Communications of the Association for Information Systems

Volume 52 Article 18

2023

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Accepted Manuscript

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Please cite this article as: Lyytinen, Kalle; Topi, Heikki; Tang, Jing : MaCuDE IS Task Force Phase II Report: Views of Industry Leaders on Big Data Analytics and AI, *Communications of the Association for Information Systems* (forthcoming), In Press*.*

Communications of the Association for Information Systems

Research Paper ISSN: 1529-3181

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Abstract:

This paper represents the Phase II report of the Management Curriculum for the Digital Era (MaCuDE) disciplinary task force on information systems (IS). Aligned with the current work of the AIS (Association for Information Systems) and ACM (Association for Computing Machinery), we focus on the current and future industry driven educational needs and requirements posed by big data analytics (BDA), artificial intelligence (AI), machine learning (ML), and related innovations. In this report, we probe and report on the views of industry leaders regarding BDA/AI education needs. We conducted 18 rich semi-structured interviews with a representative sample of industry leaders around key changes and issues related to workforce demands in digital transformation and associated educational needs. We performed a grounded theory based analysis of key themes in reported education needs. We note the shifting meaning of AI and BDA phenomena and identify three main organizational level needs for the digital era -capability improvement and transformation, decision-making strategies and tactics, and changes in operations or products- and connect them to three individual professional competencies- fundamental environmental competencies, data information and content, and system design competencies- necessary to deliver them. Based on the analysis we outline several novel competency-based IS curriculum recommendations for the master's and undergraduate level IS education.

Keywords: Big Data Analytics, Artificial Intelligence, Digital Transformation, Industry Needs, IS Curriculum Recommendations, Curriculum Design, Business Education, AACSB.

[Note: The authors contributed to the report equally.]

This manuscript underwent [editorial/peer] review. It was received xx/xx/20xx and was with the authors for XX months for XX revisions. [firstname lastname] served as Associate Editor.] **or** The Associate Editor chose to remain anonymous.]

1 Introduction

AACSB International's Digital Transformation Affinity Group (DTAG) was established in February 2019. As its first major initiative, DTAG launched the Management Curriculum for the Digital Era (MaCuDE) project for which PricewaterhouseCoopers (PwC) has provided funding and Stevens Institute of Technology operational leadership. The MaCuDE project is tasked to recommend changes to business curricula based on digital technologies' transformational impact on organizations (regardless of their type and size) and especially explore the impact that these changes have on resources that business schools need to fulfill their educational mission. *The initiative is specifically motivated by and expected to heed particular attention to the impact of the wide use of big data analytics (BDA) and artificial intelligence (AI) technologies in organizations' operations, organizing, and decision-making.* The project comprises nine task forces. Most of them explore the impact digital technologies have on a specific business discipline or an area of practice and related curriculum needs such as those related to accounting, operations, finance, information systems, innovation management, and marketing. The initiative has also cross curricular task forces focused on analytics, cybersecurity, and future of learning/work. The project website at *macude.org* describes the initiative and each task force in more detail.

One of MaCuDE's disciplinary task forces focuses on information systems (IS) education at business schools. The Association for Information Systems (AIS) and the Association to Advance Collegiate Schools of Business (AACSB) jointly formed this task force in early 2020. Dr. Kalle Lyytinen (Case Western Reserve University, MaCuDE IS Coordinator) leads the task force in collaboration with Dr. Heikki Topi (Bentley University, AIS VP of Education 2017-2021) while Dr. Jing Tang (RIT) serves as the project coordinator. As with the other task forces, the IS group follows a three-phase work plan. The first phase (2019-2020) focuses on describing the current status of IS curricula in business schools, the second phase (2021) on exploring industry leaders' views regarding the expectations for future graduates of IS programs in business schools, and the third phase (2022) on developing more detailed curriculum and policy recommendations based on the results of the first and second phases by integrating the findings into a set of recommendations regarding future curricula and educational policies and related institutional changes. The MaCuDE IS project finished its first phase during the spring of 2021 (the timeline was extended due to COVID-19). The results have been reported in Communications of the AIS article (Lyytinen et al., 2022).

This article reports the results of the second phase which focuses on industry needs related to BDA and AI and future education associated with the two. The study was carried out as an open, interview-based field study, which involved interviewing a representative sample of industry leaders making decisions about hiring and educational needs associated with development and management of BDA and AI based applications. This report draws on rich semi-structured interviews that focused on the current status and the future use scenarios for BDA and AI across industry settings and organizational contexts. In particular, we aspired to know the educational needs and related policy implications that arise from such growing use.

We recognize from the outset significant ambiguity regarding the project's focus and related scope of the analysis. Therefore, a few clarifying caveats are in order. Both "Dig Data Analytics" and "Artificial Intelligence" are now widely used terms everyday discussions and industry reports. In the last few years, they have received somewhat faddish treatment, and their exact definition is hard to pin down. They lack universally accepted definitions even across the individual disciplines covered in the MaCuDE project, and each discipline may have different perspective on what these terms mean in their setting. Moreover, the terms continue to evolve as new innovations push the frontiers of computing capabilities to amass, manage and process large data sets and of associated algorithmic capabilities to derive and use insights from such data sets using various 'learning' or 'artificial intelligence' capabilities. The change is also fast in that what was deemed 'big data' five years ago may not be so 'big' anymore.

To clarify the boundaries and the nature of this nascent field, the authors reviewed several recent commentaries of and introductions to special issues on big data and AI in the recent IS literature (see (Abbasi et al., 2016; Baesens et al., 2016; Berente et al., 2021; Chen et al., 2012; Grover et al., 2020; Lyytinen et al., 2021). These reviews reveal a broad range of perspectives on these topics and show the evolving and varied nature of the focal phenomena associated with BDA and AI. Furthermore, a multitude of logical and functional connections link big data to other digital technologies beyond AI, such as analytic online processing, data management (event databases, non-relational databases), edge computing, cloud and software service stacks. Given the BDA and AI fields' immature nature and the definitional fluidity, this report does not aim to fully clarify these concepts or characterize these technologies at the detailed level. In contrast, we will proceed with the following broad assumptions which help recognize a multitude of novel technology features that BDA and AI currently and in the future are likely to exhibit:

- The terms big data and analytics—forming the notion of BDA—highlight the growing importance data ('new oil') in organizational operations, innovations etc., often captured in the phrase 'data is the new oil of business'. This is reflected in the exponential growth in volume and richness of data. This growth poses unprecedented demands for the availability and variety of data integration and processing capabilities. Many of these flow from the recent rise of five trends that drive the growth in the IT use: social media, mobility, analytics, cloud, and Internet of Things—often called the emergence of SMACIT (i.e., Social, Mobile, Analytics, Cloud, and Internet of Things) technologies. These technologies offer now a new technological ecosystem of generating, storing, processing, displaying, and distributing data in unprecedented scale and speed. These novel capabilities offer unparalleled opportunities for organizations to design, deliver and implement new types of products and services and to gain data driven insights of their use. Similarly, the term artificial intelligence (AI) is associated now with massively data driven analytical solutions that offer new insights into services or operations and/or allow their continued improvement (such as Siri). These and other broad definitions offered for BDA and AI identify typically not only unique foundational technology features that characterize these technologies but also note their dependency on emerging lower-level IT capabilities that require, deploy, or enable specific organizational BDA or AI applications (such as 5G, mesh networks, edge computing, and blockchain, just to name a few).
- These emerging and dynamic IT capabilities show inextricable links to both big data and AI uses. Many recent innovative organizational applications of IT require that organizations use both BDA and AI capabilities to become genuinely transformative in their business development (so called digital transformation). For example, many AI applications rely on data at an unprecedented scale and volume to truly become useful. Similarly, many big data applications apply AI-based approaches to carry out complex analytics that arise with the complex data sets. One emergent area where both big data analytics and AI are needed together is the emerging field of Industry 4.0 and related uses of the Internet of Things (IoT) (Eley and Lyytinen 2022).
- The terms BDA and AI cover not only the analytical processes and presentation approaches associated with and necessary for big data and related AI uses. They also address the organizational issues related to managing and governing the data and AI tools and new types of organizational tasks and functions required by the use and maintenance of such technologies.
- Artificial intelligence in our analysis is not limited to any specific AI method (such as logic programming, symbolic processing, and learning algorithms) or application area (such as natural language processing, vision, machine learning, recommendation systems, or robotics). Rather, in this discussion it covers any application of AI techniques and technologies in a range of organizational contexts now common in many organizations that deal among others manufacturing robotics, robotic process automation, natural language processing (as part of service), autonomous vehicles, and so on. It also covers emerging application areas such as medical and health applications for predicting heart attacks or developing new ways to treat cancer.
- Overall, our assumption is that BDA and AI in combination when connected to new critical infrastructure elements (such as sensors, ultra-speed networks, edge computing, software service stacks, and virtualization) provide an unprecedented technological foundation for organizational innovation. The stream of innovations enabled by these technologies will help organizations and their management to address in new ways well known organizational problems (such as routing, automation of workflows, quality control in manufacturing processes, and marketing decisions). These innovations will also make it possible to create novel organizational products and services (such as how to manage fleets of AVs, how offer new types of AI-based educational offerings). Many of these innovations share similar goals with the goals of past IT applications that the IS discipline has been studying since its inception (e.g., goals and functions for decision support systems, executive information systems, and

business intelligence system) (Chen et al., 2012). In this regard, not all that relates to these technologies and their uses is totally novel.

These features and boundary conditions guided the selection of the issues that we investigated and probed in the field study reported below. The remainder of the report is organized as follows. First, we offer a short introduction to MaCuDE project. Next, we will discuss the goals of this industry need analysis within the project and report on the research approach chosen for project. We will then discuss the key findings related to the current understanding of BDA and AI in the industry and its characteristics, the views how BDA and AI technologies contribute to organizational innovation and transformation, and the critical individual level competencies identified during the field study that help set up the future education needs. We will also cover how university education and curricula can help in fulfilling these needs and in which role as part of the wider educational ecology. Towards the end we will review how the new needs identified in this report relate to past educational offering as outlined in published curriculum recommendations of IS 2010 (Topi et al., 2010), MSIS 2016 (Topi et al., 2017) and IS 2020 (Leidig et al., 2021). We conclude by summarizing the key findings into a list of key changes and trends, which are taking place in the BDA and AI applications in the industry and where the university education can help address those needs. The key focus of this report is on the industry expectations for current and future IS graduates given the importance of BDA and AI as essential capabilities for organizational transformation. We acknowledge that the implications of these expectations may vary significantly depending on the institutional context and emphasize that the purpose of this report is not to make specific program recommendations. Instead, we hope that this document will contribute as a source of information and ideas for both local conversations and discussions regarding the future direction of the IS discipline (including Phase III of the MaCuDE project).

2 Key Activities of the Project

The MaCuDE IS Task Force publicly launched its work with a workshop at the International Conference on Information Systems (ICIS) in Munich in December 2019. MaCuDE project leader and about 40 faculty members from all over the world attended this meeting. To ensure that the project receives broad-based, globally diverse guidance on educational and industry needs and their local variation, the task force also established in 2019 an advisory board comprising of several leading senior IS scholars who have either participated in major curriculum initiatives (such as IS 2002, IS 2010, and MSIS 2016), served in educational leadership roles in the IS community (such as AIS VP of Education), and/or are known for their current pedagogical or discipline-specific research in the big data analytics and artificial intelligence areas. Individuals on the advisory board have changed slightly over time; and during the tenure of the project the following individuals have served on the board:

- Jan vom Brocke, University of Lichtenstein, Lichtenstein (2020-)
- Helmut Krcmar, Technical University of Munich, Germany (2020-)
- Bernard Tan, National University of Singapore, Singapore (2021-)
- Mary Tate, University of Wellington, New Zealand (2020-2021)
- Olivia Sheng, University of Utah, USA (2020-)
- Joe Valacich, University of Arizona, USA (2020-)
- Ramesh Venkataraman, Indiana University, USA (2020-2021)

The task force organized five advisory board meetings in 2020 and four in 2021. In addition, the advisory board members participated in the task force's public workshops at ICIS in December 2019, 2020, and 2021 (all organized jointly with the AIS Education Committee). About 50 IS faculty members from all over the world have attended each public workshop. Furthermore, the advisory board has continued to play an advisory and executive role in the second phase during both data collection and analysis.

