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Managing artificial intelligence projects: Key insights from an AI consulting firm

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Abstract

While organisations are increasingly interested in artificial intelligence (AI), many AI projects encounter significant issues or even fail. To gain a deeper understanding of the issues that arise during these projects and the practices that contribute to addressing them, we study the case of Consult, a North American AI consulting firm that helps organisations leverage the power of AI by providing custom solutions. The management of AI projects at Consult is a multi-method approach that draws on elements from traditional project management, agile practices, and AI workflow practices. While the combination of these elements enables Consult to be effective in delivering AI projects to their customers, our analysis reveals that managing AI projects in this way draw upon three core *logics*, that is, commonly shared norms, values, and prescribed behaviours which influence actors' understanding of how work should be done. We identify that the simultaneous presence of these three logics—a traditional project management logic, an agile logic, and an AI workflow logic—gives rise to conflicts and issues in managing AI projects at Consult, and successfully managing these AI projects involves resolving conflicts that arise between them. From our case findings, we derive four strategies to help organisations better manage their AI projects.

KEYWORDS
agile, AI workflow, artificial intelligence, institutional logic, project management

> There's a lot of experimentation to be done, and it's not always clear which experiments will be successful and which will require more time to look into … different ways to tune the model to allow it to work better. It's kind of hard to plan out … (Data Scientist at Consult)

1 | INTRODUCTION

Industry reports indicate that global spending on artificial intelligence[1] (AI) is expected to reach $110 billion in 2024 (IDC Inc., 2020). The 'AI revolution' (e.g., Marr, 2020; Swiontkowski & Fuller, 2020) is hailed as an instrumental component of innovation in industries such as Fintech (Lagna & Ravishankar, 2021), healthcare (Wessel et al., 2019), and credit services (Wong et al., 2012), among many others. In addition, technical developments in AI itself are constantly redefining the boundaries of our ability to leverage data to create value, with ongoing contributions in domains such as machine learning, natural language processing, understanding and generation, computer vision, and robotic process automation, among others (Benbya et al., 2020; Collins et al., 2021).

In recent years, many organisations have launched projects to create business value using AI (Benbya et al., 2020). For many of these endeavours, ready-to-use, off-the-shelf AI systems are not available due to both the level of maturity of this field and the necessity of tailoring AI systems to the organisation's unique situation (Zhang et al., 2020). Thus, AI projects often involve a certain level of development that can be performed in-house or in close collaboration with an AI consulting company. In the context of the present work, we view an AI project as *an undertaking that aims to deliver a working software product or service that embeds AI functionality, to be used by humans or machines toward the accomplishment of an objective*.

Managing AI projects is no simple task (e.g., Brethenoux & Karamouzis, 2020; Ransbotham et al., 2017; Reis et al., 2020), with one report indicating that '85% of AI projects ultimately fail to deliver on their intended promises to business' (DeNisco Rayome, 2019). While some research examines the impacts of AI on users (e.g., Fügener et al., 2021; Reis et al., 2020), organisations (e.g., Borges et al., 2021; Li et al., 2021), and industries (e.g., Lou & Wu, 2021), practitioners seeking to better *manage* their AI projects can only draw on a limited number of studies. For example, research has examined the tensions that arise when domain experts and developers interact during the AI system development process, as well as data accessibility issues that arise during AI projects (e.g., van den Broek et al., 2021; Vial et al., 2021).

Practitioners also cannot solely rely on their previous managing experience, as one main ingredient differentiates AI projects from other IS development projects: the AI workflow. This workflow involves *collecting, manipulating, and transforming data to be used as inputs for coding, training, evaluating and interpreting, fine-tuning, and implementing complex mathematical models*. The AI workflow is characterised by sequential dependencies, major feedback loops, and an indeterminate number of data exploration/experimentation cycles (Amershi et al., 2019; Google, 2018). The fine-tuning of these complex mathematical models is heavily influenced by the nature and quality of data, which—as the data scientist noted in the quote above—makes it difficult to predict, plan, and manage the experimentation cycles. While practice-based approaches for performing various parts of the AI workflow do exist (e.g., Google, 2018; Microsoft Corporation, 2018), they largely focus on how to perform AI workflow tasks, and less guidance exists on how to *manage* the overall AI project. Thus, there is a paucity of guidance on how organisations arrange tasks, people, and resources to leverage AI to deliver value.

Motivated by these challenges faced by practitioners, this work seeks to provide a deeper understanding of the issues that arise during these projects and the practices that contribute to addressing these issues. To accomplish this, we performed an in-depth exploratory case study of Consult, a growing North American AI consulting firm founded in 2017 that has successfully delivered several customs AI solutions to a variety of customers who operate primarily in logistics/supply chain industries.

The management of AI projects at Consult is based on elements from three approaches: elements from traditional project management that help define and manage the project in broad phases; elements from agile practices that are used to organise the work in iterative, incremental cycles; and elements from AI workflow which drive the tasks required for AI model development, training, and fine-tuning. While the combination of these elements enables Consult to successfully deliver AI projects to their customers, the case study also demonstrates that managing AI projects in this way draws upon three core ways of thinking about the work involved in these projects. Inspired by the conceptual foundation of institutional logics (Berente et al., 2019; Thornton et al., 2012) that guided our analysis of the case, we use the term *logics* (i.e., commonly shared norms, values, and prescribed behaviours which influence actors' understanding of how work should be done) to capture each of these ways of thinking about AI projects. We identify that the simultaneous presence of three logics—a traditional project management (PM) logic, an agile logic, and an AI workflow logic—gives rise to conflicts and issues in managing AI projects at Consult. In particular, we highlight the importance of the emerging AI workflow logic and reveal eight novel conflicts that arise when this third logic is added to the management of AI projects.

From our case findings, we derive four strategies that can help organisations better manage their AI projects. The first strategy is to assess early on and then, at regular intervals, the viability of the project both for Consult and for their customer—effectively being ready to 'fire your customer' if needed. The second strategy is to consider that AI projects require a different conceptualization of progress based on the completion of tasks specific to AI workflow, essentially 'rethinking your definition of done'. The third strategy is to ensure that data science work is only pursued if it adds business value for customers rather than based solely on technical merit, thereby 'questioning the marginal value of data science'. The last strategy is to encourage a business consultant and a data scientist to work closely with one another, 'cultivating an AI power couple' to drive the project forward.

In the next sections, we introduce the case of Consult; describe how they manage their AI projects by borrowing elements from traditional project management, agile practices, and AI workflow; outline and summarise the three key logics underlying their approach, and analyse how the presence of these three logics gives rise to eight conflicts experienced during the course of their AI projects. Then, we detail four strategies derived from our findings at Consult. Finally, we reflect on the implications of our work and discuss avenues for future research.

