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ADDRESSING AI-BASED CAPABILITIES IN SYSTEMS ANALYSIS AND DESIGN: A PEDAGOGICAL PERSPECTIVE

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Abstract:

This paper explores the integration of artificial intelligence (AI) based capabilities into organizational systems with a specific focus on the ways in which increased proliferation of AI affects systems analysis and design (SA&D) pedagogy. Existing IS literature on the links between SA&D and AI capabilities appears to be very limited, and there are only few published papers on the role of AI in IS education in general. This paper explores the reasons why AI capabilities often must be integrated into organizational systems for the organization to gain full benefits from AI and provides an initial analysis of how the inclusion of AI capabilities affects various SA&D activities, including the identification of new types of analysis and design uncertainty caused by AI. The findings suggest that it is essential for the IS community to study the best organizational practices on AI integration into systems projects and use these findings to improve the ways in which we prepare IS students for advanced application of AI in organizational systems.

Keywords: Systems analysis and design, Artificial Intelligence, IS pedagogy

I. INTRODUCTION

The purpose of the research project reported in this paper is to draw the Information Systems education community's attention to a substantial gap in IS education literature. The area that appears to be almost untouched is the role of artificial intelligence (AI) capabilities in systems analysis and design (SA&D) education. There are good reasons why AI should attract the attention of IS educators: the visibility of and interest in AI-based system capabilities and their actual use in organizational systems have increased significantly during the past few years. Consequently, it is essential for business/systems analysts (later referred to as BAs) and other IT professionals working on SA&D projects to be able to understand and specify how the requirements for AI-based capabilities are specified, how these capabilities are developed and how they are integrated into organizational systems. Furthermore, it is likely that the close integration of AI capabilities into systems projects will have project planning and execution implications. Consequently, the integration of AI topics into these systems should also be an increasingly important topic in SA&D education.

To understand the state of the art of AI and its integration with other types of system capabilities in the SA&D process particularly from the pedagogical perspective, we reviewed the IS education literature published in key journals publishing IS education papers (CAIS, JISE, ISEJ) and conferences (AIS SIG-ED, EDSIGCON, and education and curriculum tracks of ICIS, AMCIS, ECIS, and PACIS) in early stages of this project. To our surprise, the result set was very small—little research or structured guidance exists for IS educators who would like to include coverage of specification and development of AI-based capabilities for the purpose of integrating them with the overall system in their SA&D courses.

The lack of literature in this important area motivates this paper. Our goal is to articulate the missing type of literature, justify its significance, and propose the types of scholarly and pedagogical contributions that we believe will be not only useful now but increasingly beneficial in the future. We also hope that this paper might allow us to identify existing literature that we failed to locate in our attempt to discover relevant material.

Artificial Intelligence

In this section, we will provide a brief definition of what we mean by Artificial Intelligence. This cannot be exhaustive, given the complexity and multidimensionality of the topic, but we hope that we are able to clarify the boundaries of our exploration. Benbya (2020, p. ix) define AI as "the ability of machines to perform human-like cognitive tasks, including the automation of physical processes such as manipulating and moving objects, sensing, perceiving, problem solving, decision making, and innovation." Benbya et al. (2020) identify the following categories of AI technologies: machine learning, deep learning, neural networks, natural language processing, rule-based expert systems, robotic process automation, and robots. Obviously, these categories are frequently used together and integrated with each other. Most AI technologies are currently in the category of *weak AI*, in which a particular AI application can address one task at a time without an ability to transfer skills from a domain to another. In this paper, we explore various forms of weak AI, but recognize that many of the examples are based on machine learning or deep learning. Also, many of the questions related to the integration of AI-based capabilities with organizational systems are less challenging with rule-based expert systems that are modified by human intervention only.

