Unleashing the Potential of Argument Mining for IS Research: A Systematic Review and Research Agenda

Pablo Weingart
Universität Kassel, weingart@uni-kassel.de

Thiemo Wambsganss
EPFL, thiemo.wambsganss@epfl.ch

Matthias Söllner
Universität Kassel, matthias.soellner@unisg.ch

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Pablo Weingart
University of Kassel
Pfannkuchstraße 1, 34121 Kassel, GER
weingart@uni-kassel.de

Thiemo Wambsganss
Swiss Federal Institute of Technology in Lausanne (EPFL)
INF231, Station 14, 1015 Lausanne, CH
thiemo.wambsganss@epfl.ch

Matthias Söllner
University of Kassel
Pfannkuchstraße 1, 34121 Kassel, GER
soellner@uni-kassel.de

Abstract

Argument mining (AM) represents the unique use of natural language processing (NLP) techniques to extract arguments from unstructured data automatically. Despite expanding on commonly used NLP techniques, such as sentiment analysis, AM has hardly been applied in information systems (IS) research yet. Consequentially, knowledge about the potentials for the usage of AM on IS use cases appears to be still limited. First, we introduce AM and its current usage in fields beyond IS. To address this research gap, we conducted a systematic literature review on IS literature to identify IS use cases that can potentially be extended with AM. We develop eleven text-based IS research topics that provide structure and context to the use cases and their AM potentials. Finally, we formulate a novel research agenda to guide both researchers and practitioners to design, compare and evaluate the use of AM for text-based applications and research streams in IS.

Keywords: Argument mining, natural language processing, literature review, socio-technical systems

Introduction

Research areas on information systems (IS) seek to theorize based on the analysis of textual data, e.g., in contexts such as user-generated content or social media (Lukyanenko et al. 2018). Thus, novel technological approaches towards text analysis can usually serve as a starting point for new research opportunities. For example, the development of sentiment analysis allowed to capture positive or negative stances in conversations at scale, and offered different potentials to increase efficiency, accuracy, and rigor of more nuanced theory development in domains such as social media (Pang and Lee 2008). More recently another research field, also rooted in natural language processing (NLP), has emerged, and is readily applied in several contexts, with own tracks and workshops being established at major NLP conferences (e.g., ArgMining 2021). This field is coined argument mining (AM) and represents the unique use of NLP techniques to extract arguments from unstructured data automatically. Whereas popular sentiment analysis solutions only capture what opinions are being expressed, AM also addresses the reasons for these opinions (Lawrence and Reed 2020). In more technical research disciplines, such as computational linguistics, interest in AM has been steadily increasing in recent years and, by leveraging state-of-the art deep learning algorithms, both researchers and practitioners can rely on an increasingly strong technical foundation to embed argumentation in software applications (Lawrence and Reed 2020). The prime example for a novel AM system is "Project Debater" which can debate humans in real time (Slonim et al. 2021). Early, smaller scoped designs indicate that existing natural language use cases can be extended with AM to provide additional value for researchers and users. Among the tasks that have been evaluated are the creation of conversational agents that improve argumentation skills of users (Wambsganss, Söllner, et al. 2020), the extraction of arguments from discourse on social media (Dusmanu et al. 2017) and legal text (Moens et al. 2007) as well as the prediction of online review helpfulness based on argument features (Passon et al. 2018). However, despite its potential relevance for the IS community, AM has hardly been applied in the IS domain, except in the context of technology-mediated learning (Wambsganss, Kueng, et al. 2021).

With advancing AM research in mind, the growing number of interdisciplinary studies and use cases for AM (Lawrence and Reed 2020) highlights the necessity to better understand the application types, capabilities, and potential implications of AM. Most studies that investigate the potential of AM applications focus on a specific task or scenario. This eventually leads to a fragmented literature base and sometimes contradictory research results. This is evident from the existing literature reviews on AM that have emerged over the past years. The reviews are usually only motivated from technical NLP and computational linguistic perspectives, missing out on behavioral or design driven research aspects. For instance, in their systematic review (Lawrence and Reed 2020) structure practical AM studies according to the underlying technical tasks such as argument component identification, but do not consider a socio-technical perspective on the research phenomena (Bostrom and Heinen 1977). Especially for judging the relevance of this technology for an adjacent discipline, such as IS, an integrative viewpoint that goes beyond technical tasks would be of utmost importance to systematically utilize and compare different configurations of AM to form an impactful research stream (Nickerson et al. 2013). While IS research on use cases of AM is scarce, studies that leverage other NLP methods such as sentiment analysis exist in ample quantity (D. Liu et al. 2017). Since AM is a natural advancement of sentiment analyses, as it not only analyzes what opinions are expressed, but also why (Lawrence and Reed 2020), many of these existing IS use cases can potentially be improved and extended through leveraging a more advanced technology. Therefore, a consistent knowledge aggregation and literature overview on the different IS use cases, that AM can potentially be used for, will help both researchers and practitioners to systematically design, compare, and evaluate the use of AM for new or existing NLP applications or research streams in the realm of IS and beyond. In this regard, IS research can offer a promising viewpoint for classifying technological applications, which ultimately yields different configurations of the technological embedding and outcomes for different stakeholders. Also, a systematic review of empirical studies in IS for AM scenarios would enable researchers to more effectively design, evaluate, compare, and theorize how different use cases of the young field of AM impact streams in IS research. Hence, the aim of our study is first to systematically review the IS literature on potential use cases which are suitable for AM and second, to derive a research agenda that can be used to guide future research on extended or novel practical AM use cases. In effect, our paper contributes to the fields of IS and AM by answering the following research question (RQ):