2 | CASE OVERVIEW: CONSULT

Consult is a North American AI consultancy firm founded in 2017, employing about 60 people in 2019 when we entered the field. The company's mission can be broadly defined as 'helping organizations leverage the power of AI.' The realisation of this mission begins with the provision of advisory services to help customers uncover the strategic potential of data and AI for their organisation and determine if they are really ready to undertake an AI project. Projects that continue beyond this stage involve the production of custom software solutions for customers. A complete project includes delivering an information system that embeds a combination of machine learning models and mathematical optimization and, when applicable, a rudimentary user interface (e.g., reporting). Customers, who operate primarily in logistics/supply chain industries, then take ownership of the products and finalise them for deployment into their infrastructure with the help of Consult, a practice common to many AI projects (Zhang et al., 2020). Table 1 provides three sample vignettes illustrating previous projects delivered by Consult.

TABLE 1 Sample projects at Consult

Vignette #1—Project OmegaPort: OmegaPort, a multimodal maritime port in North America, needed a tool to help identify containers carrying critical cargo for the fight against COVID-19 (e.g., personal protection equipment) in order to fast-track them. Consult developed a reporting tool empowered by a prediction algorithm based on natural language processing to analyse customs declarations and cargo manifests to precisely identify such cargo. The AI algorithm had an over 80% success rate in identifying critical cargo. One year after going live, the system has helped reduce the average dwell time for critical containers by up to 50% compared to regular containers. Post-pandemic, the system can also be used for other types of cargo deemed 'critical' by the port.
Vignette #2—Project AlphaAir: A North American airline gave Consult a mandate to inform its pricing strategy by improving demand predictions. Consult used a combination of classical operations research optimization (using the customer's data on historical patterns) and machine learning (using data from external public sources on upcoming events in specific locations, for example, a large conference for medical professionals) to deliver a system that analyses demand prediction. The analysis results are presented visually using a heat map to subject matter experts, enabling more rapid diagnosis and problem-solving to optimise aircraft capacity planning.
Vignette #3—Project GammaGas: A North American chain of retail gas stations hired Consult to optimise fuel prices. For this project, Consult used machine learning algorithms to model customer behaviour and a time series model for demand forecasting. Both outputs are then fed into a non-linear optimization model to help set fuel prices.

Consult is at the forefront of AI practice. The company can be considered an exemplar because its employees are successful at managing AI projects while many other companies are struggling to do so, providing a suitable research setting for a *revelatory case study design* (Yin, 2013) (please see Appendix A for additional details on our case selection strategy and our research methods). Teams working at Consult manage multiple AI projects in parallel, allowing us to study common issues and patterns across projects. Consult projects go beyond the theoretical development of an algorithm and involve the delivery of a working solution (e.g., a fine-tuned model): Consult will often initially develop a pilot or proof-of-concept, which is then refined into a minimum viable product that will form the basis of the solution delivered to customers, a common approach in the industry due to the emerging nature of this field (Benbya et al., 2020). Their solutions typically employ a combination of machine learning techniques and mathematical optimization, an approach that is gaining popularity (van den Broek et al., 2021; Zhang et al., 2020). Finally, employees working for Consult have extensive training or experience in either project management, software development, or AI. Their staff also includes scientific advisors, who are academic researchers who provide input on cutting-edge data analysis tools and techniques.

2.1 | Managing AI projects at Consult

To manage AI projects, employees at Consult borrow elements from three main approaches.[2] Elements from traditional project management are used to break down the projects into major phases geared toward managing the overall project for the customer. Elements from agile practices are used to execute the project work in short cycles in an iterative and incremental manner. Elements from the AI workflow are used to manage the experimentation and fine-tuning of the machine-learning models that will be integrated into the final product. While there are approaches, recommendations, and guidelines for performing the AI workflow (see Appendix B), there is currently no authoritative source on how to manage AI projects. Consult therefore crafted their own integrated approach to managing AI projects by leveraging their internal expertise based on the need to deliver innovative solutions to paying customers.

2.1.1 | Traditional project management

Consult structure their AI projects across five phases (see Table 2). Between each phase is a gate serving as a checkpoint to evaluate progress and reassess the project's feasibility. Future phases are not planned in detail until the end

TABLE 2 Phases of artificial intelligence projects at Consult

Phase	Main objective(s)	Illustrative quotes
Ideation	Develop a solid understanding of business requirements with customers and advise them on how to proceed with the AI project. Scientific advisors evaluate the project's technical feasibility based on those requirements and a preliminary assessment of the availability of data.	'[In this phase, we] sort out what we should be working on based on impact for the business and feasibility basically'. (VP Product Delivery) 'There's the 2–4 weeks advisory. Which is "Where do I use AI in my business?" That's a little bit more consultancy, some data review some sort of "what can we do here," but there's no technical delivery in that'. (VP Solution Engineering)
Blueprint	Draw a clear outline of the project's business requirements, the scientific techniques (i.e., the mathematical models) that can be used to fulfil those requirements, the data required for these models to function, and the technical infrastructure needed to implement and deploy the envisioned product.	'[The purpose of the blueprint] is to find out what exactly is the problem, how can we approach it and take a look at data availability because sometimes they want to do things but they just do not have the data to make it work or they do not have any information system to support the eventual solution that could be developed, so the blueprint is there to make sure that the problem is feasible, that they have data and that eventually they will have the infrastructure in place to make the tool applicable'. (Scientific Advisor) 'Then there's the 4–8 weeks we call the blueprint. There it's "give us data we'll solve it in the lab." Deliverables are more of a Jupyter notebook. we have a model we have applied, it may or may not have good results, but we can start to estimate what the business value is going to be'. (VP Solution Engineering)
Proof-of-Concept (PoC)	Deliver a raw prototype of the solution using historical customer data based on the specs contained in the blueprint. To do so, data engineers clean and prepare the data; data scientists implement, test, and adjust models based on recommendations from scientific advisors; and software engineers build the application that will host the model.	'It's a continuation, basically you start coding, the science, the algorithms, just to see if it works. I would say there is still some back and forth in terms of business understanding because you cannot figure out everything 100% in a blueprint, so when you get into the science then you always have to go back'. (Chief Supply Chain Officer) 'The main role of the proof of concept is to document the benefits that will come from having the full-fledged tool in place'. (Scientific Advisor) 'But even up until the end of a POC, you still have to convince, there's a go, no go of if this thing works and if it's worth doing'. (Chief Supply Chain Officer)
Minimum Viable Product (MVP)	Deliver a refactored, optimised version of the proof-of-concept with all the features required by the customer. The MVP is built to rely on live customer data and should be able to be put into production by the customer. During this phase, the business team also ensures that the customer receives initial training on the solution so that they can take ownership of the MVP and support its implementation in their organisation.	'MVP becomes this refactoring productization, knowledge transfer, and deployment type of phase'. (VP Product Delivery) 'You might build some quick and dirty stuff in a POC just to see what the algorithm is spitting out, but the real, real interface is the final, final solution. It's the cosmetic of, that layer that sits on, it's a face that sits on top of the science, the algorithm and it's very driven by the end users and what they want to see and what should we design. [...] The real work happens at the MVP'. (Chief Supply Chain Officer)

