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Artificial Intelligence in Business: A Literature Review and Research Agenda

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Abstract:

The rise of artificial intelligence (AI) technologies has created promising research opportunities for the information systems (IS) discipline. Through applying latent semantic analysis, we examine the correspondence between key themes in the academic and practitioner discourses on AI. Our findings suggest that business academic research has predominantly focused on designing and applying early AI technologies, while practitioner interest has been more diverse. We examine these differences in the socio-technical continuum context and relate existing literature on AI to core IS research areas. In doing so, we identify existing research gaps and propose future research directions for IS scholars related to AI and organizations, AI and markets, AI and groups, AI and individuals, and AI development.

Keywords: Artificial Intelligence, Information System Research, Research Agenda.

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1 Introduction

The term artificial intelligence (AI) refers to various digital technologies and product capabilities that automate cognitive tasks. More traditionally, researchers used the term AI to describe a study area in the computer science discipline. This research focuses on designing machines that possess human-like levels of intelligence, especially as it relates to the ability to solve complex cognitive problems and learn from the environment (Russell & Norvig, 2010). Researchers have also used the term AI to the intelligent machines themselves and to their capabilities, such as machine learning (ML), logical reasoning, pattern recognition, and natural language understanding (Burgess, 2018). Advancements in basic AI research, increased computing power, and the availability of large volumes of data that one can use to train models have enabled a wide range of commercially viable AI applications (Brynjolfsson & McAfee, 2014). As a result, AI promises to unleash a new wave of digital disruption and create tremendous positive potential for society and the economy (Pradhan, 2017).

According to PricewaterhouseCoopers (PwC), AI will account for up to 14 percent of the growth in global GDP by 2030 (Rao & Verweij, 2018). Championed by technology giants such as Google, Amazon, and Baidu, investments in AI have grown quickly (The Economist, 2017). At the same time, AI start-up funding has risen: over 550 AI startups raised US$5 billion in funding in 2016 alone (CBInsights, 2017). Yet, integrating AI into organizational business processes remains in its nascent form, and a sizable gap between AI ambition and AI execution exists in most companies. In a report, BCG and MIT *Sloan Management Review* found that 91 percent of executives believe that AI will allow their companies to create value in the next five years (Ransbotham et al., 2018). However, only 20% of companies have incorporated AI in some of their processes, and less than 39% of all companies have an AI strategy (Ransbotham et al., 2017).

Like other disruptive information technologies (IT) before it, AI represents a unique research opportunity for IS scholars. AI differs from traditional decision support tools and business intelligence solutions due to its emphasis on action automation. AI also differs from traditional automation-centric IT due to its ability to learn from the environment, adapt, and make decisions on its own, which affords it higher autonomy among incorporating IT artifacts (Russell & Norvig, 2010). The differences between AI and traditional IT inspire myriad research questions, such as:

- In what ways will human interactions with AI resemble or differ from their interactions with traditional IT?
- How will AI influence group and organizational dynamics?
- How should organizations implement and manage AI to maximize value creation?
- What effect will AI have on markets?
- What social position will AI-enabled artifacts occupy?

Researchers have not yet examined most of these questions since as academic AI-related research still primarily focuses on developing and testing specific AI capabilities. We searched for publications in top information systems (IS)[1] journals from 1970 to 2018 and found only 171 publications that explicitly mentioned the term “artificial intelligence” in their titles, abstracts, or keywords. These papers predominantly focused on designing and applying expert and decision support systems, which represent earlier AI technology generations. As such, it seems that behavioral and organizational AI research represents a virtually untapped opportunity for IS scholars.

For IS researchers to seize this opportunity, they need a comprehensive agenda for behavioral and organizational AI research. Such agenda should build on a solid understanding of technical AI research and ensure that behavioral and organizational AI research aligns with the IS academic core and pertains to AI business practice. In this paper, we develop a research agenda by analyzing extant academic and practitioner discourse on AI and examining its relationship to core IS research areas (Benbasat & Zmud, 2003; Sidorova, Evangelopoulos, Valacich, & Ramakrishnan, 2008; Taylor, Dillon, & Van Wingen, 2010). Specifically, we address the following research questions (RQ):

[1] Journals included in the search were *MIS Quarterly*; *Information Systems Research*; *Journal of Management Information Systems*; *Journal of the Association for Information Systems*; *European Journal of Information Systems*; *Information Systems Journal*; *Journal of Information Technology*; *Scandinavian Journal of Information Systems*; *Management Science*; *Decision Support Systems*; *Decision Sciences*, and *Information & Management*

RQ1: What key themes do academic and practitioner publications on AI in business address?

RQ2: How do these themes relate to traditional IS research areas and what directions show promise for future AI in business research?

We address these questions via quantitatively reviewing the relevant research and practitioner publications. We use latent semantic analysis (LSA) to identify key themes that appear in academic and practitioner publications and relate these themes to the core IS research areas that researchers have identified as part of the IS identity discourse (Benbasat & Zmud, 2003; Taylor et al., 2010). Our analysis suggests that the themes in academic AI in business publications skew towards IS development, whereas the themes in the practitioner discourse show more balance across the five core IS research areas. Our results suggest that, by focusing on AI's behavioral and organizational aspects, IS researchers will be able to make a significant contribution to theory and practice.

This paper proceeds as follows: in Section 2, we summarize important AI concepts and briefly review AI discipline's evolution. In Section 3, we review key IS identity frameworks and summarize core IS research areas that we identified in the extant literature. We also outline the assumptions and principles we relied on as guidance to develop an AI research agenda that aligns with the IS academic core and pertains to AI business practice. In Section 4, we describe the quantitative literature review we conducted, which includes how we collected and analyzed data, and summarize the key themes that we identified in the analysis. In Section 5, we relate the themes we identified in the practitioner and academic AI in business discourse to the core IS research areas and offer suggestions for future directions for organizational and behavioral AI research. In Section 6, we conclude the paper.

2 What is AI?

One cannot easily define AI because the term encompasses various underlying technologies that have changed over time. This evolution in technical composition, combined with AI researchers' varied goals, results in numerous definitional approaches which differ in their specificity (Wang, 2008). Contemporary definitions center on "a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019, p. 17). The intelligent agent concept has a central position in AI research and practice. In AI research, an agent refers to "anything that can be viewed as perceiving its environment through sensors and acting upon that environment through actuators" (Russell & Norvig, 2010, p. 34). A rational agent seeks to optimize its performance measure and selects the best available actions given the available information about the environment. An intelligent agent learns about its environment and the effect that its own actions have on the environment. In addition, an intelligent agent uses available information to make optimal action choices and to execute the actions. Therefore, from the computer science theory perspective, one can view an intelligent agent as an IT artifact that exhibits high autonomy due to its sensing, learning, decision making, communication, and acting capabilities. However, in practice, organizations typically deploy AI agents as components of larger IT systems embedded in organizational business processes, which constrain any singular intelligent agent's autonomy. As a result, one can best view AI agents as components of AI-human labor platforms on which they can conduct various roles, such as substituting for human actors, augmenting human activities, or working collaboratively with humans in human-AI assemblages (Rai, Constantinides, & Sarker, 2019). IS researchers typically focus on these capabilities that distinguish AI since they will likely influence human-AI interactions' psychological, social, and economic aspects and AI's social and organizational positions.

The active role that AI plays in knowledge creation (which ML enables) and application constitutes the key differentiating characteristic between traditional IT and what researchers commonly refer to as IS. Researchers conceptualize machines' ability to learn as a key AI component before coining the term itself. In his seminal paper "Computing Machinery and Intelligence", Alan Turing conjectured that machines should be able to emulate a child's learning process (Turing, 1950), and researchers originally defined AI with reference to learning along with automated reasoning and communication capabilities (McCarthy et al., 1955). Notably, learning has not always driven AI research and practice. Early commercially successful AI incarnations, such as expert systems, relied on a complex array of rules that codified human knowledge and mimicked human reasoning. However, the rule-based approach's limitations became evident as attempts to apply AI to more complex problems and more dynamic environments failed to achieve desirable results, which gave way to statistical approaches to knowledge acquisition and application known as machine learning.

ML-based AI follows the following underlying principles: 1) automate the knowledge-creation task through ML algorithms, 2) represent knowledge as mathematical models that computer applications can easily understand, and 3) subsequently use the resultant knowledge representations for cognitive task automation. The four basic ML algorithm types include supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. These algorithms, individually or in combination form the foundation of most today's AI capabilities and applications, such as image recognition, natural language processing, prediction and forecasting, pattern and anomaly detection, and others (Jordan & Mitchell, 2015).

Supervised learning represents the most widely used approach to AI development at the present time. With supervised learning, one trains models by mapping a set of input variables into the output variables (labels) that one provides as a part of the training data set. Example supervised ML algorithms include linear and logistic regression, decision trees, ensemble learning algorithms (e.g., boosted trees and random forests), support vector machines (SVMs) and artificial neural networks. Artificial neural networks are computational networks that can learn, solve complex problems, and make decisions in a humanlike manner via simulating the neuron network in the brain (Daniel, 2013). One typically trains artificial neural networks through supervised learning approaches.

In unsupervised learning methods, one uses statistical or case-based algorithms to identify data's structural properties. We can broadly separate unsupervised algorithms into clustering and dimensionality reduction algorithms (Murphy, 2012). Semi-supervised learning blends supervised and unsupervised learning methods as it uses both labeled and unlabeled data for training (Zhu & Goldberg, 2009). In reinforcement learning, the algorithms learn by going through trial and error in order to maximize expected rewards (Sutton & Barto, 1998). Commercial AI applications in use today are typically built on one or more ML approaches and often use specialized model architectures. Computer vision, an AI subdiscipline, deals with building algorithms that can analyze, interpret, and understand the visual world (Szeliski, 2010), and today's computer vision applications predominantly rely on convolutional neural networks trained through supervised learning (Géron, 2017). Similarly, organizations build NLP applications through both supervised and unsupervised ML approaches in combination and use recurrent neural networks, a special type of deep neural network architecture (Hirschberg & Manning, 2015).

Due to AI's active role in knowledge creation and application and due to its anthropomorphic properties (e.g., autonomy and rationality), many expect AI to occupy a distinct position in organizations and in human society. The IS discipline has a strong ability to play the leading role in helping organizations and individuals to adapt to AI's rise by building on the rich and diverse scholarly tradition in understanding human interactions with digital technologies. In Section 3, we focus on placing AI research in the broader IS scholarship context based on the assumption that the IS discipline requires it to conduct a leadership role in this area.

3 Positioning AI in the IS Research Context

3.1 The IS Research Landscape

The IS academic discipline occupies the research space at the intersection of engineering and organizational studies. IS research draws from and contributes to disciplines such as computer science, software engineering, business process management, information science, psychology, sociology, management, marketing, economics and others (Grover et al., 2006; Wade et al., 2006). Thus, topical and methodological diversity unsurprisingly characterizes IS research (McCrohan et al., 2010; Robey, 2003; Sidorova et al., 2008). Debates about the IS discipline's identity and topical diversity's value have played an important role in shaping the current state of IS research and defining expectations about what constitutes an IS research contribution. Due to these debates, several integrative frameworks that define IS research's core have emerged. The IT-centric view of the IS discipline places the IT artifact at the center of the IS nomological net and suggests that IS research should focus on topics that directly relate to IT management, usage, and impact (Benbasat & Zmud, 2003). The interactionist view of IS research recognizes the IT artifact's importance but suggests that IS research truly focuses on the interaction between IT and humans/their collectivities. As such, this view sees the IS discipline as focusing on "how IT systems are developed and how individuals, groups, organizations, and markets interact with IT" (Sidorova et al., 2008, p. 475). Taylor et al. (2010) reconciled the two views. They considered them as representing different evolutionary stages of IS research and suggested that "the core interest of the discipline has become more system- and relationship-oriented around the 'nature of work that surrounds

IT'…than specifically addressing the IT artifact" (pp. 661-662). Such a perspective concurs with viewing the IS discipline as spanning the continuum from primarily technical to primarily organizational research, and some authors have called for research contributions at the continuum's center (i.e., the interactions between the technical and the social) (Sarker et al., 2019).