In 2020, the task force carried the first phase of the project. As noted, it focused on taking the stock and reviewing the current state of IS curricula globally and, in particular, the state of art in addressing big data analytics and AI topics in the curricula. The task force collected data using a questionnaire from March 2020 to September, 2020 of the content and goals of IS curricula across the globe. It received responses from 31 universities and colleges. The initial report of this project phase was reviewed in fall 2020 and spring 2021 in several public webinars. More detailed discussions of the content of the report were carried out with the task force's advisory committee. The discussions and the analysis culminated in publishing a tentative report in the fall of 2020 which thereafter has been expanded, reviewed, and recently published in the *Communications of the AIS* at the end of 2021 (Lyytinen et al., 2022).

In early 2021, the task force launched the second phase in which it conducted rich semi-structured interviews with industry leaders. Given the high level of uncertainty and ambiguity and the fast pace of change in applying these technologies and related applications the task force—based on the recommendation of the advisory board—decided to conduct the study during this phase as a qualitative field study. The key focus of this study was to collect as rich and varied data set as possible about the status and understanding of the use of BDA and AI technologies in different industry settings, to identify key areas where such applications are used and what their organizational uses and effects are, and to specify sets of novel competencies these applications demand from designing, managing, and operating them. The task force also decided to strive for a representative and rich sample of such interviews. Therefore, we organized the data collection together with the advisory board as to cover more varied organizational roles, settings and applications which need to interact with such emerging applications. The more detailed account of the research design and analysis and the subsequent findings will be reported next.

3 Data Collection and Sampling

The Phase II MaCuDE IS interview protocol was developed around key changes and issues related to workforce demands covering the new big data analytics environment and applications of artificial intelligence. The data collection was conducted and completed in March – June, 2021. The advisory committee members and project leadership conducted the interviews using a purposeful sample based on the structured interview protocol (covered by IRB). This report aims to identify and report the industry's current and future educational needs concerning BDA/AI. To this end we interviewed a broad intersection of functional managers, IT managers, and technical professionals in the organizations operating in high technology (e.g., e-commerce and software development), commercial services (e.g., financial services and consulting), and non-profits (education and health care) in several socio-economic settings (North America and Europe). The final sample included representatives of 18 interviewees from 16 organizations in multiple industries (one organization included three interviews). The interviewees were identified primarily through the networks of the task force advisory group and leadership team. Altogether, the data provided insights regarding 13 organizations from North America and from Europe. The interviewees carried titles of CIOs, CTOs, product managers, heads of big data consultancy, or head of big data / machine learning teams (see Table 1). Each interview lasted from 45 minutes to nearly two hours, resulting in around 20 hours of interviews in total. All the interviews were transcribed verbatim and used for coding.

Table 1. Summary of Interviewees

Occupation	Count		Industry	Count
CTO	3		AI and cloud computing	4
CIO	2		E-commerce	2
Head/Director of IT/DS/DA*	9		Finance and insurance	2
CEO/Founder	2		Consulting and business service	2
Data Scientist	2		Software development	1
			Construction	1
Organization location	**Count**		Transportation	1
U.S.	13		Education	1
Europe	3		Hospitals and Health Care	1
			Hospitality	1
			Sports	1

*Note: IT: information technology; DS: data science; DA: data analytics

4 Method

Data analysis was done in three steps. First, we conducted open coding of the transcribed interview data to identify key topics and issues around big data and related industry needs. We used NVivo to identify emerging concepts and categories in the data. The three authors independently coded the interview transcripts for the distinct first-order categories. After the first round of coding, the authors discussed and crosschecked the emerging codes when the coding labels conflicted. During the process, coders re-evaluated the coding scheme and all its dimensions. This resulted in adding new dimensions and merging some to ensure that the data was particular to a given code. For example, we added new dimension "privacy and security (ethics)" as a new dimension to distinguish it from "model and data security". We merged "search" and "dynamic pricing" into a new dimension "specific business examples" to capture one of the aspect of changes in operations or products. The second round of axial coding refined the categories and their locations in the final organization. In total, we have 49 first-order categories and 16 second-order categories[1]. We evaluated the coder reliability with Cohen's kappa statistic and received satisfied Cohen kappa scores for each first order category (0.75~0.99), which is above the threshold for good strength of agreement (0.75) (Fleiss et al., 2013).

Next step, we carried out axial coding to crosscut and relate categories and identify the similarities and differences in the first-order categories (Corbin & Strauss, 2014). During this analysis, we formed the second-order categories to represent the dimensions of theoretical interest and uncovered emerging dominant themes. The final coding structure with the identified themes is illustrated below in Section 5 in Figure 1. Three key themes emerged during the coding process: Theme I, *Key concepts and concerns*; Theme II, *Organizational transformation: Goals and outcomes*; and Theme III, *Individual (task) competencies*. Each of the themes was divided into several subthemes. The *Key concepts and concerns* theme was divided into two subthemes (big data and AI). *Organizational transformation: Goals and outcomes* had three subthemes: 1) changes in operations and products, 2) improvement in decision-making strategies and tactics, and 3) capability improvement and transformation. *Individual competencies* covered 11 themes: 1) individual foundational competencies, 2) business domain competencies, 3) database, 4) data analytics, 5) data management, 6) business continuity and information assurance, 7) individual analytics and programming skills, 8) IT infrastructure, 9) systems architecture, 10) systems development and deployment, 11) IS management and operations. Across these BDA and AI related themes that were identified based on the interviews, we could gauge critical industry needs in multiple areas of BDA and AI and determine the individual competencies that are expected within different domains.

Finally, we conducted a three-step member-based validation process to increase the validity of our analysis. First, we presented the three themes and key elements of the codes to the MaCuDE IS Task Force advisory committee and collected their feedback. Second, we shared a full slide deck which summarized our key findings of the analysis to the interviewees and three CIOs/CTOs from other organizations not included in the sample. We asked specifically for their feedback on errors, omissions, and comments on our conclusions. We received two written responses. Third, we presented the analysis and findings in a hybrid workshop in the context of ICIS 2021. We got numerous additional comments from both academic peers and industry participants. After the workshop, we also received additional written responses from workshop participants who wanted to share additional insights concerning the results.

5 Results

Our results provide an understanding of the context and the range of effects of big data and AI, as well as their educational needs. Figure 1 summarizes the structure and order of the coding of the three main themes. It represents the core concepts and terms and their relationships identified in the interviews. Appendix B presents representative quotes for the first-order categories we identified. We report the results in two sections: section 5.1. presents analysis of big data and AI followed by a discussion on organizational transformation, and section 5.2. discusses individual competencies.

[1] We also coded for the "providers of competency development". For this, we have 10 first-order categories which are not listed here. They are "Challenges of big data, AI training at companies, collaboration with universities, commercial training providers (self-paced online learning), commercial training providers (synchronous learning experiences), communities of practice, internal training in competency development (strengths, weaknesses), platform providers as education partners, research collaboration as a mechanism for competency development, role of formal recognition of learning (certificates, degrees), universities as competency development providers (strengths, weaknesses)"

5.1 The Big Data and AI Environment

5.1.1 The Definition of Big Data and AI

The first step in our analysis was to examine the emergent definitions of big data and AI as understood by industry representatives. During the interviews, we asked the interviewees to discuss how they understand the terms “big data” and “AI” in the context of their organization and current tasks. The definitions of “big data” and “AI” varied based on the interviewee’s understanding of their role and task and consequent specific aspects of BDA/AI use resulting in what features they stress on in their definition. The variation appeared to depend which organizations they represented and in what context, what their organizations did and what the primary task was, how these organizations generated and used the data, and what was their current use and dependency on using cloud technologies.

<u>Big data</u>

We identified five first-order categories of how interviewees understood “big data,” including their definition and insights of applying big data in their organizations:

- Meaning of “big data”: volume, velocity, variety, and veracity
- Data governance
- Cloud and big data
- Data quality
- Integrating big data with large-scale organizational systems.

Interviewees stressed that their *meaning of “big data”* (dimensions of “big data” that differentiate it from ‘small data’) is constantly changing. The most important characteristics of “big data” are most commonly attributed to the four V’s of Big Data: Volume, Velocity, Variety, and Veracity. The first characteristic of the meaning heeds attention to the fast-growing size or magnitude of the data, that is, Volume (12 out of 18 cases mentioned this). The growth has been exponential for the last five years and shifted from terabytes to petabytes. Even real time edge processing can now use terabyte level data sets in dealing with, for example, customer recommendations. As noted by one Head of IT, “*’big data’ essentially just refers to enormous terabytes size of data that ordinarily you wouldn’t be able to process on a standard PC*.” The speed at which the data are generated, analyzed, and acted upon—Velocity—is another critical characteristic. This was commonly noted in organizations focused on E-commerce and business services. Variety is also commonly noted as one of the unique characteristics of big data. For most organizations, big data emanates from a large variety of sources and comes in multiple types (e.g., both structured and unstructured data). Beyond the three V’s suggested already by Laney (2001)—Volume, Velocity, and Variety—some interviewees emphasized that veracity (or its level) was critical for the usefulness of the big data sets. Veracity formed many times the key challenge for big data use, as the users needed to constantly address and be aware of the level of reliability that arises when multiple sources of data (variety) are consolidated (Gandomi & Haider, 2015). The topic was mentioned by two technical domain experts working with such data set. They noted the invisible, hard, and challenging work of assessing the reliability of large and often highly diverse data sets and the need to guarantee their quality.

> ***Meaning of Big Data:*** *“Today it’s fashionable to define big data as having the attributes of volume, variety, velocity, you know, and that is actually a pretty good definition.”*
>
> *“Big data is mostly around like ‘How do we collect the data and store it? And how do we process it?’ and then sometimes the data might not be big in terms of volume. Sometimes it is. Sometimes it’s a combination of the data volume, the speed of the data and also the use of it, how many use cases we are using those data on. My organization, “big data” could mean differently in different parts of the organization.”*

Data governance challenges emerging from such dimensions. New types of *data governance needs* were commonly identified as a salient aspect of big data. Data governance is in BDA settings more about how to put the data together, how to maintain data quality, how to store and organize the data for further effective use, and how track down and promote the use of the data across different constituencies.

Several respondents pointed out that big data is *not* about collecting just large swaths of data. Instead, the key challenge in data characterized by four Vs is the data quality and what sort of data governance you need to establish to meet specific data quality standards for any given setting. This standard varies from one context to another. Therefore, data governance and quality differ from the old 'structured' data administration which applied relatively common and unified principles and standards for data and its quality (such as financial transaction data). In this new environment organizations possess and use increasing amounts of unstructured data that originate from multiple internal and external sources. Data governance policies and practices need to address how to organize, analyze, and present such data sets.

> ***Data governance:*** *"…where the business really needs help on is 'How do I get all of this data together?' and that's been one of the like 'How do we get it together? How do we know what we have?' you know all those data governance aspects of 'Do we have a business glossary attached to it? Do you have a data catalog? What is the grain of our cable so that we're not duplicating? How do we verify data quality?'"*

Data quality, as a pertinent challenge related to big data, was heavily emphasized by several interviewees as key element of data governance. This applied especially for participants from construction, finance and insurance, cloud computing, and hospitals and health care. Based on their industrial experience, these interviewees pointed out that the quality of data, not just the size and the speed of collecting data, is a pertinent problem in their practices.

> ***Data quality:*** *"I mean the data quality is always number one, no matter how big of the data that you're dealing with. It's always a challenge, I would say, one of the constant challenges for all of the data professionals and data teams in organizations. I think two ways that we look at it, how do we solve the problem in this area, definitely build a good process around, whether or not it's data logging or collection within the data processing."*

Cloud and big data have become inherently interdependent *in* the new environment. Big data in most cases depends on the use of cloud-based storage and processing environments and their rich service stacks which offer multiple BDA and AI tools. These are commonly defined by three primary types of publicly available cloud-based platforms which all interviewers mentioned at some point: Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS). The salience of cloud processing in the context of BDA was commonly discussed together with the need for new type of data governance and data quality that comes with the cloud-based environment. Especially with cloud computing the economics matter: the small and medium size companies often need to balance the data quality, data governance and the cost of cloud computing. Using cloud service offered by platform companies—such as Google Cloud, Amazon AWS, or Microsoft Azure—is one of the key choices in developing a big data strategy for a firm. The immediate availability and use-based pricing of these services has significantly broadened the range of organizations that can fast build innovative business models on creative use of BDA and AI capabilities.

> ***Cloud and big data:*** *"By building on cloud based (SaaS or IaaS) applications overhead is minimized. The key challenge is to have high quality data and data governance. Reducing the IT stack to what is needed to move it to cloud providers helps in addressing infrastructure needs."*

How to use the big data effectively and support the organization's decision-making is another salient issue associated with big data use. It is not surprising that managers heed now more attention to problems and challenges of *integrating big data with large-scale organizational systems*. In this setting big data comes with relatively "low value density" (i.e. the data has a low value relative to its volume) while the proper analysis of big data add high value to such data (Gandomi & Haider, 2015).