(Continues)

TABLE 2 (Continued)

Phase	Main objective(s)	Illustrative quotes
		'The MVP, the minimum viable product, … is something [that is] almost the final product except it does not have, typically, it will not have every detail interface, it will be a very variable bare bones one'. (Scientific Director)
Maintenance and calibration	Ideally, customers should take full ownership of the solution past the MVP stage. However, the need to modify or retrain models delivered within MVPs, changes in data that cause drift, as well as changes in customer business rules and constraints have led Consult to offer some support and maintenance services to their customers.	'We will remain a project-based organisation. That being said the algorithms that we build are a bit hairy and it's, technology, it's complicated, and we offer yearly calibration services, and you know, things like that.' (VP Product Delivery) 'We also provide maintenance. It's part of the contract usually, there's some kind of maintenance that's planned. So, it could be retraining the model on new data, it can be accommodating for changes in the operating rules, so that might mean changing the constraints for example that are enforced and things like that'. (Scientific Director) 'Then you can have a world after that, where that's kind of an ongoing forever maintenance of the models, of the evolving of it, and so on so forth'. (VP Solution Delivery)

of the preceding phase, and details learned at the end of a phase can also inform the next phase or even lead Consult to advise customers to stop the project or put it on hold. The combination of clear objectives for each phase and the gating process allows teams at Consult to focus on achieving specific objectives while ensuring that emerging insights can be incorporated into the later phases as needed.

2.1.2 | Agile practices

Across the five main phases of a project, teams use approaches inspired by agile practices and methods. However, the same approach is not used for the duration of an entire mandate. For example, several of our informants noted that the short duration of the ideation and blueprint phases, combined with the exploratory nature of the work undertaken during these early phases, are amenable to weekly iterations with the scientific advisor using a Kanban approach: 'Blueprint is a bit more Kanban … You're exploring' (Chief Supply Chain Officer). Scrum was deemed more appropriate during the PoC and MVP phases because during these two phases, teams are developing and refining a working prototype incrementally: 'The minute that the technical team kicks in then we're full-on Scrum' (VP Product Delivery).

The iterative nature of agile processes also allows teams to uncover and address issues early on, for example, if a model underperforms or if the quality of customer data is lower than expected. As the VP of Product Delivery noted: 'I mean AI is iterative … what I like about agility is that it allows me to fail faster.' Consistent with the values of the Agile Manifesto, teams also seek to involve customers on an ongoing basis, with the end goal of letting them progressively take ownership of the solution upon delivery of the MVP. As noted by the Senior AI Consultant/Agile Product Owner:

> We wanted to involve [the customer in the experiments] and that way they would feel like they were a part of it, it is a way of conducting knowledge transfer, and also if we discuss with them that we need to do all of these experiments, they are aware.

2.1.3 | AI workflow

To build project deliverables, employees at Consult perform a variety of specialised tasks required to implement and package complex mathematical models for their customers (see Appendix B for an overview of common AI workflow approaches found in the industry). Among other things, this involves data engineers whose work focuses on cleaning up and preparing the data that will be used to train the models built and tested by data scientists. Once they are ready to be deployed, these models are shared with software engineers, who will package them into a working piece of software (e.g., a software service with an API). Our respondents often compared their work to that of scientists working on experiments: 'That's experimenting and discovery … Think of like the mad scientist throwing colored chemicals together with bubbling things in a laboratory. It's a little bit like that'. (VP of Solution Engineering). Data need to be acquired and validated; model features need to be engineered; and models need to be built, trained and tested on those data before their performance can be assessed. Like experiments in a research-based scientific process (idea—hypothesis—test—analyse results—repeat), respondents indicated that these tasks must be performed in sequence, with the output from a task becoming the input for the next task or even indicating which task should be performed next. As a result, team members often saw the tasks of the AI workflow as having a high degree of uncertainty.

3 | CONFLICTING LOGICS AT CONSULT

Our case data reveals that, while successful, Consult's approach is not without issues. Indeed, our understanding of the approach used by Consult to manage AI projects highlights the existence of three key logics[3]—defined as

TABLE 3 Logics in the management of artificial intelligence projects

	Traditional PM logic	Agile logic	AI workflow logic
Key values and goals	*Values*: Adhering to standards (e.g., PMBOK, section 1.1). Emphasis on planning and compliance with time and budget constraints. *Goals*: Deliver the project while respecting time, budget, and scope constraints (the Iron Triangle).	*Values* (*Agile Manifesto*): Individuals and interactions over processes and tools. Working software over comprehensive documentation. Customer collaboration over contract negotiation. Responding to change over following a plan. *Goals*: Frequently deliver valuable software to customers. Accommodate changes throughout the project.	*Values*: Due to the emerging nature of this field, no clear, agreed-upon values could be identified in the literature. However, some efforts are underway to define overarching values for AI in general (e.g., fairness and inclusiveness). *Goals*: Attain the desired level of model performance, for example, as defined by the optimization of an objective function. Meet AI model requirements (e.g., robustness, explainability).
Underlying assumptions	Formal planning, estimation, and control of the process facilitate project success. Phased development with stage gates helps reduce uncertainty.	Team autonomy and customer participation foster success. Uncertainty cannot be eliminated but can be managed through adaptative processes. The regularity of the process (e.g., short, consistent pace of iterations) helps move the project forward.	High-quality data represents the phenomenon of interest and is paramount to project success. Success relies on a research-based scientific process involving stages of exploration and experimentation organised into sequential tasks making a clear path forward difficult to predict at the onset of the project.
Roles and responsibilities	The project manager bears responsibility for the entire project and acts as both leader and manager of the project. The role of the project manager is highly institutionalised and legitimated by official certification bodies (Project Management Institute). Accountability and contribution to project success are evaluated on an individual basis. Project team members are highly specialised.	Responsibility and accountability for the project are assumed by a collective of individuals. Although institutionalised in official guides and certifications (e.g., Certified Scrum Master, Agile coach), roles are fluid and are not associated with specific job titles (e.g., product owner). Teams are cross-functional and enjoy a high degree of autonomy. Work is planned and performed using a collaborative approach (e.g., planning poker).	Authority is based on technical or domain knowledge and academic expertise, not managerial leadership. Team members are highly specialised. Team member roles are typically associated with job titles (e.g., data scientist, data engineer), although the degree of institutionalisation of these roles varies (some vendors offer certifications for data engineers, but there is no single authority that delivers these certifications).