While research has shown the IS discipline to possess a relative stable core of research areas, topical diversity also characterizes these research areas, which allows the IS discipline to evolve and to respond to practitioners' demands and embrace fast changes in information technology (Sidorova et al., 2008; Taylor et al., 2010). Due to the IS disciplinary core's plasticity, IS scholars adapted their theoretical repertoire and methodological toolkit to examine research questions that arose when new IT classes emerged, such as business intelligence and social media platforms. Each new IT application serves as a case for validating and refining theories about how humans and organizations develop, appropriate, and use IT and IT's individual and organizational consequences. In such a context, AI represents a unique opportunity for IS researchers to test existing theories' limits, develop new ones, and, thus, offer theoretically grounded insights about AI appropriation, use, and consequences to practitioners.

3.2 Balancing the Demands of an Applied Academic Discipline in Behavioral and Organizational AI Research

We can define a research agenda as a conceptually grounded and internally consistent set of research questions. In the IS discipline, such an agenda's value depends on its legitimacy with IS researchers. Achieving such legitimacy requires transparency about its underlying assumptions and goals and the process by which researchers developed it. In this section, we outline our assumptions and the process we followed to arrive at the AI in business research agenda that we propose here. In developing an agenda for AI research in the IS discipline, we make the following assumptions:

A1: Organizational, behavioral, and design science AI research has better theoretical grounding and methodological rigor if it aligns with the IS research core..

We make the first assumption based on the perspective that sees theory development as the key goal of science (Kerlinger & Lee, 2000) and based on the fact that, despite the excitement surrounding new IT classes, the academic community evaluates research based on its contribution to theory (Benbasat & Zmud, 1999; Rosemann & Vessey, 2008). In IS research, different research areas feature unique theoretical repertoires and include organizational, behavioral, and design theories. For example, research on IT and individuals rely on individual-level theories often derived from psychology and organizational behavior, whereas research on IT and organizations relies on organizational-level theories often derived from sociology, organizational studies, and strategic management. Design focused studies may draw on from computer science and mathematical theories in order to build new technologies and artifacts. As organizational and behavioral AI researchers seek to identify a theoretical tradition to guide their efforts, formulating their research questions in a way that is aligned with the IS research core would help them identify relevant theories and produce theoretically grounded research studies.

A2: Organizational, behavioral, and design science AI research has better practical relevance if it aligns with business practitioners' interest in AI.

We make the second assumption based on viewing IS as an applied academic discipline that features pressure to address business and IS practitioners' needs in addition to pursuing theory development (Taylor et al., 2010). Hence, evaluating IS research invariably involves practical relevance (Baskerville & Myers, 2004; Lee & Baskerville, 2003; Rosemann & Vessey, 2008). Therefore, in developing an organizational and behavioral AI research agenda, one needs to ensure that the questions it includes pertain (if not immediately so) to the business and IT management community.

Importantly, we do not suggest that differences in topics and their associated conversational intensity between academics and practitioners are good or bad. Rather, one would logically expect the discourse in these two communities to differ. For instance, IT practice often focuses on proximal operational concerns, whereas academia may focus on examining more theoretical and, consequently, more distal issues. However, we argue that identifying differences between the discourse in each community may, in some circumstances, highlight opportunities for mutually beneficial future research.

Consistent with the above two assumptions, we adopt an agenda-development process to ensure that the organizational and behavioral AI research agenda both align with the IS research core and AI and business practitioners' needs. We first separately analyze academic and practitioner discourse on AI in business and identify key themes in such discourse through an LSA study. We then relate the themes that we identified from the academic AI discourse to the themes that we identified from the practitioner AI in business discourse and to core IS research areas to pinpoint potential research gaps. Finally, drawing on the identified research gaps and practitioner interest, we propose a general research agenda and illustrate it with sample research questions. We limited the analysis to AI in business research for two primary reasons. First, the IS discipline has traditionally aligned well with other business academic disciplines; thus, a research agenda that focuses on the AI in business will likely pertain the most to the majority of IS academics. Second, by limiting our scope to AI in business, we ensure that we can become sufficiently familiar the application domain in order to adequately interpret the findings and draw meaningful conclusions.

4 Understanding AI in Business Discourse: An LSA Study of Academic and Practitioner Literature

In this section, we discuss the LSA study we conducted to discover key themes in the academic and practitioner discourse on AI in business. First, we discuss how we collected data and describe the LSA methodology. Then we separately discuss the results we obtained from analyzing academic and practitioner publications and each identified theme.

4.1 Data Collection

To comprehensively understand the academic and practitioner AI in business discourse, we searched EBSCOHost (a reference resource that supplies a fee-based online research service with 375 full-text databases, a collection of 600,000-plus e-books, subject indexes, etc.) and ProQuest (which provides content collections that encompass 90,000 authoritative sources, six billion digital pages, 20 million newspaper papers; it also includes collections of the world’s most important scholarly journals and periodicals, more than 450,000 eBooks, and other historical collections (ProQuest, 2018)) for academic and practitioner literature that used the term “artificial intelligence” and “business” in their titles, abstracts, keywords, or main content and had a publish date from 1998 to 2017. Given applied, organizational, and behavioral AI research’s emergent and interdisciplinary nature, we chose a keyword-driven rather than journal-driven approach to identify publications. This approach ensured we included relevant AI literature published outside traditional IS journals. In ProQuest, we searched Business Source Complete, a scholarly business database, to identify AI in business academic publications. To identify AI in business practitioner publications, we searched the ProQuest business database, which covers publications on the latest business information for researchers of all levels. Rather than making subjective decisions about journals’ nature as academic or practitioner, we relied on how ProQuest classified publications.

Since we sought to compare AI in business academic and practitioner discourse, we conducted two separate searches that resulted in two distinct textual corpora: the academic corpus and the practitioner corpus. For the academic corpus, we restricted our search to only academic papers. The academic corpus included 1,330 academic paper abstracts. Example academic journals in the dataset included *Communication of the ACM*, *AI Communication*, *Decision Support Systems*, *European Journal of Operational Research*, and *Journal of Management Information Systems*. For the practitioner corpus, we restricted our search to articles in newspaper, magazines, websites, and trade journals. The practitioner dataset contained 2,244 non-academic article abstracts. Example periodicals in the practitioner corpus include *AI magazine*, *Business & Finance Week*, *Business Week*, *Forbes*, *Financial Times*, *Marketing Weekly News*, *Wall Street Journal*, etc. We list document sources in detail in Appendix A.

As we note in Section 2 different communities have used the term AI to mean different things in different contexts. For instance, some have taken a highly conceptual perspective and viewed it a quest to replicate consciousness, while others have viewed it more practically as a collection of specific algorithmic approaches that one can use to complete certain cognitive tasks at a specific point in time. In this paper, we adopt the view that terms and their meaning are socially constructed and evolve over time (Wenger, 1999). Thus, rather than defining AI a priori and screening papers based on adherence to that standard, we adopted a subjective, interpretive approach and allowed the business-relevant AI definition to emerge from how the academic and practitioner communities have used it.

4.2 Latent Semantic Analysis

To identify key topics in AI in business publications, we employed LSA, a text-mining technique that one can use to represent the text's semantic meaning by applying dimensionality reduction techniques to large corpora (Landauer & Dutnais, 1997). LSA computes the similarity among terms and documents by associating terms with the contexts in which they co-occur and, thus, mimics the way the human brain approaches cognitive tasks, such as word categorization, sentence-word semantic priming, and essay quality judgments (Evangelopoulos, 2013; Landauer et al., 1998). LSA assumes that what each passage or text means relates to patterns of presence or absence of individual words. In LSA, one models a text corpus as a set of mutual equations that largely determine the extent to which words and word sets resemble one another in meaning (Evangelopoulos et al., 2012). Recent research has applied LSA to identify topics in unstructured text such as online reviews and paper abstracts (Kulkarni et al,, 2014; Sidorova et al., 2008).

We performed LSA with varimax rotation separately on two corpora (i.e., one academic corpus and one practitioner corpus) using SAS Enterprise Miner 15.1. To conduct this analysis, we followed best practices in applying LSA to analyze academic literature (Evangelopoulos et al., 2012; Sidorova et al., 2008). We relied on SAS default settings for text tokenization, which resulted in most terms being individual words with a small number of persistent phrases such as "neural networks" captured as bigrams. After we tokenized the documents, we applied term filtering using a frequency-based stop list that comprised common English words that SAS provided in conjunction with a custom stop list designed to exclude common terms specific to our context and, therefore, that did not usefully differentiate between topics. We weighted terms using the log-entropy approach after which we performed dimensionality reduction. The dimensionality one chooses for an LSA solution determines the abstraction level of topics in the corpus. While mathematically driven approaches to determining the number of dimensions exist (e.g., approaches that rely on eigenvalue threshold or change-point analysis), the final solution's interpretability often constitutes the determining factor in dimensionality decisions in using LSA to analyze literature (Sidorova et al., 2008). In preliminarily analyzing the data, we identified interpretable semantic structures at both five factors (that corresponded to high-level areas in the AI and business discourse) and 20 factors (that represented more specific discourse themes). In order to interpret and label the extracted topics, we examined high-loading terms and documents (abstracts) that corresponded to each topic. Furthermore, to ensure we could compare the academic and practitioner discourses, we created idealized documents that represented each of the 20 practitioner and academic topics (i.e., 40 ideal documents in total). We created each ideal document by including the top ten terms that loaded on the corresponding factor; we determined each term's frequency based on the term loading's magnitude. The overall size of each ideal document corresponded to the average length of the documents in the respective corpus. To identify the degree to which the academic literature addressed each practitioner topic, we amended the academic corpus to include the 20 ideal practitioner documents. We then reran the LSA analysis and identified which ideal practitioner documents loaded on each of the 20 academic factors. We repeated this analysis with the practitioner corpus and ideal documents that represented the academic topics. Including ideal documents led to a minor shift in the factor order and the terms and documents that loaded on each individual factor, although the factors' general structure and nature remained unchanged. Labeling and interpreting topics constitutes an inherently subjective process, and we used an iterative, collaborative approach to label topics as researchers have commonly done when applying LSA to review literature (Evangelopoulos et al., 2012; Sidorova et al., 2008). The topics identified below reflect the LSA topic structure extracted after the inclusion of the ideal documents. We present the topic labels that corresponded to the LSA solutions before we included the ideal documents in Appendix B.

4.3 Literature Analysis

4.3.1 Themes in AI in Business Academic Research

Table 1 presents high-loading terms that corresponded to the top five topics in AI in business academic research: 1) neural networks and forecasting model, 2) AI, humans, and society, 3) algorithms for problem solving, 4) machine learning and data classification, 5) decision support systems and knowledge management.