> *"Successful Big Data analytics requires good master data management among all IT systems. Different projects in our company show, the better you can centralize and unify your different master data, the better Big Data analytics, and artificial intelligence will work. Mastering our master data within our organization was a task that costs us years and resulted in a lot of different interfaces between different information systems before."*

<u>Artificial Intelligence (AI)</u>

We identified four first-order categories from responses' discussion on AI, they are:

- Meaning of AI

- Cloud and AI
- Meaning of machine learning
- Relationship between AI and machine learning

AI and machine learning (ML) are two separate terms that often were compared and integrated during the interviews. Sometimes, however, the interviewees used them to denote alternative approaches to AI. John McCarthy describes AI as “the science and engineering of making intelligent machines” (McCarthy, 1998, p. 2), and defined creating AI as “making a machine behave in ways that would be called intelligent if a human were so behaving” (McCarthy et al., 2006, p. 11). In their textbook, Russell and Norvig (2002) identify four potential AI definitions: systems that think like humans, systems that act like humans, systems that think rationally, and systems that act rationally. In most cases AI in the context of current uses refer to the first two definitions. Offering a more practical industry view, IBM describes AI as “leveraging computers and machines to mimic the problem-solving and decision-making capabilities of the human mind.”[2] This is relatively close to the main types and purposes of using such technologies for organizational improvement as noted below. Because of the difficulty of pinning down the exact meaning of AI in organizational setting, Berente et al. (2021) define AI pragmatically as “the frontier of computational advancements that references human intelligence in addressing ever more complex decision-making problems.” (p.1435). This aligns relatively well with what the interviewees referred to as AI in their interviews. In the interviews, the *meaning of AI* appeared to mostly originate from the push towards automating BD analytics and modeling; later, it has moved from analysis to prediction and new insights. This definition highlights three key points of AI that apply also to AI applications in practice: 1) AI is a moving frontier (meta-learning); 2) AI has an increasingly important role in decision making in organizations (outcomes and setting); and 3) the AI supporting human behavior continues to create opportunities for organizational transformation.

> ***Meaning of AI:*** *“Artificial Intelligence is the broader term that we use in our industry to refer to more of like human-level intelligence, and a subset of that that really is what we work with is Machine Learning, and the Machine Learning is a more specific problem set that we work with, such as a recommendation, and so a recommendation isn’t super broad of the human intelligence, but it’s a very, very specific problem that we’ve given a machine…”*

When talking about the *meaning of ML*, interviewees focused more on the specific ways of doing analytics or generating specific types of statistical models and treated it as a sub-field of AI (see, e.g., Grimmer et al. (2021)). Understandably and accurately, our participants identified a *relationship between AI and machine learning*. AI as such is viewed a relatively broad field and many recognized this broader term: “*AI – a discipline of automating big data analytics for an industry, making it run and making it run right, creating value*”, while ML was viewed as being composed of specific sets of techniques and related identification and learning problems. The latter were largely seen being enabled by the access to big data sets. *AI and cloud* were seen inherently related. Most these associations were noted in connection of using specific cloud-based computational tool environments such as Tensorflow.

> ***AI/ML and Cloud****: “So we migrated to the Cloud and now we use things like Bigtable and BigQuery on Google’s Cloud product …, and that has made/allowed us to move from that one billion to almost order magnitude larger in processing data, which then allows us to make better recommendations, and everything else that we use Machine Learning for is better because we have more data.”*

5.1.2 Organizational Transformation: Goals and Outcomes

The current emphasis on BDA and AI is partially driven by the very large amounts of potentially valuable data that organizations generate through various technologies that allow quantification of a variety of events within organizational processes (see Appendix A3 for specific DBA/AI examples in industries). Generally, the uses of BDA and AI are expected to result in organizational changes that in one way or another improve broadly defined organizational effectiveness. The changes can be viewed as goals that drive BDA and AI deployments in specific settings, and the success of the deployment is evaluated by comparing goals and outcomes. Many times, the use over longer time periods demonstrates non-intended

[2] https://www.ibm.com/cloud/learn/what-is-artificial-intelligence

outcomes that may or may not align with organization's and users' goals. We therefore probed from interviewees what goals drive their organization's uses of BDA and AI and to what extent learning about such goals is important for the effective deployment of BDA and AI technologies.

Generally, the effectiveness was shown to include among others improved productivity, higher service or product quality, higher response diversity, speed and agility, resiliency, or even organizational learning capacity and related survival. Such effects were shown to emerge in the short and the long term. In this regard BDA and AI need to be treated as multi-purpose or general purpose technologies so that specific impact of the technology will vary significantly across contexts, use purpose and setting (Berente et al 2020; Bresnahan and Trajtenberg 1995).

The diversity of transformation goals and outcomes was present in the interviewee responses when they were probed about the effects or impacts of BDA and AI uses in their organization or practice. Generally, these goals and outcomes could be organized into three categories:

1. *changes in products and operations* (goals concerning productivity, quality, speed, diversity; mainly short-term focus). Here organizations were reported to use BDA or AI to optimize or simplify operations, improve product features or performance, or develop new product/service features attached to existing products;
2. *changes in decision-making strategies and tactics* (productivity, diversity, speed, and agility; resiliency and learning goals; short to mid-term focus). In this category, organizations reported to use BDA and AI to generate novel insights, improved understanding, and sense-making as to support data driven decision making and developing strategies or tactics impacting organization's market position, organizational structure, or resource utilization;
3. *broad capability improvement and transformation* (higher response diversity; speed and agility; resiliency and learning goals; focus mid-term to long term). In this category, organizations would use BDA and AI to create new types of learning processes and outcomes, change task and work systems and create new types of symbiotic relationships between humans and machines which transform organizational decisions and activities to hybrids- new kinds of man-machine configurations called meta-human systems (Lyytinen et al., 2021).

Product and service improvement outcomes: *"Then we use that information to, in the product, the next time that user visits, or even in the Marketing, as we send them out a Marketing email or something,"*

"So as I mentioned, the Machine Learning of that data is used in almost every single page on the website, and almost every product on our product roadmap has just more and more of this Machine Learning embedded in it."

"Using AI technology to develop new cell therapy, like T-cell therapy, or therapy, to make personalized immunotherapy products."

Improvement of organization's decision making strategies: *"Big data could be used to identify behavioral patterns and thus identify opportunities but also needs. This is done favorably with AI functionalities. AI can also help to simplify repetitive work and thus support and relieve the business."*
"We will continue to make truly data-driven decisions (for sales, risk, finance and other departments)"

Broad capability improvement and transformation: *"We were using linear models just up until a couple of years ago, and now fast forward to today and we're using neuro networks and really sophisticated Machine Learning. So we definitely compete with companies."*

"The future workforce will be responsible for optimizing and improve AI logic by defining rules or doing training to improve the automation rate."

5.2 Individual Competencies

The broadest of the three themes was Theme III, which captures interviewees' perspectives on the importance of specific individual competencies for successful performance in organizations. The analysis divided these competencies into three main categories, which are labeled Fundamental environmental competencies; Data, information, and content management competencies; and Systems design competencies. This section will discuss the characteristics of these categories, competency groups within them, and some individual competencies at a more detailed level. One of the important ways to describe and analyze the results of this study is to compare them to the most recent IS model curricula: IS 2020 (the latest undergraduate recommendation; Leidig and Salmela (2021)), MSIS 2016 (the latest graduate recommendation; Topi et al. (2017)), and IS 2010 (prior undergraduate recommendation that is still widely in use; Topi et al. (2010)). At times the results are also compared to CC 2020 (Computing curricula 2020, an integrated report that covers all curriculum recommendations in recognized computing disciplines).

5.2.1 Fundamental Environmental Competencies

The *Fundamental environmental competencies* category consists of two main groups of competencies: *Individual foundational competencies* and *Business domain competencies* (see Figure 1, part 2 and Table 2). These two correspond closely to two of the three main categories specified in IS 2020. In IS 2020, they are called *Individual foundational competencies* and *Domain of practice competencies* (this name indicates a broader applicability of IS competencies than just within the domain of business). The specification of these two categories in IS 2020 was, in turn, built on IS 2010 and MSIS 2016. Furthermore, the distinction between individual foundational competencies and domain competencies is also recognized in CC 2020, in which the terms *Foundational and professional knowledge* and *Domain knowledge* are used.

This close alignment between all recent curriculum recommendations related to IS and these two competency groups emphasizes two viewpoints: 1) IS professionals share many of the same general competency requirements that all knowledge professionals need; and 2) IS professionals cannot succeed only with technical expertise. They need to understand the domains of activity within which they work and be able to communicate with both specialist domain experts and senior technology experts.

Table 2. Glossary of "Fundamental Environmental Competencies"

Fundamental environmental competencies		
Individual foundational competencies		
	Teamwork	Collaborating effectively with other agents in a team towards a common goal
	Communication	Communicating effectively orally and in writing with a variety of audiences and stakeholders
	Critical thinking	The objective analysis and evaluation of an issue in order to form a judgment by evaluating assumptions, making conjectures, and finding counterfactuals (adapted from Oxford Languages)
	Meta-learning	Learning how to learn and being flexible about learning approaches,
	Problem solving	Identifying and defining a problem, developing solution alternatives, selecting a solution and implementing it.
	Systems thinking	A set of synergistic analytic skills that improve the capability of identifying and understanding systems, predicting their behaviors, and devising modification to them to produce desired effects.(Arnold and Wade, 2015).
Domain competencies		
	Integrating business and technology competencies	Managing the delicate relationship between the organization's overall goals and the information technology capabilities that have been planned, designed, and implemented to support the organization's efforts to achieve its goals.
	Aligning business and IT	Applying IT in an appropriate and timely way and in harmony with business strategies, goals, and needs (Luftman and Brier, 1999).
	Identifying business value	Identifying how organizations can benefit from technology capabilities and converting opportunities created by information technology innovations into sustainable organizational value through systematic processes (IS 2010).
	Understanding the domain	Understanding at a detailed level the structure, processes, rules, and goals of a domain of human activity.

Individual foundational competencies

In this study, the respondents identified three main individual foundational competency sets as follows:

- Teamwork skills and communication skills
- Critical thinking and meta-learning skills
- Problem solving and systems thinking

All three have been included in all the recent IS curriculum recommendations, with slightly different names.

Teamwork and communication skills combines three major elements as identified in recent curriculum recommendations: collaboration and teamwork, written communication, and oral communication. In addition, IS 2020 includes presentation competencies as a separate communication element. This competency set is not surprising or new (all these elements are specified as requirements in IS 2010, MSIS 2016, and IS 2020), but based on the data, its importance as an essential competency area for all knowledge professionals continues to be strong. This is particularly true for IS professionals who continue to act as integrators and liaisons between those whose sole expertise is either in a business domain or in technology.

> ***Teamwork and communication**: "You know I think also an important thing is that, as I said earlier, attitude. You only need to find a person with good attitude, willing to learn. One thing I'm doing is also even though there are candidates with [inaudible], if his personality is not really mixed with our current employees, I don't hire them."*

P*roblem solving and systems thinking* is another competency set of which at least the first part has consistently stayed as part of expectations for IS professionals. The group consists of two separate elements: problem solving (Simon & Newell, 1971) and systems thinking (Checkland, 1999). These two domain competences are different but interdependent. Problem solving involves identifying and defining a problem, developing solution alternatives, selecting a solution, and implementing it using skills such as decomposition, synthesis, and root cause analysis. Arnold and Wade (2015) define systems thinking as "a set of synergistic analytic skills used to improve the capability of identifying and understanding systems, predicting their behaviors, and devising modification to them in order to produce desired effects." The system thinking lens is wider than that of problem solving, and it calls for capabilities to see things interdependent, holistically and from multiple perspectives, and incorporate problem solving in the process when appropriate. Of the two, problem solving has been covered in recent curriculum recommendations; systems thinking is not explicitly stated in either IS 2010, MSIS 2016, IS 2020, or CC 2020. In the current study, several interviewees identified system thinking as an important competency. Over the past 50-60 years, there have been several long-term research programs and senior scholars in IS who have focused on applications of systems thinking in their scholarly work (see, e.g., Midgley's 2003 four-volume collection) (Midgley, 2003). In IS education, however, systems thinking has not played a major role, except for some doctoral programs. The evidence in this study emphasizes the growing role of system thinking as an important professional competency and raises the question regarding the reasons why it has not received a stronger role in IS curriculum content.

