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Building AI Talent in Organizations – An Experiential Learning Approach

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ABSTRACT

Rapid digitization in industries is transforming the way corporations conduct their core businesses and interact with their customers. The proliferation of data in these corporations and the ability to process them using the latest AI/ML techniques are compelling them to transform themselves into data-driven organizations. However, acquiring new talent with data science skills and/or reskilling existing employees with deep domain experience presents a major challenge. In this paper, we illustrate how a unique collaboration between industry and academia to impart AI and machine learning (ML) skills to domain experts contributed to furthering an organization's AI aspirations. Specifically, the collaboration has created a continuous learning environment that is conducive to active experimentation and reflective practice, both of which are essential to gaining actionable business insights. Our methodology can be applied to reskill workforces in the future in transformative new-age technologies while adding value to the organization at the same time.

Keywords: Experiential learning & education, Artificial intelligence, Industry partnerships, Workforce development

1. INTRODUCTION

Given the extraordinary success of recently released large-language models (LLMs) such as ChatGPT, it is conceivable that the workplace of the not-so-distant future will be remarkably different from anything we have seen today. LLMs are perhaps the most awe-inspiring outcomes of the current data-driven revolution, which is mainly catalyzed by rapid advances in Artificial Intelligence (AI). AI is no longer an option for organizations; it is an essential strategic resource that can help organizations understand their customers better and anticipate their needs, create innovative products and services, increase productivity and operational performance, and unlock business value (Santos, 2025; Sayegh, 2024). The problem is exacerbated by the ever-widening skills gap (Horn, 2020) and the disparate production and consumption rates of AI-related technologies (Ransbotham, 2020), which hinders organizations' endeavors to derive actionable insights that drive business value. However, the ability of an organization to harness the enormous potential of AI depends on the extent to which the organizational structure (e.g., business processes) and the workforce are aligned (Besson & Rowe, 2012). A vital part of this workforce alignment is to re-train current employees in new technologies such as AI (Pederson, 2024). According to a recent survey of C-suite executives, workforce skills are trailing behind investments in AI (Skillsoft, 2024). In addition, the majority of employees want more AI-related training opportunities to advance their careers (Pederson, 2024).

Imparting knowledge of new technologies to the workforce is expensive and time-consuming, and many business leaders expect their employees to learn on the job (Whiting, 2020). However, AI requires a strong foundation in statistics and programming and involves a myriad of algorithms that are not easy to learn and apply on the job. The existing literature and case studies have investigated how to impart AI skills in an academic setting (Bačić et al., 2023; Shi et al., 2024; Zhang et al., 2024); however, very few studies address the unique challenges of training high-performing employees on the job (ElSayary, 2023). Business leaders always focus on increasing the economic value of their firms, so losing valuable employee work time to training and education requires strong justification. Therefore, in a business setting, a return on training investment would motivate managers to prioritize reskilling employees. Also, in contrast to a university setting, employees have not been in a classroom setting for many years, and in some cases, decades. This poses unique challenges. Complex and transformative topics such as AI may not be well-suited for the lightweight (i.e., short-term) learning and development approach that firms generally employ for reskilling. On the other hand, expecting busy and productive employees to take valuable time off to go to a university setting to acquire new concepts may not be considered a viable option for many.

Traditionally, universities train students for entry-level positions and leave reskilling productive employees to companies' learning and development departments. With the rapid obsolescence of information technologies, there has been an increase in demand for reskilling the current workforce (Pederson, 2024). While this creates an opportunity for academic institutions, they must adopt a pedagogical approach different from the one used to teach traditional students. It is against this backdrop that we investigate the following research question: *How do we effectively impart transformative new technologies such as AI/ML to the workforce?*

Our study outlines an efficacious approach involving industry-academic collaboration to further an organization's aspirations of training its key domain experts in AI/ML and promoting a digital mindset. Specifically, a carefully crafted curriculum anchored in the theoretical underpinnings of Kolb's Experiential Learning model was used to reskill domain experts in a large telecommunications company (Kolb, 1976, 2014). We used a case study research method to elucidate the nature of the collaboration, the challenges that were faced, and the benefits that accrued to both the university and the firm through this partnership.