Systems Analysis and Design

Systems Analysis and Design has been identified as one of the core elements of the Information Systems discipline and its pedagogical core since the beginning of the field in 1960s. For example, the first widely used curriculum recommendation for IS (Couger, 1973) already identifies Information Systems Analysis and System Design and Implementation as essential culminating experiences in the curriculum. The primary focus of systems analysis is on the discovery and structuring of the requirements (both functional and non-functional) for the planned system, whereas system design specifies both from functional and technical perspectives how the requirements will be implemented using computing technologies (see, e.g., Spurrier & Topi, 2021, p. 6-7). In addition to analysis and design methods and techniques, SA&D also addresses questions regarding the organization, coordination, and control of systems projects.

Historical Perspective

There are interesting historical anecdotes that testify about the length of the time during which the promise of AI has intrigued information systems professionals and, in some cases, led to the exploration of ways of incorporating AI in information systems education (or business education as a whole).

Kowalski (1984) formed a direct connection with AI and SA&D based on the contributions AI could make to SA&D practice. He suggested that "Artificial Intelligence allows us to execute systems analysis" (p. 39) and that "applications of AI technology … revolutionize the software life cycle, which in many cases altogether do away with program implementation and even system specification." (p. 47)

Another example of a proposal that suggested that an AI-based solution would significantly contribute to an organizational SA&D process is a paper by Majchrzak and Gasser (1991). They proposed an AI-based tool for simulating "alternative supportive organizational-technological plans for different business and technical objectives," (p. 321) called Highly Integrated Technology, Organization, and People-Automated (HITOP-A). The main objective for this tool was to improve the poor success rates that US manufacturing companies had been struggling with "computerized process and information technologies."

Kanabar (1988) is a rare example of an early paper that explored the topic of introducing AI-types of capabilities (at that time, knowledge-based and expert systems) in systems development courses (category that includes, according to the author, also SA&D courses). Martinez and Sobol (Martinez & Sobol, 1988) proposed a process for using well-known traditional systems analysis and design techniques (Context diagram, DFDs, decision trees/decision tables/structured English) to represent a specification of a knowledge-based expert system.

Salchenberger (1989) proposed a framework for bringing AI technologies into business curricula at the graduate level. In that context, she proposed that at the formalization (3rd) stage of AI introduction, "AI techniques [be] presented in graduate introductory MIS courses, Database, Computer Modeling and Information Systems Modeling courses" (p. 193). Also, she expressed with confidence that "AI technology can easily be introduced into Systems Analysis and Design, Database, MIS, and project-oriented courses." (Salchenberger, 1989, p. 195). A few years later Baldwin-Morgan (1995) advocated for the integration of artificial intelligence topics into the accounting curriculum because, already then, AI was "used in auditing, financial and management accounting, taxation and government." (p. 217). Baldwin-Morgan reviewed several papers that had in late 1980s and early 1990s proposed ways in which AI could be brought into the accounting curriculum (including Accounting Information Systems). At that time, the most widely used AI system types were expert systems and neural networks.

All these examples are from the era before or during the second "AI winter" in late 1980s/early 1990s (Russel & Norvig, 2003), a time period during which both enthusiasm about and funding for AI was significantly reduced. Unfortunately, they do not provide us much guidance regarding the integration of modern AI capabilities into organizational systems.

II. RELEVANT INFORMATION SYSTEMS AND BUSINESS EDUCATION LITERATURE

There have been several recent published articles and conference papers that have broadly reviewed core SA&D topics. This literature does not, unfortunately, help us in our quest of understanding better the role of artificial intelligence capabilities in the context of SA&D course. For example, Guidry (2011), in their analysis of IS educators' views of the importance of SA&D course topics, or Guidry and Stevens (2014), in their comparison of SA&D knowledge areas and skills, identified neither artificial intelligence nor closely related advanced AI-enabled analytics as one of the core SA&D topics. The same is true in Karanja's (2016) study on the requirements industry sets for entry level systems analysts. Senapathi (2016) does not include any references to artificial intelligence, machine learning, or AI-enabled analytics, either.