Table 1. Top Five Topics in Academic Literature

Topic ID	Topic label	Top terms
A01	Neural networks & forecasting model	neural,+network,+forecast,+neural network,financial
A02	AI, humans and society	+human,+technology,intelligence,+ai,social
A03	Algorithms for problem solving	+constraint,+problem,+algorithm,+solution,+schedule
A04	Machine learning and data classification	learning,+classification,+machine,data,+text
A05	Decision support systems and knowledge management	+system,+decision,knowledge,+support,+process

We analyzed the trends in AI in business academic research based on the total number of publications that corresponded to each topic during different periods. This approach offers insights into the dynamics of academic research during the past 20 years. We summarize our results from the trend analysis in Table 2, which shows paper counts by topic by five-year period, and Figure 1, which graphically illustrates publication trends. While the publication counts for all topics increased in the 1998-2002 period, the top five topics' popularity trajectory diverged sharply in from 2003 to 2017. Interest in decision support systems and knowledge management peaked in the 2003-2007 period, while interest in algorithms for problem solving peaked in the 2008-2012 period; however, the interest in both topics declined in subsequent years. Research on neural networks and forecasting models remained relatively steady in the two middle decades and experienced a slight decline in the 2013-2017 period. The rise in publications related to machine learning and data classification more than offset the decline in research on neural networks and forecasting models, which may signal a shift from a more algorithmic view of AI to a more applied one. Finally, research on AI, humans, and society exhibited steady growth throughout the periods before rising sharply in the 2013-2017 period, which indicates growing interest in AI's non-technical aspects.

Table 2. Topic Labels and Paper Counts for AI-related Business Research

Topic ID	Topic label	Paper count			
		98-02	03-07	08-12	13-17
A01	Neural networks & forecasting models	28	53	52	41
A02	AI, humans and society	15	35	53	107
A03	Algorithms for problem solving	13	41	78	61
A04	Machine learning and data classification	10	49	51	90
A05	Decision support systems and knowledge management	40	100	59	42

We can glean additional insights from the top 20 topics in the AI in business academic discourse to understand the topics this discourse has addressed at a finer grain (see Table 3). While some high-level topics, such as AI, humans, and society, have close analogs on the 20-topic list, the list of terms associated with these topics points to a narrower focus. For instance, two separate topics represent the decision support systems and knowledge management high-level topic. Similarly, data classification emerged as a distinct topic from the machine learning and data classification high-level topic, while machine learning contributed to more focused topics such as big data analytics and AI in financial services and to the broader learning topic. Finally, several lower-level topics emerged that focused on specific application AI areas, such as network service quality, autonomous agents, and AI in manufacturing. These lower-level topics help one better understand the high-level AI-in-business academic discourse themes.

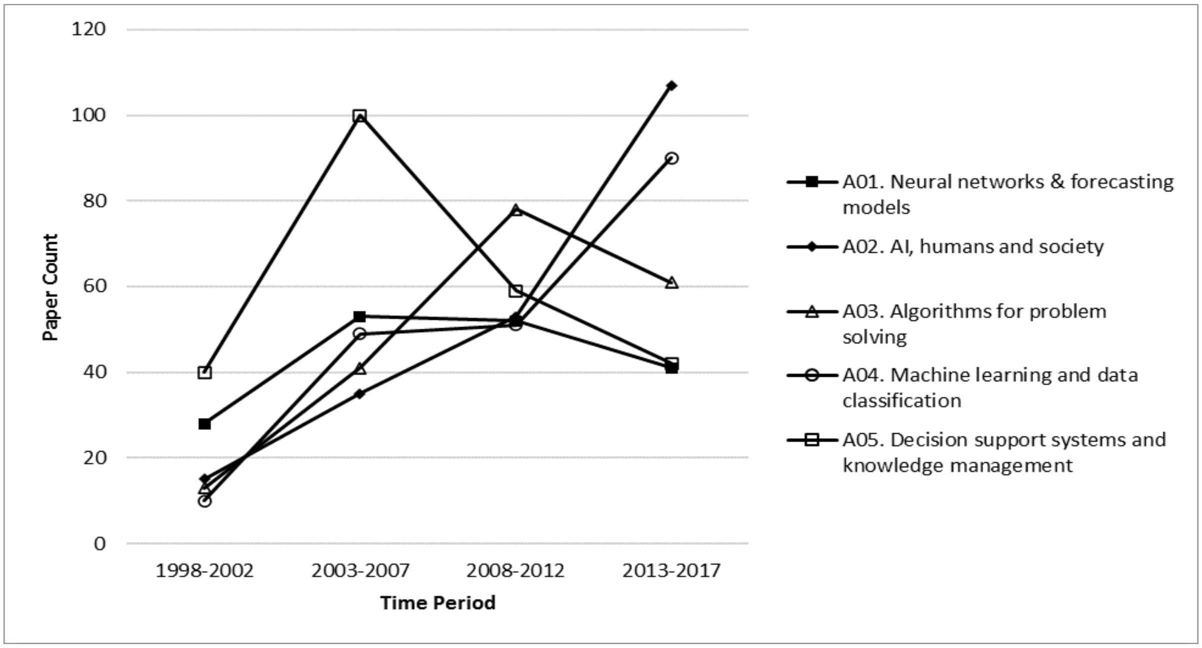

Figure 1. Trends in Academic Publications about AI and Business

Table 3. Top 20 Topics in the Academic Literature

ID	Topic label	Top terms
1	Academic research method	+research,+review,+implication,+methodology,+purpose
2	Artificial neural networks	neural,+network,+neural network,+forecast,+model
3	Problem formulation	+problem,+algorithm,+optimization,+search,+solution
4	Classification	+classification,+feature,+classifier,learning,data
5	Search and information retrieval	web,+search,+text,information,+content
6	Network service quality	+service,+network,qos,+traffic,+control
7	Decision support systems	+decision,dss,+support,+decision support system,+group
8	Autonomous agents	+agent,+multi-agent,+multi-agent system,+mechanism,autonomous
9	Case-based reasoning	+case-base,reasoning,cbr,+case,retrieval
10	Production and job scheduling	+schedule,+constraint,+time,+job,+production
11	AI and manufacturing	manufacturing,+control,+process,+production,intelligent
12	AI for stock market prediction	financial,+price,+market,+stock,+trade
13	AI in supply chain management	+supply,+chain,+supply chain,management,+supplier
14	Big data analytics	data,learning,analytics,+big,+machine
15	Learning	learning,+student,+university,+machine,machine learning
16	Human-AI interaction	+human,+robot,+ai,+people,+computer
17	AI and customer service	+product,+customer,+service,+market,manufacturing
18	Expert systems	+expert,+rule,+expert system,knowledge,fuzzy
19	AI in financial services	financial,+machine,+prediction,+bank,+risk
20	Knowledge representation	+language,knowledge,+ontology,+model,+process

In order to better understand the composition of the key academic research areas, we mapped the 20-factor solution topics to the five-factor solution topics by counting the number of documents that loaded on a particular five-factor topic and also on each 20-factor topic. Then, for each five-factor topic, we identified the top three most relevant 20-factor topics, which we depict in Figure 2. IS discipline identity research has previously used this approach to mapping more granular topics into more general ones (Sidorova et al., 2008). Notably, some 20-factor topics appeared in the top-three most relevant factors for more than one five-factor topic, whereas several other 20-factor topics did not make it into the top three list for any of the five-factor topics. As for why, the five-factor solution and the 20-factor topics that mapped strongly to it may represent paradigmatic (or Mode 1) research, which focuses on developing a robust theoretical basis (Taylor et al., 2010). Thus, as a natural continuation, the 20-factor topics that did not map strongly into the five-factor solution would represent non-paradigmatic research and, as such, may indicate practice-focused research (e.g., AI in marketing) or theory-focused research that does not subscribe to the dominant paradigm (e.g., case-based reasoning research). Overall, the way the five-factor solution maps to the 20-factor solution points to the AI in business academic discourse's techno-centric, solution-oriented nature.

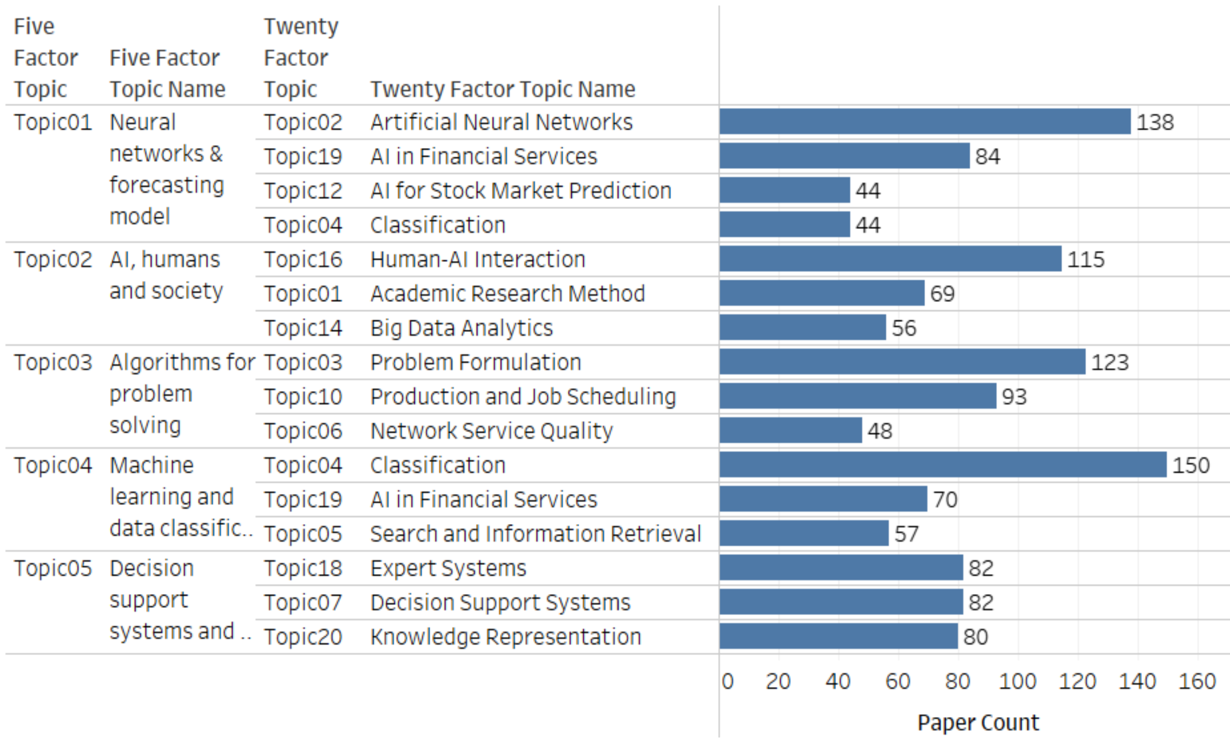

Figure 2. Academic Five-factor to 20-factor Mapping

4.3.2 Exploring AI in Business Academic Themes

Neural networks and forecasting models: algorithmic developments in machine learning (specifically in using deep neural networks (DNN) to predict and classify problems) have fueled renewed interest in AI in the 21st century. In the AI in business context, research efforts have focused on examining whether neural network models, such as DNN, can feasibly address certain business problems; in particular, this research has frequently examined forecasting models. In the 1998-2002 period, neural networks and forecasting models topic appeared as the second most popular topic in the AI in business academic research. Authors applied neural networks to business problems such as financial market predictions (Ko et al., 2001; Tan & Dihardjo, 2001), stock index forecasting (Wang et al., 2012), production scheduling (Metaxiotis & Psarras, 2003), corporate acquisitions (Ragothaman et al., 2003), fashion retail forecasting (Au et al., 2008), and direct marketing (Cui & Man, 2004). Neural networks and forecasting models remains a key topic in AI business research as organizations continue to use neural networks to improve their products, operations, and overall performance.