Our paper makes several contributions. First, it demonstrates how an experiential learning approach that follows the learn-apply-reflect cycle accelerates the acquisition and reinforcement of AI/ML concepts and skills and enables employees to understand when and under what conditions they can be used. Second, the key takeaways of this case study are invaluable to both researchers and practitioners alike. The lessons learned unravel many issues that academic staff members can investigate to deepen our understanding of what organizations must do to reskill their employees and reinvent themselves digitally. Further, practitioners can use these lessons to guide their efforts in promoting a data-driven culture within the organization. Finally, an unanticipated but desirable outcome was the diffusion of a digital mindset across the organization as the trained employees shared their learning with other employees in the organization.

The remainder of the paper is organized as follows. The next section provides a review of the literature on AI/ML skill development and introduces Kolb's experiential learning model. After that, we present our research design including the context of our study. Subsequently, a description of the program development and delivery process will be discussed. Section five focuses on data collection and interpretation of our findings for industry and academia. The final sections discuss our contributions to research and practice, future work and conclusions.

2. BACKGROUND LITERATURE

The section briefly reviews the reskilling literature and provides an overview of Kolb's model of experiential learning, which provides the theoretical foundation for the reskilling program used in this study.

Reskilling the workforce is not a choice but a strategic imperative that can provide a competitive advantage to firms. According to the World Economic Forum (Wood, 2023), it is expected that 23% of roles will experience changes in the coming five years. A detailed survey of Industry 4.0 (Li, 2022) concludes that employees need to pick up new skills on the job. The most important of the new skills is the ability to learn and adapt to AI/ML in the workplace (Ameen et al., 2022; Bodea et al., 2024; Morandini et al., 2023).

2.1 Previous Literature

Previous literature on acquiring new AI/ML skills highlights the importance of educating and preparing students in university settings for the future. For example, Bačić et al. (2023) detail their experience in building a data analytics graduate certification; Zhang et al. (2024) explore how to train technical and non-technical students in data mining; and Shi et al. (2024) highlight a new report-oriented teaching method for business intelligence courses. Liu and Murphy (2021) put forth a method of providing both technical and soft skills training to graduate education, whereas ElSayary (2023) investigates the impact of developing teachers' digital competence. Although several papers highlight education programs for professionals on the job (ElSayary, 2023; Liu & Murphy, 2021), the unique challenges posed by reskilling in AI/ML have not been addressed adequately. Recent studies by Paul and MacDonald (2020) and Stanton and Stanton (2020) highlight the importance of connecting industry needs with coursework in AI/ML. However, there is a paucity of studies that highlight the development and delivery of a successful AI/ML curriculum geared toward reskilling working professionals.

Learning AI/ML is not an easy undertaking. AI/ML is an interdisciplinary field that rests on the foundations of mathematics (e.g., linear algebra), statistics and probability, computer science (specifically, programming and algorithms), and computational linguistics (e.g., natural language processing or NLP) (Mike et al., 2023). There is a myriad of concepts to be learned, ranging from data preprocessing to feature engineering, model building, and evaluation. In our experience, classroom instruction and homework assignments alone are not adequate to provide the depth of understanding required of data scientists. Furthermore, it is not enough to learn the algorithms underlying supervised, unsupervised, and reinforcement learning techniques. The participants also must understand how to identify problems that lend themselves to AI/ML. Problem formulation is yet another challenging task, as students rely more on their experience and past methods to solve problems. We developed a learning model based on Kolb's experiential learning theory to facilitate reskilling industry professionals in AI/ML skills.

2.2 Kolb's Experiential Learning Theory (ELT)

Our collective experience in teaching AI/ML suggests that an iterative/cyclical approach that facilitates the concomitance of formal instruction, praxis, reflection, and subsequent assimilation of knowledge is more effective than a week or two of intensive training in machine learning with little time for practice and experimentation. Kolb's (1976) Experiential Learning Theory (ELT) provides an appropriate framework to design the instructional model to teach AI/ML in a corporate setting. According to Kolb (1976), learning occurs in a four-stage cycle. These are concrete experience (CE), reflective observation (RO), abstract conceptualization (AC), and active experimentation (AE). The learning process starts with CE, when individuals learn new concepts and/or immerse themselves in a new experience. They then reflect on this new concept or experience and assess it from different perspectives during the RO stage. Such reflection enables the individual to gain a deeper level of understanding of the concept or experience during the AC stage. Finally, during the AE stage, the individual applies the new knowledge to solve problems, thus creating a continuous cycle of learning and applying, leading to further enhancement of knowledge.