If we take a broader perspective, we can evaluate the general role of AI and related topics in the context of the Information Systems curriculum recommendations, which the IS discipline has published for the field since 1970s. The most recent model curricula in IS—IS 2020 at the undergraduate level (Leidig & Salmela, 2022) and MSIS 2016 at the graduate level (Topi et al., 2017)—pay only very modest attention to artificial intelligence. IS 2020 references machine learning once (in the context of a competency area entitled Data / Business Analytics (3.2.2)) and artificial intelligence not at all. MSIS 2016 does not include any references to machine learning and mentions artificial intelligence only once, as one possible new career path for MSIS graduates. AI is not included as an either required or elective competency in either one of the recent IS curriculum recommendations. Information Systems is not alone with this omission: Software Engineering, the other computing discipline that directly cares about context outcomes, does not recognize either AI or machine learning in its SE 2014 undergraduate curriculum.

Broadening the scope even more, we briefly explored the role of artificial intelligence in business education as a whole. The topic has received considerable interest during the last few years. Some examples of this include the AACSB MaCuDE (Management Curriculum for the Digital Era) project, which has been ongoing since 2019 and intends to provide recommendations for business schools regarding the ways in which digital technologies—in practice, particularly AI and advanced AI-enabled analytics—and requirements for digital competencies should impact business school curricula. The IS Task Force of the MaCuDE project has explored the current status of IS education (Lyytinen et al., 2021) and conducted a study of changing industry requirements (Lyytinen, Topi, & Tang, 2022); in August 2022, the task force is finalizing its recommendations that will be integrated with those of eight other task forces.

At a much more detailed and concrete level, Xu and Babaian (2021) discuss the design of a specific artificial intelligence course design targeted to non-computing and engineering majors within a business school, demonstrating that AI can be taught to students with no computing background. Their course content strives to present a balance between fundamentals and state-of-the art techniques, including coverage of knowledge representation, problem solving, machine learning, deep learning/neural networks, natural language processing, and ethics of AI. Pedagogically Xu and Babaian emphasize the importance of hands-on learning from the beginning. This important resource does not, however, discuss the integration of AI and advanced AI-enabled analytics capabilities into organizational systems. Wunderlich et al. (2021) also report on a narrower AI course targeted to business students, in their case directly focused on machine learning, which they characterize as "a branch of AI." (p. 512) This course shares many topics with those of Xu & Babaian (2021), including machine learning foundations, deep learning with neural networks, convolutional neural networks and the ethics of ML. As Xu & Babaian, Wunderlich et al. (2021) emphasize the importance of experiential learning.

III. REVIEW OF POSSIBLE USES OF AI-BASED SOLUTIONS IN AN ORGANIZATIONAL CONTEXT

How concerned should we be about the absence of coverage of AI-based capabilities from IS education literature and specifically SA&D education literature? Could we just leave this topic in the hands of our computer science colleagues who have a long history in the forefront of AI development (see, e.g., (Roberto, 2007)).

We believe the answer to this question is unequivocally no—IS programs and departments need to start to address the role of AI capabilities in the context of organizational systems, not only as a research topic but also a pedagogical opportunity. In one of the recent special issues on Artificial Intelligence in Organizations, Benbya et al. (2020, p. ix) write describing the difference between AI pilots and organizational deployments:

"Deployment, on the other hand, requires a variety of tasks and capabilities that may be in short supply—for example, integration with existing technology architectures and legacy infrastructure, change in business processes and organizational culture, reskilling or upskilling of employees, substantial data engineering and approaches to organizational change management."

Every single one of the challenges of AI deployment outlined above is familiar to IS educators and relevant for several IS courses, and particularly clearly related to systems analysis and design. On one hand, this is encouraging: given the similarity of the challenges, we (the IS community) have developed ways to prepare our students to successfully deal with these challenges, but on the other hand, we cannot blindly assume that the integration of AI capabilities into the organizational context works the same way as traditional IS capabilities.

