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Guest editorial

Supply chain management and Industry 4.0: conducting research in the digital age

Introduction

In essence, Industry 4.0 enables an automated creation of goods and services as well as supply and delivery, which functions largely without human intervention. Industry 4.0 is happening now (Vogel-Heuser and Hess, 2016; Sprovieri, 2019) and describes the trend toward automation and data exchange in manufacturing technologies and processes which include among others cyber-physical systems (CPS), industrial Internet of Things (IIoT), cloud computing, cognitive computing and artificial intelligence (AI). Decision making is predominantly decentralized, and system elements (e.g. production plants or transport vehicles) make autonomous, targeted decisions. A digital manufacturing enterprise is not only interconnected, but also communicates, analyzes and uses information to further drive intelligent actions back into the physical world.

Industry 4.0 will change how supply chains are designed and operated, yet research on promises and impacts of Industry 4.0 on supply chain management (SCM) is still scarce (Holmström and Partanen, 2014; Hofmann and Rüsch, 2017). We refer to SCM in the new era of Industry 4.0 as “SCM 4.0.” In SCM 4.0, the digital and autonomous linkages within and between companies become a focal point of SCM (Stölzle et al., 2017). SCM 4.0 represents a new stage of development in SCM, in which the coordination of materials, information and financial flows in corporate networks is largely automated and permeated with digital technologies.

This Special Issue is thus dedicated to exploring the abundant research opportunities associated with SCM 4.0 and laying down a foundation for future research on this important emerging topic. The idea is to fill gaps in the existing supply chain theory and explore the areas that are likely to be impacted by the combination of knowledge, traditional and emerging technologies. SCM 4.0 will over time manifest substantially different from conventional SCM.

Industry 4.0 components and SCM 4.0 characteristics

Industry 4.0 typically is declared as consisting of the following components and effects (based on Vogel-Heuser and Hess, 2016):

- service orientation based on CPS and the internet of services;
- CPS and multi-agent systems making decentralized decisions;
- interoperability between machine and human and virtualization of all resources;
- ability to flexible adaptation to changing requirements (cross-disciplinary modularity);
- Big data algorithm and technologies provided in real-time (real-time capability);
- optimization of processes due to flexible automation;
- data integration cross disciplines and along the life cycle; and
- access to data securely stored in a cloud or distributed data storage (e.g. blockchain).

To date, scientific literature on supply chain digitalization has often focused on specific topics and technologies such as cloud computing, big data analytics or applications in selected industries (e.g. Ivanov and Sokolov, 2012; Jede and Teuteberg, 2015; Kache and Seuring, 2017;
Supply chain digitalization is emphasized as “the new interconnected business system which extends from isolated, local, and single-company applications to supply chain wide systematic smart implementations” (Wu et al., 2016, p. 396).

The diversity of terms in both gray and academic literature reveal that a consistent understanding and concept of supply chain digitalization appears to be missing, yet many of those definitions and descriptions share common themes. The following aspects are prominent to outline key characteristics of the supply chain 4.0 (Kersten et al., 2017; Schmidt et al., 2015; Wu et al., 2016):

- **Customer-centric**: design, produce (lot size one) and sell individualized products via omni-channel approach by means of innovative manufacturing technologies such as additive manufacturing.
- **Interconnected**: customers, suppliers and partners (e.g. logistics service providers) communicate and collaborate real-time based on shared and standardized data via platforms in a network of companies.
- **Automated**: increase efficiency based on flexible automation of physical processes via robotics.
- **Transparent**: GPS and CPS enable increased visibility into the diverse aspects of the supply chain (e.g. bottlenecks, delays) as well as traceability of products (e.g. location of materials, proof of provenance).
- **Proactive**: decision makers react anticipatorily to changing conditions and unexpected events based on real-time data analytics, machine learning and AI.

As supply chains are increasingly digitalized by adopting the Industry 4.0 approach, they increasingly will evolve to supply chain ecosystems (Ketchen et al., 2014), where a business ecosystem consists of a set of organizations that are interdependent, coordinate activities and share some common adaptive challenges. According to Pidun et al. (2019), a business ecosystem is a specific governance model that competes on a modular, customized, multilateral and coordinated basis. This governance model is characterized by a specific value proposition (the desired solution) and by a defined, albeit changing, group of actors with different roles (such as producer, supplier, orchestrator, complementor). A new role in such supply chain ecosystems will play the technology providers and intermediaries supplying any kind of Industry 4.0 solutions. Given this introduction to Industry 4.0, we will now proceed to the contributions of the papers included in this special issue.

**Summary of articles**

*Toward a digitally dominant paradigm for the twenty-first century supply chain scholarship*

Stank et al. (2019) conceptually suggest that middle-range theorizing (MRT) is an appropriate means to explore the ways in which researchers can explain supply chain phenomena in the age of digitalization, and they introduce a theoretically grounded digitally dominant paradigm (DDP) framework to help guide future SCM research. They argue that “seeing” (enhanced visibility), “thinking” (improved analytics) and “acting” (heightened operational flexibility and reduced cycle time) are core components of supply chain digitalization. This paper intends to put existing supply chain practices and concepts on a “stress test” and checking their sustainability and required alterations in the changed context of digitalization. Stank et al. explicitly intend a contribution to advancing scholarly discourse and transforming (digital) SCM “[...] from a description-based research discipline to one grounded in functional theories.” We may expect a plethora of new themes and challenging questions by entering the proposed context of a DDP.
Emerging procurement technology: data analytics and cognitive analytic
Handfield et al. (2019) employ a qualitative approach that relies on three sources of information (executive interviews, a review of current and emerging technology platforms and a small survey of chief procurement officers) to elucidate the emerging landscape of procurement analytics. This study provides specific insights into the impact of cognitive analytics and big data on procurement. Although they found that the procurement analytics landscape will continue to develop, their study revealed that there currently exist a low usage of advanced procurement analytics, and data integrity and quality issues are preventing significant advances in analytics. They suggest that it is imperative for companies to establish a coherent, systematic approach to collection and storage of trusted organizational data that builds on internal sources of spend analysis and contract databases and that current ad hoc approaches to capturing unstructured data must be replaced by a systematic data governance strategy. The study also noted the issue of complexity caused by a proliferation of available platforms that could not be all integrated. Combined with a discussion about metrics, this opens avenues for new interesting research questions on the cost and complexity of increased data availability and the resulting need for analytics.

Real-time data processing in SCM: revealing the uncertainty dilemma
Lechler et al. (2019) discuss the challenges of gathering relevant, timely and accurate data under volatile, uncertain, complex and ambiguous (VUCA) conditions and use a delphi study approach to investigate whether real-time data processing reduces SCM uncertainties under real-world conditions. The concept that is framed as “uncertainty dilemma” is worth noting for researchers and practitioners: on the one hand, having more real-time data may be indeed a profound means to reduce supply chain uncertainty, but on the other hand such data may also imply new uncertainties, called data-related uncertainty. Basically, this is a revival of earlier thoughts of Russell Ackoff (1967), who suggested that information systems may also become misinformation systems. Findings on real-time systems which might simulate a false security or lacking capabilities, or talents to analyze and use the information provided in real time may raise interesting issues in contrast to the typical “better world of more data” view. Organizations retain imperfect decision-making systems which are handling “messes.” This dilemma calls for a more intense discussion and definition of “data uncertainty” and “data quality” that may go beyond “relevance, timeliness and accuracy.” It might contain questions of “correctness” or also cost of uncertainty vs value of certainty.

Stock visibility for retail using an RFID robot
Morenza-Cinos et al. (2019) follow the design science methodology and use a novel algorithm to prove that an autonomous robot can perform stock-taking using RFID for item level identification much more accurately and efficiently than the traditional method of using human operators with RFID handheld readers. In their technology-centric approach, the authors present an interesting combination of robotics and RFID in pursuing “high resolution visibility,” in this case for stock on the retail floor. While addressing the challenges related to data uncertainty and quality, this paper also provides interesting hints for further research in relation to the interface between humans and robots. The authors identified some unexplored potentials for their robots due to the fact that the robots for inventory taking had to follow human assisted recognition procedures. While a fully autonomous solution could provide better results, research is certainly needed to address the potential conflicts between an idealized technical and digital world and the social aspects of the human world.
Suggested research opportunities on SCM 4.0

Research opportunities suggested in the papers of this Special Issue are summarized and depicted in Table I.

Although the list of research suggestions in Table I is far from being an exhaustive or even comprehensive research agenda for SCM 4.0, these mentioned research ideas do cover a range of important topics in the key aspects of SCM 4.0: customer-centric, interconnected, automated, transparent and proactive. More importantly, specific research directions provided by the articles in this Special Issue center on several key areas that warrant SCM researchers' particular attention, and we offer some discussion below.

In the area of machine learning (an application of AI) in supply chain processes, the focus is on prediction rather than explanation based on existing theories, as evidenced in that fields leading journals. Machine learning implies that a system or algorithm is learning without being explicitly programmed and in practice can detect patterns that enable prediction. Handfield et al. (2019) point out the need for supply chains to go from optimization toward prediction, and supply chain researchers should embrace the challenge. This is likely to mean a shift toward more inductive research methods in SCM. Focusing more on rigorous development and use of inductive methods, as pointed

<table>
<thead>
<tr>
<th>Article authors</th>
<th>Suggestions for future research</th>
<th>Addressed characteristics of Industry 4.0</th>
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</thead>
<tbody>
<tr>
<td>Stank et al. (2019)</td>
<td>Explore ways that digitalization will alter current supply chain models and frameworks</td>
<td>Customer-centric, interconnected, automated, transparent, proactive</td>
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<td></td>
<td>Following the digitally dominant paradigm (DDP) to study how established concepts and relationships in SCM are impacted</td>
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<td></td>
<td>Guiding the use and appropriateness of inductive methods and design science approaches to establish new insights on supply chain concepts and theory</td>
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<tr>
<td>Handfield et al. (2019)</td>
<td>Explore the role of analytics centers and how they could serve specific functional analytic needs (like in procurement)</td>
<td>Automated, transparent, proactive</td>
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<td></td>
<td>Investigate ways to balance the trade-off between increased supply chain transparency and information leaks to competitors</td>
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<td></td>
<td>Addressing the human-machine role division in supply chains, i.e., elaborate on who makes what decision and what competence do humans working with machine outputs need</td>
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<td></td>
<td>Research on the change in objective of decision support systems, from supply chain optimization toward prediction</td>
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<tr>
<td>Lechler et al. (2019)</td>
<td>Investigate the contingency variables when real-time systems do not influence supply chain uncertainty</td>
<td>Transparent, proactive</td>
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<td></td>
<td>Explore and evaluate additional emerging aspects of real-time data-processing applications in SCM, as well as empirical justification in real-world contexts</td>
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<tr>
<td>Morenza-Cinos et al. (2019)</td>
<td>Contrast the performance and value of different RFID robots in the supply chain</td>
<td>Automated, proactive</td>
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<td></td>
<td>Explore the performance and value of a fully autonomous solution to the human assisted recognition procedure in SCM</td>
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<td></td>
<td>Create operational guidelines for robot operations in the SCM context</td>
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Table I. Summarized future research suggestions of the Special Issue papers
out by Stank et al. (2019), is likely to answer some of the recent calls for more managerial relevance of supply chain research. Big data in supply chains still represents a big opportunity for future research (Richey et al., 2016; Hofmann and Rutschmann, 2018). Researchers are advised to look in new places for data. Sanders et al. (2019) points to crowdsourced data as one of many potential novel data sources that supply chain researchers can access, though very few samples have been published to date (Sternberg and Lantz, 2018). Given the push for predictive methods, data accuracy becomes more important, as outlined by Lechler et al. (2019). It also accelerates the need for algorithms that can handle data sets not collected for the purpose of scientific analysis, e.g., containing missing data points and inaccuracies.

Automation in inter-organizational operations fosters the idea of self-steering supply chains. Cost pressure urges companies to make processes more efficient and unlock saving potentials. Whereas companies started to automate their (standardized) production processes during the 1970s (Kagermann, 2015), processes such as goods handling and delivery are still mainly done manually. Supply chain managers can either semi-automate these non-standardized processes by equipping employees with supportive technologies or completely automate processes with robotic solutions. Besides automated manufacturing and intra-logistics, external freight transportation and delivery is increasingly considered to be automated. Whereas the introduction of fully autonomously driving trucks is still facing technological and regulatory challenges (Flämig, 2016), automated solutions for last mile delivery (e.g., autonomous drones or delivery robots) are already tested in pilot projects, both underlining the need for future research efforts (Jennings and Figliozzi, 2019). The paper of Morenza-Cinos et al. (2019) is a good example for the automation of intra-logistics process via robots. In this regard, a critical part will be the design of the human–machine interaction (Gorecky et al., 2014).

Several of the papers in this issue have touched on the human factor in the digital age, emphasizing the importance of empowering supply chain workers and/or managers and ensuring they have the right skills to work effectively with machines. For example, in their recent paper Klumpp and Zijm (2019) outline the risk of a potential artificial divide in the human workforce as an issue for social sustainability. A goal could be a human-centered automation that efficiently combines the sensorimotor and cognitive capabilities of humans with the benefits of robotic systems resulting in highly flexible automation solutions (Pinzone et al., 2018).

As outlined by Stank et al. (2019), we do need a new set of tools to address the emerging DDP in supply chains. The quick development and the high number of issues on novel technologies in supply chain journals emphasize the need for supply chain scholars to stay up to date. Upcoming (special) issues on the theme of blockchain (Rao et al., 2017), the technology management in a global context (Heim and Peng, 2019) or disruptive technologies with focus on reconciling humans and machines (Kumar et al., 2019) will provide future research ideas on those technologies and their role in SCM.

**Industry 4.0 and SCM theory development**

The SCM field has been emphasizing the importance of theory-driven research for a long time. Applying appropriate theories not only helps us better understand and explain SCM phenomenon and elements, it also offers much needed theoretical lens to explore emerging SCM strategies and practices. Conducting research on SCM topics associated with Industry 4.0 can be challenging due to limited availability of information and data, but this makes theory application even more important because it provides necessary guidance and structure. The papers in this Special Issue make valuable theoretical contributions. Stank et al. (2019) used MRT to introduce a theoretically grounded DDP. Handfield et al. (2019) used theoretical constructs in their interviews with company executives and developed a
framework to guide future research on procurement analytics. Lechler et al.’s (2019) delphi study specifically addresses an important theoretical SCM research gap: gathering relevant, timely and accurate data under VUCA conditions. While Morenza-Cinos et al. (2019) did not apply any specific theory in their rather technical study on using autonomous robots to perform RFID stock-taking tasks, their study does present a critical theoretical implication for future research – how to address the interface between an idealized technical and digital world and the social aspects of the human world.

In total 26 papers were submitted to the Special Issue, with topics such as: autonomous logistics business models, big data, cloud logistics, autonomous vehicles, blockchains (several papers), direct manufacturing, physical internet and traceability. As can be taken from the enumeration, topic relevance was not the reason why most papers did not get published (though some topics not mentioned above were clearly outside the scope), as most topics clearly relate to core components and implications of SCM 4.0. So why did the reviewers recommend against publication of such interesting themes?

Several manuscripts lacked a significant contribution to the field. Given the novelty of supply chain digitalization and SCM 4.0 and the speed of the technological development, there are several opportunities to make contributions, yet many papers failed to provide additional insights. Conceptually describing a new technology and what implications it hypothetically might have, based on marketing material from technology providers, is unlikely to represent a significant scientific contribution to the field and many papers lacked proper application of methodology and relevant data. Conceptual papers, not using empirical data, need to be very well written and present a new phenomenon or research direction. Stank et al. (2019) in this Special Issue represent a good sample of how to conceptually advance the field in a new direction. For papers using such a purely conceptual approach, a literature review needs to do more than just compile presented insights, it needs to contribute to the theoretical understanding of the phenomena reviewed and present a forward-looking research agenda.

Plenty of research look at the potential effects of novel technologies and concepts, but research is scarce on the mechanism of supply chain adoption (Pattersson et al., 2003, Autry et al., 2010). As previously outlined, several of the papers addressing novel technologies fail to incorporate the basic question: Will this novel technology actually be adopted or not (Venkatesh et al., 2003)? Radical novel technologies do not come into existence by aggregating small changes in earlier technologies, they are the result of combinatorial evolution, i.e., evolution implies that inventions are the result of intentional combinations of existing technologies through a process that involves interplay between experience and knowledge – driven by need (Arthur, 2009). Holmström and Partanen (2014), for instance, have applied combinatorial technological evolution to examine digital transformation in supply chains.

Furthermore, the (inter-)organizational ambidexterity theory (Gibson and Birkinshaw, 2004) could serve as a theoretical lens. Ambidexterity allows organizations to simultaneously integrate and reconcile exploratory and exploitative activities in trade-off situations (Raisch and Birkinshaw, 2008). Accordingly, an ambidextrous SCM 4.0 approach would be able to simultaneously exploit current SCM capabilities and resources along the supply chain as well as explore new technological opportunities coming along with Industry 4.0 components and manage the tensions arising from pursuing both.

Regarding SCM4.0 and big data applications (like Lechler et al., 2019; Sanders et al., 2019), a further question arises: How to handle the huge amount of data in real-time circumstances in order to achieve transparency along the supply chain? An answer could deliver the (inter-organizational) information processing theory. Based on this theory, firms must organize and use information effectively, especially when they execute tasks that involve high levels of uncertainty (Galbraith, 1974). According to Galbraith, firms should either reduce their needs for information through “mechanistic” organizational means, or increase their information processing capacities. Regarding the latter, firms can
increase its information processing capacity by investing in vertical information systems (Srinivasan and Swink, 2015). Vertical information systems enable organizations to process data efficiently and “intelligently,” addressing some of the key characteristics of the supply chain 4.0 interconnected, transparent and proactive, as described above.

**Toward an agenda of SCM 4.0 research**

Clearly, Industry 4.0 represents a great shift in how supply chains are managed and call for SCM 4.0 research (Hofmann and Rüsch, 2017). In addition to several highly relevant and interesting venues for future research suggested by the included papers, plenty remains. Min et al. (2019) suggested four main directions for supply chain research: strategic nature of SCM, customer value creation as the whole purpose of SCM, supply chain orientation as an essential facilitator and interorganizational collaboration at the center of SCM. Based on the papers in this issue and the current development and characteristics of SCM 4.0, we are suggesting a fifth category of human-centric supply chain. Our aim is to inspire scholars doing research in the field of SCM 4.0 by the suggested topics in Table II.

<table>
<thead>
<tr>
<th>Category</th>
<th>Future research venue</th>
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<tbody>
<tr>
<td>Supply chain strategy</td>
<td>Explore how the digital transformation is forcing organizations to re-think their business models and roles within their supply chains (adopt vs transform)</td>
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<td>Investigate the relationship between supply chain strategy and adoption of novel technologies</td>
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<td>Examine whether the governance model “supply chain ecosystems” will prevail, and if so, which of the established actors will be disintermediated</td>
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<td>Investigate the effects of digitalization on the strategic objectives of supply chain management (network value)</td>
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<td>Customer value creation</td>
<td>Elaborate how supply chain digitalization can lead to new business models based on novel combinations of existing technologies to meet current and future needs</td>
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<td></td>
<td>Explore digitally enabled circular business models, creating value and improving environmental sustainability</td>
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<td></td>
<td>Study how to proactively detect, translate and incorporate customer needs and wants into supply chain strategies and processes through emerging technology tools</td>
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<td>Examine the effects of data driven services on supply chain thinking and supply chain management activities</td>
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<tr>
<td>Supply chain orientation</td>
<td>Study how SCM will be positioned in the organization after a transformation toward SCM 4.0</td>
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<td>Analyze the benefits and drawbacks of owning vs “renting” the technological infrastructure of the supply chain (license-and-install vs as-a-service)</td>
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<td></td>
<td>Study how some technologies can help to deal with some of today’s prevalent supply chain challenges and become integral part of supply chain processes (niche vs integrated usage)</td>
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<tr>
<td>Inter-organizational</td>
<td>Study whether the current understanding of supply chain partnership still hold true in a digitalized SCM context</td>
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<td>collaboration</td>
<td>Examine whether traditional power imbalance in supply chains can be addressed through SCM digital transformation</td>
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<td></td>
<td>Investigate how digital technologies facilitate (or hinder) the collaboration between supply chain partners while the interdependencies increase (limited vs expanded)</td>
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<td>Investigate whether supply chain actors should join an existing platform or to build up a one (join vs own)</td>
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<td></td>
<td>Whereas CPS, IIoT and blockchain-based smart contracts enable decentral decision making, investigate which SCM activities to centralize in order to achieve control (centralized vs decentralized)</td>
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<td>Explore how technical standards evolve in the supply chain (wait-and-see vs orchestrate)</td>
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<td>Human-centric issues</td>
<td>Determine the role of human in digitalized SCM applications and practices</td>
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<td></td>
<td>Explore the degree SCM should shift power and decision-rights to machine learning and AI (prescriptive vs predictive)</td>
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<td>Analyze the potential overreliance on big data and machine learning insights that could stifle innovation and collaboration efforts in the supply chain</td>
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<td>Elaborate on the appropriate leadership practices during the digital transformation of the supply chain (transactional vs transformational)</td>
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<td></td>
<td>Investigate how SCM and related departments can fill the talent gap in analytical and digital capabilities (train vs hire)</td>
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**Table II.**  
An agenda of future SCM 4.0 research
Finally, we would like to encourage SCM researchers to look outside the box not only in their quest for data and the exploration of new insights (following an inductive reasoning, Mantere and Ketokivi, 2013), but also to apply and elaborate on and extend theories (following an abductive reasoning, Dubois and Gadde, 2002) to make sense of new technologies in SCM rather than echoing PR departments of technology providers. Engaged scholarship is likely to provide SCM with deeper insights (Mathiassen, 2017). Given the many challenges society today is facing, we do well in following Kurt Lewin’s advice: “If you want truly to understand something, try to change it.”

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Notes
1. Industry 4.0 refers to the 4th industrial revolution and is translated from German. The term “Industrie 4.0” was first used in 2011 at the Hannover Fair (Vogel-Heuser and Hess, 2016). Several definitions of the concept exist.

2. Defined by Min et al. (2019, p. 45) as “the recognition by an organization of the systemic, strategic implications of the strategic and tactical activities involved in managing the various flows in supply chain”.

References
New York, NY.


Further reading

Toward a Digitally Dominant Paradigm for twenty-first century supply chain scholarship

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Abstract
Purpose – The digital advances in modern industry are accelerating changes in the broad social, economic, political and business environments within which supply chain management (SCM) is practiced. Given this extraordinary contextual upheaval, the conduct of research to identify, define, understand and explain how the digital revolution will impact key SCM concepts is imperative. The purpose of this paper is to introduce a theoretically grounded Digitally Dominant Paradigm (DDP) framework that demonstrates how digital concepts and insights can be infused into existing elements of best-practice SCM, in order to help guide future research.

Design/methodology/approach – Middle-range theorizing is proposed as a means to explore the ways in which researchers can explain supply chain phenomena (i.e. build theory) in the age of digitalization.

Findings – An example of how a DDP framework can be applied to a well-entrenched logistics/supply chain concept is provided, and the authors conclude by identifying exemplary research propositions for future exploration.

Originality/value – The broad goal of the paper is to spark forward-looking supply chain scholarship based upon development of a DDP of SCM.

Keywords Paradigm, Digital, Industry 4.0, Middle-range theory, Supply chain digitalization

Paper type Conceptual paper

As supply chain academics, [...] (w)e must pursue research that accurately and confidently describes the world around us, explains how key relationships work, prescribes appropriate strategy and behavior, and sets the stage for further inquiry. (Fawcett and Waller, 2011, Journal of Business Logistics Editorial, p. 5)

When goods are digital, they can be replicated with perfect quality at nearly zero cost, and they can be delivered almost instantaneously, [...] The answer is not to try to slow down. Instead of racing against the machine, we need to learn to race with the machine. That is our grand challenge. (Brynjolfsson, 2013, TEDx, Long Beach, California)
Introduction
Researchers have adhered to Fawcett and Waller’s (2011) advice by conducting research that describes, defines, explains and enhances our understanding of the many concepts and relationships inherent to the supply chain management (SCM) domain. Since the turn of the century, numerous researchers have contributed to the development of a theory of SCM that advances key postulates describing how organizations create form, time and place value (e.g. Carter et al., 2015; Defee and Fugate 2010; Mentzer et al., 2004). Yet, the broad social, economic, political and business contexts within which SCM is practiced are continually changing; regulatory issues, geopolitics, human demographics, consumer trends and expectations, and technology all impact key SCM concepts and their complex interrelationships. And so, at the dawn of a business era that has been termed Industry 4.0 (see e.g. Hofmann and Rüsch, 2017), the broad environmental impacts on SCM seem to be accelerating.

Industry 4.0, conceived originally as a high-tech future investment strategy in Germany in 2011 and increasingly embraced as a vision of the future across the industrialized world since then (Hofmann and Rüsch, 2017), has been described as “the next phase in the digitization of the manufacturing sector” (Baur and Wee, 2015). The vision is driven by the connection, via the internet, of astounding computational power and unprecedented levels of data with physical processes (Hofmann and Rüsch, 2017). Such connectivity will enable increasingly sophisticated applications of advanced analytics and business-intelligence capabilities and facilitate new forms of human–machine interaction such as advanced robotics and 3-D printing (Baur and Wee, 2015, p. 1). Kevin O’Marah (2017), a prominent supply chain industry thought leader, has proclaimed that such digital advances are “the dominant force for change in supply chain today [...] rewriting the rules of business and supply chain”.

If industry observers and scholars are to be believed, we are on the cusp of an age where conventional supply chain processes will soon dramatically change, or alternatively, become completely usurped by electronic information streams, as was recently projected in an article published in Harvard Business Review provocatively titled, “The Death of Supply Chain Management” (Lyall et al., 2018). For example, the Physical Internet concept is gaining significant attention and funding in Europe through a program called Horizon 2020 (Ballot et al., 2014). Under this concept, supply chain logistics assets such as transportation and distribution networks owned and operated by states and private enterprises are connected seamlessly through information networks to collaboratively optimize supply capacity and demand requirements, promising a 30 percent reduction in logistics costs and assets with a similar improvement in service performance (Alliance for Logistics Innovation Through Collaboration in Europe, 2019).