TABLE 3 (Continued)

	Traditional PM logic	Agile logic	AI workflow logic
Background and training	*Background*: Official body of knowledge built on project management initiatives in engineering (large-scale military and civil projects). *Training*: Official certification paths and exams (e.g., PMP certification, PRINCE2).	*Background*: Experiences and knowledge of a group of software engineers. *Training*: Official certification paths and exams (e.g., Certified ScrumMaster).	*Background*: Scientific knowledge is primarily gained in higher-level education (e.g., Doctoral studies). *Training*: Certification and exams provided by specific vendors are emerging (e.g., Microsoft Certified: Azure Data Scientist Associate).

commonly shared norms, values, and prescribed behaviours which influence actors' understanding of how work should be done—that help us understand why individuals perceive that there is a legitimate way of executing the project: a traditional PM logic; an agile logic; and an AI workflow logic. Table 3 provides an outline of each of these three logics across four overarching dimensions[4]: (1) key values and goals; (2) underlying assumptions; (3) roles and responsibilities; and (4) training and background (Berente et al., 2019). As there is no single authoritative source describing a given logic, we developed the content of Table 3 by drawing on literature (e.g., the Project Management Body of Knowledge for traditional project management; the Agile Manifesto and the Scrum Guide, which are rooted in IS development but have since expanded beyond) combined with our knowledge as researchers, teachers, coaches, and practitioners in these three areas.

Based on the existence of these three logics, our analysis reveals the presence of conflicts between (i) the traditional PM logic and the AI workflow logic, and (ii) the agile logic and the AI workflow logic,[5] which are summarised in Table 4. Both traditional project management (e.g., Mignerat & Rivard, 2012) and agile practices (e.g., Hoda et al., 2017) have matured over the years, and their underlying logics are explicit, as illustrated by the publication of bodies of knowledge (e.g., Project Management Institute, 2017) and professional certifications (e.g., Scrum Alliance, 2013). While a common approach to *managing* AI projects does not currently exist due to the emerging nature of this phenomenon, a common understanding of the basic components of AI workflows is emerging (Google, 2018; Microsoft Corporation, 2018; further information is available in Appendix B). The AI workflow logic is thus less developed than the other two logics.

3.1 | Traditional project management logic versus AI workflow logic

3.1.1 | Conflict #1: Different assumptions of uncertainty

According to traditional project management logic, the feasibility of a project is determined in earlier stages, and the range of uncertainty decreases over time. However, due to data issues and the mathematical complexity inherent in AI workflow logic, the degree of uncertainty can remain constant or even increase as team members perform scientific experiments. As the Data Scientist noted:

> During the project, a lot of time was spent trying to understand the data and the flaws in the data and the data gaps that existed because we really started receiving a large amount of data as the project was going on … there was a lot of analysis that … we had to kind of re-do once we started receiving the raw data.

Consult's Chief Supply Chain Officer noted that uncertainty could also be felt throughout the project on the business side:

> I would say there is still some back and forth in terms of business understanding because you can't figure out everything 100% in a blueprint, so when you get into the science, then you always have to go back. And sometimes the scope changes when you get to a point and say 'Oh, you know what, how about we do something different.' You kind of go back to the drawing board.

She further noted that navigating this uncertainty with the customer throughout the project can be difficult:

> It's not a one-time thing. You present the presentation, they forget, but it's more of a continuous and consistent thing and reminder. Some clients are easier than others. Some clients you do your education all you want and at the end of the day, they just get into a not-happy mode if things don't go well … I would say education and awareness, transparency, all of that [is important] moreso on AI projects because they are more uncertain in nature. You don't know if the science would work or if the science [doesn't], if they have the data …

3.1.2 | Conflict #2: Different approaches to deliverables

Part of traditional project management logic is that the customer and provider sign off on the project deliverables at the start of the project. According to AI workflow logic, however, uncertainty is present throughout, and results cannot always be delivered as planned. Thus, actual project deliverables are not always known apriori, and customers can be dissatisfied as a result. Reflecting on this issue, Consult's Chief Supply Chain Officer explained that it was important for the customer to understand the risk inherent in AI development and be willing to invest in something that may not succeed as per traditional project management expectations:

> That's inherent in the nature of [AI], especially machine learning [in] which you don't know until you do it. […] That's a little bit more uncertain, and then it takes some maturity and willingness on the client's side to put their money where their mouth is and be OK if it fails, stops, or is inconclusive.

3.1.3 | Conflict #3: Weakly correlated targets

According to traditional project management logic, the goal or target of a project is to meet specific, predetermined success criteria, which are often directly linked to improving business value. For several of Consult's customers who operate in logistics, it may also mean optimising a specific process (e.g., how long it takes to complete a task). AI workflow logic tends to focus on statistical targets defined by a mathematical model's objective function, with the Data Scientist noting that he was focused on running experiments to see if there was a 'gain in model performance'. Sometimes, however, improving model performance has little or no effect on business value, as described by Consult's VP of Solution Engineering:

> It's not like a fundamental research project where [we] say 'Can we change this value?' No, it's like 'Can we create business value for shareholders?' These are two different things. Theoretically, changing a number may not do anything for shareholder value.

TABLE 4 Conflicting logics at Consult

Conflict	Sources of conflict	How conflict surfaces
Traditional project management logic versus AI workflow logic		
1. Different assumptions of uncertainty	*Traditional PM logic*: Feasibility is determined in earlier stages, and the range of uncertainty is significantly reduced with each stage. *AI workflow logic*: Uncertainty can manifest throughout the AI workflow due to data issues and mathematical complexity.	Customers expecting uncertainty to be high only in the early stages of the project need to understand that feasibility and uncertainty remain significant issues throughout the project. Even in later stages, uncertainty can still be quite high and delay a project or make it difficult to continue with the current direction.
2. Different approaches to deliverables	*Traditional PM logic*: Customer and provider agree on the scope and schedule of deliverables apriori, and the customer pays for that scope when delivered. *AI workflow logic*: Uncertainty throughout the AI workflow means it is challenging to specify the scope and schedule of precise deliverables in advance.	Customers seeking specific ROI-style results may be unsatisfied. Deliverables should instead focus on progress on their AI opportunities.
3. Weakly correlated targets	*Traditional PM logic*: Aims for specific project success criteria reflecting business goals (i.e., increasing business value or improving a business process). *AI Workflow logic*: Aims to achieve the statistical target defined by the model's objective function (e.g., 95% prediction accuracy).	AI may offer a statistical solution that cannot be directly converted to business value (e.g., not practically useful, not used, or not implementable).
4. Different quality expectations	*Traditional PM logic*: Project quality management means meeting (not exceeding) selected quality criteria. *AI workflow logic*: Data scientists—heavily involved in the AI workflow—have a research background and are often focused on cutting-edge data analysis techniques.	Data science 'gold-plating' does not fit with project-based based minimum quality criteria.
Agile logic versus AI workflow logic		
5. Different organisation of work tasks	*Agile logic*: Iterations should be kept the same length and should focus on finishing (not partially completing) specific tasks. *AI workflow logic*: A process-driven approach involving a series of mini-experiments, based on algorithms with unpredictable and variable run-time. Interim experiment results determine the next task to do.	AI experimentation leads to changes even during iteration, making it hard to formalise iteration content, complete tasks within one iteration and/or maintain consistent sprint duration. Limiting such within-iteration changes may cause unnecessary AI work.
6. Different sources of change	*Agile logic*: Processes built around scope/feature changes. Most changes are customer-driven. *AI workflow logic*: Task changes are mainly driven by intermediate data output and data science considerations.	Mismatch between the typical role of customers in agile projects and their expected role in AI projects.
7. Different measures of progress	*Agile logic*: Principle of frequent delivery of a working product. Working product is the primary measure of progress. *AI workflow logic*: Organised around mini-experiments and hypotheses.	Intermediate outputs of AI workflow do not enable frequent delivery of working, tangible solutions.

