exploitation following identification.

As with identification, the pursuit of this phase is also optional and dependent on context. The Design activity involves Sense Making and/or Insight Generation and draws on internal/external corporate transactional and other data as distinct from, and perhaps in addition to, pre-processed SMA data (box 7-B).2 For example, if customer buzz SMA reveals a product design concern, a company could use SMA-based information, along with internal design and engineering-related data, and other relevant internal/external data (e.g., regarding outsourced components), in its efforts to address the concern. Sense Making (box 7-A) has been defined in different ways: developing cognitive maps of the environment [46]; reducing confusion, structuring the unknown, creating order, making retrospective sense of what occurs, and making things rationally accountable3 [55]; and, a motivated, continuous effort to understand connections (among, people, places, events) to help anticipate their trajectories and act effectively [28]. Klein et al. [28] also note that Sense Making could entail, but is different from, creativity, comprehension, curiosity, mental modeling, explanation, and/or situational awareness. Insight Generation (box 7-c) has been characterized as discerning why a situation is what it is [50], generating new information that yields actionable ideas [11], understanding, in a very clear way, the true nature of something [40], and developing knowledge in the form of perspective, understanding, or deduction [8]. Broadly speaking, Insight Generation draws on Descriptive, Predictive, and Prescriptive Analytics techniques/tools.

Whereas Insight Generation may proceed independently of Sense Making, we view Sense Making as a prerequisite for Insight Generation with complex analytics tasks. This is depicted by the dotted arrow proceeding from box 7-A to 7-C in Fig. 1. Evaluation (box 8) accompanies the Design activity. The kinds of analyses foci exemplified in Box 8B (e.g., cost reduction, revenue increase, and design change) and the generation of corresponding Output (box 8- A) guide this evaluation.

It is possible that Sense Making/Insight Generation about a Problem/Opportunity situation are the end goals of the analysis. More often than not, they either separately or together provide the fodder for Making Decisions about such problems/opportunities as depicted by Box 9 (Further Choice & Implementation) in Fig. 1. One may think of Sense Making as focused on, "What is

Fig. 1. A comprehensive business social media analytics framework.



ness needs.
Also notice box 4-K labeled, “Other Procedures” that denote any needed human-supported activities such as creating taxonomies, manually coding data, and designing reports. In addition, this box accommodates techniques such as Emotion Analysis, for example, not explicit in the framework.
Consider Box (5): Evaluation (i.e., phase “d”) next. The choice of SMA techniques and tools are driven by an analyst's choice of Statistical and Business Metrics. Common Statistical Metrics include: accuracy (the ability to correctly detect true positives/negatives or the probability of a correct decision; e.g., [31]), R-squared (a measure of the “goodness of fit” of a model to training data; e.g., [2]), root mean squared error (RMSE; the standard deviation of the difference between predicted values and actuals; e.g., [15]), false positives/ negatives (mistakenly accepting something as true/false; e.g., [30]), and area under the curve (AUC; a measure of the discrimination ability of a particular model; for example, area under a Receiver Operating Characteristic curve or a Survival curve; e.g., [14]).
Common Business Metrics include: return on investment (the net proceeds from an SMA outlay over its costs; e.g., [26]), conversion rate (the proportion of SM site visitors taking a desired action (e.g., purchasing/ subscribing/ registering/downloading); e.g., [34]), churn rate (the proportion of entities (e.g., customers/employees/suppliers) who cut ties with a business; e.g., [43]), engagement measures (i.e., measures for customer/employee/brand/ content participation or involvement; e.g., [22]), and data source costs (i.e., hardware/software/ subscription prices; e.g., [42]).
An analyst must decide which metric(s) from each category (i.e., Statistical and Business) to use in evaluation and, oftentimes, must reconsider use of procedures and evaluation metrics while the analysis is ongoing. At various epochs during, and at the end of, the Design and Evaluation activities, outputs are generated (box 5-C) in the form of reports, visuals, alerts, or some combination of these (i.e., dashboards).
Examples of tools that facilitate data capture, analysis, and output generation include DashThis, Google Alerts, Google Analytics, Klipfolio, Meltwater, ReportGarden, Senfluence, SocialMention, and TwitterCounter.
Stapleton [49], describes Business Intelligence Gathering as securing covert or open information, data, opinions, and knowledge on markets, competitors, prospects, influencers, and clients. We view SMA as one means of gathering business intelligence – Intelligence Gathering (box 1) involves the execution of the Attention, Acquisition, Design and Evaluation phases of Fig. 1. Sometimes, Intelligence Gathering may be the end goal of SMA, as when a manager just wants to “stay informed.” At other times, one gathers intelligence with some other goal in mind or social monitoring signals the need for further steps due to the presence/ likelihood of problem situations requiring attention or opportunities for possible exploitation. Thus, Intelligence Gathering (box 1) is an essential pre-requisite for the remaining goals in box 1, i.e., Sense Making, Insight Generation, and (final) Decision Making, that follow problem/ opportunity identification.
Box 6: Choice & Implementation represents the next two phases (i.e., “e” and “f”), where an analyst makes and implements decisions related to Problem Recognition (Box 6-A) and/or Opportunity Detection (Box 6-B). Whether or not an analyst chooses to engage in such activity is context dependent. Klein et al. [28] define Problem Recognition as, “the process by which people first