Kolb's ELT has been widely used in the field of education (Grøder et al., 2022; Hall, 2018). The appropriateness of this theory for our study may be inferred from its ability to explain learning and ideation in phenomena such as test-driven development (Bhadauria et al., 2020) and entrepreneurship (Corbett, 2005; Gemmell et al., 2012). The process of learning concepts in the classroom, and subsequently a) gaining concrete experience by applying it to a specific problem; b) reflecting (either through observation or by discussing with faculty) on how the concrete experience aligns with current understanding; c) abstracting from insights gained through reflection; and d) experimenting with the new-found generalized concepts actively resonates with the articulation of Kolb's iteration-based ELT in both test-driven development (Bhadauria et al., 2020) and "entrepreneurial ideation" (Gemmell et al., 2012). We developed the learn-ideate-apply-reflect model of learning based on Kolb's ELT, which forms the basis of our reskilling program. This will be described in section four. In the next section, we will outline the context of our study and research design.

3. RESEARCH DESIGN

We used the case study research method (Yin, 2009). This research methodology is well-suited for studying a contemporary phenomenon in its natural setting. The case study research method has been extensively used in IS research to investigate transformative organizational phenomena such as the adoption of CASE tools (Orlikowski, 1993) and agile software development practices (Nerur et al., 2005). The case study approach gave us a unique opportunity to observe and investigate the evolution of AI/ML capability as well as its dissemination through the organization as it unfolded. Specifically, being embedded in a real context allowed researchers to delve into details and gain insights that would have been difficult to obtain through other empirical means such as surveys.

A single case design was employed. The North American division of Ericsson, a large multinational telecommunications company, was the site of our study. Ericsson manufactures cutting-edge mobile communication networks that form the foundation of innovations. In 2023, Ericsson employed over 100,000 people and generated revenues exceeding 24 billion USD. The company has recognized that, with the explosion of data driven by the adoption of 5G technology, many current practices relying on traditional problem-solving methods will soon become inadequate. Furthermore, new technologies, such as 5G Advanced, will use machine learning to adjust networks to environmental demands (Toskala, 2020). The future 6G technologies, which are being standardized by Ericsson and which are called cognitive networks, will be fully automated through advanced machine learning and prediction to identify patterns in resource utilization and optimization in real time. Nowadays, traditional telecommunications corporations focus on developing AI/ML native air interfaces as network applications become more complex. Therefore, Ericsson focuses on developing new AI/ML technologies to tackle the challenges posed by 5G, 5G Advanced, and 6G mobile networks of the future more effectively.

In its efforts to become a data-driven organization, Ericsson built a large team of data scientists and formed an AI R&D center. These new hires included novice data scientists as well as experienced ones; however, very few had experience in telecommunications. Due to the complexity of knowledge in the telecom industry, employees often spend years to acquire domain expertise. The initiative to embrace and apply data science within Ericsson was promoted by pairing telecom domain experts with data scientists from the AI R&D teams. While the domain experts understood the limits of their existing tools, they had high expectations from the solutions offered by AI/ML. The newly hired data scientists, although well-versed in the latest analytic techniques, did not fully comprehend the complexity of the domain and the problem space.

Within the first year of the AI R&D strategy, it became apparent that more time would be needed to achieve the expected results. In some cases, data scientists resigned after a significant investment by Ericsson due to misalignment of expectations and project outcomes. Loss of these experts led to delays in innovation and decrease in company efficiency. Additional approaches were needed to drive the transformation. As an alternative approach, managers encouraged their engineers to self-learn analytics techniques through online training programs. Although this method was successful to some extent, change was difficult, and there were problems in motivating employees to learn and in bridging the gap between acquiring knowledge and applying knowledge to problems in their domain. A different approach was needed to integrate data science skills into the organization. The company approached a major university for a solution, and a comprehensive program was developed to train selected employees in AI/ML skills and to facilitate an organization-wide change in their approach to problem-solving and decision-making. Ericsson provided an ideal setting to investigate the effectiveness of our approach to reskilling employees in AI/ML-related skills.

4. RESKILLING PROGRAM DEVELOPMENT AND DELIVERY

To be successful, a reskilling program must meet the objectives of the organization. This requires collaboration among university faculty, senior managers in the organization, and employees who participate in the program. The program design and delivery process are presented in this section.