(Continues)

TABLE 4 (Continued)

Conflict	Sources of conflict	How conflict surfaces
8. Different approaches to collaboration	*Agile logic*: Participative in nature (self-organising teams, each should contribute beyond just their specific skill set, etc.). *AI workflow logic*: Approach based performing on mini-experiments and using data science tools that are generally not designed for collaboration beyond a narrowly-defined specific skill set.	Hyper-specialisation of knowledge, methods and tools used in AI that favour solo work are in conflict with the agile collaborative approach.

Likewise, the statistical value may not translate into improvements in the target process, as illustrated in this example from Consult's Scientific Advisor:

> One of the challenges in our field is the time it takes to solve the problem. It can … look simple on the surface, but it can take hours to solve it. You can have a machine operator or a truck driver waiting for the result, and it cannot take hours to tell them where to go next.

3.1.4 | Conflict #4: Different quality expectations

The logics underlying traditional project management suggests that quality management should be delivered according to pre-specified quality criteria, and exceeding quality expectations (termed *gold-plating*) is seen as detrimental. However, data scientists—who occupy a prominent role in AI work—are heavily influenced by their academic research background (all data scientists at Consult had a PhD). As a result, they are often focused on using cutting-edge techniques, which at times are at odds with the techniques that will meet the minimum quality required by the customer. The VP of Solution Engineering described this struggle exists "because [data scientists] would like to use the latest and greatest snazzy Ferrari techniques. […] But there's a pragmatic view that you should have the baseline based on what has been proven and worked in this field."

3.2 | Agile logic versus AI workflow logic

3.2.1 | Conflict #5: Different organisation of work tasks

Agile logic emphasises fixed-length (often time-boxed) iterations during which team members focus on completing tasks pre-selected during a sprint planning meeting. However, AI workflow logic includes a process approach that is organised around a series of small experiments based on algorithms with unpredictable and variable run times. As Consult's VP of Product Delivery explained, 'You might say "OK there's promising results, we should move forward with tweaking these things," but [the data scientists] don't know what the tweaking is going to be … So it's less known'. The Data Scientist also described this challenge:

> There's a lot of experimentation to be done, and it's not always clear which experiments will be successful and which will require more time to look into … different ways to tune the model to allow it to work better. It's kind of hard to plan out two weeks in advance sometimes exactly how much time you expect to be spending with a certain model, experimenting with it …we would put in story points, for example, expecting it to be finished in a couple of days, and it would kind of

> get pushed as I would discover that it would take more time to really, fully experiment with this model. It would get pushed to later and later sprints, and so the story point estimates became less meaningful.

Sometimes intermediate results require changes within an iteration, as the Agile Coach explained:

> Sometimes you realize after five days [in the middle of a sprint] that you are better off saying "I'll stop, I won't go all the way, because what I discovered means that there is no point in continuing [down this path]."

At other times experiments require multiple scheduled iterations to complete. The VP of Product Delivery described the need to be flexible due to the nature of the AI workflow: 'You have to allow for some science deliverables to span over two or even three sprints. There's no other way.'

3.2.2 | Conflict #6: Different sources of change

Both agile and AI workflow logics involve change throughout the process, but the source of change is different, which can impact the role of the customer during the AI project. According to agile logic, change is welcome throughout the development process, and many of the changes are driven by the customer. For AI workflow logic, changes are primarily driven either by intermediate outcomes or by the availability of new techniques to address a problem. The Senior AI Consultant/Agile Product Owner spoke about the impact of such intermediate outcomes:

> The data scientists will start by finding the data, working with it, gaining knowledge. All that knowledge, if it changes, it impacts everything … maybe not the scope but the type of model we will use… maybe it will be more of a scientific question. But the clients don't change the scope.

3.2.3 | Conflict #7: Different measures of progress

One principle of agile logic is to deliver a working product at the end of every iteration. Embedded in AI workflow logic, however, is that the use of and dependence on small experiments and hypothesis testing mean that intermediate outputs are not necessarily working, tangible solutions. As such, it may be difficult to demonstrate progress in terms of added value or tangible ROI to the customer. This was illustrated with an example from Consult's Project Team Lead, where the team spent considerable time on data profiling and was showing the results to the customer during sprint review:

> It was a profile of our data and the column that has values, the one that has lots of notes and so on. Actually, we're not doing anything with [some of these columns]. This is the fact. But we need to eventually address the issues that we have in this data, and showing that to the client does give them a better understanding of what's happening with the reality [of their data]. So, even though it's just a task and we're not giving the ROI yet, we're still progressing because … we need to take [these] actions, and it drives the rest of the work.

3.2.4 | Conflict #8: Different approaches to collaboration

Agile logic underlines the importance of self-organising and autonomous teams. However, our respondents described AI development differently, noting that their work was often hyper-specialised and performed alone—described as 'solo work' by the VP of Solution Engineering—in line with the roles and responsibilities that form the foundation of the AI workflow logic. As noted by the Agile Coach:

> What was different [here] is that people have very specific expertise. In theory, what we want in agile planning is that everyone should be able to estimate, everyone should be able to detail [the items in the backlog]. These [AI projects] are so specific that often the data engineer will write their task and will do the task because there is no-one else who knows what it is [and how to do it].

This conflict is further illustrated by the tools used by team members. For instance, the VP of Solution Engineering explained that consistent with agile practices, software engineers routinely use software tools to manage their team's tasks, enact version control, and build software collaboratively. However, the AI workflow logic focuses more on individual and hyper-specialised roles. The data scientists and data engineers at Consult are not used to employing these types of collaborative tools:

> You've got, you know, JIRA. You've got whatever tool is there [in Agile]. And everybody's working on the same table, right? … There's no equivalent in the data science exploration and experimentation phase right now. We're still hacking it together with the tools that we have… it's not collaborative right now.

This conflict becomes especially apparent during the later stages of a project when both software engineers and data scientists need to work more closely together. As described by the VP of Solution Engineering: 'The data scientist can [share Jupyter Notebook files] between themselves and then you have a software engineer that will be like "Oh my god, what is this?"'