framework, we re-emphasize several points that Simon [47] makes:

(i) while we depict these phases as generally occurring sequentially, multiple phases may be undertaken in parallel;

(ii) analysts may also move back and forth (i.e., flit) between phases in an ad hoc manner; and,

(iii) the performance of any phase could entail decision making (i.e., the performance of all eight phases, also called, "the wheels within wheels" phenomenon).

In our Business SMA framework (Fig. 1), an analytics endeavor is predicated on one or more of four overarching end goals – Intelligence Gathering, Sense Making, Insight Generation, and Decision Making (box labeled, "(1) Analysis Goal(s)," in Fig. 1). Further, specific goals may entail employee/employer-generated social media content (i.e., internal content), content generated by customers, suppliers, retailers, other enterprise partners, competitors, and regulatory bodies (i.e., external content), or content generated by both categories of participants as with crowdsourcing, co-creation, and open innovation endeavors (i.e., hybrid content). Such data sources are shown as a "cloud" (labeled, "(2) Social Media") in Fig. 1.

Box (3): Attention & Acquisition corresponds to phases "a" and "b" of our decision process model and depicts data acquisition to facilitate an SMA endeavor. Relevant data sources are tracked using suitable, automated procedures such as APIs, RSS feeds, or HTML parsing (box 3-B) and, possibly, manual copying/downloading (box 3-A). Automatically tracked data may be processed using Data Stream Analysis (box 3-C) and/or captured and stored (boxes 3-D and 3-E) for later use.

With Stream Analysis [3], while one may opt to also store captured data, the emphasis is on in-memory, record-by-record, speedy analysis of data, "in motion." An analyst might also resort to stream processing due to excessive data volume, data flow rate, and/or data variety concerns that magnify data capture and storage complexities. Regardless, Stream Analytics is able to generate results in milliseconds from data arriving at millions of records per second, whereas traditional Relational Data Base Management Systems (RDBMS) and distributed file systems like Hadoop process a few thousand records per second (SQLStream.com). Given the increasing business interest in Stream Analytics, several well-known vendors offer nuanced or general-purpose software solutions (e.g., IBM's Infosphere Streams; Informatica's Rule Point; Microsoft's Azure Stream Analytics; SAP's Event Stream Processor; Software AG's Apama; SQLStream's Blaze; Tibco's Stream- Base and Live Datamart; Vitria Technologies IoT Analytics Platform) besides open source products like Apache Storm and VideoEye.

Box (4): Design corresponds to phase "c." Acquired data are subject to data pre-processing. The types of analytics we wish to perform determines the types of data sources we exploit. Together, they determine the types of pre-processing undertaken. Business SMA can entail many types of analytics. Trend Analysis ([10]; box 4-E), Topic Modeling ([6]; 4-F), Sentiment Analysis ([33]; 4-G), and Text Classification ([1]; 4-H) require pre-processed textual data (4-A). Social Network Analysis ([7]; 4-I) requires pre-processed social interactions and inter-relationships data (4-B). Activity Analysis ([12]; 4-J) requires pre-processed participant action data (4-C). Each box also shows examples of the typical preprocessing tasks involved in each case. An analyst may use each approach alone or in combination with others, based on busiindustry (e.g., technology, banking) are extracted using automated tracking and manual copying. The data extracted could include quantitative measures (e.g., number of fans/followers or postings and posting frequency) and/or qualitative metrics (e.g., sentiment or emotion). Data extraction is a continual process. The gathered data are pre-processed and subject to appropriate analytics techniques, including text mining, sentiment analysis, and social network analysis. A firm may compare analysis outcomes with those for any competitor and the resulting "competitive intelligence," used to advantage.