AI, humans, and society: an umbrella theme in AI in business research, AI, humans, and society covers research into the non-technical aspects of AI development, implementation, and use. As early as late

1990s, social scientists and futurists made predictions about the impact that AI would have on the human condition and the blurring boundary between humans and machines (Kurzweil, 1999; Pearson, 2000). Some early empirical investigations focused on AI economics, such as work that investigated the relationship between AI spending and the performance of high-technology economy sectors (Gebhardt, 2002). In the early 2000s, research into AI's social impact focused on specific areas of human activity, such as education (Xu & Wang, 2006), e-commerce, and personalized online advertising (Adams, 2004). As widespread AI adoption became a more tangible prospect in the mid-2000s, general human-AI interaction issues gained prominence, such as trust, security, and regulation (Fasli, 2007); the effect that automation has on labor and creative work (Brown, 2006); and the possibility that machine intelligence could surpass human intelligence (Bell, 2003). The emergence of a wide variety of commercially available intelligent IT applications elevated interest in intelligent digital technologies' moral and ethical implications, which authors have examined from a both top-down ethical theory perspective and a bottom-up goal-setting perspective (Wallach et al., 2008). Such investigations have addressed AI's legal status as a person (Calverley, 2008; Torrance, 2008), responsibility and accountability for AI actions (Johnson, 2015), and the effects that human-machine collaboration have on workplace dynamics (Hirsch, 2017).

Despite growing attention that researchers have paid to AI, humans, and society, we believe that this research area remains in its nascent form. As AI applications expand in scope and variety, we expect researchers to pay more attention to AI's behavioral, organizational, and societal aspects, which will give rise to several related research streams.

Algorithms for problem solving: AI applications rely on several types of computer algorithms, and efforts to develop and refine these algorithms form the core of basic AI research. In the AI in business discourse, algorithmic research focuses on developing optimization and machine learning algorithms for solving specific business problems. As ML algorithms and computing capabilities increased in sophistication from the early 2000s to 2010, the focus shifted from traditional operations problems such as production scheduling (Ottaway & Burns, 2000; Schmidt, 1998) and dynamic vehicle routing (Savelsbergh & Sol, 1998) to less tractable business questions such as strategy evaluation and selection (Ozfirat & Ozkarahan, 2010), and algorithmic choices broadened to include genetic algorithms (Sadegheih & Drake, 2011), artificial bee colony algorithms (Szeto et al., 2011), heuristic algorithms (Burke et al., 2006), and so on. In the mid- and late 2010s, interest shifted to ML and deep learning algorithms, which emerged as a distinct research area that took attention away from non-ML algorithms.

Machine learning and data classification: machine learning refers to machines' ability to learn from experience. In practice, today's ML approaches rely on iteratively developing and refining mathematical models that one uses to then represent relationships among data (SAS, 2018). Although early research on using statistical machine learning to address business problems emerged in late 1990s (Mitchell, 1999; Piramuthu et al., 1998), interest in the topic picked up in mid-2000s as people began applying statistical ML algorithms to develop ML-driven recommendation and search agents and evaluate their impact on user experiences and business outcomes (Aresti et al., 2007; Huang et al., 2004). In the mid-2010s, research on ML applications expanded to business areas such as tax law (Alarie et al., 2016); quality assurance (Ko et al., 2017), accounting and auditing (Dbouk & Zaarour, 2017), and customer analytics (Wang et al., 2013). We expect this topic to maintain its popularity due to the emergence of deep learning and reinforcement learning algorithms and the need to examine their relative performance and efficacy in relation to different business tasks and applications.

Decision support system and knowledge management: this topic combines two distinct but related research areas that both relate to knowledge representation in AI. DSS and KM have their roots in the idea that knowledge creation constitutes a uniquely human endeavor but that machines can help them curate and apply knowledge by making such knowledge more readily accessible in the decision-making process (Hess et al., 2000). In the AI in business context, research has focused on developing software agents and architectures to support organizational knowledge curation and use (Rao et al., 2012) and to support complex organizational decisions, such as strategy formulation or process evaluation (Kathuria, Anandarajan, & Igbaria, 1999). KM and DSS research has emphasized handcrafted and human-readable knowledge, an approach that characterized the first AI wave. As big data emerged and research interest shifted to statistical ML methods, the interest in KM and rule-based DSS declined and gave way to ML-based approaches and techniques (He et al., 2014; Carneiro et al., 2013).

4.3.3 Themes in AI in Business Practitioner Articles

To gauge how the practitioner AI in business discourse has evolved, we extracted and labeled the top five and top 20 topics from the practitioner AI in business corpus. We followed the same procedures for topic extraction and labeling as we used to identify research topics. Table 4 presents labels and highly loading terms corresponding to the top five topics: 1) machine learning and data analytics, 2) AI-enabled systems, 3) the AI industry, 4) AI for digital transformation, and 5) advances in AI research.

We analyzed the trends in AI in business practitioner publications based on the total number of publications in practitioner corpus corresponding to each topic during different periods. The results illustrate the changes in the AI in business practitioner discourse during the past 20 years. We summarize the results in Table 5, which shows paper counts by topic over time, and Figure 3, which graphically illustrates these trends.

Most notably, we found much fewer practitioner publications compared to academic publications during the first three five-year periods, though their number spiked during the 2013-2017 period. Of the five topics, we found fewer than 15 publications for three (machine learning and data analytics, the AI industry, and AI for digital transformation) prior to 2013. The two other topics (AI-enabled systems and and advances in AI research) had a steady but relatively low number of pre-2013 practitioner publications. The sharp increase in the number of publications in the 2013-2017 period occurred across all practitioner publication topics, though we observed the steepest increase in publications on machine learning and data analytics and on AI for digital transformation. This sharp increase in interest in AI in business stands in stark contrast to the relatively steady interest in the topic in the academic community.

Table 4. Top Five Topics in Practitioner Literature

Topic ID	Topic label	Top terms
N01	Machine learning and data analytics	data,+learning,+machine,analytics,machine learning
N02	AI-enabled systems	+system,+network,+agent,+model,+decision
N03	The AI industry	google,apple,amazon,facebook,microsoft
N04	AI for digital transformation	digital,+market,+service,+customer,+industry
N05	Advances in AI research	+university,+research,+robot,+ai,+computer

Table 5. Topic Labels and Paper Counts for AI-related Business News

Topic ID	Topic label	Paper count			
		98-02	03-07	08-12	13-17
N01	Machine learning and data analytics	0	4	3	323
N02	AI-enabled systems	43	48	54	144
N03	The AI Industry	3	2	7	266
N04	AI for digital transformation	5	0	4	348
N05	Advances in AI research	15	36	34	235

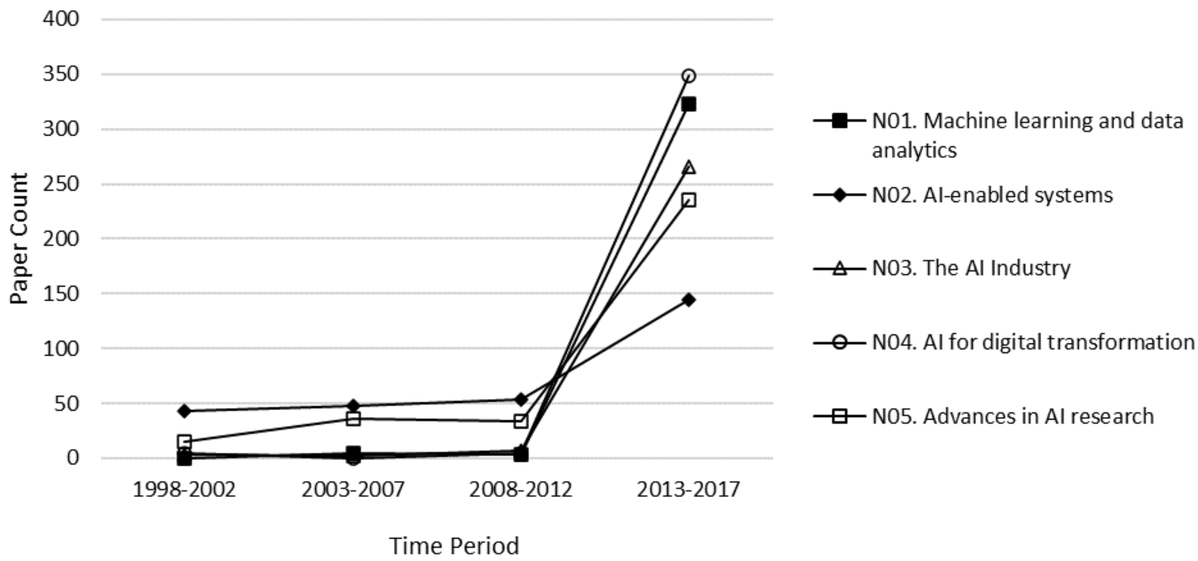

Figure 3. Trends in Practitioner Publications about AI and Business

We present the top 20 topics in practitioner literature in Table 6, which highlights key themes in the AI practitioner discourse. These topics illustrate the topics this discourse has addressed at a finer grain. Unlike academic topics that often focused on classes of business problems, many topics in the practitioner discourse focused on specific industry players, such as IBM, Nvidia, Baidu Google, Amazon, Microsoft, and Apple. The 20-topic view highlights several points of convergence between academic and practitioner AI-in-business research. These points of convergence include research in neural networks, big data and financial applications of AI.

Table 6. Top 20 Topics in Practitioner Literature

ID	Topic label	Top terms
1	Academic AI research	+university,+research,+science,+student,+school
2	Machine learning	+learning,+machine,machine learning,+cloud,digital
3	Modeling problems	+problem,+job,+schedule,+constraint,+model
4	Big data analytics	data,analytics,+big,+learning,+science
5	AI vendors	google,amazon,apple,alphabet,microsoft
6	AI hardware market	nvidia,+chip,+stock,+price,nvda
7	NLP	+language,natural,natural language,+process,+learning
8	IBM Watson / cognitive computing	ibm,watson,cognitive,health,jeopardy
9	Autonomous vehicles	+car,+vehicle,autonomous,+self-drive,+system
10	AI industry news and events	+agent,+conference,+workshop,news,+award
11	Digital transformation consulting	accenture,digital,+industry,+future,percent
12	AI in China	baidu,+search,chief,+company,china
13	AI in financial services	financial,+bank,+risk,+service,insurance
14	Artificial neural networks	+network,neural,+neural network,+model,social
15	AI in supply chain management	+supply,+chain,management,+supply chain,+plan
16	AI ventures and startups	+fund,+investment,+venture,capital,+start-up
17	AI and marketing	+customer,+market,+product,+brand,+experience
18	Intelligent agents	+ai,+system,+agent,+decision,intelligence
19	AI-based automation	automation,+service,wipro,+award,+announce
20	Human-AI interactions	+human,+robot,+computer,+machine,+people

As before, we mapped the 20-factor solution topics to the five-factor solution topics and identified the top three 20-factor topics for each five-factor topic, which we show in Figure 4. Again, some 20-factor topics appeared in the top-three lists for more than one five-factor topic, whereas some others did not make it into the top-three list for any five-factor topic. Although the notion of paradigms is not commonly used to describe practitioner discourse, we can view each topic in the five-factor solution as representing a community of practice (Wenger, 1999). We can view each topic in the five-factor solution as representing a community of practice (Wenger, 1999). Accordingly, we can interpret the five-factor topics as corresponding to five communities of practice: 1) ML and analytics professionals, 2) executives and digital transformation consultants, 3) industry analysts and investors, 4) marketing and customer service professionals, and 5) AI thought leadership and the R&D community. We can view the 20-factor solution topics that map to more than one five-factor topic as community-spanning topics, and we can view topics that map strongly to specific five-factor topics as representing the core practice in the community.