3.3 | Summary

To manage AI projects, employees at Consult borrow from three approaches: traditional project management, agile practices, and AI workflow. Managing AI projects in this way draws upon three core ways of thinking about the work involved in these projects: a traditional PM logic, an agile logic, and an AI workflow logic. Although issues associated with the mixing of traditional project management and agile practices have been previously examined

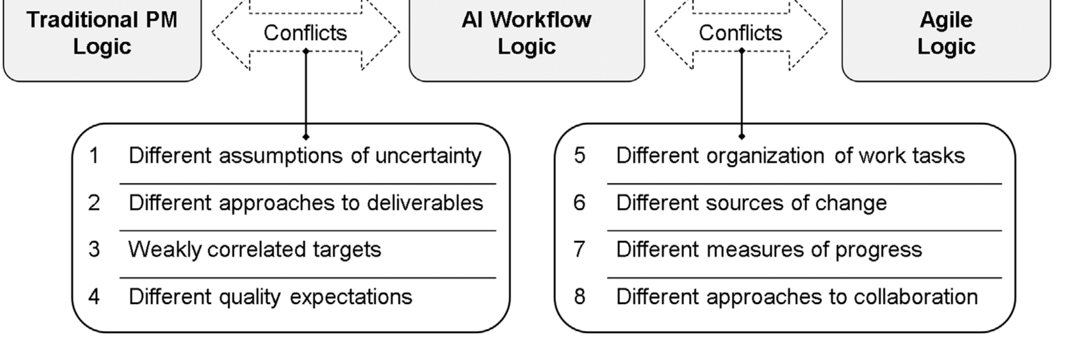

FIGURE 1 Conflicts involving artificial intelligence workflow logic at Consult

(e.g., Fernandez & Fernandez, 2008; Hoda et al., 2017), the case of Consult reveals the novel conflicts that emerge when the AI workflow logic—which is central to any AI project—is added to the mix (see Figure 1).

4 | IMPLICATIONS FOR MANAGERS: FOUR STRATEGIES USED BY CONSULT TO SUCCESSFULLY MANAGE AI PROJECTS

In this section, we outline four strategies used by Consult to address the conflicts they face in their AI projects. These four strategies do not represent a comprehensive analysis of *all* the ways these conflicts can be resolved, but instead, highlight ways this AI company found to successfully navigate these conflicts. Although the case of Consult is based on projects undertaken for external customers, the three logics we have identified, the conflicts that arise between them and the strategies to address them also apply in the context of AI projects undertaken within a single firm.[6] Our discussions with AI leaders and practitioners working in other firms and industries (e.g., logistics, supply chain, financial services and healthcare) indeed suggest that these issues are pervasive. Table 5 summarises each strategy, explains how it works, and indicates the conflict(s) that it helps to address.

4.1 | Do not be afraid to fire your customer

The field of AI involves ever-evolving analytical techniques such that skill sets can quickly become outdated, making it especially important to constantly monitor a project's viability. The Senior AI Consultant/Agile Product Owner

TABLE 5 Four strategies employed at Consult

Strategy	How it works	Related conflicts
Do not be afraid to fire your customer	Employees at Consult perform preliminary assessments of customer maturity and readiness, and use stage gates to (re) assess a project and customer viability at regular intervals. Sometimes, it is more beneficial, both for the customer and for Consult, to stop or cancel the project for all parties involved.	Conflict #1 (different assumptions of uncertainty) Conflict #2 (different approaches to deliverables) Conflict #6 (different sources of change)
Rethink your definition of "done"	For their projects, consultants run AI experiments that provide intermediate results, for example, to validate elements for the design of a final solution. While these intermediate outcomes may not conform to the typical definition of project deliverables, they are nevertheless important for project teams to drive their projects forward.	Conflict #5 (Different organisation of work tasks) Conflict #7 (Different measures of progress)
Question the marginal value of data science	There is always some potential to increase technical performance in AI. For Consult, this only makes sense if the target to achieve is aligned with the project's business objectives. Employees at Consult strive to ensure that work is driven by the potential to create meaningful, additional business value for customers rather than to increase technical performance (e.g., model accuracy).	Conflict #3 (Weakly correlated targets) Conflict #4 (Different quality expectations)
Cultivate an AI power couple (ignore the unicorn)	Rather than trying to find a single person who can handle all aspects of a given project (i.e., a unicorn), Consult's approach pairs a business consultant with a data scientist to improve communication and strike a balance between business and technical requirements for their projects.	Conflict #8 (Different approach to collaboration)

noted that at times, 'it is better to switch to another project because we—individuals and companies—build AI experience by implementing interesting projects … staying 6 or 12 months in one bad project is an issue when trying to build a portfolio.' Thus, the opportunity cost of staying in a problematic project can be particularly steep in a fast-moving field such as AI. Multiple types of problems can jeopardise AI project success, but one particularly salient source of problems at Consult relates to customer knowledge and expectations, which are key components of conflict #1 (different assumptions of uncertainty), conflict #2 (different approaches to deliverables), and conflict #6 (different sources of change).

The customer's participation—whether an internal customer from another department or an external customer—is crucial to success in AI projects. Notwithstanding, Consult's VP of Solution Engineering observed that with some customers, 'even at a very conceptual level, saying you "train data and then you reproduce that prediction." You are already talking gibberish. … So there's a huge divide. That gap is even widening between the haves and the have nots in terms of their ability or their understanding of AI.' Recalling weekly meetings with a customer company's Director of AI, who repeatedly asked basic questions, the Scientific Advisor described it as 'completely discouraging, the lack of sophistication and data literacy, he was just lost.' The lack of customer knowledge sometimes translates into a poor understanding of their own data, which the VP of Product Delivery illustrated using a car engine analogy: 'It's never easy on the data side … the [customer] businesses always think they have it, they want to start fast, then we open the hood and say "Oh no!"'. While Consult could continue to bill a customer while helping them become AI-ready, the opportunity cost is often too high, both for Consult and for the customer.

To address this issue, employees at Consult have established an approach allowing them to halt a project—effectively firing (albeit politely) a customer. This is in contrast to traditional project management, where the project manager works to fulfil the contract previously signed with the customer, or agile practices, where stopping decisions remain the purview of the customer. Consult's approach to halting a project relies on two mechanisms. The first is a preliminary assessment of customer readiness performed at the start of the Ideation phase, which the Senior AI Consultant/Agile Product Owner was refining to include a formal assessment of the customer's data quality, technology and infrastructure to support the volume of data required, AI maturity, and approach to AI uncertainty. Consult's VP of Solution Engineering described this assessment as an important "enabler" for customers to avoid 'wast[ing] data scientists time on [customers] […] because if you go into the blueprint [second phase] and you don't know what you're doing, you're wasting everyone's time.'

Even after the customer passes this readiness assessment, Consult can use their stage-gate approach with go/no-go decisions at the end of each phase to halt the AI project. For Consult, this is part of the learning process several of their customers have to go through to eventually become ready to implement AI solutions: 'So we have to tell the client "guess what? It was just not enough, we are stopping the project, the blueprint is going to stop, but in a year if you do these five things, we might have something"' (Chief Supply Chain Officer). Consult's Scientific Advisor noted that these stage gates allow Consult to tell the customers when the project's success is in jeopardy, and it should be stopped—effectively firing their own customer, to everyone's benefit. Our respondents indicated that this strategy also allows customers to take time to reconsider their projects or seek other avenues for help in educating themselves about AI before re-engaging with Consult at a later date.