RQ: *What are potential research areas and use cases from IS research that can be augmented with argument mining?*

To address the RQ systematically, we perform a systematic literature review according to Webster and Watson (2002) and vom Brocke et al. (2015). In this vein, we rigorously searched the literature databases on journal papers from the AIS Senior Scholars' Basket. To include the latest research results, we also searched the proceedings of the ICIS and ECIS conferences. In total, we collected a data set of 256 relevant papers which display text-based IS use cases and in consequence potential use cases for AM in IS. As a guiding lens, we apply and modify the quantitative IS research topics by Jeyaraj and Zadeh (2020) to manually code and cluster the papers into eleven text-based IS research topics. The topics represent research on use cases that potentially profit from incorporating AM. To provide IS researchers and practitioners a comprehensive overview, we outline the potential of AM for each of these topics. We analyze the three largest as well as most insightful in greater detail and deduct a research agenda for them to guide further research in IS. The paper is structured as follows. First, we explain the NLP foundation on which AM operates. Then, we introduce AM, elaborate on potentials for the use of AM in future IS research and outline the research gap that motivates the study. In the methodology**,** we describe how we performed the systematic literature review and formed the IS research topics for AM. In the results, we present the text-based IS use cases we found for each text-based IS research topic. Next, we discuss the potentials of AM for these use cases and deduct the research agenda. Finally, we discuss the limitations and contributions of our study.

Theoretical Background

Natural language processing for IS research

NLP consists of methods for making human language accessible to computers and is an interdisciplinary field of computer science, machine learning, artificial intelligence, and computational linguistics, but also plays a significant role in emerging fields like digital humanities and computational social sciences (Eisenstein 2019). The latter intersects with the IS field by analyzing the interplay between technology and social science (Bostrom and Heinen 1977). Text mining is a related term that is typically less concerned with linguistic structure and more interested in fast algorithms compared to NLP (Eisenstein 2019). Use case driven IS studies usually leverage NLP in their design artifacts to analyze large amounts of natural language data at scale where manual analysis is not feasible. Commonly used NLP tasks in IS include sentiment analysis, information retrieval and semantic annotation (D. Liu et al. 2017). Studies in IS that employ NLP techniques cover a wide variety of use cases such as analyzing the influence of social media sentiment on stock market movements (Li et al. 2017), structuring research articles at scale (Fteimi and Basten 2015), teaching skills to students (Wambsganss, Kueng, et al. 2021) or grading the knowledge quality of user-generated content (Velichety et al. 2019). We describe these IS use cases in more detail in the result section. In this work, we differentiate descriptive and predictive IS use cases. The former explore data to discover potential hypotheses whereas predictive approaches aim to predict future events (Tukey 1977).

Potentials of argument mining

Lawrence and Reed (2020) define AM as “the automatic identification and extraction of the structure of inference and reasoning expressed as arguments presented in natural language“. Precursors and interrelated research areas to AM are opinion mining, sentiment analysis, controversy detection, citation mining and argumentative zoning (Lawrence and Reed 2020). The main advantage of AM over implementations that use these and other, more traditional, NLP methods, is that more insights can be retrieved. Where opinion mining and sentiment approaches only consider what opinions are expressed, AM generates insights on why these opinions are expressed (Lawrence and Reed 2020). AM thus expands existing sentiment approaches. For example, practical AM studies predict the usefulness of online reviews (H. Liu et al. 2017), detect deceptive reviews (Cocarascu and Toni 2016), explore and decompose arguments in user-generated text (Goudas et al. 2015) to analyze strength and presentation of arguments in a persuasion context (Manzoor et al. 2020), extract arguments about a certain topic from news articles and tweets in the context of marketing (Skiera et al. 2022) or generate and explain recommendations from online reviews (Donkers and Ziegler 2020). Going beyond a pure textual context, Chakraborty et al. (2022) quantify the argumentation skill of job candidates in video interviews to support hiring decision processes.

Theoretically, AM is based on argumentation theory which analyzes the structure and connection between arguments (Wambsganss, Söllner, et al. 2020). A popular model to structure argumentation is given by Toulmin (2003) who asserts that an argument consists of a claim, premise or evidence that supports the claim and an inference from the premise to the claim. Claim and premise make up the components of the argument (Toulmin 2003). Although this and other models were initially intended for manual argumentation analyses, they are now replicated in AM studies (Wambsganss, Kueng, et al. 2021). In contrast to manual analysis, the main advantage of AM is the ability to process large amounts of unstructured text at scale (Lawrence and Reed 2020).

Notably, AM is a subfield of NLP and leverages the same key technologies that other contemporary NLP techniques also use. Early papers built AM systems using features from varying NLP techniques, e.g., textual entailment or LDA topic models (Lawrence and Reed 2020). Per the general trend, like other NLP research branches, recent state-of-the-art AM research uses pretrained transformer models. Primarily, derivatives of BART or BERT, such as RoBERTa, are used (Wambsganss, Molyndris, et al. 2020). GPT models, specifically the powerful and publicized GPT-3 and InstructGPT models by OpenAI, are not widely in use yet in AM papers, at the time of the writing. A key differentiation and contribution of AM is the design of labeled datasets that specifically embed argumentation theory to generate insights with respect to argumentation. While identification tasks are usually derived relatively closely from sequence classification (e.g., Wambsganss, Kueng, et al. 2021), AM researchers design more distinct tasks for more complex analysis tasks, allowing researchers to analyze textual data in greater depth compared to other, more basic tasks. With the relative novelty of the field in mind, no standard set of tasks has been established yet. Instead, developing existing and new argumentative tasks is ongoing, thus differentiating the field further relative to other NLP techniques and fields. Since this is not the focus of the work, we only provide a brief overview to the major tasks in the next paragraph. Typically, AM research uses similar metrics to measure model outputs compared to other NLP subfields. A popular accuracy measure for classification tasks is the F-score. The accuracy scores reached in the literature vary by dataset and the (argumentative) complexity of the task. They largely range between 0.7 and 0.8. Although these scores are promising by themselves, they typically do not reach human performance yet (Lawrence and Reed 2020).