In the same way Van der Aalst et al. (2018, p. 472) state that "Through such AI systems, IS become smarter and hence will increasingly substitute more complex human work and decision-making," "One may further imagine how such systems influence the strategic role of IS," and "one may ask what the role of IT product and service providers will be in helping organizations (and users) leverage the potential of AI." Again, these questions all point out to the essential role of integration of AI capabilities to organizational systems through carefully considered Systems Analysis and Design processes.

Below, we will provide examples of the types of AI-based capabilities that are likely to be integrated with organizational information systems. Some types of AI solutions are used and can be beneficial relatively independently, but as can be seen based on this section, there are plenty of forms of AI-solutions that reach their full potential only as parts of a larger system.

The list of organizational opportunities that can potentially be realized by integrating AI-based capabilities as services into a broader system context (potentially removing a human decision) is long (see, e.g., Das et al., 2015, Benbya et al., 2020) and getting longer all the time. What follows is an illustrative categorization of a small subset of AI-based capabilities that will provide their full value only when integrated with other organizational systems:

AI-based system capabilities can be used to evaluate stakeholders' past behavior as a foundation for expectations regarding future behavior in areas such as:

  - Decisions regarding mortgages, car loans, credit card credit lines, etc. building on an AI-based analysis of behavioral profiles on the reliability of debtors (Bahrammirzaee, 2010)
  - Decisions regarding a consumer's access to a service or determination of its pricing (mobile communications, cable TV, streaming services, on-line gaming, etc.)
  - Recommendations regarding entertainment consumption (e.g., video and audio streaming, gaming) or product selection (Da'u & Salim, 2020)
  - Targeted advertisements and recommendations of additional services building on highly granular AI-based market segmentation (Haag, Hopf, Menelau Vasconcelos, & Staake, 2022)
  - Use of AI in HR for decisions regarding future responsibilities and opportunities within an organization based on past achievements (Qamar et al., 2021)
  - Decisions supporting application security and identifying threats
  - Forecasting organizational sales performance (Fahse, Blohm, Hruby, & van Giffen, 2022)
  - Predicting financial markets moves based on past behavior

- AI-based system capabilities serve an increasingly important role in various medical systems, supporting, for example:
  - Evaluation of patient's past medical history to understand diseases or propose treatments (Amisha et al., 2019)
  - Analysis of medical imaging results
    - Improving performance of cytology screening (Lew & Wilbur, 2021)
  - Controlling medical devices (Amisha et al., 2019)
- AI-based system capabilities used for controlling the actions of physical objects as part of a larger system
  - Evaluation of the condition of physical environments and objects, such as jet engines, engines of large vessels and trucks (Rødseth et al., 2017)
  - Actions of autonomous vehicles
- Action planning
  - Route planning (Hu et al., 2020) and resource scheduling (Ansari & Bakar, 2014)
- Analysis and creation of natural language documents (see, e.g., (Carvalho et al., 2019))
  - Summarization
  - Sentiment analysis
  - Information retrieval, question answering, and machine translation
  - Prediction of decision outcomes based on documentary inputs
  - Automated summarization of documents created by humans

- Visual or auditory identification of humans, animals, or other objects and actions taken based on the results (speech recognition, facial recognition, object recognition)

The broad range of AI-based capabilities that can provide true organizational value and that significantly benefit from (or depend on) integration into organizational systems forms an obligation for us as IS educators. It is essential that the IS education community—and particularly scholars focused on systems analysis and design—will develop and maintain a cohesive understanding and well-designed resources that will help IS educators in their task of preparing future IS professionals for increasingly extensive organizational use of AI and its integration with other systems.