4.2 | Rethink your definition of done

Embedded within the traditional project management logic is the concept of a task or an activity, defined as a 'distinct, scheduled portion of work performed during the course of a project' (Project Management Institute, 2017, p. 525). Traditional project management assumes that tasks have predetermined predecessors and successors such that having a task that is 'done' moves the project forward to that task's successor(s). Agile also takes a task-based approach, with iterations focused on finishing certain tasks according to a pre-established definition of done, which moves the project forward. However, AI workflow logic does not follow this approach. It is instead organised around a series of hypotheses and small experiments, which produce intermediate results but may not equate to a 'done' task that advances the project. Tailoring agile approaches is common (e.g., Conboy & Fitzgerald, 2010; Fitzgerald et al., 2003), but the modifications required are even more significant for AI projects. Thus, alternate approaches are needed to measure and demonstrate project progress—related to both conflict #5 (different organisation of work tasks) and conflict #7 (different measures of progress).

Working with the Agile Coach to tailor the agile approach, the teams worked on three elements. First, they focused on defining 'what is a task' and how to break the tasks into smaller pieces. Several approaches and ideas were brainstormed, including using 'Definition of Ready' to help teams break user stories into smaller technical or analytical pre-tasks that could be moved into the backlog for a specific sprint. Second, they tried to determine what was meant by 'done' in the context of small-scale experiments and hypothesis testing. For small experiments, discussions centred around defining a task as 'done' when an answer to the hypothesis was obtained, allowing them to move on to another task or hypothesis. Third, teams worked on communicating data-driven intermediary results to customers. This was particularly challenging for tasks that are a series of experiments. If one of those experiments fails, it should not be seen as a failed task. Rather, it represents an invalidated hypothesis that helps the team move forward in a different direction. Thus, measures of progress are less about agile's focus on tangible progress on a working solution and more centred on the results of hypothesis testing and their interpretation. As the Agile Coach explained:

> When you do consulting, you want to deliver results to your customer, and I helped [the teams at Consult] understand that the fact that you have tried something and it did not work [e.g., an invalided hypothesis], that is a result. You should be proud of it; you should demonstrate it and say that we have learned something and [now] we can go further.

4.3 | Question the marginal value of data science

Reconciling AI results with business value is a challenge in many AI projects. In our findings, this challenge was primarily related to conflict #3 (weakly correlated targets) and conflict #4 (different quality expectations). While employees at Consult strive to deliver business value for their customers based on the definition of performance indicators (e.g., productivity increase, pricing, or stock level optimization), it can be difficult for data scientists to translate these indicators into the kind of performance measures typically used in AI models (e.g., accuracy, precision). At the same time, the AI workflow logic encourages using the most advanced techniques available to achieve incremental gains in model performance. Evaluating model performance gains and how these gains translate into marginal increases in customer value against the costs of achieving these gains in both the short-term project work and long-term requirements in terms of processing power and data infrastructure is a difficult task. It is especially challenging due to the fact that with machine learning and AI, 'you don't know until you do it' (Chief Supply Chain Officer).

The strategy employed at Consult is to continually assess the marginal returns of undertaking additional technical work. To do so, consultants strive to continuously maintain awareness of the customer's context, needs, and goals to ensure that any technical or scientific work undertaken by their project teams is based on the need to create business value rather than to demonstrate technical prowess. Team members need to sufficiently understand the customer's business targets and quality expectations to be able to translate them into mathematical values, statistical thresholds and stopping criteria. Sometimes, technical solutions are simply not viable in practice. Consult's Scientific Advisor reflected on this risk, recounting one specific project where lack of marginal business value required them to significantly change focus:

> There was a project … about managing manpower. We talked about all kinds of ways to improve the assignment of employees to tasks. One day they said "you know what? All of [your outputs] make

> perfect sense but there's no way we could implement them because of the union rules”. So they said we have to find another objective.

4.4 | Cultivate an AI power couple (ignore the unicorn)

Organisations strive to find data science ‘unicorns’ that are proficient in multiple technical and business aspects of their AI projects (Lo, 2019). At Consult, multiple managers noted that it is difficult for a single person to excel in all aspects of an AI project, given the highly specialised nature of AI tasks. The knowledge and training underlying the AI workflow are complex and highly specialised, as evidenced by the fact that all data scientists hired at Consult had a PhD and at least 5 years of industry experience. It is rare for data scientists to have this deep knowledge of their AI specialisation and deep knowledge about other areas such as traditional project management, or the business domain of customers. Similarly, few non-data scientists are trained in the specifics of the AI workflow.

To successfully manage their AI projects, Consult decided not to wait for the rare unicorn and instead cultivated a *power couple* approach. On each project, one business consultant is assigned to work in tandem with one data scientist. The data scientist shares all interim results with the consultant, who helps interpret the results' business meaning, questions the data and offers ideas on the next business questions to ask the data.

This power couple strategy helps Consult tackle conflict #8 (different approaches to collaboration). The AI workflow logic involves mostly solo work, and—considering the rarity of the data science unicorn—this would not effectively support Consult's AI projects with various customers. Agile logic is more participative in nature and is often organised around daily stand-ups where everyone shares their progress and helps each other with any issues that arise. The deep knowledge of the data scientists at Consult—combined with the fact that there was often only one data scientist assigned to each project—made it difficult for them to meaningfully share their status and make progress on their issues through this daily stand-up approach. Thus, neither the AI workflow solo approach nor the agile participative group approach would be sufficient, and a much more strongly entwined *power couple* emerged at Consult. The VP of product delivery noted that a power couple working in tandem is a key success factor at Consult, and their Chief Supply Chain Officer described its effect on project success:

> I guess whenever it breaks down is that the business consultant doesn't mesh very well with the data scientist. They have to be like a couple—a power couple—very close to each other, understanding exactly what the business team [needs]. [The business side is] not driving the science on an algorithmic side but saying “OK, this is what we need to know, you figure out how but this is what we are driving towards.” Being outward driven instead of “let's just run models because it's cool!” That guidance comes from business team. Once info comes back [from the data scientist], “OK this is what the model spit out, what does it mean? Does it make sense? Yes? Fantastic. No? What's next? How do we adjust?” For the teams when that dialogue, that power couple thing works well, it's magic. When it doesn't, then it's bad.

5 | IMPLICATIONS FOR RESEARCH

From a research perspective, our study of Consult offers two key contributions. First, our work provides insights into the management of AI projects. As organisations seek to further leverage the potential of AI to create value (Benbya et al., 2020; Berente et al., 2021; Ransbotham et al., 2017; Vial et al., 2021), few works highlight how AI projects are managed and the issues that arise over the course of these projects (van den Broek et al., 2021; Vial et al., 2021; Zhang et al., 2020). Our study addresses this gap by providing a detailed record of the approach employed at one company to manage AI projects and identifying eight conflicts that were encountered during those projects.