Foundational to all AM endeavors is the presence of argumentation in textual data. The respective datasets are used to further train the chosen models for downstream tasks. Public datasets are available for multiple data sources such as tweets, essays or, to mention a specific use case, (textual) business model pitches. Characteristic of AM is the current restriction to supervised learning and consequently the lack of large-scale datasets due to the time-costly annotation process that is necessary to construct a suitable dataset. While there have been significant endeavors to produce larger datasets, the datasets are neither large nor diverse enough to support the domain-independent analysis of argumentation (Lawrence and Reed 2020). Hence, models based on these datasets do not necessarily generalize to other settings. Having the complexity of argumentation in mind, ensuring sufficient annotation quality is a challenge for researchers. Through leveraging the vast theory on the design of annotation guidelines, researchers can alleviate this issue and reach promising inter annotator agreements. Still, the agreements vary by complexity of the underlying argumentation (Lawrence and Reed 2020). Finally, general shortcomings of the used NLP techniques apply, e.g., lack of explainability when using transformer-based models.

The two primary and traditional AM tasks are argument component identification and argument relation identification. The corpus annotations and models vary by task. Argument component identification classifies the components based on the used argumentation scheme. Common components are claim, premise, evidence, and conclusion. The identification of argument relations is more complex. First, this task derives the general relations of the components within a document, e.g., whether component X is a premise for Y. Second, the components of one document are put into context with those of other documents, specifying if an argument in document A is an instance of another argument in document B (Lawrence and Reed 2020). Argument quality analysis is a more recent task and ranks or scores documents on persuasiveness. These scores can then be used for student feedback (Carlile et al. 2018). Key point analysis is a tangential task which extracts a set of statements that concisely summarize the arguments of a given text (Bar-Haim et al. 2020).

Reviewing the occurrence of NLP tasks in IS research articles, D. Liu et al. (2017) did not find articles using AM techniques for the years from 2004 to 2015. Instead, the articles often employ simpler sentiment approaches. This gap is also present in other related research disciplines, as shown in a review about the use of NLP in management sciences by Kang et al. (2020). Our IS literature review, going up to the year 2021, largely confirmed this trend as almost all articles still relied on traditional NLP techniques. The exceptions were studies on technology-mediated learning that helped students develop argumentative skills (Wambsganss, Söllner, et al. 2020). Likewise, we did not find any literature review that systematized the use of AM in IS research, highlighting the research gap that initially motivated our study.

Classifications of argument mining in IS research

The classification of a literature phenomenon within a systematic review, at its most basic level, can be a cognitive aid that allows researchers and practitioners to manage the complexity created by multiple factors of interest (Nickerson et al. 2013). Although such classifications were originally formed based on empirical evidence, they are now also based on conceptual evidence (Nickerson et al. 2013). They can facilitate knowledge exchange, provide a better understanding of inter-object relationships, and thus aid decision-making (Bailey 1994). Finally, they may provide a fundamentally distinct understanding of how AM in IS can be used and, from a pragmatic standpoint, how the different levels of AM might benefit academics and practitioners in conducting IS research, assuming an abductive reasoning approach.

There exist multiple literature reviews already that cover AM extensively (Lawrence and Reed 2020; Lippi and Torroni 2016). Unlike our study, these reviews structure the existing AM studies by tasks similar to the ones we previously described. In consequence, they provide holistic views on the discipline itself from technical and methodological perspectives, but do not cover the socio-technical perspective (Bostrom and Heinen 1977). To the best of our knowledge, reviews about AM in the context of other research disciplines, such as marketing do not exist yet either. To apply the socio-technical perspective, our review aims to provide a holistic view on IS research topics and their respective potential use cases for AM. Thus, we do not limit our review to studies on AM, but also include studies that relate to textual data and natural language processing since we argue that AM can extend many of these use cases, if only the underlying textual data is argumentative. This is due to AM approaches being technologically more complex and being able to derive more insights compared to traditional approaches. Notably, AM acts as a logical continuation to sentiment approaches (Lawrence and Reed 2020) which are commonly used in IS research related to NLP (D. Liu et al. 2017). For consistency, we refer to these use cases as text-based IS use cases.

Methodology

In order to gather a representative coverage of literature on text-based use cases in IS literature, we conduct a systematic literature review according to the principles of Webster and Watson (2002) and vom Brocke et al. (2015). We align the search process to the process, source, coverage, and technique dimensions. We perform the search process sequentially using the databases of the AIS Senior Scholars' Basket as the *source* up to the year 2021. Furthermore, we add the ICIS and ECIS conference proceedings to include more novel research. To reach a *representative coverage* we employ TIKEAB (title, keyword and abstract) search and comprehensive forward and backward search as *techniques*. In the following we describe the steps we took to come to the final set of relevant literature.