Given the potential for such extraordinary upheaval in supply chain practice, it is incumbent upon SCM researchers to explore the impacts that digital supply chains will have on key theoretical concepts in the SCM scholarly domain (Holmström and Partanen, 2014; Goldsby and Zinn, 2016; Calatayud et al., 2019). Specifically, research must be conducted to identify, define, explain and understand how the digital revolution will impact key SCM concepts such as alliances and relationships, supplier selection and management, social responsibility, outsourcing, and time-based strategies, among many others.

The purpose of this paper, therefore, is to proffer a new theoretical paradigm of SCM thinking that considers the potential impacts of the digitalization[1] of form, time and place value, and how this transformation to a new standard of digitally enhanced operational execution would fundamentally recast core elements of SCM theory and practice. The broad goal is to respond to the challenge posed by Fawcett and Waller (2011) by re-invigorating supply chain scholarship through a forward-looking discourse focused on the development of a Digitally Dominant Paradigm (DDP) of SCM to spark research that formulates and tests...
hypotheses that explore the plausible relationships between digitalization and established supply chain concepts. This goal is accomplished in three specific ways, including:

1. introduction of a framework grounded on the principles of middle-range theory (Merton, 1968) to demonstrate how digital concepts and insights may be infused into key elements of best-practice SCM to help guide future research;

2. providing an example of how the framework can be applied to reframe thinking regarding a well-entrenched and highly impactful concept from the logistics and supply chain domains – time-based supply chain strategy choice; and

3. posing researchable propositions to provide initial input into future empirical and analytical exploration.

The shifting theoretical and practical foundations of SCM
An effective starting point for this discussion is the consideration of how digitalization has increasingly influenced the practice of SCM over the past three decades. Throughout the 1980s and 1990s, for example, Walmart’s SCM practices, characterized by long lead-time and high-volume anticipatory orders to drive scale efficiencies in procurement, manufacturing, transportation and warehousing, were considered by many to be the state of the art. These and other similar practices, including low-cost country sourcing, more than tenfold growth in container shipping[2] during the last 30 years, and consolidation of local warehouses into mega-regional locations to support a proliferation of stores, subsequently cascaded through industry. Such ideas emerged from fundamental assumptions regarding the characteristics of business during an analog age, which Bowersox (2002) summarized as a situation where supply was scarce compared to demand; the technology available to capture, move and analyze information within reasonable timelines was limited; and the relationships between and among supply chain entities were adversarial.

These early SCM era assumptions began to be challenged in the 1990s. A new brand of Dot-com retailers and communications companies, such as Webvan, Boo.com and Worldcom, used the internet to directly reach consumers, elevating the idea of leveraging customized demand information at the individual consumer level to new heights (Wollscheid, 2012). Although this initial movement was met with mixed success, it did, however, set the stage for firms like Alibaba, Amazon and JD.com to emerge as disruptive leaders in the retail space. The approach to business performance practiced by these new era retailers can best be described as a marriage of SCM with digital technology. Other firms such as WeChat, a Chinese multi-purpose messaging, social media and mobile payment app with over 1bn monthly active users, help to facilitate this value revolution by enabling other retailers, and increasingly manufacturers, to make their products directly available to consumers via mobile purchasing and electronic payment (www.economist.com/business/2016/08/06/wechats-world). These firms, and others like them, have revolutionized business by establishing a new expectation for value creation, where consumers expect an ever-expanding array of products available with one- to two-day delivery to their homes or offices as the norm (and in some large metropolitan markets 1–4 h has become the norm).

The ability to combine massive data collection, previously unimagined information connectivity and visibility, and ever-improving analysis capabilities, combined with a physical network consisting of broad geographic network coverage, local fulfillment presence and parcel/postal delivery, have positioned these twenty-first century retailers as leaders of the digital supply chain era. It may be inferred from these Industry 4.0 era success stories that the fundamental assumptions underlying competition are changing or indeed have already changed. Contrary to Bowersox’s (2002) postulates from an earlier era of SCM, the availability of supply to serve customer demand is munificent; the technology available
to capture, move and analyze information within reasonable timelines is abundant; and the
relationships between and among supply chain entities is shifting toward collaborative.

The reversal of Bowersox’s basic postulate – from supply scarcity to supply munificence
from the customer’s perspective – is brought about by digital supply chains such as
Amazon’s. The broad array of product information made available by these supply chains
enables customers (both business customers and end user/consumers) to purchase products
globally. In addition, digital supply chains are infused with much more knowledge about the
demand patterns and tastes of individual consumers. This enables digital supply chains to
personalize offerings to match the requirements of individual consumers who, in turn, see a
growing collection of products offered to them.

In his classic treatise on paradigms and paradigm shifts, Kuhn (1962) asserts that the
conduct of scientific inquiry is akin to putting together a puzzle – a puzzle bound by the
rules of the reigning paradigm, or collective mindset of the scientific community, consisting
of concepts, frameworks and practices that define a discipline. However, when the existing
rules fail, the search for new ones ensues, sparking revolution – a period when the accepted
model of reality undergoes large-scale transformative change. The violation of Bowersox’s
analog age assumptions suggests that the SCM academy is at the cusp of just such a
revolution. If this is indeed the case, then a new paradigm that considers the impact of
digitalization on SCM becomes necessary for advancing scholarly discourse.

**Toward a Digitally Dominant Paradigm for SCM research**

Despite the wealth of evidence that digitalization is impacting global commerce, academic
research in the logistics and supply chain fields has yet to meaningfully address
digitalization concepts and outcomes. A review of a prevailing theory of the supply chain, as
posited by Carter et al. (2015), provides a useful example of why and how this should occur.

Adopting a conceptual theory building approach that draws on two decades of literature,
Carter et al. introduced foundational premises about the structure and boundary of an
idealized supply chain for physical goods. Among these premises was that a physical goods
chain possesses a bounded horizon; that it can only be identifiable from the perspective of
the focal firm for a focal product; that it consists of direct/physical and indirect/support
functions; and that its performance is attenuated by constraints such as physical distance,
cultural distance and network distance. However, despite the intellectual allure of these
premises and the strong foundations they provide, Carter et al.’s (2015) theorization stopped
short of including artifacts of a supply chain that is digital-dominant, and it also theorized a
supply chain design at a higher level of abstraction than the supply chain processes that
would underpin it.

Thus, though Carter et al.’s contribution contributed enormously to the understanding of
a physical goods supply chain, logistics and SCM scholars still lack the perspectives and
frameworks necessary to understand the impacts of digitalization on the micro- and macro-
economic, environmental and social domains that comprise the business operating
environment within which contemporary supply chains exist. SCM has evolved from a
description-based research discipline to one grounded on foundational theories that define,
explain and unravel complex interrelationships, resulting in the identification of the
discipline’s primary domain and major conceptual relationships – which we can collectively
refer to as the “what” of SCM. Yet, while these aspects have served to establish the primary
building blocks of the discipline, such foundational theories often lack the domain specificity
necessary to understand the inner workings within key conceptual relationships – the
how’s, when’s and why’s – that drive actualized outcomes.

Further development of SCM research must consider the numerous ways that
digitalization will alter current models and frameworks (Goldsby and Zinn, 2016).
Ultimately, though, it is difficult to understand what digitalization means for SCM when
very little attention has been paid to the operational impacts of digital business models in relevant supply chain contexts. The limited research on the subject has occurred primarily in the fields of computer science and information systems (e.g. Büyüközkan et al., 2018; Vössing et al., 2019) and industrial/systems engineering (e.g. Tao et al., 2018; Emelogu et al., 2016; Vanderroost et al., 2017), with the vast majority of the work focused on what digital transmissions are and how they work. There has been little research that explores the influences of digitalization on SCM, such as the physical conversion, transference and storage of goods and materials, and the associated value creation for customers, although there have been some scholars who are beginning to explore these issues (see e.g. Saberi et al., 2019). And, while much of the attention paid in the popular business press has been on the need to “get smarter” about applying digitalization to transform supply chain performance (e.g. Kerr, 2018; Robinson, 2018), very few substantive insights about the true nature of such transformations have emerged in academic research. Though managers and researchers alike can learn from industry observations, they fall short of the rigorous scientific inquiry needed to understand the impacts of digitalization on SCM concepts. Rather, academic research that explores the near-term impacts of the digital transformation on the theory and practice of SCM is required.

We propose a DDP framework as an enabling guide for supply chain scholars, supporting researchers in conceptualizing, explaining and relating new theoretical frameworks and testable propositions to help move the discipline into the digital era. The new assumptions associated with the digital age, including supply munificence, abundant technology and a collaborative posture, form the keys to understanding the changed perspective possible in the DDP. As highlighted in Table I, these changing assumptions alter the mechanisms through which supply chain managers make decisions: how they gather information, analyze this information and then execute decisions, which we might characterize as “seeing,” “thinking” and “acting.”

| Seeing | From: leveraging visibility to achieve assured supply, in order to meet forecasted demand | From: orchestrating visibility technologies to build forecast-driven supply chain operations due to blind spots in information flow | From: limited visibility due to opportunism, incomplete and filtered information sharing within supply chains |
| Thinking | From: demand forecast-driven analyses to manage capacity in a competitive supply-side environment | From: supplying chain decisions based on advanced technology support and access to seamless real-time data and insights | From: firm-level analysis and decision-support tools to optimize firm performance and minimize operational risks |
| Acting | From: anticipatory management of inventory and operational capacities based on demand forecasts | From: technology support for human-driven supply chain operations | From: silos of supply chain operations to counter functional and firm-level inefficiencies |

Table I. Changing mechanisms associated with the new assumptions of DDP
The fundamental characteristic of digital dominance is the notion that SCM decisions and solutions will be increasingly governed by an emphasis on time and process efficiency. Whereas prior dominant perspectives have focused on cost and/or service, the essence of digitally enhanced SCM is the ability to utilize abundant information to heighten execution speed and process design in creating the precise bundles of form, time and place value required to optimize the cost/service balance, and thus maximizing the profitability of each transaction. This essentially ushers in a revolutionary way of viewing SCM strategy development and resource allocation. As a result of these changing mechanisms, the emphasis of the DDP is an articulation of new ways and means by which SCM adds value to firm performance and the marketplace at large. More importantly, the focus is on the underlying infrastructure that facilitates SCM decision making, and how the realities of this new way of executing SCM processes will emerge as dominant, setting new standards in the delivery of form, time and place value.

**Middle-range theorizing (MRT) as a foundation for the DDP**

In proposing the DDP, we build on the foundations of MRT (Merton, 1968), to provide the logic and perspective required to address the gap in understanding represented by the impact of digitalization on supply chain concepts and practice. Recent articles in logistics journals have called for MRT research, which involves researchers focusing on the inner workings of logistics and SCM phenomena to develop a deeper understanding of the mechanisms through which these phenomena impact outcomes, and conditions under which such outcomes are more or less manifested (Craighead et al., 2016; Stank et al., 2017; Pellathy et al., 2018). MRT enables researchers to navigate within established general relationships and explore the contextually specific aspects within those relationships; contextual relationships that are often not discernable when leveraging broader general theory (Stank et al., 2017). A middle-range approach also heightens the actionable impact of academic research by focusing on “how, why and when” questions; questions that provide a framework to dig into contextual areas that are increasingly the interest of SCM managers and students (Pellathy et al., 2018).

Figure 1, adopted from the study by Pellathy et al. (2018), portrays a framework for using MRT to conceptualize how digitally dominant thinking may be infused in supply chain research. This process begins with the formulation of middle-range theories grounded in

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**Figure 1.**
A process for exploring domain-specific constructs at the middle range

**Source:** From Pellathy et al. (2018)
empirical evidence that have accumulated about a phenomenon within a specific discipline (Moore et al., 1980). Such evidence may have come from research that was originally motivated by general theory but may also have come from more inductive observations of practice. MRT then consolidates the empirical regularities that a community of researchers has established within the field into theoretical propositions that reflect the established body of evidence (Pellathy et al., 2018). This enables researchers to move directly from empirically derived constructs and relationships into new explorations that seek to deepen contextual understanding of phenomena (Stank et al., 2017). Essentially, middle-range theories are deeply embedded in disciplinary knowledge, lying between day-to-day working hypotheses and all-inclusive general theories (Merton, 1968; Garver, 2019).

Applying the DDP: an illustration
Using the MRT framework as a backdrop, an application of the DDP of SCM may now be derived. While the high-level $X \rightarrow Y$ relationships established through SCM research remain valid, digitalization drives a fundamental change in the mechanisms that influence relationships. The relationship between time-based fulfillment strategy choice and performance, for example, provides an interesting specific context for applying the generalized framework to generate research questions that might be motivated by a DDP in SCM. Time-based strategies represent the choice domain in which firms decide to postpone form and/or time and place value creation until after a customer order is received; or speculate by finalizing final form, time and place value creation prior to an actual customer demand cue. Time-based supply chain strategy choice, first conceptualized in SCM research by Zinn and Bowersox (1988), draws on the concepts of cycle time acceleration and total costing to postulate different applications of form/time/place value to create different cost/service bundles that conform to specific customer requirements. In essence, time-based strategies focus on managing the cost/service tradeoff through process orchestration and lead-time management.

Subsequent development of the concept proposed and empirically determined that varying levels of input variables such as demand uncertainty, product or service variety, length of the product/service lifecycle (i.e. amount of time before the product or service is replaced by a new variant), contribution margin and average markdown determine whether to use anticipatory, lean, leagile or agile time-based techniques to optimize revenue, cost and asset performance while delivering desired levels of customer value (e.g. Fisher, 1997; Goldsby et al., 2006; Pagh and Cooper, 1998; Van Hoek, 2001; Waller et al., 2000). Contingency theory further posits that if the appropriate time-based strategy is chosen based upon the varying levels of the input variables, then performance will improve. For the purposes of this example, the relationships between the input variables and time-based strategy choice described in previous research will serve as the baseline understanding of the concept (i.e. the $X \rightarrow Y$ set of relationships as portrayed in Figure 1).

Adoption of various types of digitalization tools promises to dramatically alter the mechanisms that impact the base relationships among the critical time-based strategy input variables and strategic choice. It may be possible under digital age assumptions of supply munificence, abundant technology and collaborative postures to make different time-based strategic choices given conditions of the various input variables than those prescribed under analog age assumptions and improve upon the tradeoffs in required levels of service and total cost performance output. Observations from supply chain practice suggest that demand-based and targeted pricing practices, availability of rich unstructured data from social media, and immediate capture of orders via online and mobile applications dramatically improve demand certainty, and thereby, create vision into supply requirements (Hall, 2019; Olivero, 2015; Stank et al., 2018). Further, improvements in computational capabilities from big data analytical techniques, unstructured data analytics
and artificial intelligence (AI)-aided decision-making promise to make prediction of demand and supply requirements more precise and timelier. Finally, enhancements in automation emerging from flexible robotics, 3-D printing, autonomous vehicles, drones and crowd-sourced delivery options provide the promise of a much lower total operating cost profile and shorter operational cycle times (Stank et al., 2018).

These and other digital mechanisms enhance the ability of supply chain managers to see, think and act upon the time-based strategy input variables and thus alter the nature of the cost/service performance output tradeoff associated with different time-based strategy choices. Thus, input variable conditions such as low demand uncertainty, low numbers of product/service variants and low profit margins that had indicated choosing a speculation strategy in the analog age (so as to lower operating costs at the expense of holding inventory to achieve prescribed service levels) may now be postponed until an actual order is placed and still optimize the total cost/service tradeoff relationship. Custom mixing a soft drink ordered from a Coca-Cola Free-Style machine, provides low-cost postponed creation of a product that has infinite product options and completely unpredictable demand (see www.coca-colacompany.com/stories/coca-cola-freestyle-unveils-next-gen-fountain-dispenser-new-ope). Similarly, Amazon owns a patent to install 3-D printers on delivery vans so that some products on an order can be made on their way to being delivered (Boyle, 2018).

Conversely, input variables that influenced decisions to postpone form, time and place value creation in the analog era due to the high uncertainty of the final customer order and therefore the high cost of holding costly inventory that is likely to be incorrect or obsolete once an actual order is placed may, in the digital age, be made and/or located and held in advance of demand based upon speculation if the prediction of actual demand and the operational response time can be dramatically improved using enhanced digital tools. Thus, Amazon can flow deliveries of products that have not yet been ordered to certain metropolitan areas or zip codes knowing that by the time they arrive in the area it is highly likely that an actual order for that specific product in that specific area will have been placed based on shoppers’ online search activity.

The following narrative provides insight into practical scenarios of digitalization that change the nature of mechanisms that impact the input variable – time-based strategy choice relationship.

“Seeing” – enhanced visibility
Digitalization improves the quality of demand information, enabling firms to better pinpoint the product or service variant demanded as well as the location and the timing of the demand, thus dramatically reducing demand uncertainty (Rossman et al., 2018). As a result, firms have a lesser need for postponement because postponement is an uncertainty reduction management tool (Zinn, 2019). For example, when products are made to order, there is no uncertainty as to the customer requirement, so there is no need to postpone the product’s final form. Better demand information will additionally impact customer service. One competitor’s ability to shorten delivery time and improve its quality will raise customer expectations for the entire industry. The resulting elevated industry standard impacts all competitors, whether they have better information or not (Masters et al., 1992; Holmström et al., 2016). Better demand information is also helpful to improve production planning, purchasing activity and inventory management, thus speeding order cycle times (Cachon and Fisher, 2000; Ojha et al., 2019).

Visibility further reduces uncertainty in supply chains. It extends the benefits of better demand information to the entire supply chain (Zhu et al., 2017). These benefits are of two types. First, suppliers get the same benefits as their customers if the information is shared. Second, the sharing of information further leverages the benefits for both supplier and customer as they work together. Visibility also enables managers to have a faster response
time to unanticipated problems. This represents another reduction in uncertainty. In an
environment laden with high uncertainty, this type of visibility is an incentive to postpone.
As managers do not know the nature of demand, they can postpone decision making until
they do and then react quickly to satisfy the demand. In environments where uncertainty is
low, the benefit of postponement is also low.

“Thinking” – improved analytics
Organizations continue to adopt new analytical techniques to better leverage the improved
visibility they have gained in their supply chains. Analytics systems using AI not only
enable descriptive, predictive and prescriptive insights simultaneously, but also learn from
and interact naturally with humans (Jarrahi, 2018). These new analytics capabilities
promise to enable firms to use the massive availability of so-called big data to predict future
scenarios and even prescribe solutions to future problems and opportunities as they
manifest (Calatayud et al., 2019). In this way, companies can obtain more unique, timely and
accurate insights to inform a host of decisions, from when to release a new product to
determining value loss/gain from adopting sustainable supply chain practices.

Using cognitive analytics systems that utilize AI-based systems in areas such as inventory
management, operations planning and transportation are finding deeper and more impactful
ways to employ technology to support and guide decision making in their supply chains
(Aouad, 2019; Hamilton, 2018; Wilkins, 2019). AI systems have the potential to help supply
chain teams achieve resolution to supply chain challenges more quickly and more robustly by
suggesting options based upon past behavior or underlying data, arming managers with
valuable insights and data that they would not otherwise have. AI technology might also be
used to easily bring diagnostic tools or work instructions to manufacturing floor personnel or
immediately answer complex and ever-changing international trade questions for shipping
personnel, aid supply chain strategy teams in understanding data patterns from unstructured
sources such as social media, or alert supply chain planners to potential shortages and quality
issues from suppliers (Stank et al., 2018).

The benefits of improved predictive capabilities emerging from digital age analytical
systems promise to radically alter the calculus of time-based strategic decision making. As
with improved visibility, as the ability to predict accurately and swiftly reduces uncertainty in
planning for demand and supply, and risk decreases – thus making speculative value creation
performed in advance of demand more effective at achieving specific customer value needs.
As it is also more efficient, the digital age may enable application of speculative time-based
strategies that fulfill demand better and at much lower total cost. Conversely, it may also make
the allocation of capacity for response-based strategies more accurate and efficient, enabling
more and better value creation that is postponed until after a customer order is booked.

“Acting” – heightened operational flexibility and reduced cycle time
Digitalization, with the use of tools such as robots, 3-D printers and speed factories, impacts
the time-based strategy decision by enhancing the ability of operations to easily and
economically shift from doing one task to another and by accelerating the time needed to
manufacture products or create service value (Hofmann and Rüschi, 2017). As a
consequence, they cut the time to process orders.

Robots and 3-D printing are both tools capable of shortening operating time and enhancing
flexibility. Robots automate operations, enabling firms to produce cheaply and with fewer
errors. The strength of their impact depends upon the cost of the robots, themselves. At an
earlier stage of the technology’s development, robots were relatively expensive and therefore
tended to be used in fewer, centralized facilities where the ability to do a repetitive task favored
high-volume operations. This makes postponement less attractive because products are
manufactured away from customers and, consequently, with a potentially long delivery time.
However, as the technology evolves, cheaper and more capable robots can be employed in larger numbers and closer to customers. This creates an incentive to postpone. 3-D printers present a similar case. As they become more cost effective and expand the range of products that can be printed, the incentive to postpone is also expanded. Cheap robots and 3-D printers are similar in this respect. Faster order processing time reduces inventory (especially of C parts), warehousing cost and transportation cost. It also improves customer service. Increasingly, digitalization presents scenarios such as this – where costs are reduced, and service is enhanced simultaneously.

Using MRT to drive research that explores DDP mechanisms
As described in the last section, MRT provides the logic and perspective required to address the gap in understanding the impact of digitalization on supply chain concept and practice, enabling researchers to navigate within established general relationships and explore the contextually specific aspects within those relationships that are not discernable from the broader general theory. MRT facilitates a process for scientifically compiling evidence from research that was originally motivated by general theory but may also have come from more inductive observations of practice, consolidating the empirical findings that a community of researchers has established within their field into theoretical propositions that may be explored to deepen contextual understanding of phenomena (Pellathy et al., 2018; Stank et al., 2017).

In compliance with the tenets of MRT, such observations of the potential impact of digitalization on the key mechanisms of the time-based strategy decision can help define the types of how, when and why questions that must be considered to better understand key relationships in the digital age. Specifically, DDP-based research questions should address how, when and why digital applications that change managers’ ability to see, think and act differently will alter the previously identified relationships between input variables and time-based strategy choice.

Using the how, when and why format, Table II exemplifies the application of MRT to the DDP in the context of the time-based strategy decision. This is followed by a few sample researchable propositions to further illustrate the application of the DDP framework. The purpose is to provide an example of how the process might work, not to advance the body of research in time-based strategies, per se.

Recall that the purpose of the proposed DDP is to infuse digital concepts and insights into established supply chain relationships. Accordingly, the base relationships forwarded in Table II can be distilled down further into researchable propositions related to the strategic time-based choices to postpone form and/or time and place value creation until after a customer order is received or speculate by finalizing final form, time and place value creation prior to an actual customer demand cue. The following researchable propositions illustrate this point:

**P1.** Firms in digital supply chains are more likely to speculate than firms in analog supply chains as (a) the use of digital sources increases the speed of capture, the overall volume of inputs and the quality of demand information; and/or (b) the application of digital age analytics improves the quality of the data used to plan production and to allocate product within supply chains.

**P2.** Firms in digital supply chains are more likely to postpone than firms in analog supply chains as manufacturing and warehousing automation enables them to customize products closer to the moment of consumption.

To clarify, the purpose of these propositions is not to suggest specific hypotheses relevant to the time-based strategy decision that would require the time-tested research process of exploring the literature, gathering field data, and designing robust methods for testing. Rather,
<table>
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<th>Mechanism</th>
<th>Time-based strategy (TBS) decision logic under analog age assumptions</th>
<th>Time-based strategy (TBS) decision logic under digital age assumptions</th>
<th>DDP research questions applied to TBS selection decision</th>
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</table>
| Seeing    | Supply scarcity, limited technology and adversarial posture make “seeing” information across the supply chain more costly, more time consuming and less effective. This influences TBS decisions to choose the appropriate strategy that balances total cost and service given the inherent lack of both supply and demand visibility. | Supply munificence, abundant technology and relational posture make “seeing” information across the supply chain less costly and timelier and more effective. This may cause a shift in the total cost/service decision inherent in the TBS selection decision, as the enhanced visibility to capture demand and supply data will change the relative balance in the total cost/service tradeoff. | How/When/Why does improved visibility change the relationship between key input variables (level of demand uncertainty, number of product/service variants, etc.) and the TBS selection decision? Specifically, some interesting questions include:  
  - What becomes the role of supply chain employees in such an environment?  
  - How does the business interface with other entities up and down the supply chain?  
  - Are new platforms/intermediaries introduced to capture data and create customer value? |
| Thinking  | Supply scarcity, limited technology and adversarial posture make “thinking” more costly, more time consuming and less effective. This influences TBS decisions to choose the appropriate strategy that balances total cost and service given the inherent lack of technology available to capture, share and analyze data to provide sound input to decision making. | Supply munificence, abundant technology and relational posture make “thinking” less costly and timelier and more effective. This may cause a shift in the total cost/service tradeoff decision inherent in the TBS selection decision, as the enhanced ability to capture, share and analyze data precisely and timely will change the relative balance in the total cost/service tradeoff. | How/When/Why does improved analytics change the relationship between key input variables and the TBS selection decision? Specifically, some interesting questions include:  
  - Again, what becomes the role of supply chain employees in such an environment?  
  - Does the placement of generic SKUs in the supply chain (decoupling point) move up- or downstream because of enhanced “thinking”?  
  - Are new platforms/intermediaries introduced to analyze data and create customer value? |
| Acting    | Supply scarcity, limited technology and adversarial posture make “acting” more costly, more time consuming and less effective. This influences TBS decisions to choose the appropriate strategy that balances total cost and service given the inherent lack of technology available to quickly and efficiently create specific form, time and place value bundles. | Supply munificence, abundant technology and relational posture make “acting” less costly and timelier and more effective. This may cause a shift in the total cost/service tradeoff decision inherent in the TBS selection decision, as the enhanced ability to create highly specific levels of form, time and place value quickly and inexpensively will change the relative balance in the total cost/service tradeoff. | How/When/Why does automation change the relationship between key input variables and the TBS selection decision? Specifically, some interesting questions include:  
  - How might terms of sale evolve to reflect new ways of creating value/doing business?  
  - What challenges emerge for intellectual property rights when manufacturers outsource their designs for others to produce goods?  
  - How can increasingly unique bundles of form, time and place value be created at a profit as demographics shift to urban areas?  
  - How can this be done sustainably? |
the purpose is to illustrate merely a few of the many interesting and important questions that researchers may ask to spark exploration into the new mechanisms – the how’s, when’s and why’s – that impact key SCM relationships in the digital age. It is highly likely that the truths that have been established over decades of research conducted under assumptions that prevailed in the analog age may no longer ring true – or at least not in the ways that they rang true – under assumptions of the digital age. Thus, this is a call to arms for SCM researchers to begin to explore the new universe of unknowns made possible by the digital revolution.