IV. USING SYSTEMS ANALYSIS AND DESIGN METHODS TO DISCOVER POTENTIAL AI CAPABILITIES

Some of the higher level challenges related to the successful development of artificial intelligence solutions (such as those based on machine learning) are similar to those associated with systems analysis and design: identification of potential business needs and use cases, ensuring that development resources are invested in solutions that are aligned with the core organizational needs, articulating the ways in which the business can be supported with a computing solution, and determining requirements for data and its transformation (see Nalchigar et al., 2021, p. 237). Nalchigar et al. (2021) also describe the difficulties caused by the conceptual gap between business experts and technology experts in a way that closely resembles perpetual challenges in SA&D processes.

Nalchigar et al. (2016) acknowledge the difficulty of discovering and specifying the requirements for data analytics and, later, also AI/machine learning solutions. The challenges are similar to those associated with traditional SA&D processes: even though the abstract business goals might be clear, it is not easy for business experts to discover the mechanisms through which AI-based technology can be used to support achieving the business goals. Therefore, the requirements for technology may at least appear to change rapidly when different stakeholders learn more about the opportunities the new technologies offer. Stakeholders focused on business speak a different language and have often different priorities compared to those whose focus is on technology. Nalghigar et al. (2016) developed a modeling framework for addressing the challenge of closing the gap between stakeholders with different orientations and for clarifying the relationship between design decisions. The framework includes three modeling views: 1) The Business View that is intended for discovering and structuring analytics/AI requirements; 2) The Analytics Design View represents a high-level view of the analytics/AI capabilities; and 3) The Data Preparation View represents the processes that are required for preparing data for the analytics/AI purposes.

Another example illustrating the close connections between SA&D methods and techniques is an article by Lukyanenko et al. (2019) in which the authors describe how CRISP-DM (Cross-Industry Standard Process for Data Mining) can be used not only for its initial domain (Data Mining) but also for Machine Learning, with the following life cycle model:

- Business Understanding – equivalent to Business Analysis; “Effective ML is impossible without first carefully examining and understanding the business objectives for a particular ML project, and the specific goals the project seeks to achieve. Acquiring this information is akin to eliciting information systems requirements, a phase of systems development that has benefited historically from the use of conceptual models.” (Lukyanenko et al., 2019, p. 173)
- Data Understanding – conceptual data modeling grammars (ER, UML) are widely used for this and provide an essential tool for ensuring that all parties understand fully the concepts and their attributes and relationships
- Data Preparation — the transformation processes that are needed to prepare the original data (often from transaction systems) through ETL processes that are similar to those used in the context of data warehousing (Lukyanenko et al., 2019, p. 175)

- Modeling – conceptual modeling as a mechanism for defining the relative importance of various data elements
- Evaluation – conceptual models provide a context for understanding the emerging models
- Deployment – using process modeling tools (such as BPMN) to understand and document the ways in the business processes will change when a ML-based algorithm is deployed to address a business problem.

Overall, Lukyanenko et al. (2019, p. 179) suggest that conceptual models (both static—such as conceptual data models—and dynamic—such as process models) can effectively support the integration of ML models to organizational systems by 1) documenting and explaining the required process changes; 2) improving the transparency of ML-based models; and 3) improving the performance of ML models.

We propose that the IS education scholars should explicitly propose, design, and identify methods with which desired AI capabilities can be discovered, documented, and integrated with the rest of the system, particularly with the needs of IS education in mind.

V. INTEGRATION OF AI INTO SYSTEMS ANALYSIS AND DESIGN ACTIVITIES

In this section, we will explore ways in which the need to identify and integrate AI-based capabilities into organizational systems will affect SA&D activities throughout the SA&D process. The analysis is based on the SA&D activities as they are specified in the Systems Development Process Framework in Spurrier and Topi (2021): Initial Visioning, Business Analysis, Project Planning and Implementation Approach Selection, Functional and Initial Technical Design, Final Project Approval and Execution Planning, and Iterative Construction/ Configuration. Please note that based on the organization and the project, the sequencing and repetition of these activities may vary significantly. Specifically, this set of activities is not intended to describe a waterfall-like linear process. Also, it is important to understand that this section does not focus on the use of AI to support SA&D work; instead, it maintains our focus on outlining the capabilities that business analysts and other SA&D professionals need so that they will be able to benefit from the opportunities AI technologies provide.