Selection of search string: Based on a recent literature review (D. Liu et al. 2017) we identified different keywords and synonyms that researchers use when presenting work on text-based IS use cases. To also include literature directly related to argumentation, we also added "argument" as a keyword. This resulted in the following search string: ("natural language" or "NLP" or "text analysis" or "text mining" or "sentiment mining" or "sentiment analysis" or "opinion mining" or "argument"). We continuously refined our search string during the research. We used all variations of the keywords such as singular, plural, with, or without a hyphen to generate further input. Table 1 summarizes the database hits and number of hits we selected for the review.

Database	AisEL	Ebsco	ProQuest	ScienceDirect	Total
Total hits	411	127	39	12	589
Relevant after screening abstract	172	53	2	0	227
Relevant after detailed analysis	118	41	1	0	160
Forward search results	15	24	1	0	40
Backward search results	34	21	1	0	56
All results	167	86	3	0	256

Table 1. Database hit summarization

Selection of databases: We choose the eight journal databases of the AIS Senior Scholars' Basket as a source for our literature to cover all research that has successfully been published in a high-quality journal, indicating higher quality of the papers. Hence, the following journals are covered: Management Information Systems Quarterly (MISQ), Journal of Management Information Systems (JMIS), Journal of the Association for Information Systems (JAIS), Information Systems Research (ISR), European Journal of Information Systems (EJIS), Information Systems Journal (ISJ), Journal of Strategic Information Systems (JSIS) and Journal of Information Technology (JIT). To include cutting edge research, we also add the databases of the ICIS and ECIS conference proceedings.

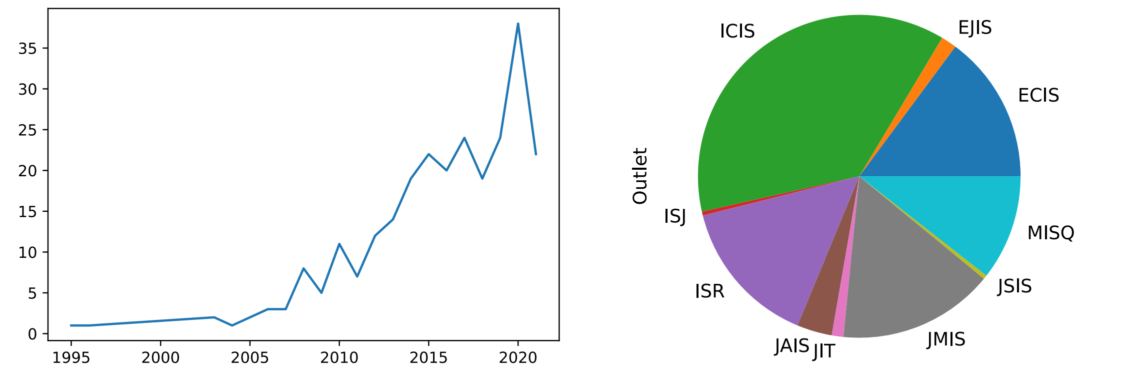

Figure 1. Year and outlet distributions

Selection of papers: When searching by title, abstract, and keywords of the papers, the outlet-based search yields 589 hits. In the screening process, the identified papers are analyzed based on their abstracts and, if unclear, text. The primary criterion for relevance is that the specified task or problem supports the processing of natural language. This criterion is necessary because AM strictly operates on argumentative text. Hence, we only included papers which aim at solving a practical text-related task, e.g., predicting a review's helpfulness based on characteristics of the text. We don't further select on criteria whether AM is suitable for the underlying task or problem since we want to outline where and where not AM can be helpful in the discussion. We find 160 relevant papers according to our criteria. Performing forward and backward search, we went through all the references of each paper. We again filter the references by database, as specified in the previous step, and identify 96 additional relevant papers, 56 through backward and 40 through forward search. This is shown in Table 1 for each database. In Figure 1, the distribution of years and outlets is shown. If a paper was found multiple times during backward and forward search, only the first occurrence was counted.

Analysis of papers: The 256 relevant papers are analyzed from a concept-centered perspective. We create a concept matrix according to Webster and Watson (2002). The concept matrix consists of the IS research topics by Jeyaraj and Zadeh (2020). They describe 35 IS research topics in total, based on a sample of 2962 papers published between 2003 and 2017 in the AIS Senior Scholars' Basket journals. They also provide keywords that researchers use to describe these topics. An excerpt of the IS research topics and their keywords is shown in Table 2. We chose these topics as a base to structure our identified papers into common IS research topics because they were created quantitatively with topic modelling and are therefore less prone to bias. We attempted a similar approach based on our own samples but did not receive clear results. Possible reasons might include the small sample size and the strong bias of papers towards leveraging user-generated data, resulting in similar keywords, and consequently overlapping topics.

Initially, we coded our papers directly to the IS research topics by Jeyaraj and Zadeh (2020). The coding of the concepts was done, when possible, by matching the keywords of the paper with the ones associated to the IS research topics. Otherwise, the concepts represented in the abstract or, if needed, full text were compared to the keywords of the IS research topics. We focused on comparing the keywords to reduce coding bias. If the keywords matched for multiple topics, the topic that represented the dominant use case was assigned. For example, if a paper evaluated online reviews from online communities to predict product demand in e-commerce, the paper was coded to e-commerce. The codings were performed by two researchers independently. To solve differences in coding, a third researcher was consulted. Some research topics such as "research methodology" or more traditional IS research topics such as "IT adoption" were omitted since no papers were classified accordingly. This was expected as not all topics fit the practical scope of our work or rarely study text-based use cases applying NLP techniques.