Conclusion

It is worth re--emphasizing that digitalization is increasingly impacting the practice of SCM, to the point that SCM processes and activities in 2020 and beyond will no longer be recognizable vs the ingrained processes and activities that emerged from the twentieth century/analog age and upon which most organizations practice SCM still today. One need only scan the daily SCM industry briefs to recognize that the digital world is here to stay, and organizations that cannot or will not adapt to new technologies will soon be overtaken by disruptive competitors. It is not a coincidence that, as of the second quarter of 2019, the six largest global firms based upon market capitalization are firms whose business models revolve around digital technology, including Apple (which in early August 2018 topped $1 trillion in market capitalization, the largest in history), Amazon, Alphabet (parent company of Google), Microsoft, Facebook, and Alibaba[3]; the first traditional product-oriented firm (ExxonMobil) does not appear until the tenth spot on the list (Statista, 2018).

Still, most organizations remain uncertain as to how to begin to leverage digitalization to revamp their business model. Further, most SCM researchers are similarly unsure as to how to adapt or begin research streams that seek to identify, define, understand and explain digital concepts and their impact. The re-stated purpose of this paper, therefore, is to act as a call to arms for an increased emphasis on exploration of a DDP in SCM research. Herein, we position MRT as a valid justification and framework for exploring new phenomena. MRT enables researchers to ask how, when and why digitalization will impact the X \( \rightarrow \) Y relationships among established SCM concepts, as well as what new concepts and relationships may emerge, observing trends and correlations generated from practice to infer possible hypotheses suitable for future testing.

Finally, we contribute to understanding how the DDP can be leveraged by introducing a contextualized scenario of time-based strategic choice to demonstrate how a research stream based upon the tenets of MRT may be applied to the exploration of the impact of digitalization on established relationships. It is important to note that the scenario was chosen simply as an exemplar and that the DDP framework can apply to a number of other research streams and topics in SCM. The research topics that may be explored are limited only by the bounds of creativity and innovation of researchers. Interestingly, it is quite certain that topics that are not now in the mainstream will emerge as key concepts of the digital age. Importantly, a DDP encourages not only exploration of how changing mechanisms impact established concepts and relationships in SCM, but also invites new enquiries that should be explored, for example, the changing nature of human interfaces with digital tools, issues with cybersecurity and potential applications of cryptography, etc. As with the actual application of digital tools in SCM, future research deploying a DDP is limited only to the innovation and creativity of SCM researchers and scholars.

The potential application of the DDP we propose provides a relatively unique opportunity for academic research to not only explore current supply chain practices, but also to lead industry in the generation, dissemination and application of knowledge related to digitalization in SCM, answering the call of Goldsby and Zinn (2016) to illuminate the path forward. This will require that both scholars and journals become more broadly focused on different methodologies required to describe, explain, understand and define concepts
within a transformed paradigm. The various sub-disciplines that comprise the overarching domain of SCM should seek to become more knowledgeable about the use and appropriateness of inductive methods and design science approaches to establish new insights on established concepts and on new theory (for further discussion of this issue, please see Holmström et al., 2009; Saberi et al., 2019). It is hoped that our theory will contribute to a continuing discourse on how such a vision can be made reality.

Notes
1. At this point, it becomes useful to draw a distinction between the root concept of digitization, which refers simply to the conversion of focal information from analog to digital form, vs digitalization, which describes the use of digital technologies to change a business model and provide new revenue and value-producing opportunities (www.gartner.com/it-glossary/).
2. US intermodal container traffic grew from 152m tons in 1985 to 1,834m tons in 2017, as per the US Maritime Administration (www.MARAD.dot.gov).
3. Of note, Facebook suffered a massive devaluation in July 2018 due to market concerns over data security and validity, a major concern of the digital age.

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Further reading


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Emerging procurement technology: data analytics and cognitive analytics

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Abstract

Purpose – The purpose of this paper is to elucidate the emerging landscape of procurement analytics. This paper focuses on the following questions: what are the current and future state of procurement analytics; what changes in the procurement process will be required to enable integration of analytical solutions; and what future areas of research arise when considering the future state of procurement analytics?

Design/methodology/approach – This paper employs a qualitative approach that relies on three sources of information: executive interviews, a review of current and emerging technology platforms and a small survey of subject matter experts in the field.

Findings – The procurement analytics landscape developed in this research suggests that the authors will continue to see major shifts in the sourcing and supply chain technology environment in the next five years. However, there currently exists a low usage of advanced procurement analytics, and data integrity and quality issues are preventing significant advances in analytics. This study identifies the need for organizations to establish a coherent approach to collection and storage of trusted organizational data that build on internal sources of spend analysis and contract databases. In addition, current ad hoc approaches to capturing unstructured data must be replaced by a systematic data governance strategy. An important element for organizations in this evolution is managing change and the need to nourish an analytic culture.

Originality/value – While the majority of forward-looking research and reports merely project broad technological impact of cognitive analytics and big data, much of it does not provide specific insights into functional impacts such as the impact on procurement. The analysis of this study provides us with a clear view of the potential for business analytics and cognitive analytics to be employed in procurement processes, and contributes to development of related research topics for future study. In addition, this study suggests detailed implementation strategies of emerging procurement technologies, contributing to the existing body of the literature and industry reports.

Keywords Big data, Data analytics, Cognitive analytics, Procurement technology, Technology roadmap

Paper type Research paper

1. Introduction

Scholars and practitioners have long emphasized the critical role of technology in improving information flows across supply chains. Sharing of information in buyer–seller relationships has been highlighted as being important (i.e. Handfield et al., 1994; Handfield and Nichols, 1999; Narayanan et al., 2009; Waller and Fawcett, 2013; Wang et al., 2016). Technology has shaped how information is exchanged, from paper-based to electronic communications (Narayanan et al., 2009). Given the important role of technology in supply chain management, scholars have investigated the benefits and challenges from adopting IT-enabled systems such as ERP (e.g. Kelle and Akbulut, 2005), EDI (e.g. Narayanan et al., 2009), cloud computing (Wu et al., 2013), and RFID (e.g. Angeles, 2005; Sarac et al., 2010; Tajima, 2007).

Information technology has continued to revolutionize the environment of supply chain management. The rise of cloud-based computing, mobile technology and distributed computing has led to the current era of massive volumes of real-time data, both structured and unstructured (Handfield and Linton, 2017). Researchers project that in the next five
years more than 200bn connected devices (IDC, 2014) and 12bn machine-to-machine devices will take place (Machina Research, 2010). In addition, computing power has increased significantly, and computer algorithms and techniques have also become much more sophisticated. This growth of the digital landscape provides a growing opportunity to mine previously unobtainable data and derive new business intelligence, especially in the world of buyer–seller relationships. It presses researchers to study how to process and interpret this massive amount of data for prescriptive supply management capabilities (Wang et al., 2016; Wieland et al., 2016).

Press and industry reports project potential changes in the digital landscape of business applications (Ernst and Young, 2014, 2015; IBM Institute for Business Value, 2015; Ransbotham et al., 2015a, b; Geraint, 2016). Many of these forward-looking reports envision a future in which these emerging technologies will enable improved decision making. Academic projections (e.g. McAfee and Brynjolfsson, 2012; Waller and Fawcett, 2013; Wieland et al., 2016; Wang et al., 2016) also provide insights into how these technologies will impact business disciplines. Decision making in procurement management is not exempt from the influence of these emerging technologies (Chen et al., 2015), as procurement has need of strong analytical support perhaps more than any other business function (Wang et al., 2016; Wieland et al., 2016). However, improved clarification is needed to map out how “procurement analytics” (enabled by these technologies) can lead to improved decision making and outcomes for supply management-related problems (Monczka et al., 2016).

In this paper, we address the following questions:

RQ1. What are the current and future states of procurement analytics?

RQ2. What changes in the procurement process will be required to enable integration of analytical solutions?

RQ3. What future areas of research arise when considering the future states of procurement analytics?

This study contributes to the literature as follows. Most importantly, we provide researchers in supply management with a new set of emerging constructs and insights on the current and future states of procurement analytics. Previous studies on IT-enabled systems such as ERP, EDI and RFID reveal the key benefits and implementation issues (Angeles, 2005; Bendoly and Schoenherr, 2005; Narayanan et al., 2009; Sarac et al., 2010). While these studies highlight the salient theoretical constructs (e.g. information visibility) that procurement analytics ultimately attempts to realize, emerging procurement technologies include previously uncovered but functionally ground-breaking features (e.g. the advent of intelligence and the integration with external data). This technological advance opens up unforeseen domains in the academic understanding of procurement management (Chen et al., 2015). We not only identify the current and future states of procurement analytics but also specify a technology roadmap for how emerging procurement technology may shape the workplace. In this manner, our study reduces the gap between academia and practices. Another contribution is that the results offer insights for how organizational culture may need to adapt to the next generation of emerging procurement analytics. Prior studies have shown successful adoption of emerging technologies requires shifts in organizational culture (Angeles, 2005; Narayanan et al., 2009; Wu et al., 2013). Since procurement analytics (i.e. both data analytics and cognitive analytics) fundamentally change the information flow and decision making in procurement management, new insights for the successful adoption of such analytics are necessary.

This paper is organized as follows. Section 2 offers a literature review of emerging procurement technologies from the practitioner and academic research, and points to the relationships among key functional decisions and practical analytic outcomes. Section 3 presents
our research framework and methodology. Section 4 offers the results from our analysis. In Section 5 we pull together the findings and discuss in detail how the results would affect the key supply management concerns from data governance to organizational culture. Section 6 considers emerging trend and future research implications. Finally, Section 7 concludes with a discussion of limitations.

2. Literature review of procurement technology

2.1 Procurement analytics

As management executives rely more on analytically derived business decisions, a large number of leading firms are seeking ways to employ data-driven decision making (McAfee and Brynjolfsson, 2012). As one of many diverse applications of business analytics, procurement analytics denotes a data-driven approach to derive solutions to supply management-related problems (Monczka et al., 2016). Typical problems and decisions are related to management of spending and budgets, cost reduction, supplier management, cost modeling, category market intelligence, supplier evaluation, procurement-led innovation, market strategies, supply chain risk and stakeholder value improvement (Monczka et al., 2016). Approaching and solving these problems requires a set of technological components, called procurement technology, and a vehicle for clustering data from multiple sources (e.g. ERP systems, the internet, procure-to-pay systems, contract management systems (CMS) and third-party providers), processing and presenting information to users, who then act on this information. We refer to such integrated data systems as procurement platforms.

The practitioner literature is fairly consistent in defining the new forms of procurement and platforms that are beginning to emerge. There are two representative ways of procurement analytics being developed: data analytics and cognitive analytics. Data analytics is a systematic approach that provides data-based explanatory and predictive modeling to provide insights into business problems (Chen et al., 2015). Tools used in data analytics include statistics, graphical visualization tools, simulation and mathematical algorithms. Data analytics typically operates on structured data. Structured data include data that have been classified into variables and parameters, typically using databases produced by internal systems. Cognitive analytics refers to a more sophisticated approach to data using machine-based learning (MBL) and artificial intelligence. It operates on both unstructured and structured forms of data and grapples with technical issues in combining both forms of data (Phillips-Wren et al., 2015). Unstructured data can be generated not only from internal sources (e.g. emails, tweets, reports, etc.) but also from external sources (e.g. social media, company reports, blogs, news feeds, etc.) (Chen et al., 2015). Technology required for cognitive analytics is still at a nascent stage, and to date, there are few commercial platforms using cognitive analytics.

Cognitive analytics differs from data analytics in multiple aspects and holds the promise of being able to perform a number of different functions that will be important to procurement. First, while data analytics is conventionally defined as data processing through which labeled or formatted quantitative data are transformed into business insight, cognitive analytics is primarily defined as data processing specialized in recognizing and understanding of diverse, complex, heterogeneous and qualitative data. For example, Watson, developed by IBM, can read 800m pages per second (Noyes, 2016). Cognitive computing can begin to understand language through MBL systems, whether through natural language or visual communication. Second, cognitive technologies can reason and understand not only information but also the underlying ideas and concepts. As an independent and intelligent agent empowered by a high-performance computing infrastructure, a cognitive analytics system mimics cognitive models that the human brain employs (Gudivada et al., 2016). As their reasoning ability becomes more advanced over time, they are able to deduce outcomes and identify relationships between different parameters and variables. They can form hypotheses, make
arguments and prioritize recommendations to help humans make better decisions. Finally, cognitive computers never stop learning: machines can ingest and accumulate data and insight from every interaction, continuously. The system becomes more valuable with time.

2.2 Academic studies of procurement analytics and platforms
Academic research on procurement analytics and platforms is nascent. Many prior studies tend to focus on data-analytics-based solutions (e.g. Papert et al., 2016; Wu et al., 2017) or procurement platforms that operate on structured data (i.e. EDI) (e.g. Narayanan et al., 2009). While these studies provide limited features of emerging technologies, they introduce several primary theoretical constructs that procurement analytics operationalize in transforming data into managerial insights. Such constructs are needed to be employed in defining the key features of current and future procurement analytics. Overall, previous studies attempt to address questions as to how information is understood, how further information is captured and how quickly information is captured in the supply chain. These questions correspond to the following theoretical constructs: talent, information visibility and real-time data technologies, respectively.

*Talent.* Prior research on the movement of materials suggests that individuals must be groomed to adapt to how they perceive and encounter data analytics (Rai et al., 2006; Hult et al., 2002). More specifically, individuals with an analytical thinking style, rather than an intuitive one, perform significantly better on a stock-flow problem (Weinhardt et al., 2015). In data analytics, individuals with a global, rather than a local, thinking style do not necessarily perform better. An organization’s capability to respond quickly to procurement data rests on individuals monitoring the explicit needs of customers for materials, information, services, knowledge and capability (Chen et al., 2015).

*Information visibility.* Researchers who study information sharing in the supply chain often invoke the notion of visibility. It refers to greater access to high quality information describing various factors of demand and supply (Barratt and Oke, 2007) and to the quality of specific types of information extracted from information sharing between business partners (Williams et al., 2013). Increasing information visibility between supply chain participants can help all parties reach their overall goal of increased stockholder value (Monczka et al., 2016). Improved access to supply chain data contributes to increasing asset velocity (e.g. inventory turns), the ability to move material quickly through supply chains. Data visibility thus improves responsiveness to shifts in demand and disruptions (Handfield and Linton, 2017), contributing to managing supplier risk and supplier performance (Wang et al., 2016).

*Real-time data technologies.* While the issue of visibility has been invoked for many years (Barratt and Oke, 2007), we are only now seeing the technology that makes real-time data a reality (Handfield and Linton, 2017). Generally, problems associated with real-time data technologies arise from difficulties of data acquisition and processing (Richey et al., 2016; Waller and Fawcett, 2013). Access to information in real-time requires conditions of event transparency, material flows and a time-defined component (Chen et al., 2015). The ability to disperse procurement data rapidly is enabled by technological capabilities of inexpensive cloud-based computing, distributed computing and the growth of a digital ecosystem (Handfield and Linton, 2017).

2.3 Practitioner projections of procurement analytics and platforms
A recent study (IBM Institute for Business Value, 2015) of over 1,200 CEOs projects major disruptions that will rapidly shift processes in procurement and other business areas. The study highlights that a digitized ecosystem emerges through the on-going collection of available data, processed through connected products, GPS technology and acceleration of
computing power. It also predicts the important role of talent in establishing analytic and predictive capabilities. A study conducted by Ernst and Young (2014) suggests that advanced analytics will be the most disruptive force impacting the procurement function, ahead of risk, sustainability, globalization, integration, finance, innovation, transparency and people. The data will come from multiple objects in the supply chain, including supplier delivery performance metrics, automated payments and smart contracts. The study also forecasts that artificial intelligence will facilitate predictive analytics and automated decisions based on vast amounts of data.

Other reports forecast even more drastic changes. One prediction is the elimination of the current procurement workflows and the re-arranged role of machines and humans. A study by Accenture (Nowosel et al., 2015) highlights a number of specific technologies in procurement analytics: a cloud-based data exchange, shared information space to interpret analytics, innovation platform among strategic suppliers, a virtual gathering place to track in-flight projects and simultaneous connection with the supply market. A study by KPMG (Der Gracht et al., 2016) similarly seeks to build a futuristic view of different plausible technological scenarios facing procurement. The authors suggest the possibility of procurement being replaced by digital technologies. The study predicts new applications of artificial intelligence, to handle future contract management using algorithm-based solutions to draw up and negotiate smart contracts independently.

Several studies highlight the challenges that lie ahead for digital procurement. Future of Supply Chain Survey of 2015 (Geraint, 2016) suggests that a significant number of respondents see key analytics technologies as having unclear usefulness. Ransbotham et al. (2016) caution that buying the latest technology alone may not lead to success and that a good amount of hard work encompassing data management, cultural change, leadership and strategy and skills development is needed. A recent study by SCM World (Geraint, 2016) similarly suggests that most procurement technologies are primarily about automating the procurement process rather than addressing the ability to use information to deliver value.

3. Research framework and methodology
Most emerging procurement technologies are not fully realized, and only a few leading firms have adopted such technologies with notable outcomes. As such, employing a survey with a generic industry sample would provide extremely limited insights for this emerging technology. Therefore, we turned to collecting interview data as the primary source of information, augmented by a short survey of procurement executives of large companies and an investigation of procurement technology platforms in the market. We selected large companies as these were the primary investors in emerging procurement technology platforms.

By triangulating several exploratory methods against a small targeted sample of executives who are pioneering the development of procurement analytics, we sought to capture both quantitative and qualitative features as well as emerging trends, as shown in Figure 1. Triangulation of quantitative and qualitative methods has been shown to be an important approach for exploration of supply chain management issues that are in the early stages of development (Handfield and Melnyk, 1998). This approach also assures the reliability of findings but also as an approach to capture a more holistic portrayal of a subject matter (Jick, 1979). Practically, the mixture of survey and interview methods has been widely used in research aimed at capturing intangible evidence (e.g. Fawcett et al., 2008).

First, we defined key concepts such as data analytics and cognitive analytics and identified functional constructs of procurement analytics from both the practitioner and academic literature. From academic articles, we categorized the theoretical constructs typically cited by academic scholars in the analytics literature. From practitioner articles, we reviewed the functional applications being discussed by industry thought leaders. The applications and theoretical constructs were used as the foundation to guide the research. Using the theoretical
constructs and functional applications that our literature review pointed to, we categorized procurement analytics and considered those areas of procurement analytics that the theoretical constructs and domain-specific functional applications were related. These itemized categories were used for the survey and interview in the latter phase[1].

In the second phase, we assessed the breadth of procurement platforms and identified their primary output to managers for decision making. We analyzed how the trends of technologies embedded in procurement platforms have changed over time, the functional applications of procurement platforms are currently available, and what applications are currently under development. Platforms included in this analysis were selected using the following criteria. A platform refers to a specific operating system that collects data from different systems (e.g. ERP systems, procurement catalogs, procurement card systems, etc.) and combines them into a database for the purpose of procurement. Examples include Ariba, Coupa, Bravo and Zycus. Next, we identified the analytical outputs produced by each platform that were important for managers in making decisions. As a result, we found 164 separate and distinct procurement applications, as of November in 2016, and assessed them against the technological features identified in our practitioner review. In each of these cases, we reviewed the website for the provider, conducted a “web-demo” of the application (where feasible) and interviewed sales personnel (where feasible) from the organization. Notes were taken in each case and coded to specific outcomes and characteristics.

Third, we gauged the analytic needs for types of procurement analytics by industry, employing a survey targeted at procurement executives. In this stage, we investigated what analytic functions and data the industry prioritized, what functional areas the industry was likely to invest in and what analytic functions were likely to be realized. This survey was
administered to the Chief Procurement Officers (CPO) or Chief Supply Chain Officers of Fortune 500-type companies that make up the CAPS membership base. CAPS refers to this survey as the CPO Insight survey. We obtained a set of 25 survey responses out of 110 eligible member firms. The participants of this survey are shown in Table I.

Finally, we interviewed technology experts and executives, qualitatively comparing and contrasting findings from the prior three stages. This iterative process allowed us to deduce technological trends based on our procurement platform review and procurement executive survey. In particular, by checking the consistent and inconsistent findings between the stages, we built a maturity model that projects a technology roadmap. Both the supply chain and information technology management literature (Lockamy and McCormack, 2004; Wendler, 2012) have used maturity models to explain how the progression of change occurs in a process or an organization. Based on the prior application of maturity models, we believed it served as a useful approach for characterizing emerging technologies. The maturity model was also helpful in positioning insights from the interviews with subject matter experts, and enabled us to shape recommendations for future adopters. The interview participants included executives across three primary categories: industry experts and consultants; software providers; and industry procurement executives. We interviewed multiple individuals in each of the three categories, including 6 major procurement consultancies, 9 large procurement software providers and 20 procurement executives conducting or implementing analytics projects. A list of these participants is shown in Table I as well as the interview protocol. All interviews were captured in notes and distributed to the research team for analysis and dissemination. The execution of the research and the resulting frameworks were evaluated based on rigorous criteria (Lincoln and Guba, 1985), summarized in Table II. The second column of Table II provides information on how the qualitative interview and survey outcomes shaped the operationalization of key constructs and results.

Because many emerging technologies for procurement analytics are still in the early stage of development, firms who had actively implemented or developed procurement

<table>
<thead>
<tr>
<th>ID</th>
<th>Survey participants</th>
<th>Size</th>
<th>ID</th>
<th>Interview participants</th>
<th>Type</th>
<th>Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>S-1</td>
<td>Consumer goods</td>
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<td>I-1</td>
<td>Software companies</td>
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<td></td>
</tr>
<tr>
<td>S-2</td>
<td>Consumer goods</td>
<td>$1bn</td>
<td>I-2</td>
<td>Software companies</td>
<td>$160m</td>
<td></td>
</tr>
<tr>
<td>S-3</td>
<td>Consumer goods</td>
<td>$11.5bn</td>
<td>I-3</td>
<td>Software companies</td>
<td>$85m</td>
<td></td>
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<tr>
<td>S-4</td>
<td>Consumer goods</td>
<td>$16bn</td>
<td>I-4</td>
<td>Software companies</td>
<td>$124m</td>
<td></td>
</tr>
<tr>
<td>S-5</td>
<td>Consumer goods</td>
<td>$76bn</td>
<td>I-5</td>
<td>Software companies</td>
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</tr>
<tr>
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<td>Industrials</td>
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<td>Software companies</td>
<td>$20m</td>
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</tr>
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<td>I-7</td>
<td>Consulting companies</td>
<td>$33bn</td>
<td></td>
</tr>
<tr>
<td>S-8</td>
<td>Industrials</td>
<td>$25bn</td>
<td>I-8</td>
<td>Consulting companies</td>
<td>$6bn</td>
<td></td>
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<td>S-9</td>
<td>Industrials</td>
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<td>Consulting companies</td>
<td>$37bn</td>
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<td>Consulting companies</td>
<td>$2bn</td>
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</tr>
<tr>
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<td>Industrials</td>
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<td>Consulting companies</td>
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<tr>
<td>S-12</td>
<td>Semiconductors</td>
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<td>S-14</td>
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<td>S-18</td>
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<td>S-20</td>
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<td>$26bn</td>
<td></td>
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<td>I-21</td>
<td>Private companies</td>
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<td></td>
</tr>
<tr>
<td>S-22</td>
<td>Financials</td>
<td>$26bn</td>
<td>I-22</td>
<td>Private companies</td>
<td>$26bn</td>
<td></td>
</tr>
</tbody>
</table>

Table I.
Interview and survey participants
analytics enabled by the emerging technologies were relatively rare and hard to find. Rather than seeking to grow the interview pool to the extent where statistical tests would be possible, we focused on deepening our understanding of the interviewees’ technology adoption practices by limiting the pool to 15 interviews. To make up for the weakness that arises from the small sample size and to clarify our managerial interview insights, we complemented one set of interviews within a small executive forum of CAPS Research executives. Companies at this forum included five CAPS Research member firms from the chemical, aerospace, consumer goods, non-profit and high-tech industries. This meeting took place on September 19, 2016 and was attended by 16 executives and subject matter experts. The results of this workshop were also captured in field notes, distributed to the team and analyzed as part of our research. Other interviews took place with individual CAPS members using a structured interview protocol (shown in the Appendix) by phone, whereby notes were shared with other members of the team.