Initial Visioning is an SA&D activity in which IT professionals and client representatives discover and document options for solving problems or addressing opportunities with IT-based solutions, identify key system capabilities, and analyze the high-level business benefits that can be achieved with the initially proposed system. At this stage, the focus of the process is not on technologies but the needs of the domain. However, it is essential that the professionals responsible for conducting and documenting initial visioning understand the potential benefits of all relevant technology families, including artificial intelligence. From the perspective of SA&D education, it is essential that students understand the importance of exploring the opportunities AI-based solutions offer. They must also have a sufficient comprehension of the key AI capability categories so that they can effectively participate in the process that identifies opportunities associated with AI capabilities and explores their feasibility based on the available information. Obviously, in some projects it is very quickly clear that there is not business justification for the use of AI capabilities; in others, AI offers the only option for addressing the problem or opportunity; and yet others require more detailed analysis.

Business Analysis refers to a set of activities that a) model the current business processes and core concepts of the domain, b) determine the key changes needed in business processes and data to achieve the desired changes in how the business operates (business transformation), c) model the future/desire business processes and core concepts, and d) specify an initial user-centric view of the system requirements. Within this activity, the business analysts need to be able to both a) identify opportunities for novel uses of AI-based capabilities, including the identification for business transformation that AI-based capabilities enable, and b) evaluate the advantages, disadvantages, and risks associated with these capabilities.

To achieve these goals in business analysis, BAs will require these competencies:

- Ability to analyze the business domain sufficiently well so that they can identify the essential problems to solve and the opportunities to benefit from. Obviously, not all opportunities are not based on problems—as with many generations of technologies earlier, there are cases in which AI makes it possible to change the way in which an organization achieves its goals so that the result is substantially different and not just incrementally improved.
- Ability to evaluate specific AI-based technical solution approaches so that the BA can a) identify which AI-solutions are potential candidates for solving specific problems and benefiting from specific opportunities and b) propose feasible technical AI-based solution alternatives, including a specification of the ways in which they are integrated in the broader system context. Optimally, this would also include competencies that allow the BA to develop solution prototypes and systematically analyze their feasibility.
- Ability to communicate with different stakeholder groups using language that the stakeholders are comfortable with, including the difficult processes of translating between the needs of the business expressed in business-focused language and the capabilities and limitations of the technology solution expressed in technology-focused language.
- Ability to analyze solutions that other organizations are using, potentially based on very limited information, and determining the core technologies that enable the new business capabilities.
- Ability to analyze and communicate the ethical implications and potential consequences of overall system capabilities and, in specific, the ways in which the AI-based components affect various stakeholders of the system. There is an increasing awareness of the ethical risks and challenges potentially associated with AI-based Information Systems capabilities (Jobin et al., 2019; Selter, Wagner, & Schramm-Klein, 2022; Siau & Wang, 2020). It is essential that current and future BAs are educated in a way that not only makes them aware of ethical implications of the solutions they discover and propose for future development but also enables them to make choices governed by ethically sound principles. Enholm et al. (2021), based on Yudkowsky et al. (2008), identified biased outcomes, black-box algorithms, lack of transparency and accountability, security concerns, and harm to society and the environment as potential major risks of AI-based solutions. To gain the trust of prospective users, it is essential that the ethical concerns are carefully evaluated and managed from the beginning of the process of developing AI-based systems.

As has been the case from the early days of the IS field, it is essential for BAs to have integrated domain and technology competencies so that the organization a) does not miss essential opportunities offered by a family of technologies and b) does not waste important resources by designing and evaluating solutions that are not feasible. As with other technologies, good BAs can integrate their knowledge of business and AI capabilities in a way that leads to innovative information technology-supported processes that allow the organization to achieve their goals better than earlier.