4.1 Identifying Objectives and Selecting Students

The following objectives of the program were identified after consultations with the executive management of the company: (a) to train Ericsson's domain experts in AI/ML techniques, (b) to enable them to apply these techniques to solve real-world problems to promote the immediate transfer of learning to the workplace, and (c) to facilitate the dissemination of AI/ML skills across the organization.

We consulted with senior and mid-level management to operationalize these management objectives and to refine the objectives further into a process for selecting, preparing, and training the domain experts in AI/ML techniques. They were clear in articulating that any reskilling should be within the firm's work processes to ensure minimal disruption to their productivity. The managers also thought that employees did not have spare time to get educated in new technological tool full-time. Therefore, their learning should be applied quickly to further the company's business goals. Finally, mid-level management generally sought a quick return on their reskilling investment and was reluctant to allow employees to take long periods away from their work obligations and duties.

As shown in Figure 1, a process was instituted to operationalize the objectives set by the managers and prepare the students to start the graduate coursework. Potential students were selected by upper management from a pool of domain experts across various units of the organization. These students presented details of their educational background, domain skills, duties at work, and the value that AI/ML skills would bring to their department. Supervisors would then update and forward the selected applications to the department head for consideration and funding approval. Upon approval, potential students would be interviewed by instructors to assess their readiness for the rigors of graduate-level coursework.

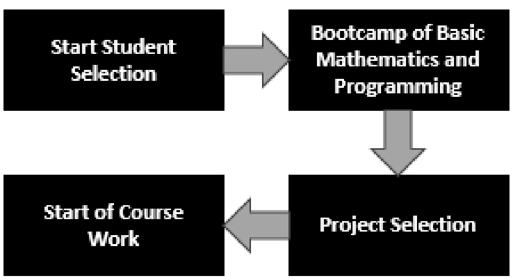

Figure 1. Student and Project Selection Process

Once the students were selected, the instructors conducted a one-day bootcamp in preliminary mathematics and programming. Although these students were from a technical background and were involved in advanced scientific problem-solving in their jobs, some basic technical skills had to be revisited in a training setting. Also, a technical bootcamp ensured that students were well-prepared to take advanced graduate-level courses on AI/ML.

Finally, the selected students were asked to solicit projects representing real business problems from different departments and choose a subset of them based on their interests and domain expertise. Since AI/ML skills were new to the firm, instructors met with the students and project sponsors (who owned the business problems) to help select and refine projects that were suitable for an AI/ML type of solution.

4.2 Program Design

The program and courses were designed to address specific challenges identified by Ericsson. A set of four graduate-level three-credit-hour courses was selected for delivery. Upon successful completion, participants earned a 12-credit-hour certificate. Graduates of the program had the option to use the 12 credit hours towards completion of a Master's degree at the university. The course content was developed collaboratively by the instructors and Ericsson to ensure its relevance and applicability to the organization's specific needs. A summary of the course descriptions is provided below:

4.2.1 Principles of Business Data Mining. This course introduces machine learning and statistical tools for practical data mining, focusing on identifying and describing structural patterns in data. Key topics include techniques for data preprocessing, cleaning, reduction, transformation, and visualization, as well as methods for classification, clustering, and association rule mining.

4.2.2 Advanced Methods for Analytics. This course covers advanced statistical inference techniques tailored for business analytics. This course prepares students to produce and interpret predictive analytics, apply statistical information, and employ evidence-based decision-making in managerial contexts effectively. Topics include probability, statistical distributions, confidence intervals, and hypothesis testing.

4.2.3 Data Science / Machine Learning. This course provides a comprehensive exploration of data preprocessing, feature engineering, and machine learning concepts using Python. Key topics include supervised machine learning algorithms such as K-Nearest Neighbors (KNN), Linear, Ridge, and Lasso Regression, Logistic Regression, I Bayes, Decision Trees, Ensembles (i.e., bagging and boosting), support vector machines (SVM), and Artificial Neural Networks. Other topics covered are natural language processing (NLP) techniques such as clustering of unstructured text, classification (e.g., detecting fake news) with explainability, named entity recognition (NER), and topic modeling. Finally, students learn to apply unsupervised algorithms, such as K-Means, hierarchical clustering, DBSCAN/HDBSCAN, and t-SNE, to make sense of complex unlabeled data.