> ***Problem solving: "**A competency is problem-solving, troubleshooting, really cause analysis. I think some of the continuous improvement concepts are actually what I'm gonna say here, too, competencies."*
> ***Systems thinking: "**I think that systems thinking needs to be called out. … By studying and discerning systems, one develops systemic patterns that allows a faster and critical understanding of a new system when you encounter it. It also allows you to 'borrow' parts of one system that solve a problem and 'inject' those borrowed parts into a new system to solve problems in new ways."*

Critical thinking can be defined as a mindset and systematic approach for dealing with and learning from multifaceted phenomena. It requires objectivity and tenacity in the analysis and evaluation of the issues of interest, combined with apprising assumptions, making conjectures, and finding counterfactuals. Critical thinking serves often as an invaluable tool in problem solving, and it underlies analytical processes guided by system thinking.

Critical thinking has been identified as one of the key foundational competencies in IS 2010, MSIS 2016, CC 2020, and IS 2020. IS 2010 and CC 2020 combine Critical thinking with Analytical thinking, whereas in MSIS 2016, it is treated as an independent competency and in IS 2020 integrated with Problem solving. In our data, Critical thinking emerged as a separate group together with a competency that none of the recent curriculum recommendations cover: *meta-learning*. In this context we refer to meta-learning by human learners (Wang, 2021) instead of meta-learning in artificial intelligence (Santoro et al., 2016;

Vanschoren, 2018). In brief, meta-learning refers to the process of building competencies for learning to learn. This is an essential competency for anybody who intends to stay professionally up to date in fields related to information technology and its organizational applications. In this study, several respondents emphasized the importance of graduates' ability to quickly adapt to new, changing environments and learn from the change experiences to develop their own learning ability as relates to specific domains and technologies. In education, one of the most interesting and challenging questions is the integration of learning and meta-learning so that learning processes also contribute to the individual's ability to learn in the future and evaluate such skills.

> ***Critical thinking:*** *"You know even if they've never touched any of the technologies I'm using at my organization, if this person is a good problem-solver, can critically think through difficult, complex problems and teach themselves what they need, that's a person I would hire."*
> *"Critical thinking for me is one that I often struggle with sometimes with people on my team and making sure… I mean certainly you can tell when someone does not have strong, critical thinking skills, 'cause our problems will always be different. The problems will always be changing."*

In sum, the main new findings regarding the individual foundational competencies are the highlighted importance of meta-learning and systems thinking. In addition, the findings confirm the consistent, long-term importance of teamwork, communication skills, problem solving, and critical thinking.

<u>Business domain competencies</u>

Given the goals and context of this study, most interviewees represented business or large public or non-profit organizations. The study takes place in the context of developing new requirements for business education. Therefore, it is understandable that the domain competencies were all nominally related to some business domains though they were not specifically identified in many interviews. The domains, however, ranged from finance and banking to sports, entertainment, hospitality, commerce, manufacturing, and healthcare. It is, however, important to note that the technology competencies that will be discussed in the next section are applicable to other domain contexts in addition to those mentioned (such as engineering, law, scientific contexts, governmental or inter-governmental organizations, etc.).

As for most business domain competencies, the interviewees recognized the following four generic business domain competency groups:

1. Integrating business and technology competencies
2. Aligning business with IT
3. Identifying business value
4. Understanding the business domain

> ***Integrating business and technology competencies****: "There is a new breed of IT that is dressed in business. It isn't dressed IT, but dressed in business, and they basically sit at a table with Senior Management providing decision in support services."*

Integrating business and technology competencies captures one of the essential requirements for graduates of information systems degree programs: the ability to manage the delicate relationship between the organization's overall goals and the information technology capabilities that have been planned, designed, and implemented to support the organization's effort to achieve its goals (Drnevich & Croson, 2013). This calls for generic understanding how IT operates as part of the business and how IT is and needs to be run as a business. Overall, this requires that IS graduates have generic understanding of organizations, how they are organized, how they are managed and how they change and can be changed and what role IT in general and BDA and AI in particular play in delivering business value. At the highest level this requires a deep understanding of not only both business and IT, but also the processes through which the organization finds, selects, and implements the most suitable technology capabilities for its current goals. IT professionals must be able to understand these capabilities and the ways in which they contribute to the processes that improve the organization's understanding of how it either changes how the existing business is conducted or creates entirely new ways of doing business. In either case, organizational change management is necessary. This is known to be a fragile and sensitive process that calls for a healthy understanding of the politics and resistance within the organization. This competency was identified as a requirement by 11 out of the 18 respondents.

One of the key goals of the integration of business and technology competencies is to create and maintain technology infrastructures that can be adapted to the changing needs of business and kept aligned with them over time. This competency is labeled as *Aligning business with IT*. This concept is by no means new (Aversano et al., 2012). For example, Luftman and Brier (1999) early on described business-IT alignment as "applying IT in an appropriate and timely way and in harmony with business strategies, goals, and needs" (p. 109). The concept has remained also salient. Based on the current evidence, the ability to successfully work on business-IT alignment continues to be one of the primary expectations that are posed for IS graduates. This idea is also reflected, for example, in IS 2020 curriculum by its inclusion of a knowledge element: "Key IT issues, trends, and alignment of IT with business" in the Foundations of Information Systems competency area, and in MSIS 2016 curriculum by the inclusion of the element "Ensure strategic alignment of IS and the domain" in the IS Strategy and Governance area.

> ***Aligning business with IT***: *"You know the business side of this, people like Produce Managers, they have to understand what is capable of being done because they're the ones who have to take the business requirements and understand the technology enough and merge it together into …"*

The third domain competency item, *Identifying business value*, is similar to one of the high-level IS capability specified in IS 2010 curriculum entitled *Exploiting opportunities created by technology innovations*. IS 2010 defines the capability as "Graduates of IS programs should be experts in seeing how organizations can benefit from technology capabilities, converting opportunities created by information technology innovations into sustainable organizational value through systematic processes" (IS 2010, p. 17) and sets high expectations for the graduates by stating that they should "see new opportunities to create value faster and with greater clarity during various analysis processes than their non-IS counterparts." The generated new business value can be based on incremental change of a current business, a radical transformation of a current business process or activity, or an entirely new business model satisfying latent customers' needs. Six out of 18 respondents commented on the importance of *Identifying business value*.

> ***Identifying business value***: *"For developing or programming our own AI solutions, our employees have no deep knowledge of mathematical models and how to build mature and value-creating AI applications. "*
> *"it is hard for us to identify areas where this technology makes sense and creates value. We do not just want to use new technology because it's new. If we use it, it has to create sustainable value."*

None of the above business domain competencies would be possible without an in-depth understanding of the specific task or business domain. Therefore, it was not surprising that *Understanding the business domain* emerged as one of the critical competency groups. This is also why all recent IS curriculum recommendations require that the students develop competencies related to information technology and its application in relation some domain of human activity, including various subdomains of business, healthcare, law, engineering, science, etc. For example, in this study we had respondents from healthcare, hospitality and public organizations in addition to business. Seven out of 18 respondents recognized *Understanding the business domain* as a required competency.

> ***Understanding the business domain: "****Passion/desire for business outcomes and understand why of everything (customers, processes, how things run), if you do the analysis right, they shouldn't be a surprise. Some instances can be surprises, need to ask 'why'"*

In sum, the results of this industry focused study closely align with the competency areas identified in recent IS model curricula for the business specific domain competencies. The group that is emphasized more strongly in this study is *Integrating business and technology competencies,* that is, being able to seamlessly communicate and collaborate with domain experts focused on either business or specific technology and build connections between these two specialty groups.

5.2.2 Data, Information, and Content Management

Data, information, and content management is the second major individual competency category (see Figure 1, part 2 and Table 3). It consists of competency groups which all have formed an integral part of IS curricula since the early years of the discipline. In the evidence collected for this study, we identified four groups in this category: *Database, Data management, Data analytics, and Business continuity & information assurance*.

Table 3. Glossary of "Data, information, and Content Management"

Data, information, and content management		
Database: Use of various computing-based database technologies to address organizational needs for structuring, storing, retrieving, and managing data		
	Foundational database competencies	Fundamental competencies related to structuring, storing, retrieving, and managing data in electronic databases
	Online analytical processing (OLAP)	The use of a set of graphical tools that provides users with multidimensional views of their data and allows them to analyze the data using versatile, easy-to-use interface technologies (adapted from Hoffer & al, 2019).
	Structured query language (SQL)	Widely used declarative programming language in the context of relational databases for managing, updating, and retrieving data. Foundation for other database languages.
Data analytics: Use of analytical tools and techniques to extract meaningful and valuable patterns from data in a way that is valuable for the organizational context.		
	Extract, transform, load (ETL)	Process for extracting data from different sources, transforming the data into a usable and trusted resource, and loading that data into the systems end-users can access and use for solving business problems (adapted from databricks.com)
	Executing analytics	Using variety of analytical techniques (including statistics) to extract meaningful and valuable patterns from data. In this study, the competency focused specifically on executing analytics with cloud-based tools.
	Storytelling	Oral or written sharing of stories with others for several reasons, such as entertaining, organizing thoughts, invoking emotions, or instructing how to live and act (adapted from Chaitlin, 2003).
		In this study, specific focus has been on the use of storytelling techniques on communicating results of data analytics.
	Visualization	Using various mechanisms of visual expression as a tool for communicating complex information and related relationships in data.
Data management: The organizational and managerial processes that enable effective and secure structuring, storage, retrieval, and analysis of organizational data.		
	Data and (AI) modeling requirements	The process of analyzing, structuring, and documenting the needs of the organization related to data and AI models.
	Data architecture	Data architecture describes the structure of an organization's logical and physical data assets and data management resources (TOGAF).
	Data science life cycle	An iterative set of activities required for successful completion of a data science project.
	End-to-end management of data life cycle	Management of data life cycle activities as an integrated whole from the beginning to the end instead of separate, independent data elements.
Business continuity and information assurance: Securing organizational IT assets and understanding the implications and potential consequences of the use of planned IT capabilities.		
	Model and data security	Securing essential organizational IT assets, such as data and (AI) models, from unauthorized access, modification, and destruction
	Privacy and security (ethics)	Understanding the impact of IT-based solution(s) affecting individual and organizational privacy and security of intangible assets. Analyzing the implications and consequences of planned IT-based capabilities based on ethical principles.

Database is a competency group focused on IT competencies typically developed in a traditional database management module of a computing curriculum. These competencies cover the 'bread and butter' of data management such as conceptual and logical data modeling, normalization, SQL, transaction management and integrity (ACID), and On-Line Analytical Processing (OLAP). The interviewees suggested that these competencies continue to form a central element in the data, information and content management competency set. This is requirement is visible also in IS 2020, the *Data / Information Management* competency area (A3.2.1) which closely aligns with the *Database* competency group of this study. Six out of the 18 respondents mentioned the need for general foundational database competencies; in addition, five interviewees identified the importance of specific database-related skills in the BDA context such as SQL or OLAP.

Data management represents a more abstract, management related set of competencies associated with managing data as an organizational resource. The first competency element in this group, *Data and modeling requirements*, includes components related to both conceptual data modeling of the business domain and processes that focus broadly on architecting and managing data. This competency element is well aligned with the graduate level competency categories at the master's level in the *Data, Information, and Content Management* competency area in MSIS 2016. The other two competency elements in this group represent two lifecycles: *Data science lifecycle* and *End-to-end management of data lifecycle*. The former focuses specifically on the needs of data science and analytics (BDA) and the latter broadly on the activities and structures to manage organizational data as a resource. These lifecycle concepts are not recognized in IS 2020, but the *data and information management lifecycle* was identified as an important competency for MSIS 2016. Altogether 11 respondents out of 18 recognized either Data and modeling requirements, Architecting and managing data, or End-to-End management of data lifecycle as an important competency area. Data science lifecycle was deemed important by seven respondents (six of whom were overlapping with those who recognized the importance of general data management).