4. Results

4.1 Key findings from studying procurement platforms

Our procurement platform review suggests that the majority of current procurement analytics has relied on structured data, although procurement analytics has been around for almost 20 years. As shown in Figure 2, the biggest growth in procurement systems occurred in the 1990s and early 2000s. During this period, Ariba and Commerce One emerged as key competitors and many of these early systems including Oracle, Zycus, Emptoris and Ivalua became known as “procurement bolt-ons.” The primary capabilities of these early systems focused on procure-to-pay (P2P) systems that captured transactional data, reduced
paperwork and improved process efficiency. The next wave of growth occurred during the period of 2001–2007, with the evolution of new cloud-based procurement systems such as Coupa, Proactis and others. Following the global recession, many procurement analytics providers began to focus on supplier risk and supplier life cycle management systems, particularly in the financial sector. During 2010–2016, a greater emphasis has moved toward mobile-based procurement systems, as well as cognitive analytics solutions such as Watson. The functions of most platforms listed are limited, wherein procurement analysts using the platforms are required to manually accumulate spend data across multiple systems. Users must run multiple reports to get an overall view of required information, and this process often requires the manual and time-consuming integration of reports in Excel by procurement analysts.

Our analysis suggests that most organizations are limited to historical spend analysis and have limited opportunities for data analytics across external supplier and customer partners. The major applications provided by procurement platforms and products include spend management, inventory management, supplier risk assessment, project procurement and broader systems that support end-to-end supply chain risk, as shown in Figure 3. Requisition and approval modules and supplier management are also among the most common features,
with 70 percent of all procurement software incorporating at least one of these two features. Expense, budget and asset management are the least common feature, with only 32 percent of software platforms evaluated having at least one of these three features – only 10 percent had all three. These applications for the most part meet the needs of current procurement strategies, such as supporting cost improvements, reducing working capital through improved inventory visibility, reducing supply disruptions and meeting regulatory requirements for assessing supplier risk and managing procurement on major projects. A small number of platforms are focused on improving real-time decision making, collaborative contracting, improving environmental performance and cost to serve analytics. A very small number of specialized platforms are creating analytics to provide insights on labor and human rights violations, virtual collaboration and should-cost estimation platforms.

Figure 4 shows the review results of emerging application areas that are under development and will likely be deployed in the near future. The results highlight a significant movement toward greater application of “risk alerts,” in a variety of areas such as spend analysis, inventory visibility and alerts in the end-to-end supply chain. For example, an application developed by a major contract manufacturer provides instantaneous visibility to global disruption events in their supply chain. A second area is related to “supply market intelligence (SMI)” that comprises any number of different situational elements involved in supplier management. Examples might include conflict minerals, regulatory compliance issues and safety and regulatory issues. Other platforms are building capability to merge external and internal data sets to create new analytical insights that provide decision support. A good example of this is Flex’s Risk Pulse, which combines external weather data and maps them onto current supplier and distribution networks, thereby providing analytical inputs into when shipments should occur to avoid hitting weather delays or other risks (Handfield and Linton, 2017). Another instance of this capability is a large display center at a contract manufacturer that creates a mobile platform for pulling information in a menu-driven format on material lead times, risk mitigation and inventory. The system allows users to download this information onto a smart phone, and a picture of the inventory pulse across the system for any customer, for any facility including an aggregated view of the total raw material, WIP and finished goods inventory in the system.

Our platform review results suggest that one of the biggest emerging fields is fraud and counterfeit prevention. Currently, applications for counterfeit and fraud prevention are provided by very few platforms, as shown in Figure 3, whereas such applications rank third
in our analysis of future analytic platforms in Figure 4. Procurement systems are beginning
to evolve to create a mechanism for encoding product genomes, which would help managers
understand where products go and where they come from. This information is critical in
combating counterfeit and fraud, which remains as one of the biggest and most overlooked
areas of lost profits and revenues.

4.2 Outcomes from procurement executive survey
In this section we review the results of the survey data collected in light of what we learned
from the review of procurement platform reviews. An immediate observation from the
survey results was the gap between the potential of procurement analytics and the current
state of procurement analytics.

Regarding the level of importance of data for analytics, internal data such as spend data,
contract compliance, ERP data, financial data and supplier contract data are the most
important sources for procurement analytics, as shown in Figure 5. Yet, we found that
external sources such as financial data and external news sources are nearly as important as
internal data, which firms primarily focus on now. These results suggest that external data
such as news feeds, event monitoring, supplier data and social media, all of which are
largely untapped, may become important data sources in the future.

As shown in Figure 6, spend analysis, price benchmarking, supplier performance and
risk alerts represent the top 4 needs for better analytics. Our survey results suggest that
procurement is still in a very early stage of building business insights outside of the
procurement function (Richey et al., 2016; Papert et al., 2016).

To understand the rationale for an investment in procurement analytics, we asked
respondents about major derived benefits. The benefits include lower prices, improved
leveraging of spend and improved insights into category any spending that will drive
strategy, as shown in Figure 7. These results imply that direct monetary benefits such as
price advantage and purchasing power will drive the development of future procurement
analytics. Respondents also believe that the potential to free up time for purchasing to focus
on higher value-added activities, improved contract visibility, reduced working capital and
greater visibility to supply chain disruptions may follow.

In light of the fact that the aforementioned benefits are realized when procurement
analytics is successfully developed and adopted, we asked respondents about the likelihood
of the investment in realizing the benefits and the difficulty in achieving them. As shown in
Figure 8, by and large, the investment likelihood and the difficulty have a negative
relationship: organizations are less likely to invest in procurement analytics that provide
benefits more difficult to achieve. To be specific, pricing power from increased leverage is expected to be the easiest benefit to achieve, whereas more complex approaches having to do with reduced contract risk, reduced supply disruption, revenue growth and freeing up opportunities for value-added work are more difficult to implement and derive benefits (Nowosel et al., 2015).

The next generation of procurement software platforms and products in the next five years can be realized only when embedded technologies enable them to run designed functions. We additionally surveyed CPOs to rate the importance of required technological capabilities, as shown in Figure 9. Drill-down visualization capabilities is rated as the most important capability; executives believe that procurement analysts will need to be able to “drill down” to more granular level of details that are able to explain why patterns are occurring. Cognitive analytics is rated as the second most desired capability. Although there are certainly some pilot programs in this area, cognitive analytics that drives insights by combining structured and unstructured data will become more important. In addition,
real-time analytics through automated data uploads in the cloud is widely anticipated as a capability that will drive quicker access to data insights. Finally, improved user experiences and visualization capabilities are expected to provide an improved and more efficient human–machine interaction.

5. Discussion
The results of the procurement platform review and procurement executive survey helped to shape our view of the future technology roadmap for procurement analytics. Our analysis suggests a number of relationships between theoretical constructs, functional applications and procurement analytics that define those areas of procurement management that emerging procurement analytics will most likely have the greatest influence on (see Figure 10). We began with theoretical constructs that reflect the key technological concepts operationalized as functional applications in the practitioner literature. These functional applications serve will be supported by the emerging set of procurement analytic platforms identified in our research.
Although primary links between functional applications and procurement analytics (i.e. solid arrows) can be inferred, each category of procurement analytics may serve decision making in more than one theoretical construct or functional application. This mapping also helped us to link procurement analytic outcomes to our primary theoretical constructs. In the mapping process, we merged SMI and risk, based on the rationale that both elements are critical in helping procurement make decisions under conditions of uncertainty in supply markets. To reiterate our prior observation, the detection of risk associated factors is indispensable and plays a key role in the SMI, and the two have been referred to as “two sides of a coin” (Monczka et al., 2016). Admittedly, one can still claim some difference between the two concepts, but we propose that they are so closely interwoven as to be undifferentiated. In addition, since effective data governance is a foundation for procurement analytics, this element was added as a primary dimension.

Using the results in Section 4, we identified the hierarchy of needs for procurement analytics, current developmental stages of procurement applications and investment likelihood by procurement analytics area. Figure 11 depicts the relative rank of the areas in

<table>
<thead>
<tr>
<th>Needs</th>
<th>Development</th>
<th>Investment</th>
<th>Prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data governance and management</td>
<td>High</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td>Spend management</td>
<td>High</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td>Contract management and supplier life cycle management</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
</tr>
<tr>
<td>Supply market intelligence and risk</td>
<td>Medium</td>
<td>High</td>
<td>Medium</td>
</tr>
</tbody>
</table>
each domain. Data governance and management plays a fundamental role in future procurement analytics, so its importance is widely recognized. The development and investment in this area are highly active, projecting rapid growth of the area. Spend management is highly prioritized on the demand side and its development into the next generation procurement analytics takes place as expected. This tendency enables us to predict that procurement analytics for spend management may grow, focusing on meeting practical demands of firms; problem-solving oriented development might lead the growth of this area. Meanwhile, contract management and supplier life cycle management appear to be less prioritized in both review and survey results. Although the long-run growth of this area is unquestionable, the expansion of capabilities may also be delayed as many organizations are seeking to pilot new block chain technologies that may re-shape this area entirely (Handfield and Linton, 2017). SMI and risk are currently not a highly prioritized area, compared to other procurement analytics areas. However, there appears to be a high level of market development responses in this area that may be due to the growth of “big data” MBL technologies. These asymmetrical interests may be attributed to the temporal mismatch between market need and technological developments in the field that are not always aligned. A significant portion of the benefits from SMI and risk is not immediately realized but over time organizations come to realize the value of having better intelligence in an exceedingly volatile market environment (Wieland et al., 2016). In contrast, the recent emergence of massive volumes of inter-connected real-time data has produced a wide array of technological innovations. We predict the growth of this area will continue to advance as these technologies mature.

From interviews with technology experts and procurement executives, we sought to identify technological adoption stages in the form of a roadmap, thereby complementing the macro trends that the results from our platform review and survey project. Such a roadmap creates the foundation for an organization’s strategic vision and action plan that maps how data will be captured, classified, aggregated and employed in the workplace. We were able to map the relative level of maturity of an organization’s progression toward an analytic culture. We proposed three scenarios depicting both the maturity of the procurement analytics area and the relevant adoption of technology platforms that are likely to occur:

Current Common Practice: the current “as is” state for most of the organizations and software platforms that we reviewed in this study. Enterprises at this level operate using traditional relational databases with structured data and Excel spreadsheets to create reports and queries.

Current Best Practice: companies in this category are employing “pockets of excellence” that are pushing the boundaries of analytics practice. They may be experimenting with new analytic tools, visualization software, running pilots and learning from these experiences.

Future Best Practice: although there are few organizations we interviewed that fall into this category, we envision that a handful will be moving into this area in the near future. These organizations will begin to utilize advanced technologies such as Internet of Things (IoT), artificial intelligence, cognitive MBL approaches and real-time data analytic KPIs.

Using the relationship between theoretical constructs and procurement analytics, as shown in Figure 10, we apply the framework to the four primary procurement analytics areas: data governance, spend management, contract management and SMI. Table III summarizes current common practice, current best practice and future best practice for each area.

### 5.1 Data governance and management

One executive noted, “you have to have the data available to be able to mine it.” Yet, current common practices in data governance and management are limited to the collection of raw transactional data. Common sources of data may include a company’s ERP system, procurement system (e.g. Ariba, Coupa, Bravo, etc.), third-party Group Purchasing
Organizations or even suppliers. Many providers restrict their data acquisition to only readily available electronic data, thereby missing a significant “chunk” of the total spend data. A common problem faced by companies we interviewed is the issue of how to structure the front-end data entry process to ensure data quality. One CPO was seeking to ensure the

<table>
<thead>
<tr>
<th>Current common practice</th>
<th>Current best practice</th>
<th>Future best practice</th>
</tr>
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<tbody>
<tr>
<td>Data Governance</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Input master data “as is”</td>
<td>Cleansed master data using algorithms</td>
<td>Master data cleansed through machine-based learning (MBL) and minimum human touch</td>
</tr>
<tr>
<td>Data in Excel spreadsheet</td>
<td>Data pulled from ERP, functional systems or dedicated supply chain data sources</td>
<td>External B2B data integration with customers and suppliers</td>
</tr>
<tr>
<td>Spend data resides in ERP systems</td>
<td>Improved data quality but poor definition of data across supply chain</td>
<td>IoT operational data and distributed computing data incorporated</td>
</tr>
<tr>
<td>Manual data cleansing and harmonization</td>
<td>Restricted input access to super users with dropdown menus</td>
<td>Big data structured in larger volumes</td>
</tr>
<tr>
<td>Spend management</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Historical Batch processing</td>
<td>Direct tie of procurement to financial metrics via aligned GL codes</td>
<td>Cognitive capability creates visual maps based on user queries</td>
</tr>
<tr>
<td>Procurement-focused</td>
<td>Forecasted spend impact on annual budgets and profitability</td>
<td>Leveraging big data to create insights</td>
</tr>
<tr>
<td>Mostly internal transactional data sources</td>
<td>Integration of contract data and supplier metrics</td>
<td>Predictive analytics and scenario analysis</td>
</tr>
<tr>
<td>Static reporting monthly or quarterly</td>
<td>Real-time spend analytics</td>
<td>Customized user interface</td>
</tr>
<tr>
<td>Focus on part</td>
<td>Analysis of spend variance by buyer across different business units and sites</td>
<td>Spend updated in real time</td>
</tr>
<tr>
<td>complexity reduction</td>
<td></td>
<td></td>
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<tr>
<td>Contract management</td>
<td></td>
<td></td>
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<tr>
<td>Historical contracts</td>
<td>Contract pricing linked to P2P system for pricing, discounts, payment terms, etc.</td>
<td>Contract pricing linked to P2P system for pricing, discounts, payment terms, etc.</td>
</tr>
<tr>
<td>database</td>
<td>AI tools can guide purchasing through decision tree to appropriate contract template</td>
<td>Contracts linked to external market indices</td>
</tr>
<tr>
<td>Contracts searchable by supplier</td>
<td>Search “Best Practice” contracts</td>
<td>Contract system generates alerts linked to external big data environmental triggers</td>
</tr>
<tr>
<td>Static reporting monthly or quarterly</td>
<td>Comparison of terms and conditions across contracts</td>
<td>External events (regulatory, currency) trigger contract renegotiation clauses</td>
</tr>
<tr>
<td>Contract templates available</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Contracts sorted by spend categories 100% spend under contract</td>
<td></td>
<td>Contract renewal periods drive CM workflow</td>
</tr>
<tr>
<td>Supply market intelligence</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Website scanning and trade journals</td>
<td>Customized SMI reporting by 3rd parties</td>
<td>Real-time pricing updates and future triggers</td>
</tr>
<tr>
<td>Reading generic SMI reports</td>
<td>SMI COE analysts develop reports on demand</td>
<td>Predictive analytics linked to market expenses</td>
</tr>
<tr>
<td>Monthly price index reviews</td>
<td>Standard pricing updates and market news on procurement portal</td>
<td>Scenario analyses support category technologies</td>
</tr>
<tr>
<td>Downloading public data</td>
<td>SMI keyword searches yield news feeds</td>
<td>Analytics identify emerging technologies, market events and multi-tiered insights</td>
</tr>
<tr>
<td>Developed prior to contract renewals</td>
<td>Linkages of supply and demand strategies</td>
<td>Historical machine-based learning (MBL) analysis with predictive capabilities</td>
</tr>
<tr>
<td>Tacit information in the heads of procurement SMEs</td>
<td>Knowledge management systems</td>
<td>Linkage of supply-side and buy-side events align forecasting of shortages or surpluses</td>
</tr>
</tbody>
</table>

Table III. Current common, current best and future best practices by the four functional areas in procurement
integration of data being used across 40 different countries and 23 ERP systems and noted as follows:

We have so many platforms, tools, and databases that we cannot integrate them all. We need to be able to look at our spending, our individual suppliers, and conduct analysis on our operational activities. For example, we need to be able to understand the velocity of parameters such as dollars per FTE, which is a key operational procurement metric. This is an important metric that justifies being able to invest further in procurement tools, to make our current FTE’s more productive.

Although the degree of freedom in the data entry is low, many users are prone to enter information incorrectly into purchase order and procure-to-pay systems, which degrades data quality. Many executives we interviewed reported the challenges of procurement systems that allow a lot of “free text” in the user interface. Furthermore, variation in data sources makes it difficult for procurement units to integrate their data in monitoring their operational activities. Because of inadequate data governance programs in most organizations, low usage of analytics is the current norm.

Some companies have adopted a best practice approach. When building a new master data, they move to “start from scratch” or just limit the data they integrate to a single year’s worth. One of the most important foundational shifts in procurement technology is the assurance of greater flexibility and visibility into the classification and enrichment process (Pierce et al., 2016; Williams et al., 2013). Increasingly, more advanced organizations are starting to look for the ability to classify spend to one or more taxonomies at the same time (e.g. customized UNSPSC and ERP materials code). ERP systems are typically not designed to provide easy user interfaces that enable effective on-going master data integrity (Stevens and Johnson, 2016). Thus, they may require additional third-party providers to provide data cleansing services. Emerging automated technologies employ algorithms that recognize an item or vendor code and map it to the same referential coding system.

In the future, more fundamental data governance will be required to realize the benefits of analytic technologies. Master data governance will increasingly become an automated function, as human user inputs into the system will be replaced by learning algorithms that recognize data errors. Once data is captured, coded and enriched, the real power of the data can be leveraged through merging with other data forms for analytic queries, dashboards, data visualization and cognitive computing. Many of the data inputs will be automated through barcode sensors, which will track received shipments at the loading dock. Purchase orders may be eliminated entirely, replaced by blanket order contracts (Der Gracht et al., 2016). Suppliers will virtually track demand and service requests through system integration and will fulfill customer demand based on reorder point triggers and sensors.

5.2 Spend management
Procurement is often forced to resort to surveys to attempt to measure supplier performance and analyze their spending. About 60 percent of companies that we interviewed are still not able to obtain detailed spending summaries by category. Current platforms provide a limited number of spend analysis functions that can be deployed. They are leveraging the spending per category through supply base consolidation, organizing control of spending to centralize and coordinate category management, establishing contracts that span multiple products or services with the same suppliers and reducing the complexity of parts by identifying common parts with different part numbers. Other than this limited set of functions, spend analysis is currently being used to enable improvements in cost, but provides limited insights.

Currently, a number of platforms are available that provide additional analytic insights using query abilities combined with visualization graphics. In particular, spend management technologies, that connect spend data with user data, business unit origin and suppliers, are able to create unique visualizations that are proving to be informative. These technologies
offer enabling views of spending history and provide structured data sets that can be used for “deep dive” analysis. They are also being “fed” into category strategies to establish a basis for predictive forecasting of spending. One of the executives noted:

Three years ago, the decision was made to apply analytics to the upstream procurement supply chain […]. the focus was instead of prioritizing, creating visibility of spending against a baseline by region, and developing should-cost models to prioritize the scale opportunities to create leverage. This is still in the early stages, which have started with spend data as the base data set.

One important improvement is linking spend data to general ledger (GL) codes. This process requires some level of integration between procure-to-pay systems and financial reporting systems. Many companies struggle to assign the proper linkage between spend categories and GL codes, but this integration is an important component that can lead to discussions with the higher management level. In particular, many dimensions of spending including inventory, indirect procurement (HR, IT and others) are often tied to working capital GL codes, and this can provide important insights into how to impact an organizations’ balance sheet.

In the future, procurement analytics in spend management will provide solution-oriented insights, by leveraging big data, generating visual maps based on user queries and reporting results based on predictive analytics and scenario analysis. In particular, real-time spend analysis combined with visualization techniques and structured queries on contracts will provide another level of value[2]. Also, integrated together, internal and external data will provide additional insights beyond the simple spend analysis and contract renewal periods (Chen et al., 2015). By using such an analysis, procurement will understand not only their current spending and contractual obligations but also their entire end-to-end supplier performance, risks and opportunities for collaboration.

5.3 Contract management and supplier life cycle management
Currently, the application of contract analytics helps drive efficiency and effectiveness within the contracting process and also helps in gaining an understanding of the procure-to-pay workflow cycle. CMS helps companies focus better on proactive management of spend and revenue as opposed to management based on historical data.

Current best practices are associated with application of searchable contract databases, allowing comparison and rapid access to contract information, as well as comparison of contractual terms and exposure for common suppliers, categories of spending and specific price benchmarking internally. One of our interviewees noted:

If they use our solution, it can break down contracts and assign them into metadata and the terms and route for workflow and just use it as a repository without authoring capabilities.

When spend analysis is combined with contract expiration data, important insights can be derived. For example, CMS inform when contracts are expiring, which can trigger buyer-level activities, such as assignment of resources and timing of preparation for contract renegotiation. CMS can also provide insights into outstanding terms and conditions, and those out of line with corporate policies. The real value of CMS, however, is the actual data contained in contract terms and conditions. Data obtained from contracts can be sent to a data warehouse for cleansing and processing and eventually be used in business intelligence and possible statistical analysis (Ernst and Young, 2014; Der Gracht et al., 2016). Data from CMS can be used for upstream/downstream analysis, comparing how customer needs are translating into supply market capabilities, prices and capacity requirements. This ability to link supply and demand characteristics of the market place is the true value of supply chain analytics.

In the future, CMS will evolve as the systems interact with other various management systems and external data. Future best practices in contract management will include
linking Accounts Payable invoice processing to contractual pricing terms and conditions. Today, there is disconnect between negotiated contract terms and actual payments. Early payment discounts, pricing tied to external market indices, quantity discounts and other negotiated terms are often not applied to supplier payments unless they are caught after the fact in an audit. Cognitive search tools may be able to provide links to sudden shifts in market conditions that may lead to price differentials or other factors. Links to market intelligence can provide benchmarks around pricing related to other shifts in the market such as elections, interest rates and other factors that may influence contractual terms and conditions. During a negotiation, CMS may also have cognitive mechanisms that will review proposed changes to a contract and provide legal insight using AI to approve minor changes and modifications. Future CMS would also provide “in-process” contract alerts if there are discrepancies between invoice pricing on a PO and the negotiated term. Intelligent CMS will be linked through cognitive analytics to enable “smart query” capabilities, allowing procurement staff to pose queries and quickly create visual analytics that provide insight. This type of capability will require some period of training for the machine to be able to better articulate the question.

5.4 Supply market intelligence and risk
SMI refers to the process for creating competitive advantage and reducing risk through increased knowledge of supply market dynamics and supply base composition. Effective SMI involves: monitoring supply markets and trends and interpreting the impact of these trends on company strategies; identifying the critical materials and services required to support company strategies in key performance areas; developing supply options and contingency plans that support company plans; and supporting the organization’s need for a diverse and globally competitive supply base (Monczka et al., 2016).

Currently, the intent of risk analytics is to provide early warning of looming threats to supply disruption. The process of creating intelligence and risk insights involves the application of individual and collective cognitive methods to weigh data and test hypotheses within a socio-cultural context. Much of the current practices involve having individuals scan websites, trade sites, blogs, news feeds and other static sources of information. They note information that is of interest. Organizations also use static applications to share documents with others and maintain an inventory of historical reports, information and data. The challenge with these current practices is that data are already historical by the time it reaches decision makers, are almost always backward-looking, and often are subject to multiple interpretations and follow-on actions. One of our interviewees noted:

If you look at our projects and innovation projects, they monitor risk right in the first five minutes. Twitter is the most valuable source of a risk on earth. There are some great engines for early detection of risk. The systems have to be nimble to take advantage of that.

Current best practices rely on human resources to secure SMI. Human analysts capture and codify information from multiple sources into “digestible” nuggets of market intelligence. One executive noted that:

Our tool provides an interactive interface to help business professionals mine large amounts of text for new business insights. For example, a user might see a rising number of references to a specific component or product in call center logs over time indicating the need to investigate whether the increased references are an early indicator of a problem or of new interest in a product capability.

Some organizations have also begun to create specialized teams of analysts in Centers of Excellence. This specialized team of internal or third-party analysts collects data from multiple sources and provides them in a more easily consumed form (often PPTs or reports). Companies are also working to create pooled databases that can be used as a basis for
exploring specific category problems. These databases often rely on enriched and coded spend data as the foundation, upon which are layers of other forms of data that address specific problems and questions that arise over the course of time.

In the future, driven by advances in technologies, semi-autonomous systems that aid SMI and risk will emerge. These systems will require some form of both human and machine-based inputs to make decisions and to perform activities based on those decisions. The development in the real-time data technologies will fuel the growth of this domain (Chen et al. 2015). Such technologies will capture external market data and create alerts and hedge positions based on market data. There are also technologies with keyword searches that will “crawl” news feeds and company websites to highlight key articles and information that must be scanned and reviewed by human analysts and condensed into a form that is digestible by internal knowledge consumers. Finally, predictive models based on historical data are being used to build market forecasts and predictive scenarios that can create insights, used as input to hedging strategies and on-going market planning. These new changes will help managers shift from the conventional strategy based on buffers to a situation and analysis-based risk management (Giunipero and Eltantawy, 2004).

5.5 Building an analytics culture

Beyond the technology issues, we also considered the implementation issues. Adopting a new innovative technology does not guarantee improved performance; rather, adopters could suffer from confusion and difficulties in implementing the new system, as pointed by practitioners (Geraint, 2016; Ransbotham et al., 2016) and academic scholars (Richey et al., 2016). Successful adoption of emerging procurement technologies requires effective integration of system and data, organizational actions and, most importantly, analytic culture necessary for decision making (Richey et al., 2016). Using our interview results, we present an organizational model for building a procurement analytics culture, as shown in Figure 12. Although every organization has a unique culture, we believe this transformation approach is generalizable enough to provide a basis for adoption across different environments.

Stage 1 – build a data management and governance discipline. A foundation for an analytics culture is a strong grounding in data that people can trust. For that reason, it is imperative that organizations specifically address the creation of a data management governance program as the basis for an analytics culture. Ad hoc approaches to capturing unstructured data must be replaced by a data governance strategy. Data governance should be based in the tradition of “quality at the source.” In other words, data must be properly
captured and coded at the point they enter the database or system. One of our interviewees noted as follows:

Our spend accuracy is in the high 90th percentile – but we didn’t get there by accident. You can’t procure materials here without using a standard process, and you can’t get the product shipped and paid for unless you work it through the process. The process ensures that we are gathering data in a methodical way. We have codes established at the enterprise level, and individuals who want to buy a part are required to add additional data (not a lot) and ensure the right descriptors are in the system. Also, you can’t add a supplier without going through a formal process review, which is key for supplier consolidation. All of our processes require you to add data in a precise and specific way.