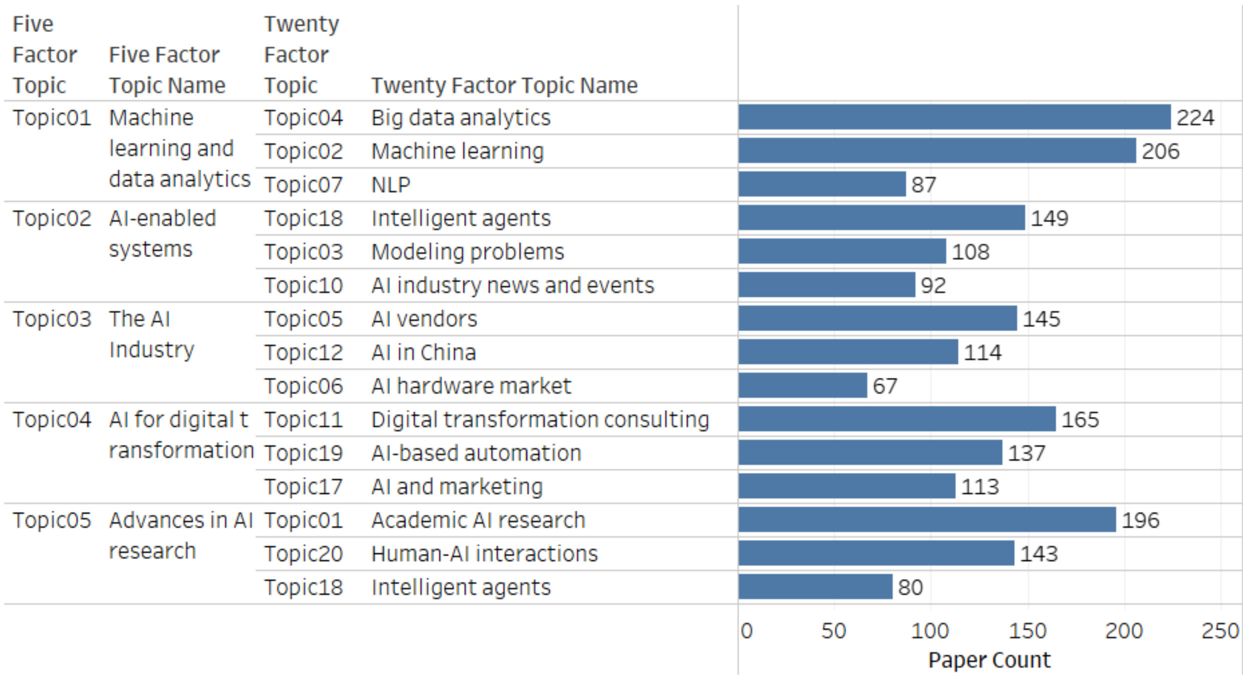

Figure 4. Practitioner Five-factor to 20-factor Mapping

4.3.4 Exploring AI in Business Practitioner Publications

Machine learning and data analytics: practitioner interest in machine learning and data analytics (ML and DA) started to emerge in early 2000s and entered the mainstream by the mid-2010s thanks to the increased availability of organizational data (big data), technological breakthroughs in big data and ML technologies, and the release of several big data analytics tools and platforms (Fontana, 2004). By the late 2010s, organizations increasingly used ML to analyze large, diverse datasets in order to make more accurate and faster predictions (Branscombe, 2017). In particular, the financial services and telecommunication industries stood out as leaders in leveraging ML and DA for financial analytics and high-frequency trading (Eastwood, 2017). Some players in financial services use clickstream analysis, real-time website content customization (McGeer, 2017), and IoT analytics for operational decision-making (Slowey, 2017). We expect practitioner interest in this topic to continue as more companies across industries embrace ML and algorithm-driven decision making.

AI-enabled systems: although some AI-enabled systems existed before AI became a household name in the mid-2010s, attention to this topic rose sharply after 2013 following the rise in commercial AI applications. The majority of publications reported on, or made predictions about, AI adoption in different industries, such as finance, healthcare, and retail, and described specific AI use-cases (Ainger, 2017; Jones, 2017; Vignesh, 2017). Similar to ML and DA publications, AI-enabled systems publications document AI use cases in various industries and functional areas but with a focus on real-time decision automation rather than insight generation. Example use cases include fraud detection; customer service enhancements and insight generation (Greenwood, 2017); tax planning, internal controls evaluations, and risk assessment (Ovaska-Few, 2017); and resume screening and talent acquisition (Greenwald, 2017). Another important use case in AI-enabled systems involves chatbots, a means to automate service functions from customer service to guide employees through onboarding and other administrative tasks (Meister, 2017). However, some authors caution that automating such tasks may impact engagement and reward strategies (Fordham, 2017) and may also result in job displacement (Boulton, 2017). Although authors expected AI-enabled automation and robotics to have the highest impact on lower-skilled jobs (Shewan, 2017), AI's growing ability to automate higher level repeatable cognitive tasks has raised concerns about AI replacing human in white-collar jobs as well (The Economist, 2015). Advances in AI will likely create new, high-skilled jobs and opportunities for new types of creative occupations, and experts have called for new education and training that would enable the workforce to adapt to this change (Marr, 2017).

The AI industry: practitioner interest in AI paralleled the emergence of the AI industry itself as technology companies such as Google, Facebook, Amazon, Apple, Baidu, and Microsoft made significant investments in AI-related research and development (R&D) and sought to establish themselves as AI leaders in the mid-2010s. The battle over AI leadership highlights a common strategy: using internal operations as a test bed for AI innovations to then incorporate them into software products and services offered to the external market. Amazon has built its infrastructure and AI capabilities to power its internal product recommendation system, enable warehouse automation, and optimize its delivery service (Stevens & Safdar, 2016). It then leveraged its AI talent and R&D capabilities to offer the first viable voice-activated home assistant, Amazon Echo (Yu, 2017). Google invested heavily in its internal AI capabilities that it used in its search engine, Google Assistant mobile app, and Google Home intelligent speaker (Waters, 2017) and to categorize content on YouTube, identify objects in the Google Photos app, and optimize the Android operating system (Simonite, 2017). Both Amazon and Google have also leveraged their internal AI capabilities by becoming leading cloud-based AI service providers. Microsoft has used a somewhat different strategy: it officially named AI as one of its top priorities and noted it would focus on building best-in-class platforms and productivity services for an intelligent cloud and an intelligent edge infused with AI (Novet, 2017). Consistent with this goal, Microsoft established an AI school at its Redmond campus to educate workers how the company applies AI technology in its products (Murgia, 2017).

AI for digital transformation: discourse on using AI for digital transformation has grown as AI-powered virtual assistants such as Apple's Siri and Google have fundamentally changed customer interactions and companies across different industries have incorporated AI-enabled chatbots, conversational agents, recommender systems, and service personalization systems into their business processes (Schneider, 2017, Martin, 2017). Such efforts have resulted in mixed outcomes that stem not only from the significant limitations to chat bot capabilities but also the sometimes overlooked need to integrate such components into the broader IT ecosystem (Adrianne & Wohl, 2017). As a result, researchers have called for more structured approaches for devising AI strategies and making AI investment decisions and for companies to create AI governance roles such as a chief artificial intelligence officer (CAIO) (Gangwani, 2017; Ng, 2016). As AI enables companies to obtain intimate knowledge about their customers, many predict AI to fundamentally change marketing by eliminating the need for expensive yet ineffective large-scale marketing campaigns.

Advances in AI research: the emergence of commercially viable AI applications fueled practitioner interest in the state of AI research. Related practitioner publications overview significant AI research outcomes, new AI-enabled technologies, noteworthy workshops and tutorial programs, and new AI-focused partnerships between industry and academic institutions. For example, publications reported Google's efforts to develop autonomous vehicles (Gaudin, 2012), efforts to develop AI-powered bots that can write a news story (Rutkin, 2014), and efforts at Carnegie Mellon University to develop an AI program that can beat four of the world's top poker players by a margin of US$1.7 million in chips (Maher, 2017).

4.4 Comparative Analysis of Academic and Practitioner Discourse

We analyzed the extent to which the ideal practitioner documents loaded on academic topics to determine the extent to which academic literature addressed practitioner topics and present the results in Figure 5. More intense coloring in the figure represents that an ideal document loaded more strongly on the corresponding factor (the higher the loading, the darker the color), while a 1 indicates that the loading was sufficiently large to suggest correspondence between the ideal document and the factor. Thus, the sum indicates the number of factors on which the ideal document loaded.

	Academic Topic Name																				
Practioner Ideal Document Name	Academic Research Method	AI and Customer Service	AI and Manufacturing	AI for Stock Market Prediction	AI in Financial Services	AI in Supply Chain Management	Artificial Neural Networks	Autonomous Agents	Big Data Analytics	Case-Based Reasoning	Classification	Decision Support Systems	Expert Systems	Human-AI Interaction	Knowledge Representation	Learning	Network Service Quality	Problem Formulation	Production and Job Scheduling	Search and Information Retrieval	Grand Total
AI ventures and startups	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
AI education and jobs	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	2
Modeling problems	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0	3
Machine learning and cloud	0	1	0	0	1	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	4
Big data analytics	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	0	3
AI hardware market	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
AI vendors	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IBM Watson / cognitive computing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AI-based automation	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	2
NLP	0	1	1	0	0	0	0	0	0	0	1	0	0	1	1	1	0	0	0	0	6
Digital transformation consulting	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Autonomous vehicles	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
AI-enabled search, AI in China	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
AI in financial and insurance services	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	4
Human-AI interaction	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
AI and marketing	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
AI research	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	2
AI news and announcements	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
AI conferences and events	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1
Executive concerns	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1
Grand Total	0	5	1	3	2	0	2	1	4	0	2	0	1	5	1	4	1	1	1	1	35

Figure 5. Practitioner Ideal Documents Mapped to Academic Topics

Not surprisingly, the NLP ideal document loaded on the largest number of academic research topics, which made it the most broadly studied practitioner-relevant topic. This finding likely reflects the significant role that academic research plays in enabling NLP applications in practice and academics' interest in such applications. Other practitioner ideal documents that loaded on more than one academic topic include modeling and problem formulation, machine learning and cloud, big data analytics, AI in financial and insurance services, and AI education and jobs. These documents represent well-researched areas that practitioners find relevant and where the academic community likely already makes significant contributions to practice. Some practitioner ideal documents that loaded on one or no academic factors represent uniquely practitioner areas, such as AI hardware market, AI vendors, IBM Watson/cognitive computing, AI news and announcements, and AI conferences and events. One would expect this outcome as academic research focuses on creating generalized knowledge rather than company-specific topics and news. However, other ideal documents that loaded on one or no academic factors may represent practitioner-relevant areas that the academics have not extensively studied and, thus, represent opportunities for future AI research. Such factors include AI ventures and startups, digital transformation consulting, autonomous vehicles, AI-enable search/AI in China, AI and marketing, and executive concerns. Notably, while the practitioner ideal document for human-AI interaction loaded on one research topic, the high loading suggests that, while IS research has actively addressed this area, it still represents an important research opportunity.