> ***Database:*** *"the modern day data storage and then the data processing paradigm is one of the keys that I think students probably need to spend more time on understanding what to learn in this area."*
> ***Data management:*** *"A lot of data coming in a structural format, so the skills to understand and be able to handle and process those various different type of data is key, but when you see this various type of data coming from different formats, coming from different systems, then how do you process it?"*

The *Data Analytics* competency group includes competencies that are close to those included in the Data/Business Analytics competency area in IS 2020, the first IS curriculum recommendation that included data analytics in the core of the curriculum (in earlier curricula Analytics was identified as important elective competency). The four specific competency sets that emerged in this study as dimensions of analytics were competencies for staging data *Extract, Transform, and Load (ETL)*, *Executing analytics in the cloud (e.g., BigQuery)*, *Storytelling (*providing meaningful accounts of what analytics results mean in the domain*)*, and *Visualization* (ability to illustrate and display visually complex relationships between data). An important and interesting omission in the competencies is immediately visible. No identified competency refers explicitly to the core analytical modeling and problem-solving during data analytics (such as Competency 4 in the IS 2020 curriculum: "Perform exploratory data analysis from inception to the value proposition"). Seven respondents out of 18 mentioned at least one of the competency sets in the *Data Analytics* competency group.

> ***Executing analytics in the cloud: "****There is a lot of discussion about the prevalent use of the cloud. I suggest also mentioning the services provided by clouds beyond compute and storage such as in GCP services such as BigQuery, Dataflow, Tensorflow, etc."*
>
> ***Visualization: "****Data visualization is very important, especially when you're presenting it to Managers and Corporate Executives. It's just that from the standpoint of my team, we're more into innovation,…"*

The fourth competency group in the *Data, Information, and Content Management* category is labeled *Business continuity & information assurance*. This group captures two separate competency sets related to privacy and security. In MSIS 2016 and IS 2020 these two themes are represented at a higher level of abstraction, as separate competency areas, labeled "Business Continuity and Information Assurance" and "Secure computing," respectively. In this study, one of the interesting and novel competency sets within this group was model security integrated with data security. Model security refers to the security of developed AI models, which now often are critical contributors to the way in which organizations run their businesses and achieve and maintain competitive advantage. Consequently, they are valuable, rare, inimitable, and non-substitutable assets requiring safeguarding. The *Privacy and security; ethics* competency set captures a broader set of issues when compared to *Model and data security*. The former covers comments in which the participants emphasized the importance of graduates' general understanding of the ethical implications of the BDA and AI solutions, whether they relate to customer privacy, securing organizational computing infrastructure, potentially harmful consequences of the AI powered decisions, or any other impact of BDA or AI based solutions (see, e.g., Siau and Wang (2020)). This competency closely aligns with the *Ethics, impacts, and sustainability* competency area in MS 2010 and *Ethics, use, and implications* in IS 2020. Five out of 18 respondents identified one or both competency sets within *Business continuity & information assurance* as required competencies.

In sum, the new findings in the Data, information, and content management area are: 1) a stronger emphasis on several life cycle models and concepts than those recognized in the recent model curricula; 2) strong focus on new dimensions of data analytics (such as communication related elements of storytelling and visualization); and 3) a heightened emphasis on the importance of ethics as a key foundation to ensure privacy and security. Furthermore, the evidence from this study demonstrates the continued critical importance of the development of database and data management competencies among students.

> ***Ethics:*** ***"****Ethics is a framework for making moral decisions, a set of tools to help you apply your morals and values,' and I think that would be very useful in an IT sense as well, and so those kinds of things I think should come into the curriculum."*
>
> ***"****This topic of Ethical AI, in which is AI adheres to well-defined ethical guidelines regarding fundamental values such as individual rights, privacy, non-discrimination, and non-manipulation, is growing rapidly. Businesses that ignore this area risk reputational, regulatory, and legal actions."*

5.2.3 Systems Design Competencies

The last broad competency category consists of five technical competency groups: Individual analytics & programming skills, IT infrastructure, Systems architecture, AI systems development and deployment, and IS management and operations (See Figure 1, part 2 and Table 4). These groups align with MSIS 2016 and IS 2020 competency areas as follows:

- *IT Infrastructure*: the same competency area name in both curricula,
- *IS management and operations*: same name in MSIS 2016, *IS Management and Strategy* in IS 2020,
- *Systems architecture*: *Enterprise architecture* in MSIS 2016; included in *IT infrastructure and SA&D* in IS 2020, and
- *Individual analytics & programming skills*: substantial overlap with *Systems development and deployment* in MSIS 2016 and *Systems development* in IS 2020.

The characteristics of these competencies do not essentially differ from the specifications in the existing curriculum documents. Thus, MSIS 2016 and IS 2020 provide useful background and content statements regarding the meaning and structure of these competency groups.

Table 4. Glossary of "Systems Design Competencies"

Systems design competencies		
Individual analytics and programming skills: Capabilities that individual professionals need to serve as productive members of teams of designing and constructing IT-based solutions.		
	Programming	Expressing and implementing systems requirements in a chosen programming language that can be executed as a solution as part of an IT application or infrastructure module.
	Statistics	Developing and studying methods for collecting, analyzing, interpreting, and presenting empirical data (stat.uci.edu).
IT infrastructure: An organized set of information technology resources and associated communities that enable and support information systems functions and capabilities within an organization or industry		
	Machine learning, various subareas of AI	Implementing an appropriate set of IT infrastructure functions to enable the use of required AI capabilities.
	Managing cloud resources	Design and use of on-demand IT resources offered by an external service provider (typically through the public Internet) which effectively to address organizational IT infrastructure needs related to storage, processing and specific IT functions.
Systems architecture: High-level description of the structural organizing decisions regarding organizational information systems components and their relationships		
	Architecting for cloud	Developing effective IT infrastructure models that rely on externally provided on-demand IT resources.

	Open source	Using and developing software applications and component made available for free (open licensing) by their creators and related user communities.
	Understanding data structures, architectures, and governance	Evaluating and interpreting organizational actions dealing with high-level structure and management of organizational data (adapted from Spurrier & Topi, 2021).
Systems development and deployment: The activities required to convert requirements and functional designs into systems that actively support the organization's pursuit of its goals.		
	Machine learning: building and managing ML models	Identifying opportunities to design, develop and implement machine learning models to address organizational problems and take advantage of opportunities to achieve the organization's goals. Machine learning algorithms improve their own performance based on historical data and analytical experience.
	Machine learning: technical foundations of ML	Selecting an appropriate set of technical capabilities and designing working solutions to enable effective use of machine learning to address the needs of a specific organizational context.
	UI/UX	Designing user experiences (including user interfaces) that allow users to benefit maximally from an IT solution.
	Using platform tools	Using cloud-based computing resources organized as a platform of development tools for the development of a variety of systems solutions
IS management and operations: Organizational managerial and operational activities that enable the systems to serve their role in the organization's pursuit of its goals.		
	Project management	Structuring IT-related work as projects and managing them in a way that will lead to desired outcomes in terms of system capabilities and the resources used by the project.

There are, however, elements in the System design competency category that provide additional input for those designing relevant BDA/AI focused curricula at business and management schools. First, the four groups identified above include new competency sets not included in the existing curriculum recommendations. These include *Statistics* as part of *Individual analytics and programming skills* and *Subareas of AI* as part of *IT infrastructure*. Second, the fifth competency group within the System design category is new: *AI systems development and deployment*. It consists of three competency sets: *Building and managing (deep) machine learning models*, *technical foundations of machine learning*, and *UI/UX development*. Obviously, this is not an exhaustive list of required BDA and AI-related competencies (much more is ultimately needed than machine learning), but it highlights the competencies that emerged as the most relevant ones among the respondents in this study.

It is also important to note that all systems design efforts—whether traditional administrative systems, AI-BDA-based capabilities used to address specific organizational problems or opportunities, or integration of the two—benefit from the same higher-level individual foundational competencies, which in our data set were identified under problem solving, systems thinking, and critical thinking (see above in Section 5.2.1 and in Table 2). Strength in all these areas has a positive impact on an individual's ability to contribute to various types of system-level design processes, regardless of the system type. The more detailed design competencies identified in this section are truly useful only if the individual's general design competencies are at an appropriate level.

Individual analytics and programming skills

> ***Statistics***: *"There is a minimum of 'able-to-read-software' and a minimum of statistical knowledge around in order to minimize barriers between departments."*
>
> *Programming: "So API Python is also an absolute necessity at the moment, just with how many Cloud systems we have."*
>
> ***IS infrastructure***: *"having those skill sets, understanding the different data ecosystems, different ways to process the data is one of the key skill sets in the big data/technology side. And also from the infrastructure perspective, that's just the overall architecture, understand the different ways today to use, to store and process and transform the data."*

> ***Architecting for cloud****: "And so the thing I noticed, a lot of these companies, when their data is growing so big and their database costs are running so high, they think about going towards Open Source Software, Open Source databases to store all the data and, hence, that creates a demand on the workforce to actually know how to use those. "*
>
> *Understanding data structures, architectures, and governance: "So that's his role, and the key requirement for that role again is Data Architecture, data Engineering and Data Management"*
>
> ***Building and managing machine learning models****: "Second, of course, is strong competency in the use of Machine Learning packages or models. This field is evolving aggressively."*
> *"For developing or programming our own AI solutions, our employees have no deep knowledge of mathematical models and how to build mature and value-creating AI applications."*
>
> ***IS management and operations****: "The talent sort of wars out there are really, really tough, and finding people who understand that, (how to) generate the data, use the data, think about the data, manipulate it are really, really important. I agree. It used to be you had to have people with Project Management. That was critical and that was everyone competed for that, and now it's that plus the data, the Machine Learning."*

Based on the data collected in this study, we cannot offer a clear answer to the questions of how BDA and AI affect areas that do not belong to the two main areas of the study. Given, however, how quickly BDA and AI have grown and how substantial related resource requirements are in organizations, it is clear that they already have an impact on several competency needs such as: programming language selection, selection of BDA and AI tools based on cloud-based solutions, data architecture, data governance, service repertoires available on platform environments, and special characteristic of BDA and AI projects and how they affect education for project management needs and competencies.

5.2.4 Summary of Findings Related to Individual Competencies

Generally, we observe a strong alignment and continuity between the recent information systems curriculum recommendations and the findings of this study. The data highlights the continued importance of IS core topics covered in all past curricula, such as data management, systems development, IT infrastructure and architecture (including security), and IS (project) management.

The results also highlight also multiple areas that need more emphasis and careful design decisions when schools plan and implement their BDA and AI based programs:

- Integration of business and technology competencies in ways that allow seamless communication with both business and technology experts
- A stronger emphasis on multiple life cycle models and concepts related to data management and data science than in the recent model curricula focused on system life cycles
- Heightened focus on new dimensions of data analytics competencies (including communication related elements such a storytelling and visualization)
- The growing importance of ethics as a foundation for ensuring privacy and security of BDA and AI models
- Need for more skills in statistics
- Understanding the novel requirements that AI solutions set up for IT infrastructure
- The importance of competencies in AI systems development and deployment.