As emerging technologies begin to roll out and become part of our working toolset, it will be critical to have a robust data platform in place to be able to create and identify visual graphical interfaces that is based on clean, enriched data platforms. Historical ERP data, spend data and contract data are the bedrock upon which further procurement analytics will be built. However, it is important to “get started” and begin pilots that exploit this data and layer them with other external data.

Data management starts with appropriate data acquisition. Common sources of data can be pulled from the materials management information system, GL, master files, purchase orders or even paper receipts that are scanned. Major challenges in using advanced analytics include lack of access to news feeds, financial updates, sentiment analysis, price trends, market risks and other important data (Lavalle et al., 2010, 2011). Once acquired through any number of different buying channels or external sources, data need to be checked for completeness and accuracy. Access to the right data and accurate and properly coded data provides the foundation for pricing agreements, quantity discounts, value analysis, supply base optimization and other important cost management activities. Data cleansing and enriching involve ensuring that the data have no duplicates, and are organized into a logical structure in a database.

The classification of products using coding systems is commonplace in many industries; however, few companies have taken the time to fully embed these codes into procure-to-pay systems. Before uploading the information into an ERP or P2P system, system programmers need to ensure the system can recognize the product and enrich it with the correct manufacturer name and item number, UNSPSC code and descriptions. Many providers acknowledge that not every product code is matched, leaving an unknown number of items with no match that was not uploaded into the contract database. The ability to accurately match UNSPSC codes to items is dependent on the accuracy and transparency of the original data set.

Stage 2 – identify target areas for analytics pilot. In building an analytics culture, the mantra of “learning by doing” is essential. The essence of learning involves developing a working culture that encourages managers to experiment, a tolerance for failure and an ability to derive lessons learned, as well as supporting the launch of new project based on the lessons learned. Analytics is not the same as a massive ERP implementation, which typically focuses on interdependencies, customized coding, data integration and business process mapping components. In contrast, for analytics, the emphasis should be on the speed of implementation, a mandate to experiment with different types of software and building a repertoire of approaches that work best. The catch-phrase, “Pilot quickly, and kill projects quickly” (Khanna et al., 2016) provides an appropriate moniker for the evaluation and adoption of analytics solution that has proven to be effective. In doing so, experimentation with the multiple forms of analytics in pilots can be important, especially for small- and medium-size enterprises that cannot commit to a major technology investment without being sure of the return (Villalón et al., 2002).

Before launching a pilot, however, it is essential to pick an area where there is a high likelihood of success and learning. Success is determined by selecting a target project that
has a strong appeal to a significant stakeholder (Anand et al., 2016). In building data governance initiatives, it is a good idea to start small, and start with an area where you are confident that you will be able to find savings. Start with spend data, which is really the “bedrock” of an analytics project, and then you layer in other forms of data. One executive during our interview noted as follows:

Roughly 50% of the data required for a project is spend data. When you are able to prove out the power of analytics on a single project, you can make the case for a broader data management strategy. You can begin to define how much data and what type of data needs to be refreshed in real-time, daily, weekly, monthly, or quarterly. This can also help to build the business case for investment in a broader analytics investment project, based on early successes in the pilots.

Stage 3 – explore application of alternative analytic approaches. The importance of communicating a digital strategy is not to begin the conversation with a focus on analytics. The key is to start with the business problem. This requires understanding the context and nature of the challenge facing the business. A research question may ultimately lead to an exploration of what digital strategies that must be established to address broader sets of business-related challenges, and this exploration will lead to an exploration of solution providers that are aligned with the characteristics of the business need. In this way, a company would not become beholden to one analytic approach but would keep its options open.

The goal of cognitive tools is to automate the processes of searching for prospective suppliers through online catalogs, evaluating suppliers with respect to multiple attributes, screening qualified suppliers and completing the purchase order, preventing specification ambiguity. Achieving this goal relies on an agent-based purchasing system to act as a substitute for the role of the human decision maker. Such agent-based systems can support purchasing managers in a series of strategic and tactical purchasing decisions, as opposed to traditional operations research techniques that have tight problem boundaries (e.g. supplier selection for a specific award). However, to use cognitive analytics requires the ability to “ask the right question.” This is where procurement must serve as the bridge between the stakeholder and the analytics provider. The best way to address this issue is to pilot the analytics discovery process, one step at a time. The journey needs to progress in stages, accompanied by organizational learning at each stage. The broader enterprise must evaluate their capacity to absorb the new analytical approaches, which requires education, experimentation, training, and pilot projects.

We found that several organizations have established a “Center of Excellence” that forms the basis for development of analytics capabilities; after all, specialized human capital is one of the key success factors for big data analytics (Richey et al., 2016). When we interviewed to understand industry models for managing the flow of analytics and intelligence projects, one of the trends that emerged is the need for a centralized core that is tasked with managing the flow of assigned projects. One of our interviewees explained the current status of the benefit as follows:

Today, the analytics team has begun embedding different functional subject matter experts into the center, and projects are prioritized based on business need. Some of the areas being explored are end to end supply chain optimization, risk assessment and categorization, and source to deliver interactions that can improve economic outcomes. The team has begun to hire data scientists from universities who arrive with a strong skill set, and also fund subject matter experts to work with the scientists who can share their knowledge and add context to the project data insights and interpretation. This is a key component of the sourcing initiative. Our biggest successes are when we can take a belief and put a number to it.

The organizations that seek to create an analytics capability should consider establishing a centralized Supply Chain Center for Analytics that is responsible for leading key analytics
initiatives that support the organization. This can create visibility, improved capacity planning, and aggregation and leveraging of key analytical skills from across the company. The center should also use project management software to better keep track of how major strategic initiatives are coming along, as opposed to the tactical day-to-day activities that are often assigned priority over these.

Stage 4 – create a roadmap for procurement technology evolution. A number of emerging technologies will impact procurement digitization and analytics strategies in the future. Some of the important emerging technologies include the following:

- IOT (distributed computing);
- block chain technology;
- MBL (artificial intelligence);
- real-time analytics enabled by cloud computing;
- voice recognition;
- rapid data visualization;
- advanced prescriptive/predictive analytics;
- intelligent automation (robots, vehicles, etc.);
- immersive technologies (augmented reality); and
- conversational systems (chatboxes using voice recognition).

These technologies will likely have a significant impact on procurement management as they mature; yet, the evolution and applications of the technologies may not necessarily turn out to follow the initial prediction. More importantly, emerging technologies often create key values through complementarity with existing or other emerging technologies (Wu et al., 2013). One of our interviewees noted:

Consider the cell phone. When smart phones came out, people first discovered they could use a browser. But recall the first time you used a browser on a phone: it was awful! So then we became smarter about designing websites so browsers could be used more easily – and that in turn led to Apps, which are a better way to use smart phones. And eventually, the evolution of the cloud service platform led to revolutionary mobile platforms, which require complementary capabilities.

Defining a “future state” technology roadmap is one of the most fundamental and indispensable activities for taking advantage of the effective and early adoption of emerging technologies (Phaal et al., 2004). Supply chain leaders must assess their risk culture in order to determine their readiness to adopt such emerging technologies. In response to the ontological and combinational unpredictability involved in the evolution of procurement technologies, technology road mapping provides a structured means for exploring and communicating the relationships between evolving and developing markets, products and technologies over time (Phaal et al., 2004). Given the variety of emerging platforms, defining the path ahead and the objectives sought from technology can provide a strong bias that is needed to assess emerging technologies and evaluating their value for adoption. A well-constructed roadmap can help organizations navigate turbulent environments of technology change by providing a means for scanning potentially disruptive technologies, evaluating them and tracking their performance relative outcomes. Technology roadmaps are deceptively simple in terms of format, but their adoption requires adoption of strong management leadership. In particular the scope is generally broad, covering a number of complex conceptual and human interactions.
6. Implications for future research

Our results should be interpreted with caution. They are based on potential future procurement analytic applications which are mostly untested. However, the grounded approach of this study, which is largely based on practitioners’ insights, suggests several key predictions and trends that are likely to evolve. With this cautionary limitation in mind, we offer the following implications we hope may guide future research directions in procurement analytics.

The first prediction is that procurement analytics will continue to grow and evolve, which is perhaps obvious given the growth in platforms found in our field analysis. The procurement analytics landscape suggests that we will undoubtedly continue to see massive changes in the sourcing and supply chain environment in the next three to five years. As emerging procurement technologies become more readily available, the opportunities for creating new business insights that generate the next level of value for procurement will continue to expand, as technology plays a role in encouraging and facilitating a new fabric for designing supply chain operating models (Stevens and Johnson, 2016). As in the previous eras enabled by the introduction of IT systems, the cloud and the internet (Wu et al., 2013), the new capabilities offered by emerging procurement technologies will provide new processes and decision-making agility in terms of tools, techniques, resources and approach (Stevens and Johnson, 2016):

• Implication 1: procurement analytics enhanced by emerging procurement technologies will create new forms of agile business insights into supply management.

To date, supply management has relied on historical data from basic ERP systems and has evolved into a level where current spend data are analyzed to capture cost savings while leveraging CMS to ensure compliance. In the future, supply chains will be increasingly managed through real-time data and analytics, which no longer rely on historical spend data, but enable decision making on what is happening today! The availability of real-time data and analytics as a new set of decision-support tools will lead to this incremental, initial change in analytics. Managers will have to learn how to deal with steady flows of information and process them quickly into decisions. Over time, analytics will become more “predictive” in nature, suggesting a range of potential outcomes. Customized data-based solutions will provide anticipatory and proactive visual graphics for business strategy problems and will dominate the advance of procurement management, as consistent with the prediction on the analytics for supply chain management (Waller and Fawcett, 2013). Figure 13 illustrates the gradual transformation of analytics:

• Implication 2: in the short term, real-time data and analytics will lead the advance of procurement management, and in the long term, predictive analytics will dominate the landscape.

The growth of procurement analytics will not only impact information technologies, but will likely alter structural components of supply chains impacting elements such as multi-tier visibility, information flows between parties, relationships through social media, data governance and transmission standards and cybersecurity between buyer and suppliers (Stevens and Johnson, 2016). However, despite the hype around supply chain analytics, the majority of organizations we interviewed are in the early stages of this evolution. Most organizations are only beginning to explore the power of analytics through early steps to cleanse and categorize spend data, and adapting a more rigorous procure-to-pay process that embodies a disciplined data governance approach. This eventually leads to more sophisticated approaches to connect spend and contract data, enabling greater insights into current and future sourcing obligations, as well as opportunities for leveraging supplier relationships in ways not formerly apparent. Over time, market intelligence analytics can
link external market events to internal spending patterns and trends, and provide improved analytical insight into total cost of ownership, should-cost models, pricing and market events and supplier risk insights. Finally, an evolution toward a fully integrated, real-time set of data analytics is looming large:

- Implication 3: in the short term, the integration of structured data in a disciplined manner will be the basis for analytic insights, and in the long term, the adoption of unstructured and external data will become the basis for broader application of analytics.

An important element of competitiveness for organizations in this evolution is managing change. People in the sourcing organization will experience massive changes in their daily work lives, involving greater interaction with digital interfaces, spanning the areas of cognitive computing, searchable databases, distributed computing and real-time KPIs. Adapting to this deluge of data will require a difficult transition for those who are not comfortable moving from their current ways of working, while others may embrace the new technology and adapt quickly. Change management approaches that create a realistic vision for the end goal, involving decisions such as how much analytical discovery vs standard platform governance will need to be debated. Suppliers will also need to be taken along on this journey, as their data will need to be integrated into existing platforms to drive collaborative planning and execution. These will be monumental shifts that cannot occur without significant executive involvement and support. The fundamental organizational changes involving the establishment of analytical learning, combined with senior executive support, is critical as the basis for an on-going program of success.

Implication 4: effective change management practices focused on the creation of an analytic culture will be an antecedent to the successful adoption of future procurement analytic technologies.

Our research suggests several key future research areas in the interface between procurement analytics and procurement management. While the impact of data analytics on future practices is well recognized, detailed applications of data analytics are still in question – many of them are in the developmental stage. Thus, some of the key questions for research include: how will analytics centers serve specific functional analytic needs? How will we measure return on investment of emerging technologies in procurement? What would be the role of organizational roles and responsibilities in creating and capturing analytic impacts? How will buyers reduce information leaks to their competitors while promoting information visibility in their supply base?

The issue of how cognitive systems will interact with, and possibly replace procurement professionals, is of great interest to many people. However, the specific skills and
capabilities that will remain in the area of human decision making will need to be carefully
defined. As one executive said, “The procurement people we will need in this era will be
different than the ones we’ve hired in the past.” Thus, some of the key questions for research
span the human–machine interface. Who will ultimately have decision rights for issues that
arise in the cognitive analytics space (machines or humans)? What are the required skill sets
and capabilities of supply chain managers who must interact with cognitive machine
outputs? What are the required capabilities of suppliers to be who must also interact with
machines? How will news feeds and other data be interpreted vis-à-vis human intelligence
signals in procurement? How will the organization ultimately define trusted sources of
information (humans or machines)?

While standard key performance indicators needed for decision making can be
identified, the detailed processes of organizational transformation is not well understood.
Thus, some of the key questions for research include: how will structured and
unstructured data be effectively integrated to produce signals for risk mitigation and
management of unexpected events in the supply chain? How will supply chains move from
optimization to prediction of events? How will managers move from information receiving,
to active machine queries for information using the right keywords, questions,
and intelligence gathering rubrics? How will organizations improve the accuracy of
their real-time and predictive system? What will be appropriate organizational and
supply-chain-wide practices for the improvement?

There is clearly a wealth of research questions that lie ahead in the area of procurement
and supply chain analytics. We invite researchers to explore these topics, and come up with
their own from our preliminary findings in our study.

7. Limitations
There are several limitations to our study. First, the size of our survey sample is small.
Given that the advance of procurement technology and platforms first takes place in
Fortune 500 organizations, a large portion of our research relies on interviewing and
surveying experts who work for such organizations and are profoundly interested in
advancing their procurement functions. Our survey design sought to explore the qualitative
domains of future procurement technology platforms. Although a larger sample size might
improve external validity, we sought a smaller sample that also allowed us to form
preliminary insights, rather than theory testing. We believe that as emerging procurement
technology and platforms diffuse and become more widely adopted across industries,
researchers may be able to develop theoretical statements to test using large sample sizes,
which will yield more generalizable outcomes.

Another limitation is that our roadmap and recommendation for implementing emerging
technologies mostly rely on qualitative approaches. There are a few available quantitative
methodologies for forecasting future demand and technological development. However,
since emerging technologies for procurement analytics are highly dependent on the
business applications that are yet to come, it is inherently difficult for researchers to forecast
the future form of services that emerging IT solutions can provide, even using a survey.
Given this difficulty, both our roadmap and recommendation for implementation strategy
resulted from the qualitative interview process. As in the sample size issue, we hope that the
wide adoption of big data and cognitive analytics in the near future will bring us new, richer
opportunities to project the more evident rate and direction of future procurement
technology and platform as well as relevant strategies.

Finally, the temporal difference between data collection and access to this study could
impact the relevance of the findings to readers. Emerging technologies addressed herein are
still evolving rapidly. As the technologies become mature, various environmental changes
(e.g. regulations) and technological uncertainty (e.g. advent of new technologies) could alter
the technological landscape projected by this study. We hope that follow-up studies discover
a technological landscape unforeseen up until the time line of this study, enriching our
understanding of future procurement analytics.

Notes
1. See Figure 9 in Section 5 for the elaborated relationship between theoretical constructs, functional
applications and procurement analytics.
2. These features are currently being developed by software providers such as Coupa and Emptoris.

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Further reading


Appendix. Interview protocol – CAPS research

1. Where do you perceive the greatest level of need within your organization for deeper analytical insights across procurement? (e.g. spend analysis, contract management, etc.)?

2. What are the major sources of internal structured data and external structured data that you believe can create analytical insights in these areas?

3. Data governance involves establishing the right volume, variety, veracity and velocity of data used to support analytics. What are the major barriers to establishing data governance in your organization today?

4. What do you believe is the best approach to generating a business case for ROI on procurement analytics investment?

5. What do you believe will be the three most important capabilities of procurement analytical solutions to you in the next five years?:
   - cognitive analytical capabilities (where);
   - drill down capability;
   - customizable views and reporting;
   - visualization of graphics;
   - real-time uploads of data;
   - user experience in interface;
   - using cognitive analysis of external data sources;
   - sentiment analysis; and
   - mobile access.

Your insights to these questions will be invaluable in helping us to shape the outcome of this report.

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Real-time data processing in supply chain management: revealing the uncertainty dilemma

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Abstract
Purpose – Particularly in volatile, uncertain, complex and ambiguous (VUCA) business conditions, staff in supply chain management (SCM) look to real-time (RT) data processing to reduce uncertainties. However, based on the premise that data processing can be perfectly mastered, such expectations do not reflect reality. The purpose of this paper is to investigate whether RT data processing reduces SCM uncertainties under real-world conditions.
Design/methodology/approach – Aiming to facilitate communication on the research question, a Delphi expert survey was conducted to identify challenges of RT data processing in SCM operations and to assess whether it does influence the reduction of SCM uncertainty. In total, 14 prospective statements concerning RT data processing in SCM operations were developed and evaluated by 68 SCM and data-science experts.
Findings – RT data processing was found to have an ambivalent influence on the reduction of SCM complexity and associated uncertainty. Analysis of the data collected from the study participants revealed a new type of uncertainty related to SCM data itself.
Originality/value – This paper discusses the challenges of gathering relevant, timely and accurate data sets in VUCA environments and creates awareness of the relationship between data-related uncertainty and SCM uncertainty. Thus, it provides valuable insights for practitioners and the basis for further research on this subject.
Keywords Uncertainty, Supply chain management, VUCA, Delphi survey, Real-time data processing
Paper type Research paper

1. Introduction
Supply chain management (SCM) faces a business environment of volatility, uncertainty, complexity and ambiguity (VUCA) (Blackburn et al., 2015). Political stability is permanently subject to fluctuations (Baker et al., 2016; World Bank, 2018), and most recently, disruptive political decisions (e.g. Brexit) have been made quite quickly and sometimes unexpectedly. In addition, the frequency and magnitude of large-scale natural disasters and their economic effects are constantly increasing, according to the International Disaster Database. Consequently, the predictability of future events has become uncharacteristically difficult, especially as predictions based on historical data are losing their validity and relevance (Blackburn et al., 2015). Moreover, supply chains (SCs) are becoming increasingly complex due to ongoing globalization and the associated outsourcing activities and vulnerability to risks (Blackhurst et al., 2018; Cardoso et al., 2015). Likewise, the digital and global connectivity of people and, increasingly, objects is currently reshaping entire business landscapes (Brynjolfsson and McAfee, 2012; Kloetzer and Pflaum, 2017; Liu et al., 2016). In this context, the current Industry 4.0 environment in particular is fundamentally changing complete supply systems (Angeleanu, 2015; Ketchen et al., 2014) as well as the pace
of operations. Thus, organizational processes within SCs must be adapted accordingly (Pflaum et al., 2017). In order to successfully operate within the prevailing VUCA environment, and especially to deal with resulting SCM uncertainties, adaptability and agility are becoming increasingly important (Eckstein et al., 2015). The speed with which data are generated and utilized is essential as “[r]eal-time or nearly real-time information makes it possible for a company to be much more agile than its competitors” (McAfee and Brynjolfsson, 2012, p. 63). Taking this into account, having and using real-time (RT) systems can play a central role in SCM, considering their ability to generate new business-related insights that not only improve performance, but also facilitate competitive advantages (Sanders and Ganeshan, 2015). Moreover, analyzing the potential of big data for SC efficiency leads, in particular, to the observation that “velocity offers the biggest opportunity to increase the efficiency of the processes in the supply chain” (Hofmann, 2017, p. 5120). This pertains to both data generation and utilization (Davenport et al., 2012). However, identifying potential benefits of RT systems for handling SCM uncertainty is often based on the premise that data processing can be perfectly mastered (e.g. Hofmann, 2017). Characterizing the present situation as a VUCA environment, especially with regard to the massive amount of data generated in today’s SCs in the context of Industry 4.0, makes it less likely that the premise of perfectly mastered data processing reflects reality. As a result, the benefits of RT data processing with respect to reducing SCM uncertainties might not be realizable in practice.

By conducting a Delphi study, this paper aims to facilitate communication among 68 experts in order to identify the challenges of RT data processing that arise due to the prevailing VUCA environment and thereof investigates whether RT data processing affects the reduction of SCM uncertainties under real-world conditions. Therefore, the following research question is proposed:

**RQ1.** Does RT data processing affect the reduction of SCM uncertainties in the prevailing VUCA environment?

To answer the proposed research question, the paper is structured as follows. First, a brief review of relevant literature regarding uncertainties in the VUCA environment is presented. Next, the research methodology is described in detail. Then, the quantitative and qualitative results of the Delphi study are discussed, and theoretical as well as practical implications are identified. The paper concludes with a discussion of limitations and possible future research opportunities.

### 2. RT data processing in the context of uncertainties

Over the last few years, SCM has become more dynamic, volatile and complex (Christopher and Holweg, 2017; Wang et al., 2016) and the digitization and interconnectivity associated with Industry 4.0 have substantially triggered this development. Thus, the newly developing environment in which SCM operates can be characterized as a VUCA environment (Blackburn et al., 2015). Complexity is verifiably related to the high degree of uncertainty that organizations face (Isik, 2018; Tushman and Nadler, 1978). One common definition in the literature identifies SC uncertainty as a “decision making situation in the supply chain in which the decision maker does not know definitely what to decide as he is indistinct about the objectives; lacks information about (or understanding of) the supply chain or its environment; lacks information processing capacities; is unable to accurately predict the impact of possible control actions on supply chain behavior; or, lacks effective control actions (non-controllability)” (van der Vorst and Beulens, 2002, p. 413). As RT data processing does not directly influence all aspects of uncertainty mentioned in this extensive definition, the focus of this paper is set mainly on the uncertainty aspects described in the second and third items.
The VUCA environment in which SCM must operate is becoming more dynamic, to the extent that whenever gathering appropriate information about that environment is at all hampered, SCM uncertainty increases. In addition to the political trends mentioned above, the growing volatility in customer preferences and the demand for sustainable and individualized products and logistics services must be satisfied through the restructuring of processes (Akinc and Meredith, 2015; Dubey et al., 2017), also representing trends that contribute to increasing SC dynamics. Additionally, digitized functions such as production, warehousing and transportation are pushing the digital transformation of SCs (Chen et al., 2013; Gautam et al., 2017). As a result, SCs which are already complex become even more so as various stakeholders and relationships get involved (Bode and Wagner, 2015; Serdarasan, 2013). SCs become even longer and more fragmented due to increasing globalization and advances in information technology (Blackburn et al., 2015). The increased level of complexity requires increased information processing (Galbraith, 1977). However, information processing is also becoming increasingly sophisticated as higher volumes, more variety, and greater velocity of data must be handled to operate successfully in a highly VUCA environment. Thus, a lack of information-processing capacities might quickly impede gathering information or gaining and maintaining an understanding of the SC or its environment.

As a result, organizations are imperfect decision-making systems due to incomplete knowledge; thus, firms systematically seek to support decision making when uncertainty prevails (March and Simon, 1958; van de Ven and Ferry, 1980). The adoption of information technology systems improves an organization’s access to information (Karimi et al., 2004; Melville and Ramirez, 2008; Wu et al., 2013) and reduces uncertainty. However, the movement and accessibility of information in a timely fashion strongly influences the effectiveness of information processing (Tushman and Nadler, 1978). Moreover, the comprehensive exploitation of information “is only possible if we have an organization that is designed to operate in real time” (Galbraith, 2014, p. 3). Thus, the importance of velocity in information processing for the reduction of uncertainties is critical. This is also confirmed by current research that envisions new possibilities arising from the utilization of RT systems, enabling faster and more autonomous and informed decision-making procedures and process configuration from operational, tactical, and strategic perspectives (e.g. Mehmood et al., 2017; Shu and Barton, 2012).

Diverse areas are expected to benefit from RT processing of data from goods, machines and other involved parties, which characterizes Industry 4.0 ecosystems. These include SC risk management (e.g. Chae, 2015), transport management (e.g. Mehmood et al., 2017) or demand planning (e.g. Hofmann, 2017) as long as SC partners also possess the necessary processing capacities (Addo-Tenkorang and Helo, 2016). Data must be processed into useful information, which is essential for sustainable innovation within an Industry 4.0 ecosystem (Lee et al., 2014) and for RT decision making (Ruessmann et al., 2015). Thus, data must be relevant, timely and accurate, and therefore able to effect a change in knowledge (Tushman and Nadler, 1978). Data relevance refers to the extent to which data are appropriate for realizing SCM uncertainty reduction. Data timeliness is achieved when the recorded data is not out of date, while data accuracy can be defined as the conformity of the recorded value to the actual value (Ballou and Pazer, 1985). These data quality requirements show the potential for imperfections, and the challenge of detecting and managing them to enhance the precision with which the data are used to support decision making (Isik, 2018; Lukoianova and Rubin, 2014). However, due to the high volume, velocity, variety and complexity of the data, which reflect the VUCA paradigm in the data domain (Blackburn et al., 2015), and due to the VUCA environment in which SCM must function, this task is challenging. This study investigates the former, namely, complexity challenges of RT data processing, from which the answer to the research question – whether RT data processing affects the reduction of SCM uncertainties – can be derived.
3. Methodology

3.1 Delphi study design

In order to answer the proposed research question, an RT Delphi survey was conducted (Gnatzy et al., 2011; Gordon and Pease, 2006). As a modified form of the classical Delphi design which has been increasingly applied in SCM research over the past decade (e.g. Darkow et al., 2015; Hirschinger et al., 2015; Melander, 2018; Rossmann et al., 2018), RT Delphi formats calculate and provide immediate feedback to participating experts (Gordon and Pease, 2006), who are able to reconsider their individual judgments as often as they like, since they are not limited to individual consecutive rounds (Friedewald et al., 2007). The RT Delphi format mitigates the negative effects of conventional paper-based Delphi studies, such as high participation effort and long processing times (Gordon and Pease, 2006). Thus, this format increases procedural efficiency (Aengenheyster et al., 2017), while providing results comparable to the outcome of conventional round-based Delphi surveys (Gnatzy et al., 2011). A far-reaching time horizon covering future developments until the year 2035 was chosen to avoid expert participants being distracted by recent trends and already-determined future events that would weigh more heavily in a short time span (von der Gracht and Darkow, 2010). Thus, a far-reaching horizon can stimulate the expert panel’s creativity and even unconventional thoughts. In this context, experts provided their anonymous judgments on the expected probability of occurrence (EP) of each of 14 future-event statements on a scale from 0 to 100 percent; the impact (I) of each future event if it occurred, using a five-point Likert scale; and the desirability (D) of each occurrence on a five-point Likert scale. In addition, the Delphi process collects qualitative data by giving participants the opportunity to add written arguments to their quantitative assessment of each future-event statement (Tapio et al., 2011). More details on the feedback process as well as on the RT Delphi tool are provided by Gnatzy et al. (2011).