We recommend that all IS faculty members teaching SA&D courses carefully consider the importance of AI-based capabilities and, if possible, incorporate elements in their courses that allow their students to start to develop the competences required for integrating AI to organizational systems when appropriate.

During business analysis, BAs use a variety of different modeling techniques. We will briefly discuss here the impact of integration of AI-based capabilities on the use of basic modeling techniques and their coverage in the SA&D curriculum.

- Process modeling: As long as the AI-based capabilities are black-boxed and have definable inputs and outputs, they can be represented with any process modeling technique (such as UML Activity Diagram or BPMN), as long as they allow the specification of inputs and outputs and offer a way to articulate the way the outputs will be used in the system benefiting from the AI capabilities. It appears that the literature discussing this is limited, but Lukyanenko et al. (2019) provides an example of integrating a machine learning model into a medical process expressed in BPMN. They also motivate the reason underlying the modeling process: “Because deployment of ML in an organization typically results in changing an existing business process, process models and enterprise models can be used to document this change and communicate to stakeholders which part(s) of the enterprise the process affects” (Lukyanenko et al., 2019, p. 178). We believe that the process modeling techniques can be used also for a broader purpose of identifying new opportunities and designing the new processes based on the planned AI capabilities. Explainability and transparency of the AI-based models does, of course, have an impact on the extent to which existing business process modeling techniques can be used without modifications.
- Domain modeling: If domain modeling is truly used to understand the domain concepts and their relationships (instead of as a proxy for database design), it will continue to serve an essential role also in the context of AI-based capabilities. Understanding the domain requires a shared language for discussing and describing the domain, and without a systematic modeling effort this is not possible. In most cases, AI solutions are dependent on large collections of internal and external data, and AI modeling approaches benefit from a solid understanding of how the data elements and integrated concepts fit together. This can be supported with high-quality domain modeling. For example, Lukyanenko et al. (2019) demonstrate convincingly how conceptual modeling can be used to support machine learning and positively impact the application of machine learning algorithms. At the same time, it is essential to recognize that that there are also AI-based capabilities with underlying conceptual structures that go far beyond anything that we have traditionally viewed as conceptual models.
- User stories: Initial user stories are the first step in understanding how the behavior of a system supports the organization in its effort to achieve its goals. Because the role of the system capabilities is typically expressed in user stories with language of the domain so that system outcomes and their justifications are defined from the domain perspective, it is unlikely that AI will require substantially different skills for expressing system capabilities. For example, assuming the system’s goal is to determine if a customer continues to be creditworthy, the nature of the algorithm used to complete the determination does not affect the high-level user story, such as “As a credit analyst, I want to receive a reliable analysis of the customer’s creditworthiness based on their past payment behavior so that I can make final decisions regarding whether or not we should continue to extend credit to this customer.” This user story itself does not specify how the goal should be achieved. We could, however, use the story’s acceptance criteria to start to specify, for example, the algorithms that should be used to implement the credit rating capability, if that information is available already at this stage. Also, acceptance criteria could be used to document critically important ethical considerations and the constraints that they form for the design.

We recommend that, as appropriate in each local context, IS faculty members teaching SA&D courses make students aware of the ways in which AI capabilities can be incorporated in conceptual process and domain models.

Among the **Project Planning and Implementation Approach Selection** activities, we focus on one specific dimension that requires careful attention: the sourcing of the AI-based computing capabilities. Particularly from the perspective of gaining and maintaining trust of key stakeholders, it is essential that projects with embedded AI capabilities carefully consider issues of transparency and accountability. If an organization blindly buys (or acquires open source software without immediate monetary cost) AI solutions without any internal expertise and without any opportunity to understand and verify how AI algorithms perform their tasks, it incurs significant risks, both financial and reputational. The risk is not based on the use of externally developed AI algorithms—most, if not all, organizations including AI capabilities in their systems get at least some of them from external sources (excellent libraries are, after all, widely available). However, using these capabilities without access to professionals who understand the nature of the AI capabilities and the way they contribute to the integrated organizational systems is a major risk.