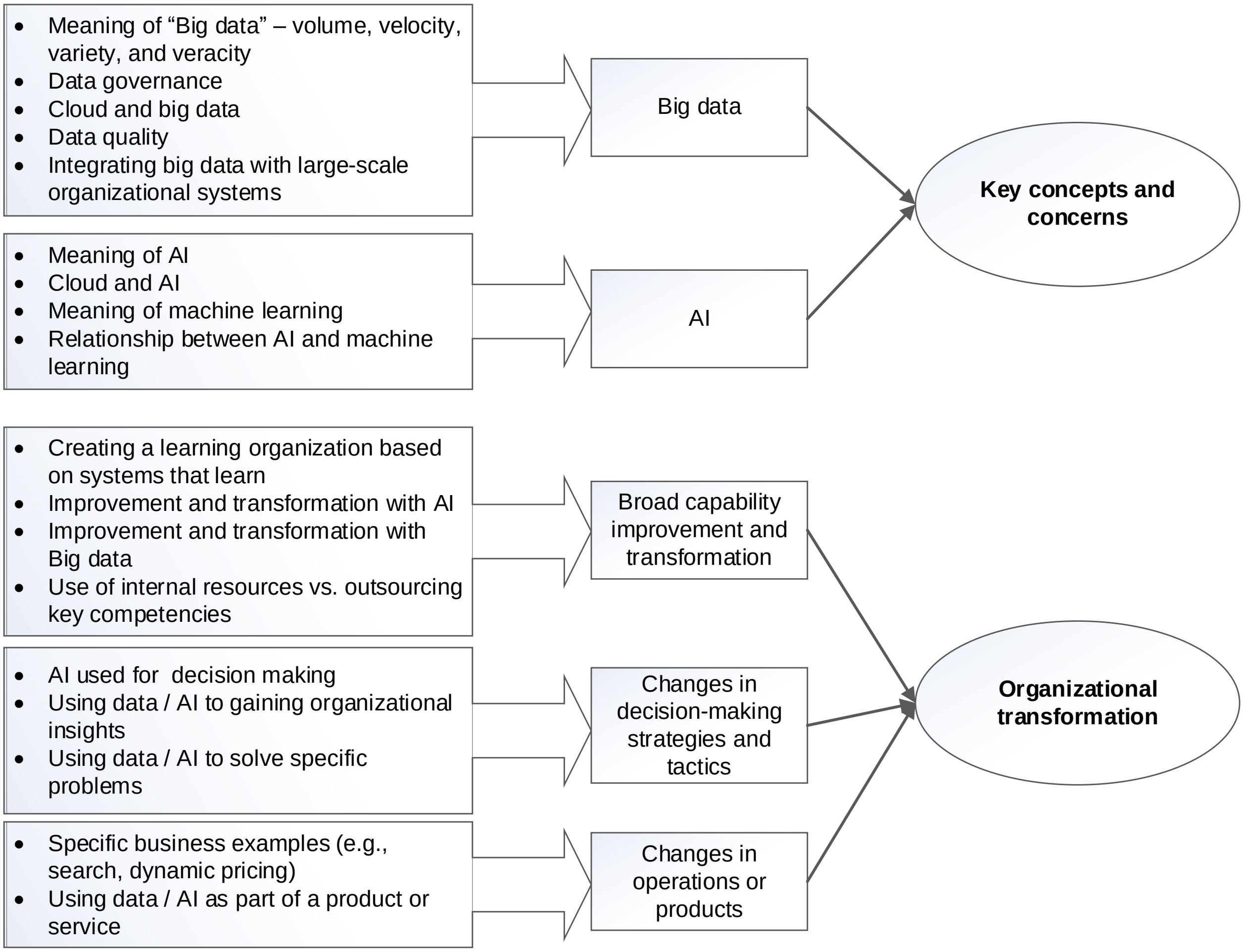

Figure 1. Final Coding Tree

6 Discussion

We will organize the discussion section in three parts. First part will discuss the emerging and novel needs created by BDA and AI for IS curricula and related education and the extent to which these needs expand or align with current curricula requirements. We are not calling for IS programs to address all the new needs in depth and even in scope. Instead, we encourage universities and programs to specify their targeted competency-training levels depending on their own educational context and industry needs. As part of this review, we will discuss the specific requirements that the new needs in combination with existing IS education demands pose for curriculum current content, requirements, and length. We will also note how it might be necessary to address these needs with specific educational arrangements that cover both undergraduate and specialized master level education in these areas. Second, we will discuss the new, unique demands these curriculum requirements pose for the educational environment, faculty development and finding talented faculty these increasingly specialized technical topics associated with BDA and AI. Finally, we observe some specific and unique penetrating aspects of these new content areas such as privacy and ethics concerns, and how to integrate technical and functional aspects of teaching AI to how they will shape and affect organizational decision making.

Generally, the emergence of BDA and AI has additive—not substitutive—effect on IS curricula. Moreover, the expansion suggests that *particularly in IS curricula there is a need to expand technical competencies associated with data and system design at the expense of some general topics within the constraints that exist for curricula in business schools.* Our findings suggest that future IS curricula at the undergraduate and masters level need to maintain all the most salient aspects of established curricula that relate to individual foundational competencies and business domain competencies (where in the latter the new demands add specific understanding of BDA/AI business value). In addition, new competencies such as system thinking skills and meta-learning skills will be more pronounced in this new environment. Similarly, nearly all topics covered in traditional data and content management competencies in the earlier IS curricula need to remain (data base, data modeling). Furthermore, new topics related to data analytics will need additional time and focus. This calls for introducing new courses and related content to current curricula. New content areas and related requirements will also emerge in managing data project life cycles and organizational data life cycles where the variety and related other aspects of big data (velocity, volume, volatility) come to the fore. This adds new data management and modeling requirements to students. New demands emerge also in statistics, model security and privacy. In the system design area the new demands are placed on machine learning and large-scale analytical techniques that are designed for and run on the cloud. Another set relates to architecting and designing BDA/AI applications systems so that they can be run on the cloud using large data sets. None of these demands have been identified in the previous curricula. Finally, all students continue to need a good understanding of project management processes and skills as they relate to managing BDA and AI applications as part of the analysis and design cycle. Of note is that AI and BDA projects have also unique characteristics (such as iterative nature, not necessarily a clear end product but evolving design) that call for new types of project management models.

In summary, if all the competencies identified per our interviews are to be fully integrated to the current curricula, this calls for adding 4-5 new courses to the core of the IS major. We recognize that this is clearly nonrealistic in most program contexts and particularly in business schools. This does, however, create a challenge that needs to be addressed: the competencies related to effective application of BDA and AI are without a doubt computing-based, increasingly important for many organizations, and essential for effective organizational transformation and integration of BDA and AI capabilities into enterprise-level systems. Together with traditional IS competencies, contemporary domain competencies, and strong personal foundational competencies they form a package of professional competencies that is highly attractive for many organizations. The benefits of program expansion towards the new integrated set of student outcomes are substantial. At the same time, each school and university has to decide in its own context where the right balance between different competency types is. The purpose of this paper is to report on the requirements that a broad cross-section of industry leader specified for current and future IS graduates. We hope that the results reported herein are helpful in the local decision-making and can inform such processes.

It is likely that in many contexts, future IS curricula need to integrate the core design competencies that cover individual foundations, data management, system analysis and design, and project management. In addition, the core must introduce a general introduction to how such aspects are designed and implemented in BDA/AI related applications and how they can create value. This minimally prepares students for careers in BDA/AI settings and lays foundation for advancing beyond those initial skills where students integrate later such deeper competencies to their skill repertoires. Many of these can be acquired either through work site learning or by attending specialized curricula that advance competencies creating analytics/AI solutions. These specialized deeper needs create a demand for many schools to advance new IS BDA/AI specializations on top of teaching core 'competencies' both at undergraduate and graduate levels. Such specialized programs for BDA and AI can be offered also as certificate programs or as separate minors for BDA/AI application development. Creating such programs calls for intense collaboration with local industry, as partners have need for such specialized talent. *We recommend that the AIS launches an effort to coordinate the content of such specializations.*

Our interviews focused specifically on IS major demands at the master's and undergraduate levels in line with current IS curriculum recommendations. Therefore, we did not probe specifically IS related skills required by other business professionals operating in BDA/AI application and development teams (such as marketing majors). Clearly the requirements for most of the individual foundational competencies, team skills and some project management skills are similar in such setting. In the data area they cover understanding data management and modeling, basic database competencies and deeper domain competencies. In analytics, they minimally call for understanding various BDA and AI techniques, data aspects of analysis and ways of visualizing and narrating the results. Nor did we ask for required skills for MBAs or 'techno' MBAs. In the latter they cover related foundational competencies, value and role of BDA and AI for organizational decision making and new organizational design forms that result from using BDA and AI solutions. Techno MBA's cover foundational database, data management competencies and BDA and AI solution development areas. It is also clear that there is not only one type of specialization as business development for BDA/AI and related project management call for one, another covers data management in cloud, and the third more technical focused on architecting and implementing cloud-based big data solutions. One of the key questions the IS discipline has to address is the balance between IS as a specialty (or a set of specialties in systems, digital innovation, IS management, analytics, cybersecurity, etc.) and IS as a provider of services in technology education to other disciplines. There are clearly societal and organizational needs for graduates of both types of IS capabilities, but each department has to determine the balance between the two. Clearly, only focusing on a service role has potential negative consequences in terms of the recognition and perceived value of the field.

6.1 Impact of Moving to a Cloud-Based Teaching Environment

Learning by doing as student move through design and implementation processes is an essential element of many—and probably most—IS programs. Traditionally, the projects students have been required to complete in IS courses are relatively modest in size. Therefore, the computing requirements for these projects have been sufficiently low so that during the past 20-30 years it has been possible for students to complete the projects on personal computers or on other inexpensive platforms offered by the school. Recently, as a result of BDA/AI needs, the situation has changed: one very clear message from the respondents is the importance of IS graduates to be able to operate in the cloud environment using primarily one of the major IaaS/PaaS platforms (such as Amazon's AWS, Google's GCP, or Microsoft's Azure). Cloud services available through the public internet have made BDA and AI capabilities available for organizations that would never have been able to afford to build required computing capacity in their own data centers. The same service stacks also provide access to an increasingly broad range of AI capabilities than most organizations are able to license or build. Learning to harness these capabilities will require focused practices to operate on the cloud, which, in turn, requires that students have access to relevant cloud resources during their study.

In practice, the cloud platform fees will constitute for many programs and departments a new, non-trivial operating cost, the level of which will depend on the extent to which cloud services are used and the types of capabilities being applied[3]. Furthermore, teaching and learning about realistic BDA and AI solutions requires the use of large data sets leading to additional challenges such as gaining access to sufficiently large and rich data sets, paying for the storage space, and managing the data storage environment. These expenses and competency requirements are not trivial and have to be covered, if a school/department wants to provide a contemporary learning environment for its students.

Strong emphasis on learning about the cloud and, specifically, learning about designing and implementing BDA and AI solutions on a cloud platform will for require a substantial investment from most departments to help the faculty to transition to the cloud environment. As will be discussed in more detail below, the learning needs at least cover three areas: operating cloud environment, understanding and mastering specific BDA technologies, as well as specific AI technologies. It is also essential that the faculty will be able to effectively operate data and operations at the scale that truly big data analytics and associated AI uses requires.

6.2 Integrating BDA and AI with the Systems Architecture

One challenge both in terms of industry practice and education is that many BDA and AI solutions are still seen as independent, innovative responses to a specific organizational need (see, e.g., Marr and Ward (2019)). This is, however, not a sustainable model; instead, BDA and AI capabilities need to be integrated to the emerging overall organizational systems architecture. In education, developing competencies related to this type of integration will require collaboration between disciplines that have not always been most effective in collaborations including information systems within business schools, statistics and mathematics, and computer science. In this cooperation, information systems as an academic discipline and IS practitioners have an opportunity to play a highly influential role by evaluating and communicating the value of state-of-the-art BDA and AI solutions for organizational practice, by developing methodologies for structuring and documenting the role of BDA and AI solutions in the overall systems architecture, and by serving in the quintessential IS role as a liaison between computing experts and domain experts. When asked about the role of education in advancing the used of BDA and AI solutions in organizations, one of the of commentators of early results of this study stated: "*We need to teach the right stuff that is useful and meet the needs of the organization.*" The statement first appears to be overly simplistic, but it

[3] It is well known that the determination of the fee charged for services in such cloud environments are extremely complex.

captures two essential requirements that all computing-based solutions should fulfill: usefulness and ability to meet the specific organizational requirements. In the BDA/AI context, IS graduates have the role of ensuring the usefulness and alignment with the requirements for all the system components.

6.3 Organizational Challenges

Broad inclusion of BDA and AI competencies into IS curricula is not without its political and organizational challenges. Universities and colleges are notoriously slow to change, and responding fully to emerging BDA and AI education needs is likely to meet resistance. In many cases, the need for existing faculty to learn new skills to teach competently in a BDA and/or AI-focused program is significant. This is substantially more than the incremental learning requirements that IS faculty most of the time faces. Particularly the mathematical and statistical requirements of truly understanding BDA and AI are substantial, and potentially highly challenging and will arise fear both among faculty and students. It is essential that IS departments anticipate and understand such challenges and seek to provide faculty with adequate opportunities and resources to learn.

It is also important that the needs of BDA and AI are carefully considered in the future departmental recruiting. This will, in practice, mean expanding faculty searches to academic disciplines a department may not have considered earlier, such as computer science, computer engineering, mathematics, or statistics. This, in turn, may lead to a need to reconsider many aspects of a departmental policies and practices related to merit evaluation, promotion, tenure, and power. A department that hires faculty members with different disciplinary backgrounds will gain a broader range of necessary specialties, but also needs to consider the growing heterogeneity in disciplinary expectations and values that comes with new hiring needs. Using industry specialists as part-time faculty (to the extent acceptable in an institution's regulatory context), inviting them as professional partners for designing curricula or courses, and developing an active advisory board all are excellent mechanisms for bringing in necessary practical expertise and at the same time helps strengthen connections with current or potential industry partners.

BDA and AI are also potential sources of organizational tension and turf battles among colleges. Addressing these questions actively and finding mutually beneficial, collaboration-based solutions instead of continuous tussles between units is essential. Gaining the types of BDA and AI competencies that the respondents in this study were asking for requires in-depth study of topics typically associated with several different disciplines, which in many university settings can be located in multiple separate schools or colleges. It is the universities' responsibility as educators to find ways to offer educational programs that allow students to gain necessary competencies, even when it requires collaboration across complex organizational boundaries. Successful collaboration will open plenty of new opportunities, not only in the context of degree programs, but also executive education and professional development. Getting involved in these important forms of competency development is potentially challenging because of competition from established commercial training providers, inexpensive on-line courses, and corporate training units (sometimes referred to as "universities.")