3.2 Delphi projection development approach

The development of future-event statements – “Delphi projections” – is crucial to deriving insightful results and findings. Thus, a systematic and structured approach was applied to develop and refine a final set of 14 Delphi projections that encompass the future of RT data processing in SCM in the year 2035 (Loveridge, 2002; Warth et al., 2013). Figure 1 illustrates the development process used to derive the projections for this Delphi survey.

An opening workshop session was held to clearly define and refine the study’s scope, based on a systematic database research. Key factors, drivers and barriers inherent in RT data processing in SCM were considered and discussed to identify an initial set of 110 influencing factors. Two subsequent creative workshops were conducted. During the first workshop, each of the six management processes related to the Supply Chain Operations Reference Model – (1)
Plan (II) Source (III) Make (IV) Deliver (V) Return and (VI) Enable – was analyzed in order to identify potential SCM uncertainties. Then, the possibilities that RT systems would encounter these uncertainties were identified and added as influencing factors to the existing pool of factors. The second workshop was conducted to validate and aggregate the existing factors, resulting in a set of 92 factors likely to influence the future development of RT data processing. The resulting set of factors was further enriched by additional database research and seven semi-structured interviews with industry experts. Subsequently, two further projection development workshops were conducted, primarily to consider the factors related to the possibilities of reducing identified uncertainties. The remaining factors were used to prompt pro and contra arguments for the first Delphi participants. With regard to the process of formulating projections, commonly accepted formulation guidelines were applied (e.g. Linstone and Turoff, 1975; Loveridge, 2002; Mitchell, 1996; Rowe and Wright, 1999). As a final step and to pre-test and cross-validate the formulated projections, five cognitive interviews were conducted with three industry experts and two scientists who had not participated in the preceding projection development phases (Dillman, 2007), resulting in the final set of 14 Delphi projections, outlined in Section 4.1. An overview of detailed information (e.g. role, industry and level of experience) on the experts involved in the projection development process is provided in Table AI.

3.3 Panelists selection
The quality and reliability of the assessments of Delphi projections are directly based on the competencies and capabilities of the panelists involved (Spickermann et al., 2014), making the selection of the experts a carefully managed process. Diversity criteria were defined at the surface level (age, gender, organizational function and position) as well as at a deep level (expertise, education, academic background and scientific contributions) (Spickermann et al., 2014), both applied to ensure a systematic selection process. Furthermore, the research was designed to survey a wide range of experts, in order to ensure a heterogeneous panel composition, minimize cognitive biases, and cover the cross-functional and interdisciplinary range of this research topic (Ecken et al., 2011; Föerster and von der Gracht, 2014; Winkler and Moser, 2016). As a result of the selection process, a total of 713 potential experts were identified and invited to participate in the Delphi survey. The final set of experts comprised 68 participants (response rate of 9.54 percent): experts from industry (35.3 percent), academia (42.6 percent) and associations or politics (22.1 percent), with an emphasis on a background in either SCM and logistics (69.1 percent) or information technologies (16.2 percent), or both (14.7 percent) from 19 different countries[1]. In addition, a Mann–Whitney U test was applied to the answers given in the initial round to compare the assessments of the early respondents with those of late respondents. Based on the assumption that the latter sample population features characteristics of non-respondents, the presence of a non-response bias could be rejected (Armstrong and Overton, 1977; Wagner and Kemmerling, 2010), since no significant difference ($p < 0.05$) could be found for the 14 projections for all dimensions (EP, I, D).

3.4 Qualitative analysis
To balance quantitative and qualitative components and thus strengthen the Delphi survey’s value (Rowe and Wright, 2011), experts were able to add written arguments for each of their projection assessments on probability, impact and desirability. A total of 924 written statements were provided. A coding procedure based on the work of Strauss and Corbin (1990) was applied to enhance and conclude the analysis. Two members of the research team broke down the content of the comments for each projection separately, in order to identify and group similar categories of content and derive descriptive codes. The results were discussed, and any divergence was re-adjusted until consensus was reached for
all codes. The final set of codes was utilized for the cross-impact analysis and eventually incorporated into the discussion of the Delphi results.

To further process the experts’ data and to identify interactions of future events, a cross-impact analysis was performed subsequent to the coding procedure. A cross-impact analysis was chosen because it proved to be a suitable tool to “process and synthesize the expert-sourced data in a structured way” (Panula-Ontto and Pirainen, 2018, p. 90) and to analyze Delphi-panel assessments in the context of investigating interrelationships within complex settings (Baňuls and Turoff, 2011; Enzer, 1971). Therefore, a cross-impact analysis was applied to identify interdependencies between single projections and their effect on the likelihood of affected relationships occurring (Turoff et al., 2016). For this purpose, a workshop was conducted with all members of the research team and two industry practitioners who had participated in the projection development. In this context, the coded qualitative arguments that had been provided by the participating experts during the Delphi runtime were utilized as the data input. These arguments were individually interpreted by every workshop participant in order to derive estimates of the causal impact that each projection may have on the probability of the remaining projections occurring (Baňuls and Turoff, 2011). The available assessments of the level of interaction ranged from (a) “unrelated” (= 0), (b) “enhancing” (+1 = small enhancing effect; +2 = medium enhancing effect; +3 = large enhancing effect) to (c) “inhibiting” (−1 = small inhibiting effect; −2 = medium inhibiting effect; −3 = large inhibiting effect) (Gordon and Hayward, 1968). The individual evaluations of the workshop participants were compared, and differing evaluations were discussed and backed up with additional literature. The evaluations were adjusted until agreement on the final entry of all assessments was reached. Consequently, the workshop participants’ role equated to the role of coders in the context of a qualitative coding procedure, as they did not provide additional data but rather structured and interpreted the already existing qualitative Delphi data.

On this basis, the projections’ active sums (horizontal absolute impact values for each projection) as well as passive sums (sum of effects in each column) were calculated (Kosow and Gassner, 2008). While the active sum describes the degree to which projection \( i \) affects the likelihood of all other projections \( j \), the passive sum shows the extent to which projection \( i \) is influenced by other projections \( j \). Based on these sums, the projections’ systematic behavior was visualized on a system grid (see Figure 2) (Gausemeier et al., 1998). The axis boundaries are described by the maximum value of the active and passive sums, while the segmentation of the resulting cross-impact grid is delimited by the mean value of the active and passive sums of all projections (Linss and Fried, 2010). According to Linss and Fried (2010), projections assigned to the active quadrant (active sum above average and passive sum below average) strongly influence other projections of the system, while projections designated to the reactive quadrant (active sum below average and a passive sum above average) are strongly influenced by other projections of the system. Buffering projections (active and passive sums below average) are not very sensitive to changes of other projections in the system, but also do not have much influence on the system. Projections designated as critical (active and passive sums above average) strongly influence the systems but are also strongly influenced by other projections and, thus, are hard to control.

4. Results, discussion and implications
4.1 Quantitative Delphi results
In the first step, the quantitative results of the Delphi survey were analyzed for all 14 projections. The results, based on the evaluation of the expert panel, for the probability (EP), impact on SCM (in case of occurrence) (I) and desirability (D) are summarized in Table I. The values describe the final aggregated assessments of all panelists and are supplemented by
### Cross-impact grid and categorization of projections’ influence

**Figure 2.** Cross-impact grid and categorization of projections’ influence

<table>
<thead>
<tr>
<th>No.</th>
<th>Projection</th>
<th>EP (%)</th>
<th>I</th>
<th>D</th>
<th>IQR</th>
<th>CV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2035: Seamless tracking of functional parameters (e.g. humidity, location, shock, temperature) on single product item has become a standard</td>
<td>73.0</td>
<td>3.7</td>
<td>4.0</td>
<td>30.0</td>
<td>-9.0</td>
</tr>
<tr>
<td>2</td>
<td>2035: Tailored service offerings have been revolutionized by RT processing of behavioral customer data</td>
<td>75.9</td>
<td>4.2</td>
<td>3.9</td>
<td>20.0</td>
<td>-17.0</td>
</tr>
<tr>
<td>3</td>
<td>2035: RT simulation and visualization of SC networks has become a common standard</td>
<td>76.3</td>
<td>4.1</td>
<td>4.5</td>
<td>25.0</td>
<td>-8.1</td>
</tr>
<tr>
<td>4</td>
<td>2035: Tactical SCM has been replaced by autonomous RT-based systems</td>
<td>54.2</td>
<td>3.9</td>
<td>3.4</td>
<td>24.0</td>
<td>-13.8</td>
</tr>
<tr>
<td>5</td>
<td>2035: External meta-platforms have become a crucial source for RT data</td>
<td>73.9</td>
<td>3.9</td>
<td>3.7</td>
<td>22.5</td>
<td>-19.7</td>
</tr>
<tr>
<td>6</td>
<td>2035: RT systems have eliminated human intervention in managing SC events</td>
<td>49.0</td>
<td>4.0</td>
<td>3.4</td>
<td>20.0</td>
<td>-16.8</td>
</tr>
<tr>
<td>7</td>
<td>2035: RT systems have enabled a 100% delivery reliability through dynamic SC and logistics adoptions</td>
<td>49.3</td>
<td>4.0</td>
<td>4.5</td>
<td>40.0</td>
<td>-14.2</td>
</tr>
<tr>
<td>8</td>
<td>2035: Dynamic pricing on a customer-individual basis has become common standard in all industries</td>
<td>60.5</td>
<td>4.0</td>
<td>3.2</td>
<td>20.0</td>
<td>-7.2</td>
</tr>
<tr>
<td>9</td>
<td>2035: Access to RT data flows has enabled a continuous monitoring and controlling of SC finance</td>
<td>76.2</td>
<td>4.0</td>
<td>3.9</td>
<td>18.8</td>
<td>-19.9</td>
</tr>
<tr>
<td>10</td>
<td>2035: Cost reductions in SCs are primarily enabled by autonomous decision-making based on RT data</td>
<td>56.5</td>
<td>3.9</td>
<td>3.9</td>
<td>18.8</td>
<td>-14.0</td>
</tr>
<tr>
<td>11</td>
<td>2035: New global standards have solved interface problems for RT data exchange</td>
<td>57.5</td>
<td>4.2</td>
<td>4.7</td>
<td>30.0</td>
<td>-12.1</td>
</tr>
<tr>
<td>12</td>
<td>2035: Contract agreements will automatically be linked to SC partners’ RT score cards and dashboards</td>
<td>61.2</td>
<td>3.9</td>
<td>3.7</td>
<td>30.0</td>
<td>-5.3</td>
</tr>
<tr>
<td>13</td>
<td>2035: RT systems have become the most important instrument for balancing the triple bottom line</td>
<td>49.4</td>
<td>3.6</td>
<td>3.6</td>
<td>27.5</td>
<td>-9.0</td>
</tr>
<tr>
<td>14</td>
<td>2035: RT systems have become the key enabler for handling SC complexity</td>
<td>69.3</td>
<td>4.1</td>
<td>4.0</td>
<td>20.0</td>
<td>-9.4</td>
</tr>
</tbody>
</table>

**Notes:** CV, convergence rate, i.e. percent reduction in standard deviation. “Consensus among panelists (IQR ≤ 25.0)
the interquartile range (IQR) and convergence rate (i.e. percent decrease in standard deviation of EP during Delphi survey process) of each projection.

As the mean impact for each of the 14 projections on the domain of SCM is estimated to be higher than 3.5, all projections can be considered substantial and important to the research topic. The expert panel’s assessments of the probability of each projection cover a range from 49.0 percent for P6 (SC events) to 76.3 percent for P3 (simulation and visualization), while desirability ranges from 3.2 for P8 (dynamic pricing) to 4.7 for P11 (global standards). The experts’ assessments converged over time, as a decrease was detected in the standard deviation of the first to the final round of the average value of EP by 12.5 percent on average. The degree of agreement or dissent can be measured using the IQR (Diamond et al., 2014; von der Gracht, 2012). If panel consensus is defined as an IQR equal to or less than 25.0, then 9 out of 14 projections reach consensus regarding the projection’s EP. Such a threshold value would be in accordance with comparable Delphi research studies (Keller and von der Gracht, 2014; Warth et al., 2013).

4.2 Discussion
As the projections are interrelated rather than independent from each other (Bañuls and Turoff, 2011), the interrelationship of the projections was considered in a second step. Thus, driving forces and their interactions within the system can be identified to prioritize strategic issues. Figure 2 shows the systematic behavior of every projection (please refer to Section 3.4 Qualitative analysis for more details on the meaning of the quadrants).

As can be seen in Figure 2, P14 (SC complexity) is the most critical projection, as it influences the occurrence of other projections to a high extent and, in turn, is very sensitive to changes in the system. Its active character can be explained by the fact that, if RT systems can significantly reduce SC complexity, the deployment of RT applications would be actively promoted. Thus, the occurrence of various projections would be positively influenced. However, with regard to the composite elements of its passive sum, an ambivalent effect of RT data processing reducing SC complexity could be revealed. Some projections’ occurrence would positively affect the advent of RT systems becoming the key enabler for handling SC complexity (P3, P4, P6, P7, P11 and P12), while others have the opposite effect on the projection’s entry (P1, P2, P5, P8, P9 and P13). The experts’ estimates regarding certain projections’ positive effect on the occurrence of P14 reveal a confirming congruence with existing literature.

To provide an understanding of the ambivalent character of P14, the interrelationship of the negative-influence projections is discussed in what follows in order to provide an understanding of how RT systems increase SCM uncertainty. First, one reason for some of the increases in complexity is the fact that RT systems enable the reduction of one complexity driver, but in turn create additional complexity for SCM. For example, with respect to P2 (tailored service offerings), the utilization of RT data enables decision makers to identify the individual preferences of their customers, which reduces uncertainty. However, individualization of services triggers complexity and the therewith associated uncertainty, as processes are no longer standardized. The same effect applies to the utilization of dynamic pricing (P8). Second, uncertainties triggered by a lack of transparency can be decreased with RT data availability. However, the significant increase in RT data flows is also expected to increase the complexity of decision making, and thus SCM uncertainty, due to the greater number of influencing variables that decision making must consider. This could lead to people losing track of complex data systems. Third, the projections with the most notable negative effect on the occurrence of P14 are those relating to RT data gathering (P1, P2 and P5). In these scenarios, the safeguarding of the relevance, timeliness, and accuracy of data sets was mentioned to be particularly challenging, consequently creating a high amount of complexity and associated uncertainty. Due to its
high significance, the challenges of ensuring data relevance, timeliness and accuracy will be dealt with in detail in the following subsections.

**Challenges regarding data relevance and timeliness.** Causes of the complex nature of ensuring timely and relevant data sets were found to be often quite similar and interrelated, which is why they are discussed collectively. In this regard, missing standards for data exchange and data security create barriers to gathering both RT SC data (P1) and external data (P2 and P5). The resulting data security concerns negatively influence the willingness of RT data sharing (Eurich et al., 2010), while missing standards for data exchange lead to interoperability problems, exacerbating the difficulties of aggregating data from various data sources and SC partners. In this regard, isolated system solutions deployed by different SC partners could also be identified as a source of complexity. However, globalization and fragmentation of SCs impede the establishment of uniform standards and system solutions.

As end-to-end availability of data is considered crucial to effectively dealing with SCM uncertainties, the capability of SC partners to share relevant and timely data is also hugely influential. Consequently, companies must ensure that their own skills as well as those of their SC partners are sufficient to process data as necessary. Ongoing globalization reinforces this issue as an increased number of companies from emerging markets, which usually possess fewer technological capabilities (Ramamurti and Williamson, 2018), join the supply network through relocation of production to low-wage countries. In addition, the SC partners’ willingness to cooperate with standards and procedures for data exchange must be ensured through trust management and collaborative efforts properly executed between SC partners (Wu et al., 2014). Globalization is expected to complicate this undertaking, as cultural differences, spatial distances and increasing numbers of suppliers must be considered. The isolation of various states (e.g. China, Russia and America) and increased SCM dynamics further exacerbate the challenges of SC collaborations and thus the availability of timely and relevant data sets. In addition, the willingness to share data is also dependent on the benefits a firm expects from sharing and on resulting agreements for sharing costs and rents as well.

With regard to customer behavioral data, country-specific privacy regulations and costumers’ refusal to share their data could create barriers to data availability. With SC partners distributed among countries with varying positions on customer data, ensuring SC-wide data availability might be challenging. In the context of gathering data from external data providers, lack of IT know-how and/or financial resources could be identified as a further hindering factor for ensuring data relevance and timeliness. Due to these shortcomings, the focal company might be unable to gather external RT data through free data mining or from meta-platforms with high costs.

However, not only could the absence of relevant and timely data pose a threat to ensuring RT data relevance, but the continuous flood of unnecessary RT data could also have this effect. The RT availability of data sets was not always considered necessary, e.g., for tailored service offerings (P2) and balancing the triple bottom line (P13). Gathering data too frequently also creates waste and increases the complexity of data handling. Consequently, a focal company must take the complexity-benefit ratio of RT data availability into account. Furthermore, considering the variety of different sources from which data is gathered (e.g. functional parameter data and external data sources), companies must identify which data are necessary for the respective RT data applications. However, identifying the required data sources and best-fitting time intervals is challenging due to the complex and interrelated nature of SC processes that are influenced by the VUCA environment. Therefore, processes are affected by a high number of different variables, often only identifiable in retrospect. Thus, ensuring RT data relevance could be identified as very challenging and, in the context of unthinkable and extremely rare events (“Black Swan Risks”), nearly impossible.
Challenges regarding data accuracy. Apart from data timeliness and relevance, safeguarding data set accuracy is also challenging. RT data gathering through functional parameter sensors carries the risk of imprecise data measurements due to sensor inaccuracy or dysfunction/aging of sensors. Especially during external data gathering, noise and ambiguities could emerge, the former triggered by unstructured data that contains meaningless information (e.g. social media posts) (Wlodarczak et al., 2014), and the latter, inter alia, by the equivocation of gathered RT data caused by the usage of natural language (van der Aa et al., 2018). In addition, the trustworthiness of the data source might also cause data-related uncertainty, especially with the acquisition of RT data from external meta-platforms from which the primary source of the acquired data sets might be unknown. Thus, the evaluation of the data quality challenges SC management. Moreover, SC partners or even service providers of external data platforms might also manipulate data due to opportunistic behavior. For example, in the scenario in which RT data is utilized for dynamic pricing applications (P8), companies might manipulate their data to achieve pricing benefits. In order to deal with quality issues of RT data sets, companies must either curb the triggers for inaccurate RT data or learn how to account for inaccuracies in their data analysis. However, the increasing complexity of SCs, as well as the VUCA characteristics of data itself, is expected to further exacerbate the difficulty of these endeavors.

Uncertainty dilemma. The listed challenges lead to the conclusion that ensuring relevant, timely and accurate data is a cumbersome and, in the VUCA environment, often not 100 percent achievable task. If relevant, timely and accurate data cannot be ensured due to a lack of the required capabilities or external environmental reasons, a new type of uncertainty related to the data itself occurs in the course of tackling SCM-related uncertainties through RT data processing. This phenomenon can be denoted as the uncertainty dilemma. The extent of data uncertainty influences whether SCM uncertainty can be reduced through the application of RT systems. Presumably, there is a threshold value for the degree of data uncertainty at which the use of RT systems results in as much SCM uncertainty as there would be without using these systems, and therein lies the uncertainty dilemma. If a company is prepared to keep data uncertainty below this threshold, RT data processing might lead to a reduction in SCM uncertainty. On the other hand, the deployment of RT systems might lead to even more SCM uncertainty than encountered by companies that do not perform RT data processing. According to the panelists, the performance of RT applications, e.g. tailored service offerings (P2), visualization and simulation of SC networks (P3), autonomous management of tactical SCM (P4), SC events (P6) and dynamic pricing (P8), is substantially determined by the availability, quality and timeliness of the underlying data. So, for example, in the case of tailored service offerings, sufficient data quality would lead to valuable insights into customers’ preferences and suitable service offerings, reducing SCM uncertainties. However, if data uncertainty occurs due to inadequate data relevance, timeliness or accuracy, such deficits might bias predictions of customer preferences. Should data uncertainty reaches the threshold (the value of which might strongly depend on the respective RT data processing application and on the data characteristic that causes the data-related uncertainty), predictions of customers’ preferred service offerings might cause the same uncertainty for SCM as there would be with no tailored service offerings. If data uncertainty exceeds the threshold value, predictions of customers’ preferences might be completely incorrect, resulting in even more uncertainty than there would be without the deployment of tailored service offerings. This is critical, as RT systems might simulate false security that renders the company unaware of the actual prevailing uncertainty. To complicate matters, the risk of data-related uncertainties occurring increases with the extent of SCM-related uncertainty that is targeted to be reduced through RT data processing. The triggers for SCM complexity
and the associated uncertainty (e.g. increasing fragmentation of SCs, globalization and more complex dynamics of SCs) also provoke the complexity of managing data-related uncertainties, thus exacerbating the difficulties in gathering relevant, accurate and timely data sets. As the RT system effectiveness regarding the reduction of SCM uncertainties depends on the extent of data-related uncertainty, more differentiated reflection on the benefits in the prevailing VUCA environment is necessary.

4.3 Implications for practice
From a managerial perspective, this paper reveals that promised benefits of RT systems contingent on the faulty premise that data processing can be perfectly mastered do not hold in the prevailing VUCA environment. In order to ensure that the deployment of RT systems leads to the targeted reduction of SCM uncertainty, appropriate data-related and organizational skills must exist to keep data-related uncertainty at a sufficiently low level. The discussion of the data-related challenges provides companies with an indication of the required skill sets. This information can be utilized to identify the extent to which a company’s capabilities meet requirements and will allow a rough initial assessment of whether the application of RT systems will be beneficial in reducing SCM uncertainty.

4.4 Implications for theory
From a theoretical perspective, this research expands the existing literature on RT data processing in SCM by applying a future-oriented assessment of context-related developments. The critical influence of data-related uncertainty on SCM uncertainty is almost unavoidable in the current VUCA environment. To account for the interrelationship, identifying the effectiveness of RT systems under realistic conditions is necessary. Moreover, further research opportunities arise from this work. First, the threshold value for data uncertainty, at which RT systems provide no reduction of SCM uncertainty, must be quantified. Second, contingency variables that influence this value should be identified. Third, the effects of each of the data characteristics (relevance, timeliness and accuracy) on RT system effectiveness should be measured, in order to provide guidance on prioritizing the management of these data-related challenges. However, these investigations must be carried out separately for each RT system, since the challenges are expected to be application-specific – for example, whether lacking data relevance is more critical than data timeliness, or vice versa, for SCM uncertainty reduction.

5. Conclusion, limitations and further research
Particularly in the current VUCA environment, RT data processing is very promising for reducing SCM uncertainties. However, the research at hand reveals the uncertainty dilemma that might occur in the midst of tackling SCM uncertainties through RT data processing. It provides a more realistic view of RT systems’ effectiveness in reducing SCM uncertainties in the prevailing conditions. This research field is still underexplored, and these findings provide valuable insights for both scholars and practitioners.

As with any research, the study at hand has some limitations that provide opportunities for future research. First, the scenarios and findings are based on the evaluation of experts who only represent the SCM, logistics and data science domains. Even though a systematic approach for selecting adequate experts was applied and the non-existence of a non-response bias was proved, the inclusion of experts from related departments with close points of contact with SCM (e.g. production and sales) could further enrich these insights and generate additional value for practitioners and scholars. Second, the evaluation of future developments in RT data-processing applications in SCM is based on 14 projections that were developed by a systematic projection development process. While the number of projections proved
adequate for ensuring an appropriate processing time and reducing drop-off rates, the selected projections do not cover the topic holistically. This leaves opportunities for future research by assessing further emerging aspects that are not yet covered by the projections. Moreover, subsequent empirical justification is needed, in order to analyze whether the results and conclusions can also be confirmed for specific industries in a real-world context.

Note

1. Australia, Belgium, Brazil, Canada, Denmark, Egypt, Germany, India, Malaysia, Norway, New Zealand, Poland, Singapore, South Africa, Sweden, Switzerland, United Arab Emirates, the UK, the USA.

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### Table AI.

Detailed information of experts that contributed to the projection development workshops and interviews.