IS research topic	Keywords
Online communities	Collaboration, online communities, health IT, virtual teams, collaboration engineering
Deception detection	Deception detection, neuro is, computer mediated communication, text mining, design science
IS security	IS security, protection motivation theory, compliance, IT risk, phishing
Decision support system	DSS, decision making, design science, group DSS, BI
E-government	e-government, IS management, service quality, IS evaluation, collaboration
Knowledge management	Knowledge management, knowledge sharing, knowledge management systems, action research, virtual teams
Online trust	Trust, virtual teams, privacy, collaboration, technology acceptance
E-commerce	e-commerce, electronic markets, economics of IS, game theory, consumer behavior
Social media	Social media, UGC, social networks, WOM, online communities
Research methodology	Research methodology, grounded theory, IS research, …
IT adoption	IT adoption, IT diffusion, IT innovation, …
…	

Table 2. Excerpt of the IS research topics by Jeyaraj and Zadeh (2020)

To better fit the scope of our work, as well as the focus on practical text-related studies, we slightly adjusted the IS research topics by Jeyaraj and Zadeh (2020). Going forward, we reference the adjusted topics as text-based IS research topics. The adjustments were necessary for two reasons. First, some papers used keywords from different topics interchangeably while representing similar concepts. This was the case for the topics "online communities" and "social media", resulting in blurry coding. Hence, we merged both topics. Second, we created new topics if multiple papers represented topics which were not sufficiently represented in the IS research topics. This was the case for papers on business intelligence (BI) and human computer interaction. We added the additional "Other" topic which includes papers that did not fit the other topics while also not being related to other papers in sufficient quantity to justify creating a new topic.

Results

In this section, we present our results based on the eleven text-based IS research topics. The topics structure recurring themes of text-based IS use cases with potential for AM. They are displayed in Table 3 alongside their recurring data sources and common components of the keywords that the studies used. Notably, most papers operate on user-generated content in the form of online reviews or social media posts. This was expected since other data is often not freely available when large volumes of data are required. Next, we describe each topic and outline the IS use cases that represent the studies we found for the topic.

Business intelligence: The business intelligence (BI) topics consist of studies that leverage text data to automatically analyze business-relevant information or predict business indicators. We found four areas for which these BI studies were primarily applied: finance, marketing, e-commerce and human resources (HR). Due to the relatively large count of papers in the initial BI cluster, and to differentiate the studies more, we created four subtopics accordingly. These subtopics do not represent IS research topics but structure and emphasize the interrelatedness to other research disciplines.

Text-based IS research topic	Count	Recurring data sources	Common keyword components
BI - Finance	43	News articles, analyst reports, social media posts, blog posts, 10-k filings	Stock, financial, lending, social media
BI - Marketing	31	Product and service reviews, social media posts, blog and forum posts	Social media, brand, consumer
BI - E-Commerce	22	Product reviews, product texts	eCommerce, eWoM, online reviews
BI - HR	9	Job listings, resumes	Job, skill, advertisement
Online communities	49	Consumer reviews, forum posts, social media posts	Social media, online reviews, user-generated content
Deception detection	21	News articles, product reviews, service reviews, messages	Fraud, fake, spam, deception
Human computer interaction	15	Conversational dialog	Conversational agents, learning, pedagogical agents
Knowledge management	16	Knowledge community posts	Knowledge, knowledge management, search, document
IS security	9	Information security messages, dark net forum posts	Incident, hacker, security, threat
Online trust	9	Product reviews, product text	E-commerce, trust, argument
Other	32	Research articles, social media posts	-

Table 3. Overview of IS research topics with AM potentials

BI - Finance: Studies in the finance subtopic are primarily concerned with predicting financial indicators. They can have a market scope such as stock market movements (Li et al. 2017). Some predict firm-scoped indicators such as the forecast accuracy (Ho et al. 2019) or the firm equity value (Chen et al. 2020). Others are person-specific and evaluate indicators such as credit risk (Wang et al. 2020). The studies relied on data from news articles, real estate listings, analyst reports, tweets or online reviews. Ren et al. (2013) also tapped the potential of 10-k filings.

BI - Marketing: The papers in the marketing subtopic analyze various marketing-related metrics. This includes metrics related to a company's brand, e.g. brand engagement (Kulkarni et al. 2020), perception (Luo et al. 2013) or favorability (Zhang and Moe 2021). Others analyze customer agility (Zhou et al. 2018), the interaction between customer and brand (Gunarathne et al. 2017) or identify competitors (Pant and Sheng 2009). These analyses rely on user sentiments from online reviews, tweets and blog and forum posts.

BI - E-commerce: The studies of the e-commerce subtopic investigate e-commerce-related metrics such as product sales (Gu et al. 2012) and demand (Choo et al. 2020), optimal pricing (Hanbing et al. 2021) and purchase decisions (Choi et al. 2019). They also explore the feedback interaction between customer and seller (Pavlou and Dimoka 2006) and reputation effects (Moreno and Terwiesch 2014). The papers largely used data from online reviews as well as product and service descriptions.

BI - Human resources: The eight studies on human resources investigate the skill supply (Gorbacheva et al. 2015) and demand for jobs and employee satisfaction (Luo et al. 2016). They operate on public employer reviews and job listings. One study analyzes the transcripts of job interviews (Tambe and Ye 2017) and another analyzes skill profiles on LinkedIn (Gorbacheva et al. 2015).