Another reason why a business school offering programs focused on BDA and/or AI may face challenges is a potential pushback from students, because of the quantitative and algorithmic rigor required in most realistic studies of both BDA and AI applications (and related preparatory and contextual topics, such as data management, cloud-based platforms, and security). For example, BDA and AI programs with any serious technical content will need at least two programming courses and a rigorous data management course before students can become successful in using BDA and AI capabilities using various software libraries. Without this type of background, it is very difficult to get students beyond the level of awareness of the technologies and related generic concepts. The awareness of the opportunities created by BDA and AI is important and can be even adequate for many business students, but *it is not sufficient* for IS students. Maintaining the quality technical standards is essential—BDA and AI-related to jobs are genuinely rewarding but also truly challenging because of the broad range of technical competency requirements in the context of quickly advancing technology.

Several previous studies have already pointed out the importance of including ethics in BDA/AI curricula. Goldsmith and Burton (2017) proposed that universities should include ethics issues as part of the AI curricula in terms of the enormous effects of AI work on society based on a utilitarian analysis. Burton et al. (2017) also introduce three necessary frames for thinking about connection between ethics and AI — deontology, utilitarianism, and virtue ethics. They advocate for exposing students to multiple modes of thinking tools, which will help students understand the inherent elements of ethics in AI. Formal ethics training to address ethics in AI curriculum (covering AI topics such as searching and planning, probabilistic reasoning, and machine learning) helps students better understand the ethical implications of the real-world applications of BDA and AI technologies and prepare them to meet the industry needs for ethics (Eaton et al., 2018; Xu & Babaian, 2021). Our industry interviewees also pointed out the increasing need for students to engage in ethical reasoning while applying BDA and AI technologies in two domains: a) data security and privacy protection as part of technical solutions and b) explicit articulation of values and principles underlying decision-making. The industry expects students to equip themselves with solid ethical thinking and reasoning based on the content covered in university curricula. The respondents also emphasized that students need to consider the ethical issues from the beginning of any product or service design that includes AI or BDA components. It is not currently easy for the organizations to find employees who are well prepared for addressing data privacy and protection or have a good understanding of ethics associated with BDA/AI. It would be useful, if the universities include formal training in ethics when designing their AI curricula. MIS programs can also include ethics training (experience) as part of the business and IT design aspects of curricula. Students need training to learn to balance between satisfying the needs for IT security and individual ethics and the needs for service innovation. In such cases students need to have the background knowledge of how decisions can be made while considering both business aspects and ethical dimensions of product and service design. In the long run, these two perspectives are often fully aligned.

7 Conclusion

This report of Phase II of the Information Systems disciplinary task force of the AACSB MaCuDE project synthesizes and analyzes the findings of 18 interviews of industry leaders whose primary focus is on the design, management, and use of advanced BDA/AI solutions to benefit their organizations. The purpose of the interviews was to gain a broad understanding of necessary organizational competency needs for graduates of IS programs. In particular, we considered carefully recent substantial growth in the use of big data analytics and artificial intelligence. The findings of the study will eventually contribute to the final, Phase III, report of the MaCuDE project. They also already provide useful overview for IS faculty and administrators responsible for IS programs of the emerging industry needs related to BDA/AI education in IS curricula. The emerging results suggest that IS educators will face continued and novel challenges in keeping their curricula relevant and reflecting the state-of-the-art needs of the industry. The faculty and administrators will need to develop in the coming years a broad range of new foundational competencies (both managerial and technical) to deliver the new BDA and AI content, which enables future students to gain salient competencies in emerging specialized areas of IT deployment such as big data analytics and artificial intelligence. Our results also demonstrate that BDA and AI are not independent areas of organizational computing but are emerging as integrated organizational system capabilities that have the potential to provide significant organizational value as they become integrated with installed enterprise-level systems capabilities.

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Appendix A: Sample and Interviews

Appendix A1. Interview Protocol

Welcome and thank you for being here today. The purpose of this session is to get your feedback on improving Information Systems curricula so that our students will continue to grow and provide value in this digital era. Specifically, we want to understand what new (digital) skills you find IS graduates and graduates in closely related fields are lacking now and will be likely to miss in the future. What emerging skills do you anticipate IS graduates to need when entering the workforce? Based on the results, once we understand the industry needs, we will provide guidance for those developing new curricula and other course offerings. You have a fresh and close perspective of what the needs will be and that is why we have invited you to this discussion. In this project, funded by AACSB and PriceWaterhouse Coopers, our emphasis is on big data and artificial intelligence space broadly defined, which includes, among others, the use of machine learning and advanced analytics methods, related techniques and infrastructures to bring business value.

Our goal today is to engage in a conversation that focuses on specific questions in a safe and confidential environment. I will guide the conversation by asking questions. If you wish, you can also respond to my comments, like you would in any ordinary conversation. It is my job to keep us on track. <add name here if applicable> is here to record and summarize your comments.

Before we get started, I want to let you know two things. First, the information that you share today will be compiled into a final report shared widely with IS community and AACSB. That report will include a summary of all received comments on the topic and some recommendations. It will be shared with our project sponsors and the broader AACSB community. Secondly, you do not have to answer any questions that you do not feel comfortable with. The focus group is anonymous and confidential; data is reported only at the aggregate level. You can also stop the interview any time if you wish show.

We will be recording this focus group and would ask for your permission to do so. <Ask for the permission to record> The recording will only be used to make sure our notes are correct and will not be heard by anyone outside of this project. If you choose to stop recording at any time let us know, and we will do it.

Individual Behaviors [important to establish the lens of the industry participant]

Q1. Please share with us your name and [an item as an ice breaker].

- Share your education, work, or personal experience that brought you where you are professionally today.

Q2. To help us understand the use of the key concepts, please discuss your understanding of the terms “Big data and artificial intelligence” in the context of your organization?

Workplace Behaviors [digital skills and technology]

Q3. In what ways do you expect big data and artificial intelligence to impact your organization’s strategy and operations within the next five years?

Q4. What are the competencies that IS and related information technology employees are required to have to meet the needs of successful deployment of big data and artificial intelligence technologies?

> Q4a. Which competencies are your IT employees currently missing to be effective in applying big data and artificial intelligence to address your company’s needs?
>
> Q4b. How effective are your employees in **integrating** big data and artificial intelligence technologies into your organizational information systems and related infrastructures? What are the key challenges here?

Q5. What is your long-term vision of a future work force and related needs for IT based anticipated organizational change in the next decade?

Future training needs

Q6. How do you expect your employees to attain the missing competencies discussed above?

Q7. What is the role of a) internal training, b) commercial training providers, and c) colleges and universities in enabling your employees to attain the missing competencies related to big data and artificial intelligence?

Q8. Does your company offer training/upskilling opportunities to assist existing employees to adapt to the changes in information technology? Do you collaborate with local universities or wish to do so to provide these opportunities?

Thank you very much for your time and insights!

Appendix A2. Description of Interview Cases

Case	Title	Industry	Country
1	Software Developer & IT Innovation Manager	Construction	Austria
2	Head of Data Analytics	Finance and insurance	Liechtenstein
3	Head of IT	Investment banking, Finance	Liechtenstein
4	Senior Manager of Operations Analysis and Solutions	transportation industry	U.S.
5	Director of Data Management & Analytics	Education	U.S.
6	Manager & Data Engineering	Cloud computing, E-commerce, AI	U.S.
7	Executive VP and CTO	Business services	U.S.
8	Head of Big Data Analytics group	Hospitality	U.S.
9	Head of AI and big data	Hospitals and health care	U.S.
10	CTO	E-commerce	U.S.
11	Head of Big data consulting	consulting	U.S.
12	Director of Data Science	*Software development*	U.S.
13	CTO	*Software development*	U.S.
14	Data Scientist	*Software development*	U.S.
15	Founding Team, Product Lead	Artificial Intelligence (AI)	U.S.
16	CIO	Robotics, AI, Automation	U.S.
17	CIO	Sports	U.S.
18	President and CEO	Cloud computing	U.S.
*Note: Case 12-14 are from one organization.			

Appendix A3. Examples of Specific BDA/AI Technologies at the Industry Level

Industry	**Specific BDA/AI technologies examples**
AI and cloud computing	Business analytics of data science; ML; techniques to collect, store, and process the data; AI for leveraging data to make decisions
E-commerce	BDA/AI in collecting platform's data, process, and transforming them to usable information; BDA/AI in generating insights for marketing strategy and business solutions, e.g., ranking search, matching, predicting purchase.
Finance and insurance	AI is applied in making truly data-driven decisions (for sales, risk, finance and other departments) or providing personalized (AI based) recommendations to support customers in decision-making; BDA and AI are used to identify behavioral patterns and thus recognize opportunities and needs.
Consulting and business service	Automated matching for decision making; Revenue models and analytics for financial planning
Software development	Gathering billions of interaction points between people and websites; Analyzing in the milliseconds; Writing code to make things in automated fashions.

Construction	Online analytical processing (OLAP) for real-time data; AI algorithms and software products that provide a higher automation level or to support employees on manual tasks
Transportation	Knowledge Discovery in Database (KDD) in data mining
Education	AI in analytics space of ensemble modeling, e.g., random forests; Cloud big data platforms; Data management and analysis of student information system platforms
Hospitals and Health Care	AI in research for cancer and heart disease, e.g., integrating AI solutions in the clinical care, predicting symptom or phenotype; Using AI to develop new cell therapy
Hospitality	AI in decision support for senior management, e.g. digital-making processes in decision-making
Sports	BDA/AI in collecting real-time video data of players; Analyzing data to support the success of players; Developing apps to help understand the dynamic pricing of tickets

Appendix B: Glossary and Codes

Appendix B1. Glossary for MaCuDE Phase II Report

Fundamental environmental competencies		
Individual foundational competencies		
	Teamwork	Collaborating effectively with other agents in a team towards a common goal
	Communication	Communicating effectively orally and in writing with a variety of audiences and stakeholders
	Critical thinking	The objective analysis and evaluation of an issue in order to form a judgment by evaluating assumptions, making conjectures, and finding counterfactuals (adapted from Oxford Languages)
	Meta-learning	Learning how to learn and being flexible about learning approaches,
	Problem solving	Identifying and defining a problem, developing solution alternatives, selecting a solution and implementing it.
	Systems thinking	“A set of synergistic analytic skills used to improve the capability of identifying and understanding systems, predicting their behaviors, and devising modification to them in order to produce desired effects.” (Arnold and Wade, 2015).
Domain competencies		
	Integrating business and technology competencies	Managing the delicate relationship between the organization’s overall goals and the information technology capabilities that have been planned, designed, and implemented to support the organization’s efforts to achieve its goals.
	Aligning business and IT	“Applying IT in an appropriate and timely way and in harmony with business strategies, goals, and needs” (Luftman and Brier, 1999).
	Identifying business value	Identifying how organizations can benefit from technology capabilities and converting opportunities created by information technology innovations into sustainable organizational value through systematic processes (IS 2010).
	Understanding the domain	Understanding at a detailed level the structure, processes, rules, and goals of a domain of human activity.

Data, information, and content management		
Database: Use of various computing-based database technologies to address organizational needs for structuring, storing, retrieving, and managing data		
	Foundational database competencies	Fundamental competencies related to structuring, storing, retrieving, and managing data in electronic databases
	Online analytical processing (OLAP)	The use of a set of graphical tools that provides users with multidimensional views of their data and allows them to analyze the data using versatile, easy-to-use interface technologies (adapted from Hoffer & al, 2019).
	Structured query language (SQL)	Widely used declarative programming language in the context of relational databases for managing, updating, and retrieving data. Foundation for other database languages.
Data analytics: Use of analytical tools and techniques to extract meaningful and valuable patterns from data in a way that is valuable for the organizational context.		
	Extract, transform, load (ETL)	Process for extracting data from different sources, transforming the data into a usable and trusted resource, and loading that data into the systems end-users can access and use for solving business problems (adapted from databricks.com)
	Executing analytics	Using variety of analytical techniques (including statistics) to extract meaningful and valuable patterns from data. In this study, the competency focused specifically on executing analytics with cloud-based tools.