<table>
<thead>
<tr>
<th>Expert's role in projection development</th>
<th>Age (years)</th>
<th>Functional area</th>
<th>Position in organization</th>
<th>Size of organization</th>
<th>Type of organization</th>
<th>Expertise (years)</th>
<th>Industry</th>
</tr>
</thead>
<tbody>
<tr>
<td>Creative workshops</td>
<td>50–59</td>
<td>Logistics/SCM</td>
<td>Senior executive</td>
<td>&gt; 499 employees</td>
<td>Corporation</td>
<td>&gt; 25</td>
<td>Industrial goods</td>
</tr>
<tr>
<td>Creative workshops</td>
<td>30–39</td>
<td>Logistics/SCM/IT</td>
<td>Department leader</td>
<td>&gt; 499 employees</td>
<td>Corporation</td>
<td>&gt; 15</td>
<td>Industrial goods</td>
</tr>
<tr>
<td>Creative workshops</td>
<td>40–49</td>
<td>Logistics/SCM</td>
<td>Senior executive</td>
<td>&gt; 499 employees</td>
<td>Corporation</td>
<td>&gt; 15</td>
<td>Transportation</td>
</tr>
<tr>
<td>Expert interview</td>
<td>50–59</td>
<td>Logistics/SCM</td>
<td>Senior executive</td>
<td>&gt; 499 employees</td>
<td>Corporation</td>
<td>&gt; 25</td>
<td>Industrial goods</td>
</tr>
<tr>
<td>Expert interview</td>
<td>50–59</td>
<td>Logistics/SCM</td>
<td>Department leader</td>
<td>&gt; 499 employees</td>
<td>Corporation</td>
<td>&gt; 25</td>
<td>Industrial goods</td>
</tr>
<tr>
<td>Expert interview</td>
<td>40–49</td>
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<td>Department leader</td>
<td>&gt; 499 employees</td>
<td>Corporation</td>
<td>&gt; 20</td>
<td>Industrial goods</td>
</tr>
<tr>
<td>Expert interview</td>
<td>30–39</td>
<td>Logistics/IT</td>
<td>Team/Project leader</td>
<td>&gt; 499 employees</td>
<td>Corporation</td>
<td>&gt; 15</td>
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<td>&gt; 499 employees</td>
<td>Corporation</td>
<td>&gt; 10</td>
<td>Logistics service provider</td>
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<td>&lt; 50 employees</td>
<td>Corporation</td>
<td>&gt; 10</td>
<td>IT provider</td>
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<td>Senior executive</td>
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Abstract

Purpose – The combination of the latest advancements in information and communication technologies with the latest developments in AutoID technologies, especially radio frequency identification (RFID), brings the possibility of high-resolution, item-level visibility of the entire supply chain. In the particular case of retail, visibility of both the stock count and item location in the shop floor is crucial not only for an effective management of the retail supply chain but also for physical retail stores to compete with online retailers.

The purpose of this paper is to propose an autonomous robot that can perform stock-taking using RFID for item-level identification much more accurately and efficiently than the traditional method of using human operators with RFID handheld readers.

Design/methodology/approach – This work follows the design science research methodology. The paper highlights a required improvement for an RFID inventory robot. The design hypothesis leads to a novel algorithm. Then the cycle of development and evaluation is iterated several times. Finally, conclusions are derived and a new basis for further development is provided.

Findings – An autonomous robot for stock-taking is proven feasible. By applying a proper navigation strategy, coupled to the stream of identifications, the accuracy, precision, consistency and time to complete stock-taking are significantly better than doing the same task manually.

Research limitations/implications – The main limitation of this work is the unavailability of data to analyze the actual impact on the correction of inventory record inaccuracy and its subsequent implications for the supply chain management. Nonetheless, it is shown that figures of actual stock-tacking procedures can be significantly improved.

Originality/value – This paper discloses the potential of deploying an inventory robot in the supply chain. The robot is called to be a key source of inventory data conforming supply chain management 4.0 and omnichannel retail.

Keywords Radio frequency identification (RFID), Retail, Robotics, Omnichannel retail, Cycle counting, Inventory record inaccuracy (IRI), Stock visibility

Paper type Research paper

1. Introduction

The Fourth Industrial Revolution, based on the latest developments of information and communication technologies (ICTs), is expected to have a significant impact on Supply Chain Management (SCM). In particular, the wide adoption of radio frequency identification (RFID) technology provides supply chain managers with item-level, high-resolution information that, in turn, requires a higher level of automation of the decision-making processes and the actions taken in response.

To achieve this objective, RFID-based cyber-physical systems are expected to play a key role, according to Hofmann and Rusch (2017). More specifically, they claim that the use of ICT and RFID brings three customer value components to SCM: the “value of availability,” which refers to the availability of goods or services; the “value of digital integration,” which enables traceability along the supply chain and, in turn, a seamless and efficient order processing and business executions; and the “value of digital servitization,” an additional value created by adding a digital dimension to physical objects. Also, Richey et al. (2016) support the view that the availability of item information at each stage of the supply chain will be a key factor in tuning up operational efficiency.

Of the different aspects of SCM, inventory management is key. Inventory record inaccuracy (IRI), the discrepancy between recorded and physical inventory, implies a loss of
value of the elements of the supply chain (Fleisch and Tellkamp, 2005; DeHoratius and Raman, 2008). In retail, the unexpected unavailability of a product is a main source of customer frustration. Interestingly, the source of IRI resides primarily on shop floors, rather than at backrooms (Goyal et al., 2016). This can be explained by: transaction errors, for instance, a wrong cash check out or return, misplacements and shrinkage, which includes theft, spoilage and damage of items (Rekik, 2011). IRI is considered one of the main causes of uncertainty and performance deterioration in information exchange in supply chains (Kang and Gershwin, 2005; Sahin and Dallery, 2009; Cannella et al., 2015).

The usual strategy for IRI mitigation is inventory correction by manual stock-taking using either barcodes or RFID technology. Unfortunately, even RFID-based stock-taking procedures are both labor intensive and inaccurate. The use of robots to automate stock-taking using RFID technology can relieve humans of a repetitive and tedious task inherently prone to errors (Sahin and Dallery, 2009) and increase the frequency of inventories (DeHoratius and Ton, 2015; Bruccoleri et al., 2014). More specifically, the use of an autonomous inventory robot can mitigate IRI and provide an almost real-time visibility of items in the store, a significant reduction in stock-outs (Moussaoui et al., 2016), a fine control of inventory levels, and the elimination of overstocking (the current strategy to ensure availability) (Sarac et al., 2010).

RFID technology is able to uniquely identify items without the need of line-of-sight visibility, at a rate of up to 750 identifications per second. RFID is increasingly being adopted by retailers given its reliability at item-level tracking and tracing (Hardgrave and Patton, 2016; GS1 US, 2015a; White et al., 2008).

In the particular case of traditional retail (as opposed to online retail), this information is critical to implementing omnichannel processes (Verhoef et al., 2015; Piotrowicz and Cuthbertson, 2014), such as ordering online and picking up at the store (“click and collect”), or fulfilment of online orders from the store (“pick and pack”). Although the solution is applicable to any retail store with a majority of items tagged with RFID, it is particularly suited for fashion and apparel stores.

This paper proposes an improvement to the traditional RFID-based cycle counting, done by human operators using hand-held RFID readers, by using a system that combines mobile robotics with RFID to achieve an automated, accurate, less expensive, and close to real-time visibility of items and their location in the store (Vaishnavi and Kuechler, 2004).

Given that in a typical retail store the density of items varies greatly from one area to another, and that RFID technology has a limited throughput in reading RFID labels, we make the hypothesis that an optimum accuracy and duration of the inventory can only be reached if the speed and other navigation parameters of the robot adapt to the different item densities in the store. On the one hand, the robot needs time to identify all items in high-density areas. On the other hand, if the robot is too slow in low-density areas, inventories may last too long. In this paper, we propose and assess a navigation control algorithm with the purpose of reaching an optimum in the trade-off between accuracy and speed.

The paper follows the design science methodology (Vaishnavi and Kuechler, 2004) since it pursues to expand the state of the art by designing a prototype and operating it in order to test the research hypothesis. The designed prototype is operated in a university library, a real but controlled environment. After the initial evaluation in the library, the results of the experiment validating the research hypothesis are further tested in an actual retail store, a less controlled, but more realistic environment. In both cases, the evaluation consists in comparing robot inventories to state-of-the-art technology used for stock-taking, namely, RFID handheld devices. The comparison aims at assessing the differential contribution of the robot compared to actual store operations. A set of specific parameters are proposed as a framework for the comparison.
The work presented offers a thorough analysis of the contribution of an RFID-driven inventory robot in real scenarios. The idea of an inventory robot has been already presented in the literature but only as a proof-of-concept in a laboratory environment, not completely implemented, assessed and validated in real scenarios. Therefore, the main contributions of this work are both the inventory navigation algorithm and the proposed framework for evaluation of the system.

The paper is organized as follows. A discussion of related works is provided in Section 2. The design of the proposed inventory robot is introduced in Section 3, including the RFID and navigation subsystems. Section 4 explains the proposed evaluation methodology and metrics. In Section 5, the accuracy of the robot at stock-taking is assessed, focusing on its relation to the navigation strategy, including results from experimentation in a real store. Section 6 discusses the implications to managers of retail chains. Finally, Section 7 summarizes the results obtained and discloses future work.

2. Related work
Warehouse operational problems are manifold, and a lack of collaboration between academic research and industry has been identified by Gu et al. (2007), who conclude that solutions should be “simple, intuitive and reliable.” A literature review on RFID in the warehouse identifies opportunities and obstacles for RFID adoption (Lim et al., 2013). An uncertain return on investment (ROI), closely related to a perceived RFID failing performance, is stressed. Fan et al. (2014) analyze the benefits of RFID technology for reducing inventory shrinkage and their results show that the contribution of RFID to accuracy improvement is critical to motivate adoption. Musa and Dabo (2016) reviewed RFID in SCM literature and found a few references that address inventory taking in terms of accuracy and duration. A recent literature review of retail store operations (Mou et al., 2018) points out that the adoption of new technologies is a must to facilitate both research and operations in the store.

Several authors have assessed the performance of RFID-based stock-taking. Bertolini et al. (2015) compared the performance of RFID and barcode inventory counting using handheld devices at a real store. They conclude that RFID inventory is more reliable than using barcodes, reporting accuracy figures that range from 90.6 to 98.7 percent. Rizzi and Romagnoli (2017) studied the performance of overhead RFID antennas installed on the ceiling of a retail store. The average accuracy of the overhead antennas was found to be 93.0 percent. Surprisingly, no other works addressing the accuracy of RFID stock-taking in real scenarios were found in the literature.

Early works exist that introduce the combination of mobile robotics and identification technologies. Thirumurugan et al. (2010) presented a line following robot that reads barcodes in a library. Harik et al. (2016) introduce the combination of a ground robot and a drone for barcode scanning goods on shelves in a warehouse. The use of RFID in robotics has been generally exploited to support indoors mapping, guidance and navigation (Milella et al., 2008; Kulyukin et al., 2004; Park and Hashimoto, 2009; Kämpke et al., 2012). However, few works presented experimental solutions combining RFID with autonomous robotics for stock-taking. Ehrenberg et al. (2007) presented a mobile platform equipped with an RFID reader that takes inventory and finds misplaced books in a library. The RFID technology used (HF) differs from the de facto standard (UHF) adopted by the industry. Their work focuses on location in one library shelf that encloses less than 30 books and does not analyze the inventory accuracy. Schairer et al. (2008) presented a prototype of a robot that uses RFID to identify products in a mock-up of a supermarket. RFID data are fused with vision and placed in a 3D model of the environment. Although the system is promising in the demo scenario, further experimentation and a detailed analysis of inventory figures are missing. In Nur et al. (2015), RFID data captured with an early prototype of an inventory robot are
exploited to create indoor enriched views of a store. Yet, performance regarding the
inventory is not in scope. Zhang et al. (2016) share experiments with a robotic inventory
system on a mock sales floor. The accuracy measured for different types of products ranges
from 84.5 percent (405 items) to 100 percent (27 items). The amount of items is not
representative of a real store and the accuracy decreases with the increase in the number of
items. None of the former addressed the specific navigation strategy of an inventory robot.

The automation of stock-taking on retail shop floors has been tackled in recent years also
outside the academic environment. The first commercial design was AdvanRobot
(Keonn Technologies, 2015), whose first prototype was presented in 2013. AdvanRobot was
granted the first patent for RFID autonomous robots in 2018 (Pous and De Porrata-Doria, 2018),
describing the architecture and algorithms on which the robot is based, which are also presented
in this work. To the best of our knowledge, only two other commercial inventory RFID robots are
available: StockBot (PAL Robotics, 2017) and Tory (MetraLabs, 2017). The navigation strategy
and performance of such robots have not been disclosed to date.

In summary, this paper addresses the questions of whether it is possible to design a
system that can use RFID tags to inventory and locate items in a store much more
consistently than a human operator with a handheld RFID reader, and whether it is possible
to optimize the effectiveness (accuracy), efficiency (time needed) and consistency over time
of such system, a need that has been discussed by Buckel and Thiesse (2014), Becker et al.
(2010) and Bertolini et al. (2012), among others.

3. Robot design
The robot is based on the combination of two subsystems: an identification subsystem, which
uses RFID technology, and a robotic subsystem that provides mobility and autonomy.
The communication between them using a navigation control-oriented to inventory is essential
to achieve the goal of simultaneously optimizing the accuracy and speed of the robot.

3.1 Identification subsystem
The identification subsystem is an RFID system that can identify items from as far as 6 m
which uses RFID technology, and a robotly mounted antennas, with its radiation patterns
pointing sideways, perpendicular to the robot's forward direction. In this way, the robot can
simultaneously identify items on both sides of an aisle. There are six antennas on each side
overlapping their identification volumes in order to maximize read rate and minimize
missed detections. The antennas are fed and controlled by three RFID readers, each in
control of four antennas. Using four readers there is no need for additional hardware
(e.g. multiplexers) to connect the antennas, avoiding additional insertion losses and
maximizing the power radiated. Furthermore, a number of readers working together imply
an increase of simultaneous identifications, which helps in reducing the time to complete the
inventories. The antennas used are Advantenna-p22 and the readers used are
AdvanReader-150, both manufactured by Keonn Technologies (www.keonn.com).

The robotic subsystem is based on Robotnik’s RB-1 commercial autonomous base
(Guzman et al., 2016), but with customizations specified by our team. It includes sensors and
actuators (laser rangefinder, RGBD cameras, IMU and motors); a CPU, the brain of the robot;
and a battery. Robotics logic is based on ROS (Open Source Robotics Foundation, 2017),
adapted and extended to the specific needs of the solution. The navigation is performed by
sections (a large storage area is divided into smaller sub-areas or sections) for efficiency and
scalability, and it is a two-stage process. The first stage, recognition (a.k.a. mapping),
consists of driving the robot around the section of interest in order to capture a map of the
environment. This stage requires the intervention of a human operator. The second stage,
inventory, is the stage in which the robot navigates autonomously, without the intervention
of any human operator, based on the information collected during the recognition stage.
Overall, the robot can identify with high accuracy items placed up to 2.7 m and is foldable for ease of transportation. An application running on an Android handheld allows the control and monitoring of the robot by non-technical users. A schematic of the robot is shown in Figure 1.

3.2 Navigation control for inventory
The design hypothesis is that the robot’s navigation must take into account the density of undetected tags in its current environment, which it infers from the throughput of identifications (new RFID tags detected per unit time), and that without this information the inventory accuracy will be unsatisfactory or its duration will be too long. This assumption comes from observing the procedure of scanning items for inventory with an RFID handheld reader. When doing so, the operator follows auditory or visual cues on the device to understand when the items in a position have been identified. After that, the operator moves on to another position. In addition, during manual scanning, axial and radial local movements (twists) are applied to diversify the orientations of the handheld antenna. In this way, the set of relative orientations between the antenna mounted on the handheld and the RFID tags in the vicinity varies, increasing the probability of detection.

The robot includes a control layer that listens to the throughput of identifications and commands the navigation. The control layer triggers the transitions between two states. On the Journey state, the robot moves forward while scanning, an acceptable behavior if the amount of surrounding items is low enough so that they can be identified while moving forward. On the Twist state, the robot stops and twists in place in order to diversify the scanning orientations, a reasonable behavior if the amount of items is so high that they

![Figure 1. Schematic of the robot](image)

Notes: (a) The RFID tower is shown with a lateral cover open exposing three RFID antennas. On its top, two RGBD cameras are placed. (b) the RFID tower is folded, which eases manual manoeuvring and transport.
cannot all be read while moving forward. The control layer takes as input the live stream of identifications \( S \) [items]. Note that, during the inventory, items are detected several times and the live stream of identifications includes all of them. However, the navigation control considers only the new items detected \( N \) (newitems) in order to make decisions. Then, the stream of new items is time-windowed to get the rate of new identifications within a time window, \( R \) [items/s]. The rate of new identifications \( R \) is compared against a pair of thresholds \( (\text{th}_{\text{twist}}, \text{th}_{\text{journey}} \text{[tags/s]}) \) and state transitions are triggered accordingly.

The navigation control is outlined in Algorithm 4.4. Initially, the robot does not move forward, and it only twists around its axis (Twist state). It will continue in this state as long as the rate of new tags (tags never read before) read per unit time \( R \) stays above a certain threshold value \( \text{th}_{\text{journey}} \). In this state, the robot does not need to advance because it is reading many new tags from its current position. But as soon as the rate of new tags drops below \( \text{th}_{\text{journey}} \), the robot changes to the Journey state and starts moving forward. It will remain in this state until the rate of new tags is higher than the threshold value \( \text{th}_{\text{twist}} \), then the robot will stop moving forward and it will start twisting again. In this fashion, the average speed of the robot adapts to the density of tags in its environment, optimizing both the effectiveness and the efficiency of the mission:

**Algorithm 1.** Navigation control algorithm

1: State \( \leftarrow \) Twist  \( \triangleright \) Robot starts in the Twist state
2: \( I \leftarrow \emptyset \)  \( \triangleright \) \( I \): inventory initialized to the empty set (no items)
3: \( N \leftarrow \emptyset \)  \( \triangleright \) \( N \): newly identified items in last time window initialized to the empty set (no items)
4: \textbf{procedure} CONTROLNAVIGATION \((S_i, t_i) \triangleright S_i \): stream of all items identified at instant \( t_i \)
5: \( N_i \leftarrow S_i \setminus I \)  \( \triangleright \) \( N_i \): newly identified items (not yet in the inventory set) at instant \( t_i \)
6: \( N \leftarrow N \cup N_i \)  \( \triangleright \) Latest newly identified items added to the set
7: \( N \leftarrow \{ n \in N | (t_i - t_n) < T \} \)  \( \triangleright \) Items identified outside the last time window filtered out
8: \( R \leftarrow |N|/T \)  \( \triangleright \) \( R \): rate of new identifications in number of tags per second
9: \textbf{if} \( R > \text{th}_{\text{twist}} \) \textbf{then}  \( \triangleright \) \( \text{th}_{\text{journey}} < \text{th}_{\text{twist}} \)
10: State \( \leftarrow \) Twist  \( \triangleright \) If rate of new identifications is higher than high threshold, stop
11: \textbf{else} \textbf{if} \( R < \text{th}_{\text{journey}} \) \textbf{then}
12: State \( \leftarrow \) Journey  \( \triangleright \) If rate of new identifications is lower than low threshold, forward
13: \textbf{else}
14: State \( \leftarrow \) State  \( \triangleright \) If rate of new identifications is between thresholds, continue as before
15: \( I \leftarrow I \cup S_i \)  \( \triangleright \) Add latest identifications to inventory set (list of items identified)

4. Evaluation framework
This section presents a set of specific layout characteristic measures and figures of merit as a framework for the comparison. Given no former works have approached an equivalent or similar comparison, the measures proposed are a novel contribution.

4.1 Accuracy computation
The robot is intended for stores that contain tens of thousands of products. Nowadays, there are no means to know accurately the actual inventory of the store, also known as a baseline or ground truth. For this reason, a novel methodology for the assessment of an inventory robot’s accuracy is proposed.

The assessment of inventory accuracy requires of a good estimation of the baseline. Doing a physical inventory, counting manually all the items is a possible solution in uncrowded environments. However, in this work, environments comprise tens of thousands of items and manual inventories are not only prohibitive but also not 100 percent accurate.
The next possible option is using the perpetual inventory, a stock record kept up to date by the retailer’s ERP system, calculated by subtracting and adding items that are withdrawn and replenished respectively from an estimated initial stock. However, such records are known to diverge from reality over time due to wrongly reported transactions, system flaws, theft or item misplacement.

Since obtaining the real baseline is not possible, we propose a method to estimate the baseline, calculating it in several steps, involving robot inventories, handheld inventories and the perpetual ERP inventory. It is important to note that RFID never outputs false positive detections. If the identification of an item is reported, it means the item is there. The actual challenge for an accurate baseline is finding the false negatives, that is, the missed detections, items that are in the store but are not detected.

To produce an estimated baseline, all available robot inventories and handheld inventories taken of the same target area are merged into a single item list, formed by the union set of all those inventories. These inventories must all have been taken in a short time window during which the inventory has not changed (typically during the night). The more inventories used to estimate the baseline, the closer this estimation will be to the real baseline. The union set of all detected items in all the inventory rounds, including robot detections $r_1, r_2, r_3, ..., r_m$ and handheld detections $h_1, h_2, h_3, ..., h_n$ represents the set of positive detections $D$. Note that the union set does not have any repeated elements, only one instance of any item detected in at least one of the inventory rounds:

$$D = r_1 \cup r_2 \cup ... \cup r_m \cup h_1 \cup h_2 \cup ... \cup h_n. \quad (1)$$

Second, the set of alleged negative detections or alleged misses $\widehat{M}$ is computed by subtracting the positive $D$ detections from the perpetual inventory record $IR$ kept by the ERP. Since this perpetual record is known to be inaccurate, the set $\widehat{M}$ is an estimation of what could be missed rather than the actual misses:

$$\widehat{M} = IR \setminus D, \quad (2)$$

where $IR \setminus D$ denotes the subtraction of sets, that is, the set of elements that belong to the inventory record set $IR$ but do not belong to the set of positive detections $D$.

Third, we manually search for the items contained in $\widehat{M}$. If an item is found, we remove it from the shelf and attempt to detect it with a handheld without obstructions. This is done to discard the RFID tags being damaged or not properly coded. Items that are both found and detectable are added to the set of actual misses $M$:

$$M = \{ \hat{m}_i \in \widehat{M} \mid \hat{m}_i \text{ found and detectable} \}. \quad (3)$$

In other words, $M$ is the subset of $\widehat{M}$ after excluding the elements that were either not found, or with defective, unreadable tags.

Finally, the estimated baseline $B$ is computed as the union of positive detections and true misses:

$$B = D \cup M. \quad (4)$$

The estimated baseline $B$ will only differ from the real baseline in those items that have not been detected by any of the robot or handheld round and are not recorded in the ERP, which should be a very small set, which makes $B$ a very good estimation of the actual baseline.
When the ERP perpetual inventory IR is not available, the estimated baseline is computed as only the sum set of all detections:

\[ B^* = D. \] (5)

The accuracy of each robot inventory round is then estimated as:

\[ accuracy_r = \frac{|r_i|}{|B^*|} \] or \[ |r_i| \]

(6)

and the accuracy of each handheld inventory round is estimated as:

\[ accuracy_h = \frac{|h_i|}{|B^*|} \] or \[ |h_i| \]

(7)

where \( |r_i|, |h_i| \) and \( |B| \) denote the integers representing the cardinality (number of elements) of sets \( |r_i|, |h_i| \) and \( |B| \).

### 4.2 Layout characteristics definitions

Since the performance at stock-taking is strongly influenced by the layout of the area to inventory, we propose three parameters that quantify the specific complexity of a particular store layout. These parameters are chosen to be a Mutually Exclusive Collectively Exhaustive set of metrics to measure the difficulty of the robot’s inventory task in a given store.

#### 4.2.1 Aisles length

Although the robot can identify items as far as 6 m, the presence of metallic or partly metallic shelves can block the RFID signal. Therefore, rather than relying on its reading reach for planning the navigation, the robot prefers visiting all the traversable aisles. In this manner, unpredictable signal blockages are minimized and the accuracy is not compromised.

We call aisles length the total length of aisles found in a given area, expressed in meters. In contrast with the area, the aisles length gives an idea of the extent of the inventory task, since it gives the actual distance the robot must travel to identify all the items.

Other factors being equal, the duration of the robot’s inventory task will be proportional to the length of the aisles.

#### 4.2.2 Intricacy

The speed of a robot navigating a given space depends on its proximity to obstacles and the type and amount of turns involved. When obstacles are close by and at turns the robot speed is reduced. Therefore, a complete navigation in wide and straight aisles is faster than in narrow aisles with many turns. Consequently, the duration of inventories will be dependent on the characteristics of the layout.

Intricacy quantifies this effect and is computed as the aisles length per unit area:

\[ \text{Intricacy} = \frac{\text{Aisles length}}{\text{Area}} \quad \text{[m/m}^2]\]. \] (8)

Intricacy can be thought of as the distance that should be traveled to scan a square meter, giving an idea of the intricacy of the layout, since the more meters within a given area, the more turns are expected. Further, it is a comparative measure of the width of the aisles when shelves at layouts to be compared are similar in size. Figure 2 is a graphical representation of two simple layouts with different degrees of intricacy.

Note that intricacy is a measure which is independent of the store size, since if the store grows in the area maintaining the same type of layout, the length of the aisles will grow in direct proportion, maintaining a constant intricacy figure.
Other factors being equal, the duration of the robot’s inventory task will increase if the intricacy increases.

4.2.3 Density. At stock-taking, a high amount of items per unit area can be a notable challenge. A usual consequence of a significant amount of references in a confined space is their placement in a very packed manner, which means RFID labels can be occluded or interfere with each other. In addition, the more items the RFID signal has to traverse, the more it is attenuated. Density is expressed as:

\[
\text{Density} = \frac{\text{Number of items}}{\text{Area}} = \frac{\text{Number of items}}{\text{Aisles length} \cdot \text{Intricacy}} \quad \text{[items/m}^2].
\] (9)

Other factors being equal, the duration of the robot’s inventory task will increase if the density increases.

4.3 Figures of merit

4.3.1 Inventory accuracy. Inventory accuracy, referred in this text simply as accuracy, is defined as the percentage of positive identifications of an inventory with respect to a baseline. The difference with IRI lies in that IRI is widely accepted to assess the accuracy of a retailer’s perpetual inventory record while inventory accuracy is a measure applicable to any inventory (Section 4.1).