3.2. Comprehensive business SMA framework

The Stieglitz et al. [53] framework is perhaps the most complete of the Business frameworks reviewed here. Still, there is room for improvement regarding business uses of SMA. Here, we introduce a more comprehensive Business SMA framework that encompasses and extends extant SMA frameworks in a manner that addresses key aspects of SMA use in business settings and that is in accord with our Business SMA definition. Our conceptual framework rests on prior, seminal, theoretical frameworks for decision making advocated by Simon [47] and Einhorn & Hogarth [13].

Simon [47] views managerial decision making as comprised of three phases: Intelligence (finding occasions for making decisions), Design (finding possible courses of action), and Choice (choosing among possible courses of action/making a final decision). Einhorn & Hogarth [13], describe the "process of judgment and choice" as comprised of four sub-processes: Information Acquisition (searching and storing information), Evaluation (assessing alternative courses of action), Action (committing to, and implementing, a course of action), and Feedback/ Learning (learning from feedback obtained about action implementation outcome). Both studies discuss challenges faced during each subprocess and emphasize complex sub-processes interactions. The two frameworks emphasize different, but complementary, aspects of decisional processes. As such, we utilize a suitably adapted version of a decision process model (first articulated in [25]), which draws on both the Simon and the Einhorn & Hogarth frameworks, as the setting for our Business SMA framework. The resultant decision process model is comprised of eight sub-processes:

(a) Attention: Searching for opportunities for Intelligence Gathering, Sense Making, Insight Generation, and/or Decision Making.
(b) Acquisition: Gathering relevant information from internal and/or external sources, as appropriate.
(c) Design: Determining alternate courses of action based on acquired information.
(d) Evaluation: Determining the relative worth of alternative courses of action, and constructing a feasible action set.
(e) Choice: Resolving conflicts in the set of feasible actions and selecting a course of action (also called "the decision").
(f) Implementation: Executing the decision. As with Choice, Implementation entails conflicts and conflict resolution.
(g) Feedback & Review: Obtaining information, both during and after Implementation, about actual/perceived outcome(s) and critically assessing the same.
(h) Learning & Behavior Modification: (Possibly) gaining new insights based on Feedback & Review and reiterating, as needed, one or more of the phases (a)-(f).

In using this decision process model as the context for our Business SMA ity traits and to assess work-related employee motivational attributes (e.g., job satisfaction). The Human Resources (HR) Analytics module analyzes employee life cycle and helps manage HR processes (e.g., hiring, retirement, engagement, talent management).

The Customer Analytics module helps perform sentiment and predictive customer analytics (e.g., to forecast future purchase, churn, spending behavior). This module relies on surveys.

The Sinha et al. [48] framework captures aspects of SMA utility in both the internal and the external business environs. Its survey-based approach to Customer Analytics and its inclusion of Behavior Informatics and HR Analytics are unique features of this Business SMA model.

3.1.3. The Stieglitz and Dang-Xuan framework (2012)/the Stieglitz et al.

framework (2014) The Stieglitz & Dang-Xuan [52] framework is focused on Political Analytics. The framework consists of a Data Tracking and Collection module and a Data Analysis module, each comprised of multiple submodules. The framework presumes that relevant data reside on Twitter, Facebook, and Blogs with each being tracked using specifically tailored automated tracking methods. The chosen tracking methods are deployed as part of five Data Tracking and Collection approaches. Three of these are focused (i.e., the self-involved, keyword/topic-based, and actor-based approaches), a fourth is unfocused (i.e., the exploratory/ random approach), and the fifth, an optional URL-based approach, extracts information in embedded URLs.

Sandwiched between the Data Tracking/Collection module and the Data Analyses module are the Data Pre-processing activities. The Data Analysis module focuses on Reputation Management and General Monitoring of the political landscape. The analyses methods for Reputation Management are the Topic/Issue/Trend-related approach (using Text Mining and Trend Analysis), the Opinion/Sentiment-related approach (using Opinion Mining/Sentiment Analysis), and the Structural approach (using Social Network Analysis). General Monitoring uses exploratory analyses (using approaches similar to Reputation Management) of data collected using the exploratory/ random approach.