4.2.4 Big Data Analytics. This course focuses on advanced machine learning techniques and deep learning algorithms using popular frameworks such as Tensorflow and PyTorch. Students receive hands-on training on deep learning models/architectures, including sequential and functional models, convolutional neural networks (CNNs), recurrent neural networks (RNNs), long-short term memory (LSTM), transformers, autoencoders, and generative adversarial networks (GANs). Advanced NLP techniques that inspired the development of Large Language Models (LLMs) are also covered.

To enhance the relevance and applicability of the program, homework assignments were tailored specifically for Ericsson, utilizing problem statements and datasets provided by the company. This approach ensured that students could apply their newly acquired skills to address real-world business challenges faced by Ericsson directly. Additionally, the assignments were reviewed and regularly updated in collaboration with Ericsson to maintain their relevance and alignment with evolving business needs.

4.3 Program Delivery

Using Kolb's (2014) theory, we developed the learn-ideate-apply-reflect model (see Figure 2), which provides the basis for the reskilling program. Participants completed four learning units. Each unit was delivered over six weeks and followed the learn-ideate-apply-reflect model. Class size was limited to a maximum of fifteen to ensure close interaction between the instructor and the students. Enrollment was restricted only to Ericsson employees so that any information that can be classified as intellectual property in the projects could be openly shared among team members. Classes were held at the Ericsson campus on a Friday afternoon and a Saturday morning to minimize disruption to employees' work schedules.

Program participants were assigned to cross-disciplinary teams that worked on the projects. The projects served two key purposes: (1) they allowed the participants to apply skills learned in the classroom to solve problems relevant to Ericsson, and (2) they engaged Ericsson's business unit managers and project sponsors, encouraging them to provide ongoing feedback on the effectiveness of the newly acquired techniques and actively participate in the reskilling program. Although these projects did not have the objective to provide a financial return to the company, some of them led to significant financial savings.

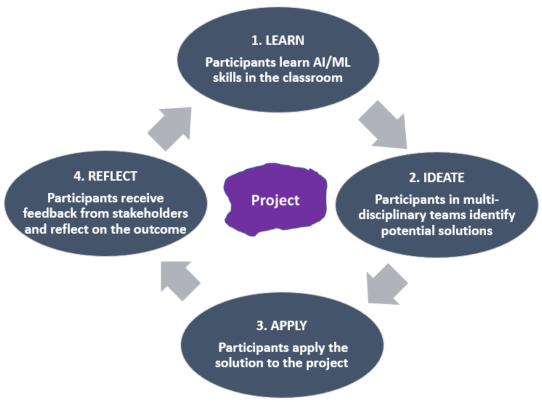

Figure 2. Process Model of the Reskilling Program

Program participants learned new skills in the classroom. Cross-functional project teams then applied these skills to identify solutions to the projects that were assigned to them. Working with participants from different functional areas exposed team members to a multiplicity of viewpoints and enabled the teams to draw upon diverse skill sets during the ideation stage. Each team was able to develop and experiment with alternative solutions iteratively based on instructors' ongoing feedback. After each learning unit, teams presented their results to sponsoring managers and senior managers and received their feedback. They were then able to reflect on the results and improve the solution based on incremental learning and managers' and instructors' feedback. This cycle of learning, problem-solving, and acting on immediate feedback ran concurrently throughout the program, fostering reflective practice (Schön, 1983).

The entire process was designed to engage employees at all three organizational levels—domain experts learned new skills and used them to solve business problems, mid-level managers served as project sponsors and benefitted from their teams' acquisition of new skills, and senior managers acted as champions of the program. The program started in Fall 2019. As of Fall 2024, six cohorts have completed the program successfully, and a seventh cohort is currently active in the training program. Graduates of the program have completed several projects for their sponsoring departments and are actively leading efforts to foster a culture of data-driven decision-making within their departments.

Figure 3 provides a selected list of projects completed by the program participants. These projects offer valuable insights that have guided decisions to optimize supply flows, improve efficiencies of field operations, optimize workflows in the Network Operations Center, and improve supply forecasts to drive more accurate planning. A project that quantified the value of automation has led to improved decision-making on how best to use a limited budget to automate processes. A project that evaluated purchase orders led to meaningful financial improvements that will continue well into the future. The current and future financial impact of these projects is estimated to reach several million dollars.