Second, our use of the concept of logics and conflicting logics (Berente et al., 2019), which guided our data analysis, helps us understand *why* conflicts occur during AI projects and highlight the key role played by AI workflow in these projects. When conflicts emerge, institutional logics can help us go beyond generic surface-level conflict resolution techniques to focus on recognising the deep institutional causes of these conflicts and design mechanisms to address them accordingly.

5.1 | Avenues for future research

Although the nascence of our phenomenon of interest provides ample opportunities to explore the management of AI projects in greater depth, we focus on three important avenues.

First, future research could formally explore how team members should address conflicting institutional logics in the context of AI projects. Future studies could examine logics conflict resolution strategies such as reconciliation, decoupling, coexistence or elimination (Berente & Yoo, 2012; Besharov & Smith, 2014; Pache & Santos, 2010). In our case, for example, when Consult cancels a project with a customer because they are not ready to implement AI solutions, they may enact elimination as a strategy to address conflicting logics. At the same time, this strategy offers customers a chance to educate themselves about AI and to improve their internal processes (e.g., data management) so that they may re-engage with Consult at a later date and fully benefit from their expertise. Theoretical insight derived from literature on tensions and dilemmas (Gaim et al., 2018; Putnam et al., 2016) could also help conceptualise the ongoing coexistence of seemingly irreconcilable logics by enacting different coping strategies (Poole & Van de Ven, 1989; Quinn & Cameron, 1988). One opportunity on this front could be to study whether the addition of another logic can help to address existing conflicts. Although our data do not indicate that this is the case for Consult, one may question whether agile logic can be used to bridge traditional project management and AI workflow logics and the conflicts between them.[7] At the same time, the insertion of another logic increases the potential for additional conflicts to occur. Through these kinds of opportunities, we can move toward building a theoretical understanding of the *process* of *managing* AI projects based on the enactment of actions by team members as they identify and respond to issues that emerge from conflicting institutional logics.

Second, future research could also explore the emerging roles and shifting responsibilities of various stakeholders in AI projects. Certain roles have emerged recently, such as data scientist (Vaast & Pinsonneault, 2021) or the scientific advisor role observed at Consult. These new roles exist on top of other, more established project roles that are likely to be impacted by the novel aspects of AI projects, including the incorporation of AI workflow logic. Indeed, it has been observed that 'the role of managers in the burgeoning societal transformation involving AI cannot be overstated' (Berente et al., 2021, p. 1434), and managers may not currently possess the knowledge required to guide these AI projects. Future research could therefore investigate the emergence of new roles (such as the scientific advisor) or how existing roles (such as project managers, agile product owners and customers) require additional knowledge and responsibilities to increase our understanding of the nature and the contributions of members of the emerging digital workforce in the context of AI projects.

Finally, while our discussions with AI professionals from other companies suggest that our findings may speak to their situations as well; future research should explore how different contexts or taking a different perspective on the management of AI projects changes the logics and/or conflicts that emerge. For example, future research could examine if the same conflicts emerge when AI projects are conducted internally or if additional logics exist in different contexts. Additionally, future research could go beyond our provider-focused work to investigate these conflicts from the customer's perspective. In this direction, future studies could investigate the strategies customers employ to navigate their AI project conflicts, such as those related to assuring AI readiness before engaging the services of an AI consulting firm such as Consult.

6 | CONCLUSION

Many organisations are currently trying to benefit from the formidable technological advances afforded by developments in the field of AI (Benbya et al., 2020). Complex tasks previously thought to be achievable only by humans are increasingly performed by systems that leverage the power of AI to augment or even replace humans in the performance of work (Fügener et al., 2021). Organisations must learn to manage AI projects to implement such systems and achieve successful outcomes.

Our study of Consult, a consulting firm at the forefront of AI practice, highlights a successful approach that draws upon three core logics—traditional project management, agile, and AI workflow. In addition, we explain the occurrence of issues during AI projects through conflicts that exist among these three logics. Specifically, we highlight the importance of the emerging AI workflow logic, which conflicts with traditional project management and agile logics that are well-established in organisations.

Drawing from those findings, we have detailed four strategies to help practitioners manage their AI projects. As we strive to bridge the gap between practice and research (Barrett & Oborn, 2018), we hope that our work proves useful for the management of AI projects as well as for researchers who are studying AI projects in organisations.

DATA AVAILABILITY STATEMENT

The qualitative data collected and analyzed for the purpose of this research and which are relevant to support the present work are included as part of our submission. These data were first anonymized, consistent with the parameters of the ethics certificate granted to the authors by their research institution. Complete source data (raw interview transcripts) are not readily available.

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ENDNOTES

[1] Our view of artificial intelligence follows the definition from Rai, Constantinides, and Sarker (2019, iii) as "the ability of a machine to perform cognitive functions that we associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem solving, decision-making, and even demonstrating creativity", and which is nowadays primarily achieved using computational approaches such as machine learning and deep learning.

[2] We do not argue that the integrated approach designed by Consult is optimal, or the only possible combination. Rather, it represents one company's experience with combining elements from three different approaches to manage the successful delivery of AI projects.

[3] Because our contribution is primarily intended for practitioners, we use the term "logic" to describe the rationale (e.g., based on norms, values, or prescribed patterns of work) that motivates how individuals perceive a legitimate way to perform their work within a given context. This is directly inspired by the concept of institutional logics which guided our data analysis and provides a way to characterise the three logics at play in AI projects. The identification of these three logics is based on our understanding of the field as both researchers and practitioners. These three institutional logics exist in practice and were not *discovered* or *defined* during our data analysis. However, iterating between our data and theory sensitised us to their existence. Please refer to Appendix C for a brief overview of this conceptual foundation.

[4] An institutional logic is characterised along four key dimensions: *organising principles* are "goals and values associated with a particular institution"; *causal assumptions* are "implied causal means-end relationships between actions and goal realisation"; *identities* are used by actors to "identify with particular roles implied by the institution"; and *domain* refers to "an appropriate practice field for drawing on and enacting an institutional logic" (Berente et al., 2019, pp. 875–876; Berente & Yoo, 2012). Since our intended contribution is primarily made to practice, we simplify the terminology used to present each dimension but remain consistent with their definitions found in Berente et al. (2019).

[5] Although our evidence also points to the existence of conflicts between the traditional project management logic and the agile logic, our analysis did not yield significant new insight on this type of conflict due to the large body of existing literature on combinations of traditional project management and agile (e.g., Batra et al., 2010; Copola Azenha et al., 2021; Fernandez & Fernandez, 2008; Hoda et al., 2017; Vinekar et al., 2006). Therefore, these conflicts are not included in our findings.

[6] We thank the Associate Editor for reflecting on this aspect of our work.

[7] We thank an anonymous reviewer for this suggestion.

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