Stieglitz et al. [53] present an enhanced rendering of the above framework. The enhanced model is also applicable in business settings and includes Innovation Management and Stakeholder Management as analysis goals, in addition to Reputation Management and General Monitoring. The model also includes Statistical Analysis as part of the Structural approach. Innovation Management is concerned with product/ service innovations that result from, listening to customer suggestions/ ideas on social media, for example. Stakeholder Management is concerned with managing key interested parties (e.g., customers) of a business enterprise. Reputation Management deals with assessing and reacting to public sentiments about the enterprise. General Monitoring watches for new developments that could influence the business. While the framework does not elaborate on this, the authors mention the need for data pre-processing and hint at store-and-process vs. streaming data analysis by referring to static vs. dynamic data analysis. This framework depicts analytics post-processing using summaries and reports.

3.1.4. The He et al. framework (2015)

He et al. [20] propose a Business SMA framework for Competitive Analytics. User-generated social media data from sites of competing firms in an

Table 2
A taxonomy of SMA activities.

Related to analytics pre-processing	Related to analytics processing	Related to analytics post-processing
Monitor (5); Collect (4); Identify (2); Detect (1); Find (1); Search (1); Track (1).	Analyze (8); Visualize (4); Summarize (3); Mine (2); Characterize (1); Filter (1); Interpret (1); Measure (1); Model (1); Transform (1).	Alert (1); Dashboard (1); Report (1).

We base the creation of a Business SMA Conceptual Framework for guiding study and practice on our Business SMA definition. In so doing, we draw upon, and extend, existing Business SMA frameworks and ground the new framework in seminal decision-making theory.

3. Conceptual framework

3.1. Review of extant business SMA frameworks

In this section, we review available Social Media Analytics (SMA) conceptual frameworks, all except one of which are entirely businessuse focused.

3.1.1. The Mayeh, Scheepers, and Valos framework (2012)

An early, simple Business SMA framework was proposed by Mayeh et al. [37]. The authors study the utility of social media data for gathering external intelligence about customers, competitors, suppliers, partners, industries, and technologies. The framework is based on the concept of Dynamic Capabilities due to Teece et al. [54]. Dynamic Capabilities encompasses opportunity sensing and seizing, and threats management/transformation. The framework views SMA as a facilitator that helps discover potential opportunities for resource creation, extension, and/or modification.

The framework is comprised of two major components: Sensing, and Seizing. Sensing, in turn, is comprised of Capturing and Analyzing. Data from relevant social media sites is gathered (i.e., captured) using monitoring tools and then "analyzed" to generate the requisite intelligence.

The framework goes beyond SMA to include acting on this intelligence with the aid of relevant organizational enablers (i.e., "seizing"). A noteworthy aspect of the framework is its business external environment focus.

3.1.2. The Sinha et al. framework (2012)

Sinha et al. [48] present a Business SMA framework that encompasses Behavior Analytics, Human Resources Analytics, and Customer Analytics. In this model, a business enterprise selects one or more "social networking sites" (i.e., LinkedIn, Facebook, Twitter, and/or BlogSpot) from which to extract data. Data is analyzed in terms of relevant attributes, (e.g., posts, likes, shares, comments, re-tweets, recommends, etc.) with intent to extract, understand, and predict information related to employees and customers.

The Behavior Informatics module draws on prior psychology theory (i.e., the Big 5 model) to relate customer/employee online behavior to their personal-

Table 1
Prior SMA characterizations.