	Storytelling	Oral or written sharing of stories with others for several reasons, such as entertaining, organizing thoughts, invoking emotions, or instructing how to live and act (adapted from Chaitlin, 2003).
		In this study, specific focus has been on the use of storytelling techniques on communicating results of data analytics.
	Visualization	Using various mechanisms of visual expression as a tool for communicating complex information and related relationships in data.
Data management: The organizational and managerial processes that enable effective and secure structuring, storage, retrieval, and analysis of organizational data.		
	Data and (AI) modeling requirements	The process of analyzing, structuring, and documenting the needs of the organization related to data and AI models.
	Data architecture	Data architecture describes the structure of an organization's logical and physical data assets and data management resources (TOGAF).
	Data science life cycle	An iterative set of activities required for successful completion of a data science project.
	End-to-end management of data life cycle	Management of data life cycle activities as an integrated whole from the beginning to the end instead of separate, independent data elements.
Business continuity and information assurance: Securing organizational IT assets and understanding the implications and potential consequences of the use of planned IT capabilities.		
	Model and data security	Securing essential organizational IT assets, such as data and (AI) models, from unauthorized access, modification, and destruction
	Privacy and security (ethics)	Understanding the impact of IT-based solution(s) affecting individual and organizational privacy and security of intangible assets. Analyzing the implications and consequences of planned IT-based capabilities based on ethical principles.

Systems design competencies		
Individual analytics and programming skills: Capabilities that individual professionals need to serve as productive members of teams of designing and constructing IT-based solutions.		
	Programming	Expressing and implementing systems requirements in a chosen programming language that can be executed as a solution as part of an IT application or infrastructure module.
	Statistics	Developing and studying methods for collecting, analyzing, interpreting, and presenting empirical data (stat.uci.edu).
IT infrastructure: An organized set of information technology resources and associated communities that enable and support information systems functions and capabilities within an organization or industry		
	Machine learning, various subareas of AI	Implementing an appropriate set of IT infrastructure functions to enable the use of required AI capabilities.
	Managing cloud resources	Design and use of on-demand IT resources offered by an external service provider (typically through the public Internet) which effectively to address organizational IT infrastructure needs related to storage, processing and specific IT functions.
Systems architecture: High-level description of the structural organizing decisions regarding organizational information systems components and their relationships		
	Architecting for cloud	Developing effective IT infrastructure models that rely on externally provided on-demand IT resources.
	Open source	Using and further developing software applications and components that have been made available for free by their creators and related user communities.
	Understanding data structures, architectures, and governance	Evaluating and interpreting organizational actions dealing with high-level structure and management of organizational data (adapted from Spurrier & Topi, 2021).
Systems development and deployment: The activities required to convert requirements and functional designs into systems that actively support the organization's pursuit of its goals.		

	Machine learning: building and managing ML models	Identifying opportunities to design, develop and implement machine learning models to address organizational problems and take advantage of opportunities to achieve the organization's goals. Machine learning algorithms improve their own performance based on historical data and analytical experience.
	Machine learning: technical foundations of ML	Selecting an appropriate set of technical capabilities and designing working solutions to enable effective use of machine learning to address the needs of a specific organizational context.
	UI/UX	Designing user experiences (including user interfaces) that allow users to benefit maximally from an IT solution.
	Using platform tools	Using cloud-based computing resources organized as a platform of development tools for the development of a variety of systems solutions
IS management and operations: Organizational managerial and operational activities that enable the systems to serve their role in the organization's pursuit of its goals.		
	Project management	Structuring IT-related work as projects and managing them in a way that will lead to desired outcomes in terms of system capabilities and the resources used by the project.

Appendix B2. Examples of Codes for Each Category

First-order categories	*Examples of interview excerpts*
Meaning of "Big data"	*Academic definition with four V (volume, veracity, variety, velocity)*
Cloud and Big data	*By building on cloud based (SaaS or IaaS) applications overhead is minimized. The key challenge is to have high quality data and data governance. Reducing the stack to what is needed to move it to cloud providers helps in addressing infrastructure needs.*
Data governance	*Now the second challenge is students come out of college taught how to wrangle data, taught how to use models on data or algorithms on data to build models on all of that. (They are never taught how to) capture data, collect data, sit back and frame data requirement for model. I haven't seen anybody capable of doing that, and that's a critical requirement in this sector*
Data quality	*I mean the data quality is always number one, no matter how big of the data that you're dealing with. It's always a challenge, I would say, one of the constant challenges for all of the data professionals and data teams in organizations.*
Integrating Big data with large-scale organizational systems	*Successful Big Data analytics requires good master data management among all IT systems. Different projects in our company show, the better you can centralize and unify your different master data, the better Big Data analytics, and artificial intelligence will work. Mastering our master data within our organization was a task that costs us years and resulted in a lot of different interfaces between different information systems before.*
Cloud and AI	*we migrated to the Cloud and now we use things like Bigtable and BigQuery on Google's Cloud product and it allows us to process almost unlimited amounts of data, as long as we can pay for it, and that has made/allowed us to move from that one billion to almost order magnitude larger in processing data, which then allows us to make better recommendations, and everything else that we use Machine Learning for is better because we have more data.*
Meaning of AI	*AI - a disciplinary of automating big data analytics for an industry, making it run and making it run right, creating value*
Meaning of machine learning	*I'd define it as approaching challenges that were solved by the human brain by applying statistical methods.*
Relationship between AI and machine learning	*So Artificial Intelligence and Machine Learning is different from programmed intelligence. Programmed intelligence perhaps is when you write a piece of code and there is a discreet logic of how to treat data and how to get to a decision point and take a decision. So that's programmed intelligence or programmed learning in models.*
Creating a learning organization based on systems that learn	*The future workforce will be responsible for optimizing and improve AI logic by defining rules or doing training to improve the automation rate.*

Improvement and transformation with AI	*We were using linear models just up until a couple of years ago, and now fast forward to today and we're using neuro networks and really sophisticated Machine Learning. So we definitely compete with companies.*
Improvement and transformation with Big data	*Then we use that information to, in the product, the next time that user visits, or even in the Marketing, as we send them out a Marketing email or something*
Use of internal resources vs. outsourcing key competencies	*You have a group of organizations that are either using the platforms, of if they're really deep in their DNA, then they're investing in their own, or they're using Open Source Software to avoid all the exorbitant bills that they get...*
AI used for decision making	*We will continue to make truly data-driven decisions (for sales, risk, finance and other departments)*
Using data / AI to gaining organizational insights	*Big data could be used to identify behavioral patterns and thus identify opportunities but also needs. This is done favorably with AI functionalities. AI can also help to simplify repetitive work and thus support and relieve the business.*
Using data / AI to solve specific problems	*Using AI technology to develop new cell therapy, like T-cell therapy, or therapy, to make personalized immunotherapy products."*
Specific business examples (e.g., search, dynamic pricing)	*We're doing some monitoring of how students are using Canvas and their engagement and utilization of it. We're starting to do some level of social media monitoring and trying to predict sentiment of certain Hashtags across the university, like with university admissions and marketing."*
Using data / AI as part of a product or service	*So as I mentioned, the Machine Learning of that data is used in almost every single page on the website, and almost every product on our product roadmap has just more and more of this Machine Learning embedded in it."*
Team work skills and communication skills	*I do think that cross-functional, cross-discipline training, even if it's just a single course or set of small courses, is really important."*
Critical thinking and meta-learning skills	*That's totally different from crunching the data. That type of practice may help. Some critical thinking.*
Problem solving and systems thinking	*A competency is problem-solving, troubleshooting, really cause analysis. I think some of the continuous improvement concepts are actually what I'm gonna say here, too, competencies.*
Integrating business and technology competencies	*There is a new breed of IT that is dressed in business. It isn't dressed IT, but dressed in business, and they basically sit at a table with Senior Management providing decision in support services."*
Aligning business with IT	*you know the business side of this, people like Produce Managers, they have to understand what is capable of being done because they're the ones who have to take the business requirements and understand the technology enough and merge it together into ….*
Identifying business value	*For developing or programming our own AI solutions, our employees have no deep knowledge of mathematical models and how to build mature and value-creating AI applications.*
Understanding the business domain	*Passion/desire for business outcomes and understand why of everything (customers, processes, how things run), if you do the analysis right, they shouldn't be a surprise. Some instances can be surprises, need to ask 'why'*
Foundational database competencies	*A lot of data coming in a structural format, so the skills to understand and be able to handle and process those various different type of data is key, but when you see this various type of data coming from different formats, coming from different systems, then how do you process it?"*
Online analytical processing (OLAP)	*...collecting and analyze all data in a centralized and information system overlapping data warehouse. To do this, skills for designing and managing a data warehouse with technologies like OLAP are essential."*
Structured query language (SQL)	*I need people who… Everyone on my team uses SQL. It doesn't matter what they're doing, whether it's API work."*
Extract, transform, load	*If you're a Data Scientist or a Machine Learning Engineer or a Technology Support*

(ETL))	*Person, you just have to understand ETL.*
Executing analytics (on the cloud)	*Data Science programs and folks coming out as new hires, and people are getting a pretty good introduction to the types of analyses that are available, how to execute those analyses, you know kind of the mechanical running the Python or the other tools, whatever it is, to do that.*
Storytelling	*The other thing I've noticed is this notion of storytelling going on, and so when I worked with <Company>*
Visualization	*Data visualization is very important, especially when you're presenting it to Managers and Corporate Executives. It's just that from the standpoint of my team, we're more into innovation,…*
Data and modelling requirements (data architecture and management)	*Now the second challenge is students come out of college taught how to wrangle data, taught how to use models on data or algorithms on data to build models on all of that."*
Data science life cycle	*I think the continuing specialization of the workforce, in terms of slicing and carving out different segments of the dataset's life cycle, that's gonna continue to take over so that not everyone needs to be a full-fledged Data Scientist the way people like to define it*
End-to-end management of data life cycle	*I think what we'd like to see is continued work around their understanding of Big data working with this. Working on the more technical side, of course, implementation, the manipulation of Big data*
Model and data security	*Since we talk about data, AI/ML, the security and data privacy, or data handling, I think it's something that we think about more and more today. It's always built into a long-term vision.*
Privacy and security (Ethics)	*Ethics is a framework for making moral decisions, a set of tools to help you apply your morals and values,' and I think that would be very useful in an IT sense as well, and so those kinds of things I think should come into the curriculum.*
Programming	*So API Python is also an absolute necessity at the moment, just with how many Cloud systems we have. I would say we have a couple of traditional ATL Developers, the Informatics people, but that's even becoming a bit more minimalized because the need for true data warehouse design is getting smaller*
Statistics	*There is a minimum of "able-to-read-software" and a minimum of statistical knowledge around in order to minimize barriers between departments.*
Machine learning, various subareas of AI	*Each one of them probably has their own big data and Artificial Intelligence angles to what they do and how they do it, and so, yeah, I would say my team is probably looking at it more from a product perspective, saying that 'Okay, our security partner is using a certain product and they're going to be studying the performance of network data, or user data, in a way that could predict something...*
Managing cloud resources	*Understanding the ever evolving offerings as well as the build vs. buy decisions (when and whether to use these services) are critical skills.*
Architecting for cloud	*I think right now they're lacking a bit of the Cloud technology data skills. That's probably my biggest gap, and I haven't had someone who could come in and say, 'We could do that project for this amount of money' in Cloud technologies to be able to counter basically that business justification of Cloud and versus on premise."*
Open source	*And so the thing I noticed, a lot of these companies, when their data is growing so big and their database costs are running so high, they think about going towards Open Source Software, Open Source databases to store all the data and, hence, that creates a demand on the workforce to actually know how to use those.*
Understanding data structures, architectures, and governance	*They need a sound understanding of concepts like data stores well beyond just your relational data stores. You know Big data stores, streaming, logging, everything in that realm, but that's more of an Engineer to get the data where it's supposed to be.*
Machine learning, building and managing ML models	*Second of course is strong competency in the use of Machine Learning packages or models. This field is evolving aggressively."*

Machine learning, technical foundations of ML	*For developing or programming our own AI solutions, our employees have no deep knowledge of mathematical models and how to build mature and value-creating AI applications."*
UIUX	*The other skill that you guys, if you're not already teaching (I think Bentley does a good job of this) is UI/UX is a big deal. It's a really, really big deal.*
Using platform tools	*It's a challenge for IS people to really understand or build skills in the platforms, and my best advice if somebody's going through this program is absolutely to build Azure and AWS skills.*
Project management	*It used to be you had to have people with Project Management. That was critical and that was everyone competed for that, and now it's that plus the data, the Machine Learning*

About the Authors

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