Functional Design that benefits AI-based capabilities includes two elements: a) the use of use cases, system sequence diagrams, or other similar interaction modeling techniques to specify how the AI-based modules communicate with the rest of the system and b) the specification of the AI-based modules based on their inputs (procedure/function calls with parameters, access to specific data element in data store(s)), outputs (return values, changes in data in data store(s), and/or error messages), and descriptions of how inputs and outputs are associated.

In the context of both requirements specification and functional design, AI-based capabilities are likely to add new types of sources of uncertainty, including the following three categories:

1. Logic: In traditional systems, we can explicitly specify all logic from the high-level to the low-level in advance of system development (in fact, in the traditional SDLC, and in principle, in agile approaches). As noted above, this is often not the case for AI systems—we don't know how the system is generating its outputs. Thus, we cannot predict in advance how the system **should** behave (e.g., can't create detail logic specs or test cases).
2. Validity of Outputs: In some cases, we know what the possible outputs are (e.g., the patient has cancer or doesn't, or the picture is of a cat or a dog, should the autonomous car stop at the intersection or keep going), but we can't in advance know how well the system will produce the outcomes. This is true (initially) of the training set, but also (or more critically) in production when the raw data is fresh and could be changing in its characteristics. This means that we must account for systems <u>that make mistakes</u>. This is quite different from traditional systems with deterministic outputs.
3. Content of Outputs: Increasingly, AI systems are generating output that we cannot even predict the possible outcomes ahead of time, for example, GPT-3 can generate all sorts of findings and recommendations in natural language that could be, for all practical purposes, just about anything. How can we utilize such indeterminate outputs in downstream interfaced/interacting systems?

The questions related to the **Construction and Technical Configuration** of AI-based capabilities are beyond this discussion, but they are obviously an essential competency set for those BAs who also work on the implementation of AI systems. Most IS graduates are likely to be working in roles in which they are users of services available in publicly (such as Tensorflow, PyTorch, and ClearML) or commercially available AI libraries and AI services provided by cloud service providers (such as IBM Cloud, Google Cloud AI tools, Azure AI, etc.)

VI. CONCLUSION

Our goal in this research project is to increase the awareness of the IS education community and specifically faculty members teaching SA&D and related systems development courses of the challenges and opportunities that the integration of AI-based capabilities into organizational information systems creates. Based on our review of existing literature, this issue has received little attention in literature on IS education, and we believe that it is essential for the community to intensify its efforts in this area. In IS, many of us might not be working on developing new AI algorithms or improving existing ones, but we have a critically important role in developing a solid understanding of a) how we can help our students understand the ways in which AI-based capabilities can best be integrated into the organizational systems architecture, b) how we can help our students navigate the project management complexities introduced by the integration of AI into organizational systems, and c) how to best help our students develop competencies that allow them to serve in expert roles that require an integrated understanding of AI, various organizational domains, and the processes that enable integrating the first two.

This is also a call for SA&D textbook authors to consider how to best build the coverage of these issues in future editions of their books. We as a field have a great opportunity to support our students in the process of becoming competent IS professionals who can evaluate and select the right AI capabilities for the right tasks. First, we have to systematically learn what this means and what the right pedagogical processes are and, then, in an equally structured way, make sure that we put what we have learned into practice. It is important to recognize the challenge of addressing these questions in pedagogy when the IS field does not yet have a well-developed body of literature regarding the best industry practices in AI integration. Given, however, the increasing importance of AI-based capabilities, the discovery of best practices and development of SA&D pedagogy have to move forward simultaneously. Overall, this area offers plenty of opportunities for critically important scholarly work.

VII. REFERENCES

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