Reference	Activity?	What?	Where?	How?	Why?
1) Melville et al. [39]	Identify.	Relevant blog subsets; influential bloggers; novel emerging topics.	Blogs.	By drawing from social network analysis, data mining, information retrieval, & natural language processing.	To extract (and drive) business insight.
	Detect & characterize.	Specific sentiment.			
2) Zeng et al. [59]	Collect, monitor, analyze, summarize, & visualize.	Data.	Social media.	By developing & evaluating informatics tools & frameworks.	As driven by specific target application requirements.
3) Yang et al. [57]	Collect, monitor, analyze, summarize, & visualize.	Data on conversations, engagement, sentiment, influence, and other specific attributes.	Social media	By developing & evaluating informatics tools & frameworks	To measure the activities within social media networks
4) Mayeh et al. [37]	Identify & analyze.	External environment information.	Social media	By scanning	To assimilate and utilize the acquired external intelligence for business purposes
5) Sinha et al. [48]	Measure; monitor.	Behavior, conversation, engagement, sentiment, influence, customer needs, information exchange.	Social networking sites.	None mentioned.	To gain deeper insights into customers' and employees' sentiments (IBM 2012).
6) Stieglitz & Dang-Xuan [52]	(Continuously) collect, monitor, analyze, summarize, & visualize	Politically relevant information	Social media	(None mentioned)	For Reputation Management (to measure campaign effectiveness and impact of/reaction to institutional online content; to offer improved services for citizens; to seek feedback, suggestions, new ideas) For General Monitoring (to identify trending political topics early)
7) Grubmüller et al. [18]	Search, report, dashboard, visualize, alert, & text-mine	User-generated public content (postings, comments, conversations, etc.)	Social media	By listening & measuring	To facilitate evidence-based, legal and ethical policy making by governments
8) Grubmüller et al. [19]	Find, filter, & analyze	User-generated content	Social media	(None mentioned)	To facilitate evidence-based, legal and ethical policy making by governments
9) Kurniawati et al. [29]	Analyze & interpret	Vast amounts of semi-structured and unstructured data	Online sources	By using analytics-based capabilities	To provide businesses with insights into customer values, opinions, sentiments, & perspectives on brands, marketing campaigns, & new product & service opportunities
10) Stieglitz et al. [53]	Track, model, analyze, & mine	Large-scale data	Social media	By developing and evaluating scientific methods, technical frameworks, & software tools	For various (unspecified) purposes
	Transform	Raw data		By using BI methodologies, processes, architectures, & technologies	For generating meaningful, useful information for business purposes
11) He et al. [20]	Collect, monitor, & analyze	Data	Social media	By using advanced informatics tools and analytics techniques	To extract useful patterns and intelligence

processing tasks. Notably, only Grubmüller et al. [18] explicitly mention postprocessing and Kurniawati et al. [29] eschew pre-processing entirely.
Turning to the Where column in Table 1, ten studies explicitly allow for multiple social media types whereas Melville et al. [39] focus only on blogs. Sinha et al. [48] refer to social networking sites (SNS) and Kurniawati et al. [29] to online sources, whereas their studies are actually concerned with social media sites. Consider, now, the entries in the What column of Table 1. Some authors (i.e., Zeng et al. [59], Grubmüller et al. [19], Kurniawati et al. [29], Stieglitz et al. [53], and He et al. [20]) specify targets very broadly. The rest are more specific to differing extents. Melville et al. [39] consider only blog-based targets.
Mayeh et al. [37] focus entirely on a business's external environment (specifically, customers). Stieglitz & Dang-Xuan [52], target politically relevant information. Grubmüller et al. [18,19] target legally/ethically relevant public content of interest to governance. Yang et al. [57] and Sinha et al. [48] each mention several specific target data types of interest. Finally, examine the How column. Sinha et al. [48], Stieglitz & Dang-Xuan [52], and Grubmüller et al. [19] are non-committal about procedural aspects. Kurniawati et al. [29] make a broad reference to "analytics-based capabilities," and He et al. [20] to "advanced informatics tools and analytics techniques." Melville et al. [39] specify processes/techniques used with text corpus's (i.e., information retrieval, natural language processing, mining, social network analysis). Mayeh et al. [37] mention scanning and Grubmüller et al. [18], listening and measuring. Stieglitz et al. [53] emphasize business intelligence tools with Business SMA. A few characterizations (i.e., Zeng et al., [59], Yang et al. [57], Stieglitz et al. [53]) also regard the development and evaluation of tools, techniques, methods, and/or frameworks to facilitate analytics as part of procedural know-how.

2.2. Business SMA definition

Because none of the characterizations, by itself, covers the collective landscape covered by the others, we capture their essence in an inclusive, yet parsimonious, definition that also emphasizes the application goals of Business SMA and provides a shared locus to facilitate developments in the emergent Business SMA field: "All activities relating to gathering relevant social media data, analyzing that data, and disseminating findings as appropriate to support business activities such as intelligence gathering, problem recognition, opportunity detection, sense making, insight generation, and/or decision making undertaken in response to sensed business needs [23]." We note the following salient aspects of this definition. First, it does not over- or under-emphasize any of the three analytics processing stages. Second, it allows for all applications, media, data repositories, and procedural knowledge, as dictated by analysis requirements. Third, it allows for an external, internal or a hybrid focus (where both the internal and the external are of simultaneous import (e.g., during crowdsourcing, co-creation, and open innovation)). Fourth, it allows for analysis of data pertaining to all business stakeholders such as employees, customers, suppliers, logistics service providers, wholesalers, retailers, financiers, competitors, regulatory bodies, etc. Fifth, the definition acknowledges that Business SMA could go beyond providing intelligence to facilitate other business support needs such as recognizing problem/opportunity situation, making sense of situations, generating insight about situations, and making relevant business decisions.