Online communities: This topic covers analyses on data from social media and other online communities which mostly consist of tweets and online reviews, like the other topics. Online communities refer to platforms, including social media and forums, on which groups of users exchange opinions. Unlike the studies seen in the other topics, which also use data from these sources, the studies in this topic analyze the data not just as means to an end, e.g., to predict product demand. Instead, they try to derive insights about the medium and how user interact with it. Regarding online reviews, the papers investigate factors that influence review usefulness (Aghakhani 2018) or emotionality (Madlberger and Nakayama 2013). Huang et al. (2020) evaluate how responses to negative reviews should be written. With regards to social media, the studies analyze textual attributes of posts in social media on outcomes such as question-answer quality (Mousavi et al. 2015), user retention (Singh et al. 2014), user emotions (Xu et al. 2013) or post persuasiveness (Shin et al. 2020). Further studies investigate the effect of such attributes on information sharing behavior, including argument quality (Ha and Ahn 2011). Others use social media posts to identify users with characteristics such as emotional distress (Chau et al. 2020).

Deception detection: The studies in this topic operate under the assumption that certain actors have misaligned incentives that makes the automatic validation or moderation of data, transactions, and content necessary. The papers classify social media posts with respect to fake news (Khan et al. 2021) and hate speech (Lee and Ram 2020). In company-sponsored social media, customer misbehavior is analyzed (Wu et al. 2021). Other papers classify spam (Glancy and Yadav 2010) and deceptive business e-mails (Ludwig et al. 2016). With regards to online word-of-mouth, suspicious stock recommendations (Siering et al. 2021) and fake online reviews (Kumar et al. 2018) are classified. Fraud is detected based on data from social media and long-form text from crowdfunding (Dürr et al. 2020).

Human computer interaction: The studies in this topic mostly relate to conversational and recommendation agents which use additional text corpora to create value for the users. To facilitate learning in the conversational context, the studies investigate the evaluation of skills and provision of feedback based on text (Piccoli et al. 2020) such as argumentation quality (Wambsganss, Kueng, et al. 2021) or provide support through question-answering (Wambsganss, Haas, et al. 2021). Other studies evaluate the user experience based on the conversations with the agent, looking at authenticity and its behavioral outcomes (Wünderlich and Paluch 2017), engagement and perceived humanness (Schuetzler et al. 2020), sale outcomes (Tan et al. 2021) and service quality in customer service contexts (Gnewuch et al. 2017). Based on the respective papers, recommendation agents are systems that provide recommendations to users based on varied input about online products. The studies use online reviews and other online resources to provide additional contextual information (Bauman and Tuzhilin 2021) or determining product recommendations (Xu et al. 2020).

Knowledge management: The sixteen papers on knowledge management relate to searching for helpful content in online knowledge communities (Liu et al. 2020) or crowdsourcing platforms (Rhyn et al. 2017) for which argument quality is a key component (Wang et al. 2009). In a similar context, Velichety et al. (2019) assess the quality of the content inside the knowledge repository. Furthermore, the studies analyze insights from public user-generated data (Qi et al. 2015), such as online reviews, and collections of documents (Spangler et al. 2003) with the aim to upload these insights to the repositories.

IS security: We found nine papers related to IS security. They cover theory on the design of information security messages which promote users' sensitivity to IS security risks. According to Schuetz et al. (2020) textual attributes such as argument nature increase the effectiveness of these messages. Other studies identify IS security risk factors from public filings such as 10-k reports (Wang et al. 2013), safety management system reports (Shi et al. 2017) and malicious insider case studies (Liang et al. 2016). Finally, they identify cyber threats, e.g. data breaches, based on posts from dark net forums (Ebrahimi et al. 2020).

Online trust: Online trust describes the willingness to be vulnerable (Kim and Benbasat 2009) in varying contexts. We found nine papers related to online trust. The studies generally investigate the influence of textual attributes on trust outcomes. For example, studies analyze the influence of argument quality on the credibility of online reviews (Cheung et al. 2012). Another set of studies show how online vendors can create trust through the placement of trust-assuring arguments (Kim and Benbasat 2009), e.g. in product descriptions. Wang and Benbasat (2007) study the effect of explanation facilities for recommendations on trust. Bansal et al. (2015) evaluate the influence of statements regarding privacy policy on online trust.

Other: The remaining studies generate insights from company documents to mine requirements for software projects (Meth et al. 2015), explore research articles (Fteimi and Basten 2015), extract insights from government documents (Guo et al. 2017), analyze how social media data can be used to improve citizens' engagement in public policy (Charalabidis and Loukis 2015) and use social media data to explore the adoption of digital technologies such as web conference tools (Hacker et al. 2020).

Discussion

In this section, we propose a research agenda that structures future research on use cases with potentials for AM. Furthermore, the research agenda illustrates how the use cases relate to our text-based IS research topics based on the socio-technical viewpoint we aimed to apply (Bostrom and Heinen 1977). First, we go through every text-based IS research topic and discuss potentials for AM based on the results. We emphasize the three largest topics specifically by structuring research opportunities and questions that form our proposal for the research agenda. They are visualized in Table 4. The two dominant topics are BI which contains 41% of the studies and online communities (19.1%), followed by deception detection (8.2%). We chose these three topics as they represent the most relevant IS research topics (68.3%) and insights. We found very few studies that used AM in the papers on text-based IS use cases. Therefore, to discuss the current state-of-the-art on such practical use cases, we also mention studies by researchers outside of IS. Finally, we discuss our contributions and the limitations of the study.