4.3.2 Effective speed. A robot that navigates in cluttered and changing environments constantly faces situations in which it needs to reroute and navigate away from the most direct course, for instance, due to unexpected obstacles or prohibitively narrow aisles. As a result, traveled distances are generally longer than the optimal path. On the contrary, a person in similar situations most of the time can manoeuvre without increasing its journey. A figure for comparing inventory speeds needs to include the excess of time resulting from distance overheads. For that, instead of looking at the actual distance traveled, the effective speed considers the length of the aisles. In addition, we propose to normalize...
the effective speed with a function that will penalize this figure of merit when the accuracy is low, to take into account the fact that the most probable cause of a low accuracy is that the robot is moving faster than it should.

The normalization function \( \eta \) is not linear because the contribution of time to accuracy is not linear. Looking at a typical plot of accuracy over time (Figure 3) one can see a typical behavior: a fast growth followed by a slow growth. Indeed, the slow growth is contributed by the difficult identifications, which are the critical to achieve an inventory accuracy above 99 percent.

The normalization function \( \eta \) must be 0 when the accuracy is 0 percent, 1 when the accuracy is 100 percent, and in between should compensate the growth of accuracy with time, in order not to give high values for robots that go fast but miss a lot of tags. The proposed expression for the normalization function \( \eta \) is:

\[
\eta(\text{Accuracy}) = 2^{\text{Accuracy}} - 1. \tag{10}
\]

Finally, the definitions of robot speed \( v \), effective speed \( v_{\text{eff}} \) and normalized effective speed \( v'_{\text{eff}} \) are:

\[
v = \frac{\text{Travelled length}}{\text{Duration}} \quad [\text{m/s}], \tag{11}
\]

\[
v_{\text{eff}} = \frac{\text{Aisles length}}{\text{Duration}} \quad [\text{m/s}], \tag{12}
\]

\[
v'_{\text{eff}} = \left( \frac{\text{Aisles length}}{\text{Duration}} \right) \cdot \eta(\text{Accuracy}) \quad [\text{m/s}]. \tag{13}
\]

### 4.3.3 Effective read rate

The effective read rate measures the throughput of new identifications. That is, the new identifications per time unit that are actually registered during an inventory. It is dependent on the navigation (time) and the density of items

![Figure 3. The evolution of accuracy over time in a real-world scenario](image)

**Notes:** A fast growth is followed by a slow growth. Around time 2000s the discovery of a new crowded area restarts the typical growth sequence. Effort does not contribute linearly to accuracy. Note the two quasi-flat regions, where a prolonged time period is needed to gain a small share of accuracy. The most likely reason is the fact that easy identifications happen in bulks while difficult ones need a continued effort.
This section presents a set of specific layout characteristic measures and figures of merit as a framework for the comparison. Given no former works have approached an equivalent or similar comparison, the measures proposed are a novel contribution.

5. Design iterations

This section describes the development-evaluation cycle based on design science. The main idea behind design science is that the design iterations are also based on the learnings obtained from the performance on the previous iterations rather than on fundamental principles alone. First, it starts evaluating the relevance of the main parameters that drive the algorithm, namely, twist motion and thresholds. Then, the evaluation focuses on the optimization of the two threshold parameters. Finally, the solution is taken to a real department store for a full assessment.

5.1 Evaluation of the relevance of the algorithm parameters

The first evaluation of the robot’s navigation algorithm is conducted at the Pompeu Fabra University, in the Poble Nou campus Library. The testbed is built by coding and placing RFID labels on books. The RFID tags used are Smartrac’s Shortdipole using the Impinj Monza 5 chip (www.smartrac-group.com/shortdipole.html). Overall, the library contains more than 3,000 labeled books. The library is chosen for four main reasons: first, books are known to be challenging to detect due to the absorption of the radio signal by paper; second, the library’s perpetual inventory is available and accessible to use it in the computation of an accurate baseline; third, the density of items is rather high at 260 items/m², which stresses the validation challenge; and fourth, the layout does not present major complications, a prerequisite to avoid its interference on the accuracy-oriented navigation control verification. A more detailed description of the advantages and challenges of using RFID in a library environment can be found in Feng (2010). Table I summarizes the characteristics of the testbed. Plate I shows the robot in the library during the verification tests.

5.1.1 Methodology. The main evaluation goal is to prove that the parameters of the navigation algorithm (twisting motion and thresholds) are essential to guarantee that the minimum accuracy is 99 percent. This minimum accuracy has been obtained by interviewing different retail logistics and operations managers, who consider this the

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type of item</td>
<td>Books</td>
</tr>
<tr>
<td>Area (m²)</td>
<td>12.0</td>
</tr>
<tr>
<td>Number of items</td>
<td>3,115</td>
</tr>
<tr>
<td>Aisle width (m)</td>
<td>1.05</td>
</tr>
<tr>
<td>Density (items/m²)</td>
<td>260</td>
</tr>
<tr>
<td>Aisles length (m)</td>
<td>5.0</td>
</tr>
<tr>
<td>Intricacy (m/m²)</td>
<td>0.42</td>
</tr>
</tbody>
</table>

Table I. Main characteristics of the validation setting.
minimum accuracy to make the inventory results usable for omnichannel. This figure is consistent with figures reported in the literature (Esposito et al., 2015).

We will study first the relevance of the twisting motion during the Twist state, and then the relevance of the two threshold parameters \( th_{\text{twist}} \) and \( th_{\text{journey}} \).

A set of tests is conducted in order to verify the parameter relevance. In test (i), the robot is set to traverse the aisle without adapting the navigation to detections, that is without stopping due to threshold, or twisting to read. In test (ii), the robot is set to traverse the aisle and stop using the thresholds, but without twisting. For that, a threshold to stop, \( th_{\text{stop}} \), is used analogously to \( th_{\text{twist}} \) introduced in Section 3.2. The most restrictive thresholds are applied (\( th_{\text{stop}} = 1, th_{\text{journey}} = 0 \)). In this fashion, the robot does not move from a position until it has identified all items at reach, and stops again as soon as a new tag is detected. These values are used to assess the contribution of twisting to accuracy. In test (iii), test (ii) is extended by applying a twist at every stop (and keeping the same threshold values \( th_{\text{twist}} = 1, th_{\text{journey}} = 0 \)). While twisting, the relative orientations between RFID tags and antennas vary during the twist motion and consequently the probability of detection increases. Noteworthy, the library presents the worst case regarding the effect of orientation in detections due to the tag placement inside the books, which is perpendicular to the antennas when the robot is traversing the aisle.

In addition, we can evaluate the impact on the accuracy of the number of consecutive passes through the same aisle. Our previous experience in RFID indicates that repeated passes contribute with a small, but significant, share to the overall accuracy. The number of passes is determined by the incremental contribution to the accuracy of each new pass. When the contribution to accuracy of a new pass is not significant anymore no more passes are done and the inventory round is finished. During our experiments, typically the four first passes contributed significantly to the accuracy.

5.1.2 Results. Figure 4 shows the average and variance of the accuracy of seven repetitions of each test. Each repetition included four passes of the robot along the aisle. The results of test (i) show that the 99 percent lower bound cannot be reached by setting the robot to navigate without an interaction with the progress of RFID identifications, even after...
four passes. The results of test (ii) reveal that by applying a control based on listening to
identifications, after a second pass the average accuracy reaches 99 percent, albeit the
99 percent figure is not guaranteed in all repetitions unless four passes are used. The results
of test (iii) show that including a twist is critical to consistently yield an accuracy above the
requirement. Indeed, the accuracy averages of test (iii) are above 99.5 percent with two or
more passes and are above the 99 percent threshold in most repetitions with a single pass.
In conclusion, the best setting regarding accuracy is \((\text{ttwist}=1, \text{tjourney}=0)\), which involves
twisting, and a minimum of two passes. Hence, the relevance of the parameters is
demonstrated since the robot can only consistently achieve an accuracy above 99 percent if
the twist and the thresholds are used.

Additionally, seven inventories were performed by store associates with RFID handhelds.
These associates were experienced in the use of the RFID equipment and had been doing RFID
inventories for several months in that store, so these inventories can be considered as
representative of what this inventory method can achieve. The average accuracy of these
handheld inventories is also higher than 99 percent. Table II shows a comprehensive view of
the measures during the seven repetitions of the handheld and the robot’s best configuration.
The robot shows a slightly better accuracy, most likely due to the fact that thresholds are

![Figure 4. Accumulated accuracy as a function of the number of passes for each of the three types of tests](image1)

Table II.
Performance of the robot compared to the handheld during the tests to evaluate the relevance of the algorithm parameters

<table>
<thead>
<tr>
<th></th>
<th>Robot</th>
<th>Handheld</th>
</tr>
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<tbody>
<tr>
<td>Average accuracy (%)</td>
<td>99.6</td>
<td>99.3</td>
</tr>
<tr>
<td>Maximum accuracy (%)</td>
<td>99.7</td>
<td>99.7</td>
</tr>
<tr>
<td>Minimum accuracy (%)</td>
<td>99.5</td>
<td>99.0</td>
</tr>
<tr>
<td>Average duration (s)</td>
<td>601</td>
<td>598</td>
</tr>
</tbody>
</table>
applied strictly as opposed to the handheld case, which relies on the operator response. Unsurprisingly, accuracy figures are very similar, which is explained by the fact that handheld inventories were performed extremely thoroughly and in a reduced area, implying a marginal chance for execution errors and oversights. Regarding duration, average times measured are comparable. Given that nowadays current stock-taking procedures involve the use of RFID handheld readers, the handheld duration is considered the benchmark. Therefore, it can be stated the robot performs the inventory in a timely manner.

5.2 Optimization of the threshold values
The importance of the algorithm parameters to achieve the desired accuracy has been assessed in the previous evaluation. Now, the threshold values \( t_{\text{stop}} = 1 \) and \( t_{\text{journey}} = 0 \) need to be adjusted in order to optimize the inventory duration. The main goal of this evaluation consists in obtaining the best accuracy within a time comparable to a handheld. A different evaluation is also undertaken aiming at bringing the duration to a minimum without compromising accuracy. The evaluation is again performed in the university library.

5.2.1 Methodology. The robot is configured to traverse the aisle with different pairs of navigation thresholds. Starting from an initial setting with \( (t_{\text{twist}} = 1, t_{\text{journey}} = 0) \), thresholds are increased until the accuracy falls below an acceptable value. Following former observations, the robot is configured to do four passes with twisting, and each test is repeated seven times.

5.2.2 Results. Figure 5 plots the duration and accuracy measured for each setting and pass. Noticeably, the inventory duration can be reduced by nearly one third by adjusting the navigation parameters without a significant effect on the resulting accuracy. For instance, a second pass on \( (t_{\text{twist}} = 2, t_{\text{journey}} = 1) \) results in an average of 423 s and 99.6 percent accuracy. If a slight reduction of accuracy is acceptable, always above 99 percent,
the duration can be further reduced. For instance \((\theta_{\text{twist}} = 16, \theta_{\text{journey}} = 8)\) and two passes yields 99.3 percent of accuracy in only 235 s.

One would initially expect the duration after four passes to be four times longer than after the first pass, but it is not the case. The reason is that with each pass, the number of new tags (tags never read before) decreases quickly, so the robot is much more often in the Journey state than in the Twist state, so that the duration of each pass is normally shorter than the previous one.

The results show that the duration of the robot inventory can be optimized by adjusting the navigation control parameters, becoming notably shorter than the handheld. Table III shows a comparison of the figures of merit between the robot’s optimized configuration and the handheld. While the robot is traveling more distance – it is doing two passes – its duration is nearly one third, which is reflected in a higher speed. However, the figure of interest is the effective speed, since it ignores the journey in favor of the aisles length. Yet, the robot effective speed nearly triples that of the handheld.

Finally, the effective read rate shows that the robot clearly surpasses the handheld’s identifications throughput. Albeit one could expect a higher difference, an intuition from Figure 3 is that there are items difficult to identify, and those are similarly difficult for the robot as for the handheld.

Remarkably, these figures are not distorted by the effects of navigating extended and complex spaces and represent the theoretical capacity of the devices rather than their actual performance in a scaled scenario. This will be disclosed in Subsection 5.3 by analyzing stock-taking in an actual retail store.

### 5.3 Evaluation in an actual store

The relevance of the algorithm parameters has been proven and their values optimized to outperform a handheld device. Now, the assessment of the robot’s performance in a real-world scenario is undertaken at a department store. This last step is required in order to prove that all previous adjustments on the algorithm are still valid in an uncontrolled environment.

**5.3.1 Methodology.** The robot is handled by the associates of the store that is in charge of managing both robot and handheld inventories. Hence, experimentation is unsupervised after an initial training period.

Validation focuses on a comparative analysis of the performance between the robot and the handheld. In an actual store, handheld scans are performed by associates as one of their usual duties. Thus, the robot accuracy and duration are benchmarked against a state-of-the-art stock-taking procedure. Furthermore, the analysis is done section by section, in sections with different layouts, which reveals the impact of the layout on the performance.

Three target sections, A, B and C, are selected by the retailer based on the known challenges they pose to stock-taking. Table IV shows the main characteristics of the selected sections. Interestingly, the merchandise involved are garments, more specifically garments

<table>
<thead>
<tr>
<th></th>
<th>Robot</th>
<th>Handheld</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy (%)</td>
<td>99.3</td>
<td>99.3</td>
</tr>
<tr>
<td>Duration (s)</td>
<td>235</td>
<td>598</td>
</tr>
<tr>
<td>Distance (m)</td>
<td>11.0</td>
<td>5.0</td>
</tr>
<tr>
<td>Speed (m/s)</td>
<td>0.047</td>
<td>0.008</td>
</tr>
<tr>
<td>Effective speed</td>
<td>0.021</td>
<td>0.008</td>
</tr>
<tr>
<td>Effective read</td>
<td>13.2</td>
<td>5.2</td>
</tr>
</tbody>
</table>

**Table III.** Figures of merit of the optimal robot configuration and the handheld in the library.

**Note:** The optimal robot configuration is the one with \((\theta_{\text{twist}} = 16, \theta_{\text{journey}} = 8)\) and two passes.
with lots of variations of models, colors and sizes. Consequently, they are the ones with the highest incidence and impact of inventory inaccuracies and the top priority to retailers.

Table IV shows the layout characteristics of the sections. It is noteworthy the increase of density from section A to section C. Aisles length in section A is about half than in sections B and C. Intricacy shows a regular increase which, along with the increase in density, poses a considerable increase of the overall complexity. Although complexity is not formally defined and quantified, it can be understood as a growing function of density, aisles length and intricacy and gives an idea of the challenge at stock-taking. Another actual challenge is the width of the aisles. Since the robot is programmed to be very cautious with the environment, the narrower the aisle, the slower the robot manoeuvres. Moreover, if aisles are narrower than the nominal width, 0.70 m, the robot may not traverse them and the final accuracy can be compromised. In this regard and exceptionally, given that the typical aisle width in section C is under the nominal value, the navigation constraints have been relaxed for the robot to attempt to traverse aisles as narrow as 0.65 m. Although negative consequences are expected, namely, a slower navigation and a critical increase of the risk of getting stuck, this is preferred over missing aisles. Overall, the main goal is demonstrating the accuracy of the robot at inventorying cluttered spaces.

Working in a real-world scenario implies constraints. The main pitfall was the absence of a perpetual inventory record since the store’s database was not accessible. As a result, the baseline was computed directly from robot and handheld inventories (Equation (5)). Also, there were no repetitions on the same day and not even on consecutive days. Thus, the baseline was built from one robot and one handheld pass. Summing up, the validation baseline is inherently less accurate than the verification baseline. Furthermore, handheld data provided by the retailer did not include the timestamps of the identifications and the duration could not be computed individually for each pass. Alternatively, the average duration of handheld scans was informed by the retailer. Nonetheless, results provide a one-to-one comparison between the robot and the handheld.

The tags used by the retailer were not disclosed. Anyway, the retailer follows the Tagged-Item Performance Protocol (TIPP) Guideline (GS1 US, 2015b), which serves as a framework for the harmonization of tag performance assurance once it is attached to a product.

5.3.2 Results. 5.3.2.1 Accuracy. During the experimentation period, the robot completed 32 inventory passes. Out of those, 14 coincided with a handheld inventory on the same day and section. Although the initial target was a higher coincidence rate for comparison, working in a non-controlled environment eventually yielded a lower outcome. In Table V, the accuracy of the robot is shown along with that of the handheld by section. The first conclusion is that the robot is very precise, delivering a consistent accuracy between 99.4 and 100.0 percent across all the passes. On the contrary, the handheld is rather imprecise, with inconsistent accuracy, that reaches the threshold only in one of the passes. Comparatively, the inconsistent handheld accuracy can be explained by the fact that the robot as an RFID system is more thorough and powerful than a handheld. The imprecision
throughout the measures is due to the known fact that humans are error-prone at repetitive and cumbersome tasks. For instance, the lower bounds in handheld figures could be due to oversights such as skipping a subset of the scanned section. Obviously, the robot is not error free and suffers failures. However, in the case of the robot, errors are traceable. In this regard, Table V does not include robot inventory attempts that were unsuccessful, self-detected and reported. A last interesting trend from the results is the decrease of average handheld accuracy with the combined increase of density, intricacy and aisles length (Section A to Section C). The most likely reason is that the more complex and prolonged a repetitive task is, the less thorough and precise and the more prone to oversights a person becomes. Note that not only the average accuracy decreases, there is also a decrease in precision. While the robot is capable of dealing with complex repetitive tasks the person is not. In conclusion, the robot excels in accuracy and precision yielding more than 99.4 percent of accuracy in all the passes, clearly surpassing the handheld.

5.3.2.2 Inventory duration. The duration was measured on the 32 inventory passes the robot completed. On the other hand, the average handheld inventory duration was reported by the retailer. Figure 6(d) shows the duration measured in each section. At a first glance, the time it takes the robot to complete a section is comparable to that of a handheld. Noteworthy, in the simplest section (A) a person with a handheld is able to complete the inventory in less time than the robot. This is explained by a person’s efficiency in simple sections: low density, aisles length and intricacy. On the contrary, when approaching complex sections, the handheld’s efficiency decreases and the trend is inverted, becoming the robot quicker.

The density, aisles length and intricacy of the three sections (A, B and C) are represented graphically in Figure 6(a)–(c). Figure 6(d) shows that the duration of both the robot and the handheld inventories are very similar, and increase with the intricacy. Figure 6(e) shows that the distance traveled by the robot increases with intricacy while the handheld’s distance remains proportional to the aisles length. This can be explained by a person’s enhanced maneuverability. First, a person can traverse narrower aisles. Second, a person can overcome or put aside unexpected obstacles, for instance, a fallen garment on the floor. In the same situations the robot needs to seek and follow an alternative path, which implies doing a walk around, and consequently increasing its journey. Thus, a person is more efficient regarding distance traveled. Besides, the robot is consistently faster since it walks more meters than the handheld in equivalent times (Figure 6(f)). A confirmed trend is that intricacy is negatively correlated to the robot’s speed (Figure 6(c) and (f)). More interestingly, the person’s speed seems to be correlated to the density of the items. The latter would confirm the superior power of the robot as an RFID system compared to a single handheld. The robot is able to simultaneously identify more items. Hence, it deals with higher densities comparatively faster.

Figures of merit are shown in Figure 6(g) and (h). Looking at the effective speed, a person is faster at completing the simplest section due to its better spatial efficiency. Notwithstanding, the trend is inverted when facing an increase of aisles length. The decrease of effective speed for the robot is correlated to the intricacy while the handheld is affected by the increase in aisles length (section B) and density (section C). The effective read rate is computed as the amount of identified items per time unit and gives an idea of the identification capacity. Remarkably, the robot’s effective read rate is correlated to the

<table>
<thead>
<tr>
<th>Table V.</th>
<th>Section A</th>
<th>Section B</th>
<th>Section C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Robot (%)</td>
<td>99.9 (99.9–100)</td>
<td>99.9 (99.8–99.9)</td>
<td>99.6 (99.4–99.9)</td>
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<tr>
<td>Handheld (%)</td>
<td>96.2 (88.4–99.0)</td>
<td>81.6 (68.0–85.2)</td>
<td>75.3 (60.0–81.5)</td>
</tr>
</tbody>
</table>

**Note:** Average values in italic and extreme values in parenthesis.
density, which implies that the robot can assume the increasing density without compromising its pace. On the contrary, the number of identified items by the handheld decreases with density and so does the effective read rate.

6. Managerial implications
In this paper, we have presented a technological system that, from a management point of view, is able to provide high-resolution visibility of the stock in the retail floor. This visibility is in three dimensions: time, space and catalogue. The resolution in time is given by how often the robot can perform an inventory, typically every day, so the resolution is approximately 24 h. The resolution in location is typically 2 meters (Morenza-Cinos et al., 2017). Finally, the resolution in catalogue is maximum, every single item is counted, timestamped and located. In summary, this solution could provide management with a daily report of what individual items are on the store (with an accuracy above 99 percent), and also where they are with a precision of about 2 meters. When one compares this with the usual inventories, normally performed for accounting or fiscal reasons, done at most every quarter, at the SKU level (not at the item level), and with no
location information, the difference is abysmal (a comparison of traditional vs RFID-based inventories is found in Hardgrave et al., 2009).

On the one hand, the positive effects that visibility of the downstream demand has on the performance of a supply chain have been reported in the literature (Holweg et al., 2005; Christopher and Lee, 2004; Smáros et al., 2003). And more specifically, the positive effects of RFID-based visibility in the retail industry have also been widely reported (Delen et al., 2007; Hardgrave et al., 2013; Sellitto et al., 2007; Pfahl and Moxham, 2014).

But the most important managerial implication of having high-resolution visibility of the inventory in the retail floor is that it opens the possibility of implementing omnichannel retail processes (Cao and Li, 2015) such as fulfillment of online orders from the store closest to the customer, to be either shipped (“pick and pack”) or to be collected at the store (“click and collect”). Without this omnichannel process, traditional retail chains would have fewer strategies to compete with online retailers, which are growing in double digits (Laudon and Traver, 2016).

When considering the use of RFID, managers need to take into account the cost of tagging every item with RFID. At under $0.05 per tag in high volumes, and with almost all traditional label suppliers able to provide the service of tagging the items at source, the cost and complexity of tagging are less of a barrier for adoption for most retailers. On the contrary, RFID adoption is seen more and more as a necessity to stay competitive (Zhang et al., 2018).

In summary, the main question for managers that have decided to use RFID technology to achieve inventory visibility is whether an RFID autonomous robot is a better alternative than associates with RFID handheld readers, and this paper aims to provide information that can help make such decision.

7. Conclusions and future work

7.1 Conclusions

The value of combining robotics and RFID for inventorying is demonstrated. The RFID robot yields an accuracy above 99 percent in the two real-world scenarios analyzed, a library and a department store. Coupling the navigation to the progress of identifications is proved indispensable to achieve satisfactory accuracy figures. Comparatively, the accuracy is higher than doing the same task manually, and the difference increases with the complexity of the space. Additionally, the robot’s precision is better than the precision of a person equipped with a handheld. Besides, while a handheld is faster than the robot in simple and small spaces, when scaling the task, the trend is inverted and the robot shows higher effective speeds. However, intricacy has a negative impact on the robot’s inventory duration, due to overheads in traveled distance and a reduction of the average speed. In conclusion, the automation of stock-taking in shop floors is proven to be feasible and figures show that it can contribute to reduce IRI. In addition, an RFID robot working continuously implies an almost live monitoring of items, thus their participation as digital elements in any cyber-physical system. Overall, the connection between physical and digital worlds is proven feasible and the high-resolution, item-level SCM paradigm enabled.

7.2 Future work

After finishing the last evaluation on a real store, several improvement lines have been perceived, which are described below in order to keep improving the RFID-driven autonomous robot in the future.

In order to obtain a complete understanding of the value of the robot in the supply chain, it is required to assess the robot’s contribution to IRI correction. Also, it is desirable to compare and contrast the presented robot with other robots that are in the market. These tasks require the collaboration of partners. Work in the direction of having a closer collaboration with stakeholders is being done, but it is still in a preliminary stage.
Regarding the proposed methodology, it is considered using it in different environments and showing its convenience in cases where the ground truth of a system cannot be known. For instance, to perform fiscal inventories.

At an operation level, the main drawback detected by retailers is the need to follow a human-assisted recognition procedure. In this regard, a fully autonomous solution is envisioned. For instance, this could be achieved by using exploration techniques. However, this type of solution can bring other challenges such as ensuring completeness, and efficiency. In addition, changing the navigation paradigm might challenge the current coupling between identifications and navigation.

A complete integration of the robot in an actual supply chain for a detailed analysis of the contributions and limitations will be pursued, as well as creating operational guidelines to ensure that the robot operates in the proper conditions that guarantee efficiency and safety of other operations.

The initial metrics indicate that the robot is able to perform the work of four store associates taking inventory full time, at a fraction of the cost, and with much higher accuracy and consistency. This projects a very high ROI and a very short payback period of the proposed solution, but more data are needed to provide quantitative proof of its economic feasibility.

Finally, the experience gained working with retailers leveraged new robot applications. The main one is the location of products, which would provide retailers with the ability to detect misplaced items or create efficient picking plans for online orders. Locating items with an RFID system is challenging due to the nature of radio frequency propagation. Nevertheless, preliminary work in this direction has shown promising results. In addition, other sensors could be added to the robot in order to increase its knowledge about the environment and supply retailers with additional information. For instance, it could take 3D maps of the environment, detect moisture and temperature, lighting conditions or dirt. All the observations could be combined in a monitoring store application to support managerial decision making. Adding new sensors with this purpose to the robot is not technologically challenging. However, assessing the value for the final user, the retailer and the shopper is not trivial.

References


Stock visibility for retail using an RFID robot


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The affected paper was originally intended to publish as part of “SCM 4.0: Supply Chain Management in the Digital Age” Guest Edited by Erik Hofmann, Henrik Sternberg, Haozhe Chen, Alexander Pflaum and Gunter Prockl.

The publisher would like to take this opportunity to thank the Guest Editors for their time and effort.

Jenny Chester