Business SMA definition that also includes novel features not found in the prior characterizations.

Section 3 begins by describing extant conceptual frameworks for Business SMA. We then introduce a comprehensive Business SMA framework that covers relevant ideas found in these frameworks and incorporates features that are either only implicit or absent in them. We follow this with a comparative analysis of our framework against prior frameworks. In Section 4, we present findings from a review of recent SMA literature in premier Management Information Systems academic journals and use select publications from the review to validate our framework. Section 5 contains concluding remarks.

2. Characteristics of social media analytics

2.1. Review of extant SMA characterizations

We begin by examining extant SMA characterizations,1 beginning with that of Melville et al. [39] and representing considerable diversity in viewpoints. To help discern commonalities across, and differences among these, we parse each characterization using the five key attributes: Activity, What, Where, How, and Why, as shown in Table 1.

To illustrate this process, consider the characterization by Zeng et al. [59] in row (2): "Social media analytics is concerned with developing and evaluating informatics tools and frameworks to collect, monitor, analyze, summarize, and visualize social media data, usually driven by specific requirements from a target application." The Activity attribute for a characterization pertains to the SMA exercise objective(s) it encompasses. Zeng et al. [59] regard an SMA exercise as entailing the collection, monitoring, analysis, summarization, and visualization of something(s). The What attribute specifies the target(s) for the activities mentioned. In Zeng et al. [59], this target is simply, "data." The Where attribute refers to the specific social media type(s) that host(s) the required target(s). Zeng et al. [59] allow for all types of social media. The How attribute specifies high-level, procedural aspects of the analytics exercise given its activities, targets, and media. Zeng et al. [59] refer to developing and evaluating informatics tools and frameworks as analytics procedures. The Why attribute articulates the larger purpose of an analytics exercise. For Zheng et al. [59], the requirements of target applications, whatever these may be, drive the exercise – the authors do not articulate possible purposes. The remaining entries in Table 1 were similarly developed. We now examine each of these attributes across the eleven characterizations in the table.

Because SMA activities, activity targets, repositories exploited, and manner of exploitation typically ought to be based on the overarching purpose of an analytics endeavor, we begin with the 'Why?' column.

Five of the characterizations indicate a business-oriented purpose. Of these, Sinha et al. [48] emphasize gaining deeper insights into customer and employee sentiments and Kurniawati et al. [29] have a marketing thrust. Of the remaining six characterizations, Stieglitz & Dang-Xuan [52] focus on politics and Grubmüller et al. [18,19], on governance.

Now, examine the Activity column's entries. In Table 2, we classify them as pertaining to pre-processing steps undertaken prior to SMA, post-processing steps undertaken following SMA, and those involving the analysis itself. The parenthesized number against an entry is a count of the total number of mentions of that activity across the eleven characterizations. As the table reveals, the greatest emphasis is placed on the analytics processing activities and the least on post-