We also analyzed the extent to which the ideal academic documents loaded on practitioner topics to determine the extent to which academic topics pertain to practitioners and present the results in Figure 6. As in Figure 5, darker colors represent a higher loading, while a 1 indicates that the loading was sufficiently large to suggest correspondence between the ideal document and the factor. Thus, the sum indicates the number of factors on which the ideal document loaded.

Academic Ideal Document Name	Practitioner Topic Name: Academic AI research	AI and marketing	AI hardware market	AI in China	AI in financial services	AI in supply chain management	AI industry news and events	AI vendors	AI ventures and startups	AI-based automation	Artificial neural networks	Autonomous vehicles	Big data analytics	Digital transformation consulting	Human-AI interactions	IBM Watson / cognitive computing	Intelligent agents	Machine learning	Modeling problems	NLP	Grand Total
Machines and human learning	1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	1	0	1	5
Classification	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	2
Problem formulation and optimizaiton	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	2
Artificial neural networks	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
Text analytics	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	3
Intelligent agents	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	3
Decision Support Systems	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	2
Knowledge Representation	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	3
Case-Based Reasoning	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
AI algorithms	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	1	0	4
AI and Manufacturing	0	0	0	0	0	1	1	0	0	0	0	1	0	0	0	0	1	0	0	1	5
Stock market prediction	0	0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	4
AI in Supply Chain Management	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
AI and Customer Service	0	1	0	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	5
Expert systems	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	1	0	3
Human-AI Interaction	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	2
Social implications of AI research	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2
AI research (general)	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	4
Production scheduling	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	3
Service quality	0	1	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	1	0	5
Grand Total	3	3	1	2	2	6	4	0	1	3	4	3	2	2	3	0	7	2	6	6	60

Figure 6. Academic Ideal Documents Mapped to Practitioner Topics

Notably, we found significantly higher cross-loadings than in the previous analysis, which likely reflects the fact that academic writing often uses more abstract language that tends to appear in various practitioner contexts. While some cross-loadings may represent spurious semantic similarities[2], we believe that the results also show that most topics that academics research indeed pertain to many different practitioner contexts. For example, research on machine learning relates to practitioner topics such as AI academic research, machine learning, NLP, and human-computer collaboration. Research on text analytics relates to NLP (as expected) but also touches on AI news and events and AI and marketing.

5 Discussion

From reviewing the practitioner and academic discourse, we found several interesting insights into how academics and practitioners have socially constructed what AI means. Whereas researchers initially conceptualized AI in a way that reflected the quest to replicate or imitate human consciousness (Turing, 1950; McCarthy et al 1955) and a goal to achieve machine autonomy formed the foundation for how the computer science discipline conceptualized AI (Russel & Norwig 2021), the AI in business publications have viewed AI in a substantially different manner. In the business context, practitioners have largely seen AI as a means to achieve a well-defined end as a part of a well-regulated process. As such, the AI in business publications focused less on creating a highly autonomous artificial actor and more on creating AI components that organizations could integrate with existing business processes and organizational routines. We argue that viewing AI in this way concurs with organizational theory whereby organizations exist to coordinate individual actors' collective effort to achieve a common goal (Klein, Mahoney, McGahan, & Pitelis, 2019; Williamson, 1973). By their very nature, organizational mechanisms mute individual autonomy in favor of integration and coordination via dividing labor, job, and role definitions, policies and procedures, and process standardization (Harmon, 2010). From this perspective, we find it natural that both the academic and practitioner discourses on AI in business have tended to conceptualize AI as means to achieve a particular organizational end rather than an autonomous intelligent agent that can pursue its individual goals. We can see this conceptualization in the research themes that we identified from analyzing both the academic and practitioner discourses and in how the themes highlight the different ways in which the two discourses view the integration between AI technological components and the rest of the organizational environment. In Section 5.1, we discuss these views in relation to the IS socio-technical continuum (Sarker et al., 2019).

[2] For example, stock market prediction loaded on AI hardware vendors likely because practitioner publications about hardware vendors often discuss fluctuations in vendor firms' stock price.

5.1 Views of AI on the Socio-technical Continuum

5.1.1 Academic Discourse and Socio-technical Positioning of AI

Overall, we found from analyzing the academic literature that it has viewed AI in four ways: in a 1) technology-centric, 2) task-centric, 3) solution-centric, and/or 4) integration-centric manner. The topics such as expert systems and artificial neural networks represent the technology-centric view, and the trends in publication counts associated with these topics reflect how the underlying AI technologies have evolved. As such, the technology-centric view falls on the technology end of the socio-technical continuum (Sarker et al., 2019). We can see the task-centric view in topics such as search and information retrieval and knowledge representation and classification. The task-centric view concurs with AI's original definition (McCarthy et al, 1955), which focused on specific cognitive tasks that one would expect AI to perform. Notably, natural language processing and computer vision tasks did not emerge from our analysis despite the fact that recent advances in AI algorithms have enabled it to reach above-human performance on such tasks (Meske & Bunde, 2020). The social position a technology occupies is, at least to some extent, a function of the tasks it is used to perform. The task-centric view focuses on generic task definitions (such as classification). Hence, the task-centric view also falls on the technical end of the socio-technical research continuum albeit closer to its center than the technology-centric view. The solution-oriented view, which topics such as AI for stock market prediction or AI in financial services represent, connects underlying AI technology not only to the immediate task that it performs but also to the broader context in which it performs it. Therefore, conceptually, the solution-centric view falls considerably nearer to the center of the socio-technical continuum compared to technology- and task-centric views. Notably, most individual publications that we found to discuss these topics tended to focus on the underlying technology and task and to divorce the discussion from the wider task context. The integration-centric view addresses this separation. Specifically, it focuses on the interactions between AI technology, the task, the context, and other environmental socio-technical components such as humans, data, and processes. The topics that represent this view include human-AI interaction and big data analytics. These topics fall closest to the middle of the socio-technical continuum as they recognize the position that AI technological elements occupy vis-à-vis other components, such as data or humans. Although publications that address these topics paid significant attention to achieving instrumental objectives, they also recognized humanistic objectives such as user satisfaction. Notably, although three out of the five high-level research areas have technology-centric names, the underlying topics represent various technology, task, and solution foci. Yet, the social perspective seems sorely underrepresented in the AI academic discourse.

5.1.2 Practitioner Discourse and Socio-technical Positioning of AI

All four ways to view AI that we identified in the academic discourse (in a technology-centric, task-centric, solution-centric, and integration-centric manner) also appeared in the practitioner AI discourse. Topics such as machine learning, NLP, AI and marketing, and human-AI interaction represented these four views, respectively. However, the practitioner AI discourse also focused on the social positions that AI occupies and the socio-technical networks and processes that surround efforts to introduce AI technologies into organizational and social eco-systems. We distinguish between the action-centric view and the product-centric view—both technology and task-agnostic views that differ in whether AI plays an active role in the surrounding socio-technical processes or simply constitutes a passive object at the center of the interactions among other actors. The intelligent agent topic best represent the action-centric view, but other topics such as AI-based automation and digital transformation consulting also represent it. These topics view AI as a participant or, at a minimum, an enabler or trigger of socio-technical processes that result in various social and economic outcomes. Although the action-centric view rarely distinguishes between the underlying technology, the capability to act in a certain way presupposes certain technological features. Thus, the action-centric view lies on the social side of the socio-technical continuum (Sarker et al., 2019) but closer to the center than the product-centric view. The product-centric view focuses on the social actors, processes, and interactions that surround AI but do not assign AI an active role. Example topics include AI vendors, AI startups and ventures, AI industry news and events, and even AI academic research. The product-centric view falls on the social end of the socio-technical continuum as it largely pays no attention to the underlying AI technologies, the tasks which they perform, or even their capability to act in a certain way.

5.1.3 Socio-technical Positioning of AI: Integrating Academic and Practitioner Views

Another useful way to understand the similarities and differences in academic and practitioner discourse involves considering the different ways to view AI on the socio-technical continuum. We found the technology-centric, task-centric, solution-centric and interaction-centric views in both practitioner and academic corpora. While these views differ in their position on the socio-technical continuum, they tend towards the techno-centric end. Interestingly, we found the more socio-centric ways to view AI, such as the action-centric and product-centric views, only in the practitioner discourse. We show each view's position on the socio-technical continuum in Figure 7. We believe that a potential explanation for the relative paucity of the academic research on the social end of the continuum reflects contemporary AI technologies' relatively recent introduction into social and organizational environments and limited opportunities to study the corresponding socio-technical interactions. The action-centric and product-centric views reflect practitioner interest in AI's socio-technical aspects, and the integration-centric and solution-centric views underscore the practical relevance of related research topics and highlight an exciting research opportunity for IS researchers.

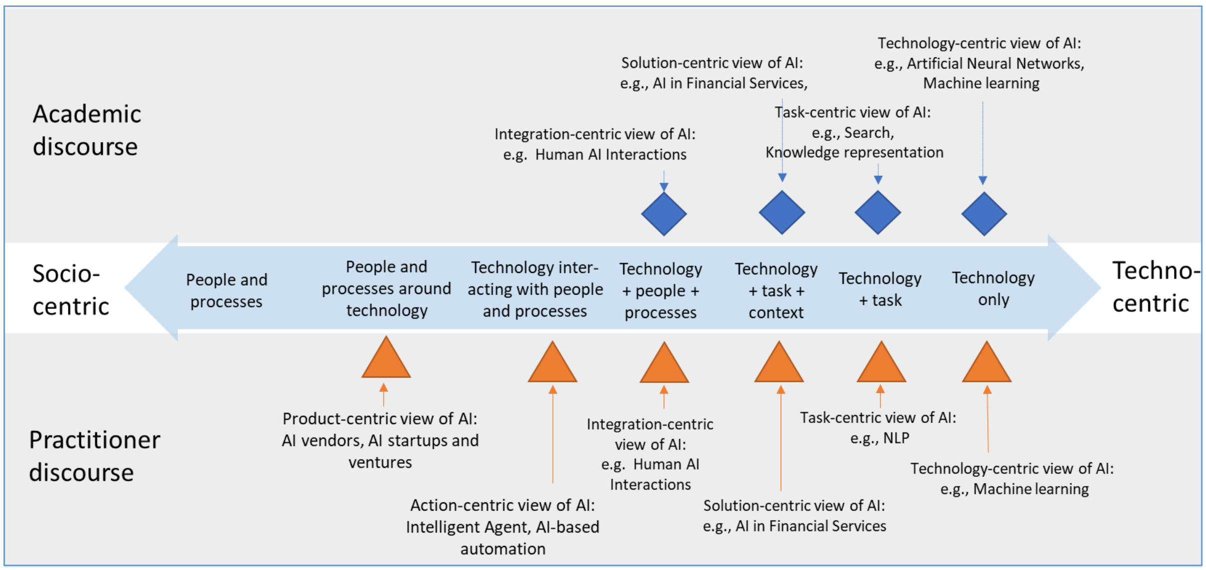

Figure 7. Ways to View AI on the Sociotechnical Axis

5.1.4 Socio-technical Positioning of AI, a Foundational IS Research Opportunity

By positioning AI views on the socio-technical continuum, we can identify areas where the IS discipline could contribute to AI research in a way that has the most impact. The fact that the AI research skews towards the techno-centric end of the continuum concurs with AI's origins and history in the computer science discipline. Techno-centric research does not concern itself with technology's social positions and does not require one to understand organizational and social structures and processes in depth but calls for the algorithmic creativity and engineering expertise. To date, AI in business research has tended towards the technical end of the continuum with topics such as artificial neural networks or machine learning. Whereas individual IS researchers may choose to align their efforts with the technology-centric and task-centric views, we expect that these areas will continue to be the primary domain of computer science and computer engineering scholars. The socio-centric end of the continuum concerns itself not with AI's technical nuances but with the social and organizational processes surrounding its emergence and integration into the business setting. While such research lacked salience in our analysis, we envision that such investigations will emerge in the management, marketing, and other non-IT focused business disciplines. While we believe that the product-centric view offers potential opportunities for some IS researchers, which aligns with Sarket et al.'s (2019) position, we argue that the central region of the socio-technical continuum represents the AI research opportunity nexus for IS researchers. In particular, the solution-centric, the integration-centric, and the action-centric views require one to understand organizational and human processes and underlying AI technologies in equal measure—skills inherent to the IS discipline.