Text-based IS research topic	**Research opportunities**	**Research questions**
BI - Finance BI - Marketing BI - E-Commerce BI - Human resources	• Text sources (e.g., product reviews or social media posts) contain insights on business indicators that can be analyzed in greater detail with more advanced technologies • Text sources provide large amounts of user feedback that can be inspected in depth and aggregated with more advanced technologies • Formal text sources (e.g., 10-k-filings) contain qualitative information that drive decision making (e.g., on risks) • Long form interview transcripts contain untapped insights on job candidates	• How does AM-derived argument quality predict business indicators (e.g., firm equity value) by data sources (e.g., analyst reports)? • How can organizations aggregate qualitative insights from crowd receptions at scale with AM (e.g., on brands, products or employee satisfaction)? • How can AM be used to drive decision making through argumentative information from texts? • How can recruiters aggregate insights from long form interview transcripts with AM?
Online communities	• Sentiment and persuasiveness of posts influence behavioral outcomes of users on social media • Sentiment and persuasiveness of online reviews influence outcomes • Reviewer writing can be improved with individualized writing support to promote review outcomes • Review response writers can be supported by providing feedback on the used argumentation to promote review response outcomes	• How does AM-derived argument quality predict behavioral outcomes on social media (e.g., information sharing behavior)? • How can writing support systems leverage argumentative features from AM to provide feedback on reviews and review responses? • To what extent can such argument writing support systems improve review and review response outcomes?
Deception detection	• Lack of argumentative soundness might indicate deceptive text such as fake news and reviews	• How can argumentative text features help moderators manually detect and combat deceptive content? • How do argumentative text features influence detection metrics of deceptive content (e.g., fake news and fake reviews)?

Table 4. Preliminary research agenda on potential AM use cases for the text-based IS research topics

Most studies rely on subjective text, expressing varied sentiments in the form of product reviews, posts in online communities as well as news and blog articles. In these sentiment settings especially, the existing predictive approaches can be improved through more quality differentiation between text documents by leveraging supplemental argumentative features. For example, Passon et al. (2018) predict the usefulness of product reviews by counting the number of arguments. Extending this research with more complex argument quality analysis, the persuasiveness of the texts could be scored to yield better prediction accuracy. When employing more complex AM techniques, similar statements can also be clustered over a range of documents and their occurrence counted. In effect, yielding additional features to extend predictive approaches and increasing explainability compared to sentiment approaches, by outlining the effect of individual arguments on the respective metric. Notably, AM is also inclined to explore reasons for these sentiments, enabling researchers to go beyond simple prediction designs. For example, key point analysis can be used to identify important statements and their argumentative foundation from the texts, thus enabling qualitative insights for both practitioners and users. Looking from a different perspective, the explainability and scores on argument quality can be used to support users in writing persuasive text, e.g., by providing feedback on argumentation. These approaches are usually generic to text and therefore applicable on use cases across the boundaries of the individual text-based IS research topics. Next, we go through each topic one by one, provide examples and highlight edge cases.

Business intelligence: The cases of the BI subtopics largely concern text expressing sentiments with varying subjectivity and argumentativeness. They relate to the prediction of metrics on finance, marketing and e-commerce. Hence, the previously mentioned AM methods can potentially be used to improve the prediction accuracy of these metrics and explain the results better. Exemplary in the finance subtopic, studies could investigate the role of specific arguments in news articles on driving firm metrics such as the firm equity value. For e-commerce, researchers could score the persuasiveness of reviews for a given product and then quantifying the effect on product sales or other metrics at scale. For marketing, aggregating similar and key claims as well as premises could provide qualitative insights to explain metrics such as brand perception. In the case of HR, we see less potential for analyzing more structured data like job listings or resumes, because the underlying text is less argumentative and more factual in nature. However, if analyzing less structured interview transcripts or cover letters, an AM approach can help to quantify and aggregate arguments, score persuasiveness and summarize key points.

Online communities: Like the BI topic, the papers on online communities generally operate on textual data expressing sentiments, resulting in similar potential use cases. For example, textual attributes such as argument quality influence review and post outcomes, for example< information sharing behavior (Ha and Ahn 2011) or review usefulness (Passon et al. 2018). In the next step, these metrics can be used to predict and explain the outcomes. According to the literature, when responding to negative reviews, certain text characteristics influence varying success outcomes of the response, including argument strength (Huang et al. 2020). AM can provide argumentative features to writing support systems to help users factor in argumentative characteristics. In a similar vein, users could be supported to write more persuasive reviews.

Deception detection: The use cases on deception detection operate with textual data that is partly argumentative. With regards to fake news, structuring the claims and evidence of such articles might aid algorithms and human fact checkers alike to detect deceptive articles and posts as well as make their argumentative foundations more comparable. For example, looking beyond research on IS, Naderi and Hirst (2018) distinguish deceptive statements in questions and answers in parliament debates using AM. Regarding online reviews, persuasion scores can possibly be used to support the detection of fake reviews. For other tasks, the role of arguments is not clear. This may be the case for deceptions like hate speech and spam that usually put lesser emphasis on arguments. However, a lack of arguments or the use of an incomplete argumentation structure, say a claim without evidence, may indicate deceptive content.

Human computer interaction: For this text-based IS research topic, we did not find general potential for the use of AM since the conversations between user and agent are often inquiry-focused and less argumentative. This is for example the case in customer service or question answering. Also, the setting is markedly different from for example BI settings because usually, in the conversations, only individual text is processed instead of large quantities. Still, in certain niches AM can provide value as was already shown exemplary through the provision of feedback on argumentation in user-written text (Wambsganss, Kueng, et al. 2021). Going further, this approach could be generalized to other writing support systems. In other contexts, when argumentative exchange is needed, the use of AM is feasible as shown by Le et al. (2018)

whose agent is able to discuss controversial topics with users. Adjusting the design to support the learning processes of the users appears feasible. If supplementing the conversation with argumentative data, as for example outlined in the topics on BI, additional value could be realized. For example, recommending products or services based on specific arguments made by reviewers and those with better argument quality could improve recommendation metrics. In these cases, the mentioned metrics on user experience might also be influenced if the provided arguments can improve metrics such as the agent's perceived humanness.