uct exposure unimaginable via traditional promotion channels.
Twitter is an example of what is referred to as 'social media' that Kietzmann et al. [27] describe as follows: "... employs mobile and webbased technologies to create highly interactive platforms via which individuals and communities share, co-create, discuss, and modify usergenerated content." There are several types of social media. These have been categorized in various ways; see examples in Mangold & Faulds [36], Sterne [51], Hoffman & Fodor [21]. The latter, for example, identify the following social media types: Blogs (e.g., web.com, eHost.com), Microblogs (e.g., Tumblr, Twitter), Co-creation sites (e.g., Nike's NIKEiD, Jet Blue's Travel Stories), Social Bookmarking Sites (e.g., Blinkist, StumbleUpon), Forums and Discussion Boards (e.g., Google Groups, MyBB), Review sites (e.g., Angie's List, Yelp), Social Networking Sites (e.g., Facebook, LinkedIn), and Multimedia Sharing Sites (e.g., Flickr, YouTube).
As of 2015, social media had attracted more than two billion people – over 30% of active Internet users globally [45]. Such use extends beyond the personal. Today, businesses increasingly take advantage of social media due to its vast volumes of useful knowledge (about products/services, customers, employees, competitors, enterprise partners, etc.), and the speed of information diffusion within such media, both of which can have impactful business consequences.
Coincident with the business interest in exploiting social media, Social Media Analytics (SMA) has gained recognition as a distinct subfield within the analytics domain, one that is experiencing growing research interest. Broadly speaking, SMA applies appropriate analytics capabilities to social media content in order to generate specific types of knowledge (i.e., gather intelligence/stay informed, detect potential problem/opportunity situations, make sense of a situation, generate insights, and/or make business decisions). For example, Sterne [51] notes that SMA could benefit businesses seeking to measure customer feedback (i.e., 'buzz') on products/services (e.g., by analyzing buzz topic trends, buzz volume, buzz diffusion rate, and resultant sales impacts), with a view toward improving their marketing strategies.
Here, our focus is on understanding the nature of SMA, specifically in business settings. While there have certainly been advances in business applications of SMA, we have two motivations in pursuing this study. First, this formative field has not reached a point where there is a common view about what is/should be involved in its study. This paper makes a step in that direction by presenting a multi-faceted characterization of the Business SMA phenomenon and introducing a relatively comprehensive conceptualization to frame its study. Second, despite algorithmic/methodological advances and the availability of several commercial tools, SMA has not yet lived up to its promise. For example, Horwitz et al. [24] note, "In a recent survey of nearly 600 practitioners, more than 50% of respondents said that tying social activities to business outcomes is still difficult." As such, this paper essentially identifies parameters that deserve consideration by scholars, researchers, and practitioners in their Business SMA initiatives. The characterization and conceptualization can serve as a language or ontology for thinking about and discussing this field.
We organize the rest of this paper as follows: In Section 2, we identify and review a variety of existing SMA characterizations, some of which target business applications. The review includes systematic comparison and contrast of the many viewpoints. The diversity of available SMA characterizations suggests that researchers could benefit from a characterization that embraces all of them in a succinct, unifying manner. To this end, we discuss an inclusive

Business social media analytics:
Characterization and conceptual framework

Clyde W. Holsapple
C. M. Gatton College of Business & Economics, University of Kentucky, Lexington, KY 40506-0034, United States
Shih-Hui Hsiao
College of Management, Lawrence Technological University, Southfield, MI, 48075-1058, United States
Ram Pakathc
Department of Finance and Quantitative Methods, C. M. Gatton College of Business & Economics, University of Kentucky, Lexington, KY 40506-0034, United States

abstract

A substantial portion of internet usage today involves social media applications. Aside from personal use, given the vast amount of content stored, and rapid diffusion of information, in social media, businesses have begun exploiting social media for competitive advantage. Its popularity has led to the recognition of Social Media Analytics (SMA) as a distinct, albeit formative, sub-field within the Analytics field. Against this backdrop, we examine available characterizations of SMA that collectively identify various considerations of interest.

However, their diversity suggests the need for adopting a concise, unifying SMA definition. We present a definition that subsumes salient aspects of existing characterizations and incorporates novel features of interest to Business SMA. Further, we examine available conceptual frameworks for Business SMA and advance a framework that comprehensively models the Business SMA phenomenon. We also conduct a survey of recently published SMA research in the premier, academic Management Information Systems journals and use some of the surveyed papers to validate our framework.

Keywords

Analytics, Business social media analytics, Conceptual framework, Social media, Social media analytics

1. Introduction

While hosting the 2014 Academy Awards, Ellen DeGeneres took a selfie featuring Hollywood celebrities including Bradley Copper, using a Samsung Galaxy Note 3 smartphone. She posted the selfie on Twitter and captioned it: "If only Bradley's arm was longer. Best photo ever.
#oscars." The tweet quickly went viral, receiving more than 1.3 million retweets and disrupting Twitter's service for over 20 min [60]. By yearend, the selfie had 3.3 million retweets spanning 151 countries. Receiving Twitter recognition as the "most retweeted tweet for the year 2014," it was also the most tweeted-about tweet of 2014, generating 254,644 tweets per minute (USA Today, Dec 10, 2014). In the process, the Samsung Galaxy Note 3 received a kind of prod-