Focusing on the central region of socio-technical continuum requires a new way to theorize AI technological artifacts that considers their positions in sociotechnical systems. As we illustrate in this paper, we found that the academic and practitioner discourses we analyzed have viewed the AI artifact largely with a focus on its implementation aspects. For example, research on neural networks and the theoretical constructs that make up its core primarily focuses on how to achieve a certain performance level for a predictive model and less on the appropriate performance levels given the social position that the model occupies. To bridge this gap, we need new theoretical constructs to capture the relational aspects of AI artifacts and the technology-dependent aspects of the social systems that AI affects.

Because AI research has focused on artifact design thus far, such research has relied on formal mathematical and algorithmic theories (which guide the vast majority of computer science research) as its theoretical basis. While highly instrumental to developing working artifacts, constructs present in such theories cannot adequately represent AI's socio-technical and relational aspects once it occupies a position in a social system. The likelihood that the underlying theoretical constructs will differ depending on the analysis level (e.g., individual, organizational, societal) further complicates efforts to create useful theoretical AI representations in social systems. Thus, IS scholars have a significant research opportunity to develop new theoretical constructions to describe AI artifacts by leveraging existing socio-technical theoretical perspectives. From comparatively analyzing the academic and practitioner topics, we can see that the academic literature has not yet fully addressed practitioner interest in AI's socio-technical aspects. For example, practitioners have significant interest in the role that AI plays in digital transformation, an inherently socio-technical topic, which the fact that we identified it as a distinct topic in the 20-factor solution for the practitioner discourse represents. Notably, research has yet to actively research AI-enabled digital transformation, which we can see in how the digital transformation ideal document failed to load on the top 20 academic topics.

The digital labor platform perspective provides a useful starting point for such theorizing as it positions AI technology as a labor performing element that one can engage to perform a task rather than, or along with, human actors. The digital labor platform focuses explicitly on human-AI hybrids and highlights important relational aspects of AI technological artifacts, such as bias, model explainability, platform openness and data guardianship, and governance capabilities (Rai et al., 2019). Providing a complementary perspective, Faulkner and Runde (2019) theorize digital objects as multilayered assemblages of material and non-material components, which can help represent both AI technology's implementation aspects and the requirements that the social systems they inhabit impose on them. Combining these theoretical perspectives can help one theorize relevant AI constructs that would represent AI's relational aspects at the individual, group, organizational, and market levels and the constructs that would help explain the AI development process's socio-technical aspects.

5.2 Relating AI Research Opportunities to the IS Intellectual Core

We can further expand on the research opportunities that we identified from examining our results through the socio-technical continuum lens (Sarker et al., 2019) by relating them to the five core IS research areas: IT and individuals, IT and groups, IT and organizations, IT and markets, and IS development (Sidorova et al., 2008). In Figure 8, we show how the most relevant 20-factor solution topics mapped to the top five topics in the practitioner and academic discourses and also juxtaposes them against the five key IS research areas (Sidorova et al., 2008).

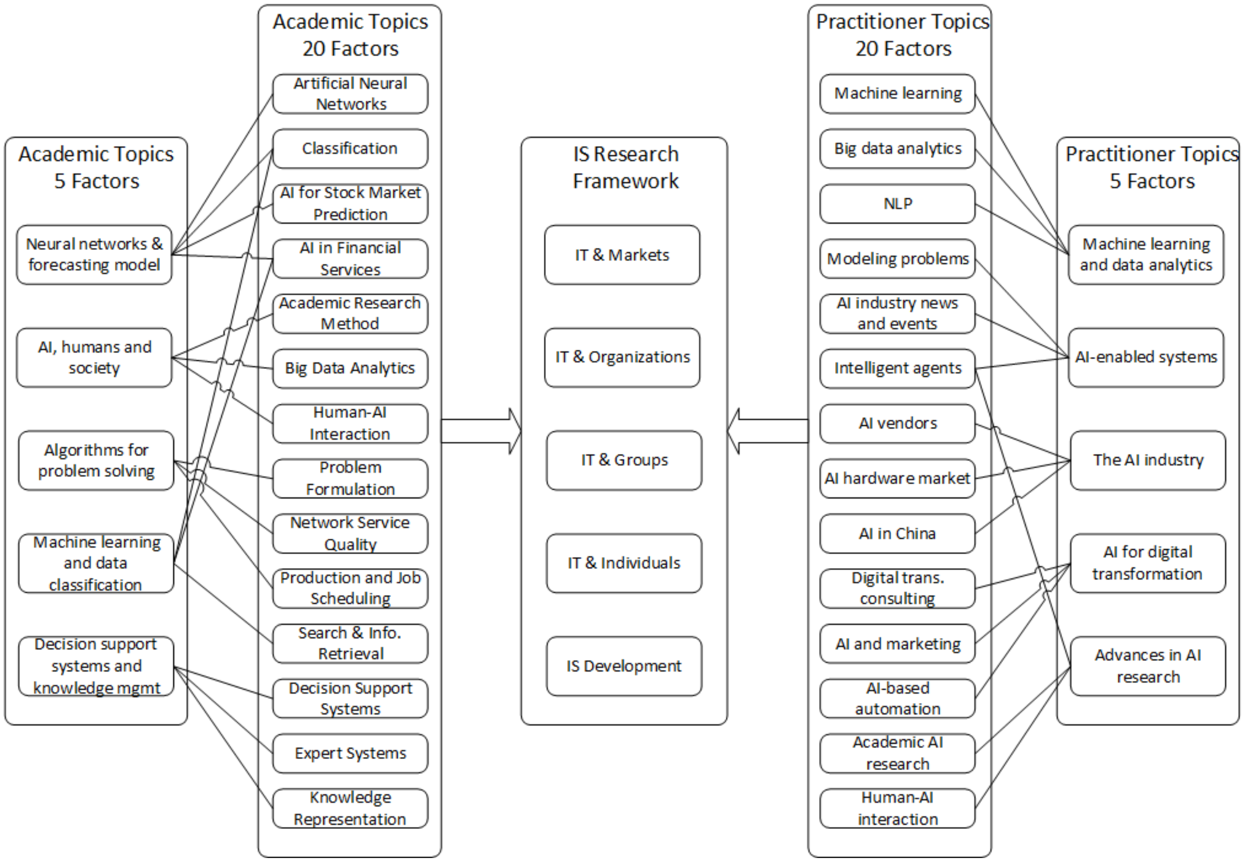

Figure 8. Relating LSA Study Results to the IS Research Core

5.2.1 Research Opportunity 1: AI and Organizations

Industry leaders expect AI to have a significant impact on organizational value-creation processes in the 2020s, which concurs with several topics in the practitioner discourse that focus on AI's organizational impacts. However, the academic discourse has focused less on organizational integration and AI-related technologies' impact: interest peaked in the early 2000s with a focus on DSS and knowledge management but declined afterwards. Considering that many generally associate DSS and KM as first-generation AI technologies (i.e., AI technologies based on hand-crafted knowledge) (Defense Advanced Research Projects Agency, 2021), we believe that organizational AI research does not yet reflect organizational adoption and the impact that current-generation AI technologies will have (i.e., AI technologies based on machine learning and big data). We expect these technologies to drive fundamental changes in organizational structures, processes, and decision-making practices. We believe that the digital transformation topic, which appeared among the top practitioner topics, represents an area with future research opportunities. Currently, the topic does not align with any of the top 20 AI research topics, but we believe that the organizational changes that surround efforts to integrate AI in organizations constitute exciting research opportunities. In line with the IS research tradition, research on AI for digital transformation could also focus on AI's value-creating potential (Plastino & Purdy, 2018; Ransbotham et al., 2017).

Two views have the most value in helping one understand the role that AI plays in organizations: the integration-centric view and the action-centric view. The integration-centric view focuses on the interaction between AI and people and the integration of AI in organizational business processes. The action-centric view focuses on the role that AI plays as an actor in organizations and on the fact that AI operates alongside human actors, substitutes for human labor, augments human activity, and/or engages in full-fledged collaborators with humans (Rai et al., 2019). To take full advantage of the integration-centric and action-centric views, researchers need to develop new constructs and theories to help relate AI as technical objects and their characteristics and components to their position as physical resources, labor, service, knowledge, flexibility drivers, and competitive barriers (Drnevich & Croson, 2013; Faulkner &

Runde, 2019). Future research inquiries may focus on broad research questions such as "under what circumstances does introducing AI result in superior organizational performance?". Providing answers to this question would require one to relate AI's technical capabilities to organizational constructs such as governance, alignment, capabilities, agility, culture, efficiency, and performance. Specific questions could examine the relationship between specific management practices such as those related to privacy and security, model and data governance, and AI technological choices (e.g., ML algorithm, model performance metric, etc.). AI-based automation and efforts to incorporate (semi-)autonomous intelligent agents into organizational environments raise questions about AI governance and AI's emergent effects on existing human capital. If we expect AI to transform internal organizational processes, academic research needs to fully understand such transformations. For example, many expect AI and ML-based predictive models to transform decision making in capital markets and, thus, to have a profound effect on core business activities (Kemp & Jenkins, 2018). However, will such transformations translate into higher value for existing company shareholders? And what side effects will accompany such transformations? We encourage organizational AI researchers to build on theoretical frameworks that gave proved successful in explaining knowledge management, organizational learning, organizational automation, and process improvement phenomena. However, because AI uniquely combines learning and automation capabilities, such researchers will likely need to develop new theoretical frameworks.

5.2.2 Research opportunity 2: AI and Markets

Apart from its internal position in organizations, AI artifacts can occupy a social position that influences inter-organization dynamics. The practitioner discourse on AI and markets reflected AI's inter-organizational aspects. The AI industry and key players theme featured prominently in practitioner publications, which have touted AI for its disruptive effect on industries and markets.