Knowledge management: Arguments play a key role in the theory of the papers when searching for helpful documents and assessing the quality of the knowledge repository, as far as text is concerned. The potentials for AM are twofold. First, the persuasiveness and the argument quality of the existing documents can be quantified to promote and display helpful documents and assess the quality of the repository in its entirety. Second, using explorative AM techniques such as key point analysis could derive important insights from large data sources such as knowledge online communities, social media, and others.

Online trust: Argumentation is also part of theories on promoting online trust. Therefore, argument features extracted from online reviews can potentially be used to make better predictions and explain trust outcomes. Furthermore, argument writing support systems could support users in writing trust-inducing reviews through guiding proper argumentation structure and giving feedback on argument quality. Also, argument features can be used to increase trust by explaining recommendations better, as was also shown in the topic on human computer interaction.

IS security: The role of arguments in the papers vary by use case. Based on theory, arguments are a component of effective information security messages. We suggest that the design of information security messages can be supported through argument writing support systems that help structuring arguments or score persuasiveness. In effect, users could potentially be supported in creating information security messages that are more effective in communicating security risks. We do not see extensive use of predictive approaches in this context due to data not being available in sufficient quantity. For descriptive cases on public filings, key point analyses could be used to collect and summarize important security risk-related statements. For cyber threat identification we do not deduct AM potentials because the used method and data, which is composed of dark net forum posts, does not appear to support argumentation.

Other: The potential of AM for studies in this topic varies depending on the role of subjectivity and arguments in the text. For requirement mining, detected claims could potentially yield insights into what is required and, if needed, why. Government documents may use complicated language and specifically argumentation. Information extracted with AM can then guide users structuring these texts. In the legal domain for example, Moens et al. (2007) derive basic argument components from varying legal texts which, going further, could be used to help law practitioners write more persuasive texts. Regarding the exploration of research articles, we see great potential as scientific text is usually highly argumentative. This is also indicated by multiple studies that use AM with varying complexity to analyze the articles. For example, Lauscher et al. (2018) identify argument components of scientific text from research articles. With more complex approaches, AM could possibly derive additional insights from a large body of research articles replacing or supplementing results from topic modelling approaches, as performed by Jeyaraj and Zadeh (2020). When investigating the adoption of technology, it appears feasible to extend existing approaches by providing additional reasoning or argumentation that is given in the online community posts.

Contributions and limitations

From a theoretical perspective, we make the following contributions. First, we integrate the current literature on potential AM use cases with IS research by classifying the reviewed text-based IS use cases to the IS research topics by Jeyaraj and Zadeh (2020). We also extended the topics to allow researchers to distinguish these use cases with less ambiguity. In doing so, we contribute to the emerging research field of AM by providing a socio-technological viewpoint (Bostrom and Heinen 1977) that has been missing in the previous literature reviews on AM. From a practical perspective, we go through every topic, describe the existing text-based IS use cases and derive potentials for AM respectively. In effect, we guide researchers and practitioners alike to design, compare and evaluate the use of AM for new or existing NLP applications and research streams. These use cases also apply across research disciplines, as indicated by the strong interrelatedness of the papers with respect to finance, marketing and e-commerce. Hence, our study is not just specific to AM and IS research but can also yield insights for other research disciplines. For the three major research topics, we also derive a research agenda that outlines impactful research opportunities and questions which researchers can pick up on to advance the fields of AM and IS. In general, we introduced AM as a method that can be used analyze text in a more nuanced way compared to the traditional methods that are currently used in IS. In effect, we hope that we can motivate IS researchers to familiarize themselves with AM and start using AM methods to advance their own research projects.

Our study contains several limitations that future research can build upon. First, we only focused on scientific literature and IS literature specifically to incorporate a socio-technical perspective for categorizing potential AM use cases in IS. Therefore, only insights on use cases for AM from academia are included. Hence, future research may adjust and extend our text-based IS research topics based on an in-depth analysis of real world use cases. Also, extending the scope beyond IS and investigating interactions with other research disciplines is needed. With our focus on IS, we only considered papers from the AIS Senior Scholars' Basket and the proceedings of the ICIS and ECIS conferences. In consequence, it is possible that less recognized text-based IS use cases were ignored. AM does compete against other NLP subfields if no specific emphasis on argumentation is evident in the underlying use case. To what extent AM can compete and coexist against other contemporary NLP approaches is not yet clear and should be investigated once applications of AM have been tested in research fields like IS more. Finally, the rapid advancement and emergence of AM as a technology might enable new tasks and functionality going beyond those that were described in the theoretical background, resulting in additional potentials that are not yet considered.

Conclusion

To conclude, our results guide researchers and practitioners on potential use cases for AM within IS. For this purpose, we identified 256 articles on text-based IS use cases through a systematic review of IS literature and introduced AM to the IS audience. We then categorized the articles according to our eleven text-based IS research topics based on the general IS research topics created by Jeyaraj and Zadeh (2020). We proceeded with deriving the primary text-based IS use cases for our results. Finally, we discussed the potentials of AM for these use cases and derived a research agenda for the three major topics "business intelligence", "online communities" and "deception detection". With the research agenda, we display impactful research opportunities and questions to advance research on the combination of IS and AM.

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