Studying the nature of AI-related market disruptions represents an interesting research opportunity for IS scholars, and the product-centric view provides the flexibility to examine the role that AI plays in relation to markets. The product-centric view abstracts AI technology's internal complexity and surrounding integrations by treating it as a product with certain utility and costs for individual and organizations. Rather, the view focuses on the economic activity, people, and processes that surround efforts to produce, distribute, and use AI products. The AI ventures and startups practitioner topic points to the new players that may emerge around AI products and disrupt not only IT markets but also markets for goods and services. In healthcare, some sources have likened AI to a new nervous system that may open new opportunities for industry players by enabling new products and services, such as faster, cheaper, and more accurate diagnostics; virtual nursing assistants; robot-assisted surgery, and so on (Accenture, 2017). This transformation will likely shift the current balance of power and influence among the numerous healthcare industry players, such as individual doctors, clinics and hospitals, and solution providers. However, due to the healthcare and AI ecosystems' complexity, we cannot easily grasp such a transformation's full scale. Thus, the impact that AI will have on market dynamics in different industries represents a fruitful direction for future research. Academic researchers have a diverse repertoire of research methods (e.g., from econometric modeling to empirical, survey-based research and intensive, qualitative methods) that they can use to better understand the industry transformation trends that AI may precipitate. We need such knowledge to ensure that both individual industry players and the society can adjust and benefit from these trends.

In addition, the solution-centric view provides useful insights into the role that AI plays in regulating markets and improving market efficiency. The solution-centric view focuses on applying AI technologies to specific tasks in specialized contexts, such as marketing or customer service. In e-commerce, AI will create a more personalized and profitable customer experience as firms rely on ML to analyze massive amounts of customer data in order to discover customer preferences in real time (Olmez, 2018). Firms can use AI to create personalized engagement marketing approaches and provide curated products and services (Kumar et al., 2019). By enabling vendors to predict customer intent and provide personalized content, AI helps speed up customer response time, automate the customer relationship-management processes, and reduce customer service costs while optimizing customer shopping experiences (Papas, 2018). However, increased insights into customer preferences may result in unintended consequences, such as price discrimination against potentially underserving customer segments that firms deem less valuable. Thus, managers need guidelines on how to use marketing AI solutions successfully (Overgoor et al., 2019). To mitigate the undesirable effects that AI adoption may have on industries and society at large, leading technology companies such as IBM, Amazon, Google, Facebook, Microsoft have joined forces with academic institutions and other non-tech organizations to create a partnership on AI best practices (BusinessWire, 2016). Their mission focuses on developing and sharing best practices in researching and developing AI and on advancing public understanding and awareness of AI. This coalition of technology companies and academicians represents a unique research opportunity for IS academics interested in B2C markets.

Thus, to capture AI's distinctive position in market dynamics, we need new theoretical constructs to capture how AI as digital objects and its properties relate to its position as a product, a market regulator or participant, a pricing mechanism, or a market efficiency enabler/inhibitor. In sum, the relative scarcity of academic research on AI's disruptive effect on industries and markets presents a unique research opportunity for IS scholars who have long researched information systems' emergent market and societal consequences. IS researchers could expand their research opportunities by pursuing research questions such as:

- How do industry leaders use AI technologies to gain a competitive advantage?
- How can AI technologies create a paradigm shift in an industry?
- How do strategic partnerships affect AI transparency in a high-stakes domain?
- How will AI influence opportunity costs in knowledge-intensive industries, such as healthcare?

5.2.3 Research Opportunity 3: AI and Groups

As a participant on a digital labor platform, AI should engage in interactions with human actors and assume group membership (Rai et al., 2019). Hence, understanding the impact that AI has on collaboration and group dynamics represents another potentially fruitful directions for IS scholars. Investigations in this area would require researchers to create new theoretical constructs that relate AI as a digital object and its components to its potential position as a group collaborator, moderator, and/or process. The integration-centric view focuses on the interaction between humans, processes and AI technologies and, thus, can be instrumental in understanding the relationship between AI technologies and group processes and structures, particularly when one uses AI to augment human activity in group settings. Although the AI and groups topic does not feature prominently in the practitioner discourse we reviewed, industry leaders believe that incorporating AI will transform the team collaboration experience and enhance collaboration workflows (Smith, 2017). Hence, IS scholars who have a rich experience with group research have an opportunity to assume thought leadership in this area. In the IS discipline, group research reached its climax around the early 2000s and has declined since then (Sidorova et al., 2008). The emergence of intelligent collaboration tools may give rise to a new wave of IT and groups research. One research direction relates to the effect that AI has on group work and team collaboration. Broad research questions may include "how can one use AI to enhance group collaboration?" or "under what circumstances would using AI result in a fundamental shift in collaborative workflows?". We encourage researchers to study how specific AI applications, such as automatic translation or chatbots, may empower the new wave of intelligent communication and collaboration.

An even greater promise lies in understanding the potential for and the nature of human-AI collaboration (Wilson & Daugherty, 2018). The action-centric view can help researchers understand the role that AI can play as it gains more autonomy to act independently and to be an active collaborator and group member. Firms can use AI to support group collaboration or employ it as a collaboration partner to work alongside humans to achieve performance improvements. Rai et al. (2019) discuss the emergence of the human-AI hybrids in digital platforms. Seeber et al. (2018) set the agenda for human-AI collaboration research around three meta-themes: the design sphere, the collaborative sphere, and the consequence sphere. These research efforts set the stage for future research contributions that may examine how to design human-AI collaboration processes, the influence that AI has on group dynamics, and the role that values and outcomes play in human-AI collaboration.

5.2.4 Research Opportunity 4: AI and Individuals

At its core, the IS discipline examines IT and individuals; in many cases, AI interactions with individuals mediate the effect that AI has on organizations, groups, and markets (organizational decision makers, employees, or customers). The integration-centric view will prove instrumental in helping researchers understand these interactions as human-AI interaction research gains momentum. Studies that have adopted this view have focused on specific AI-enabled systems, such as intelligent assistants (Moussawi, 2016), AI speakers (Yoonseock & Wonseok, 2018), and conversational user interfaces used in online storefronts (Baier et al., 2018). Motivated by concerns about security and privacy risks associated with AI, an emerging research stream examines trust in AI (Chung et al., 2017; Elson et al., 2018; Siau & Wang, 2018). Another emerging research stream examines the impact that AI has on job-related outcomes. In their study, Jussupow et al. (2018) examined how AI-enabled tools challenge physicians' professional identity (Jussupow et al., 2018). Despite the many emerging research efforts in the area, individual-level AI-research remains in its nascent form; thus, myriad research questions remain unanswered, such as:

- Do individuals interacting with AI-enabled systems perceive such systems to have intent, and how do such perceptions influence the nature of the interactions?
- Do individuals who interact with AI-enabled systems know about their ability to perceive back and to change their actions in response to users' actions?
- How does an AI-enabled system's perceived similarity to a human actor influence human-AI interactions' nature?

While existing IS theories may prove useful answering some of these questions, we need new theoretical frameworks to guide such research. Therefore, we need new constructs to relate AI's technical aspects to its position as an inanimate stimulus, as a tool (a means for achieving a goal), or as a social actor in AI-human interactions. Such constructs should seek to delineate AI's distinguishing characteristics vis-à-vis other IT types and provide theoretical guidance regarding the effect that these characteristics have on individual interactions with AI-enabled systems.

5.2.5 Research Opportunity 5: AI Development

AI development represents an area in which academic and practitioner interest converges as it is most closely relates to AI research's engineering tradition. As one would expect for an area associated with the fast rate at which technology continues to develop, AI in business research features many studies that apply specific algorithmic approaches, such as optimization and ML, to business problems. However, as organizations integrate AI's technical components into value-producing systems, we need new theoretical constructs to represent the AI development process's unique social aspects. The solution-centric view, which looks at applying AI technologies to specific tasks in specialized contexts, presents an opportunity to IS researchers who combine technical expertise with an appreciation for various business and organizational contexts.

As new AI technologies emerge and become available to IS scholars, we can expect this research stream to continue to expand. In the near term, we expect to see more studies that focus on designing, refining, and testing business applications based on supervised and unsupervised ML techniques. Such research will likely follow a design science paradigm with outcomes such as new approaches to designing cooperative and social conversational agents in customer service (Gnewuch et al., 2017). This emerging research stream also includes work that develops a framework for designing anthropomorphic conversational agents (Seeger et al., 2018) and work that applies ML-based analytics to solving racial discrimination problems on online platforms (Park & Kim, 2018). In the longer term, we can expect emerging approaches to ML, such as reinforcement learning and generative algorithms, to influence design research. Specific research questions may relate to efforts to develop business training environments for reinforcement learning agents to apply generative algorithms, such as generative adversarial networks, to business domains.

The practitioner discourse mirrors academic interest in AI-enabling technologies albeit with a broader focus. Rather concentrating on specific algorithms such as neural networks, the practitioner literature underscores the need to enable technologies such as big data and the cloud. This broader focus represents an opportunity for academic design science research that would focus on AI solutions' architectural and integration aspects. To capture this opportunity, new theoretical constructs should capture the social position of the various digital objects surrounding AI and the AI properties that would allow it to take certain social positions along with other digital objects.

5.3 Limitations

Like any study, this quantitative literature review has limitations. First, AI in business is an extremely fast moving field in which algorithmic and technical advances outpace the academic publication process. Our research does not capture research from 2008 to 2022, which constitutes an important limitation exacerbated by the fact that academic research efforts often appear several years after authors write them. Hence, we encourage readers to supplement our findings by thoroughly reviewing recent academic publication in IS academic journals and conferences. Second, we intentionally limited the review to those publications that used the terms AI and business. Therefore, we did not include many publications that lacked these particular terms but that closely related to the topic. In this way, we likely excluded applied AI research not directly related to the business domain and studies related to the business domain that did not use terms such as ML or neural networks rather than the term AI. Third, we related the academic and practitioner AI in business discourse to the core IS research in a qualitative manner: we did not do so based any quantitative way to measure the association between the corresponding textual corpora. While we believe that our effort produced interesting insights, we encourage researchers to validate them using quantitative text analysis in future studies. Fourth, while we identified how each community discussed AI based on our analysis approach, it may not fully explicate the term AI. As with human interpretation, the LSA approach we employed cannot distinguish between how different authors use the term AI without sufficient context. If authors discussing AI fail to clearly articulate their definitions and assumptions, LSA cannot discern, for example, whether AI refers to a rule-based decision-making system or a neural network (both possible given how technologies that underlie AI have evolved). Similarly, without appropriate context, LSA cannot distinguish whether the way in which an author uses “AI” refers to a specific artifact or a component in a larger system.

Conclusions

We conducted this study to summarize the past AI in business academic and practitioner discourses and to identify AI research opportunities and, thus, assist future organizational and behavioral AI researchers. As a result, we identified convergence areas and gaps between the academic and practitioner AI in business discourses. We also identified important directions for future research by examining this discourse in relation to the socio-technical continuum of IS research. We argue that the proliferation of AI-enabled IT applications creates new research opportunities for IS researchers across this entire continuum. To date, most AI-related scholarly work has concentrated on the continuum’s technical side and on developing new AI technologies and their applications to tasks that range from atomic (such as classification or forecasting) to complex (such as NLP or computer vision). As AI improves in its ability to complete such tasks and becomes well recognized, we believe the IS researchers should take advantage of the opportunities presented at the center of the socio-technical continuum and focus on applying AI to tasks in specialized contexts, integrating AI with people and processes, and examining the role that AI actors play in organizations and society. Our findings highlight the relative shortage of organizational and behavioral academic research on AI at the individual, organizational, and market levels despite significant interest in these areas in the practitioner community. Hence, these areas represent the most promising directions for future research. The relative paucity of both academic and practitioner interest in AI at group levels highlights the potential for IS scholars to make a significant contribution to AI practice by devising approaches to employing AI in collaborative settings. In recent years, design-oriented research that focuses on applying contemporary AI techniques to various business areas has emerged, and we expect this research direction to continue to be a fruitful one.

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