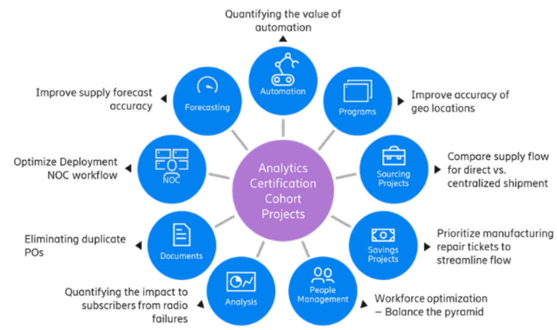

Figure 3. A Sample List of Projects Completed by Program Participants

5. DATA COLLECTION AND ANALYSIS

Semi-structured interviews using open-ended questions were used to collect data. An interview protocol was developed by the authors to guide all the interviews. Two of the authors participated in the interviews. The transcripts of the interviews were transcribed by three of the authors. We chose interviewees from three different levels in the organization: graduates of the reskilling program (who are employees of the organization), managers/project sponsors, and senior managers. Interviewees from these three groups had different perspectives and expectations regarding the program and how it would contribute to the organization's goals. Graduates hoped to learn new AI/ML skills that could be applied directly to their work problems. Managers/project sponsors expected their project goals/solutions to be accomplished more efficiently and cost-effectively. They also expected their employees to learn new skills and bring new perspectives to problem-solving and decision-making. Senior management wanted AI/ML skills and knowledge and a data-driven decision-making culture to spread throughout the enterprise. We expected to get a comprehensive view of the phenomenon by interviewing these three groups of informants.

A total of 13 people participated in the data collection process—7 graduates, 4 managers, and 2 senior managers. Table 1 provides information about the interviewees and their years of industry experience.

Each interview took 30 to 60 minutes to complete. The interviews were recorded and transcribed with the permission of the participants. The transcripts were analyzed by the authors to draw conclusions about the effectiveness of the learning process and the diffusion of knowledge through the organization. The results are clear: they support the conclusion that the reskilling program was a success. All three groups of interviewees confirmed this. According to a senior manager, "*Previously we did not have the skill sets or compute power to deal with and leverage this large amount of data. But now we are at an inflection point where everything is coming together, i.e., both people skills and compute power. As a result, we are using AI/ML for more day-to-day work.*" The interview responses also offered early evidence about diffusion of the knowledge and skills throughout the organization. Our analysis provides insights into some of the key factors that led to the success of the program and highlights some of the lessons learned.

Role	Number of participants	Average number of years of experience in the industry
Graduate	7	18
Manager/ Sponsor	4	21
Senior Manager	2	22.5

Table 1. Summary Information About Interviewees

5.1 An Experiential Learning Environment Is Paramount to Success

Consistent with the experiential learning model articulated by Kolb (2014), the courses and assignments were designed in a manner that facilitated active learning. Unlike a traditional pedagogical setting, students in the program went through learn-ideate-apply-reflect cycles in each of the learning units, as discussed earlier. These iterations occurred within and across courses as students gained new perspectives and skill sets and applied them to refine solutions for their ongoing projects. According to one graduate, "*We started the certification program with a very complex problem and improved the solution over different courses.*" The homework problems were designed carefully to simulate problems employees were grappling with at the workplace. Frequent discussions with the professor and the feedback they received from the project sponsor and/or senior management during and at the end of the course led to opportunistic solutions. More importantly, this process fostered a shift in mindset that gradually overcame inherent biases against new ways of approaching problems. This process fostered a "double-loop learning" mindset (Schön, 1983) which encouraged experimentation and intellectual inquiry and questioned entrenched assumptions.

5.2 Variety Enhancement Delivers Expanded Capabilities

Ashby's (1956) *Law of Requisite Variety* and the subsequent works of Stafford Beer (Beer, 1984) posit that an organization must have the requisite variety of information to perform well in an uncertain and complex environment. Firms with high requisite variety can exercise a broader range of actions and responses when faced with perturbations in the environment. In particular, Beer (1984) argues that *variety enhancement* is the means to acquire expanded organizational capabilities that will enable the firm to have control over its operations. Examples of variety enhancement include expanding the skill sets of employees, sourcing ideas from the crowd, creating cross-functional teams, and forging partnerships, to name but a few. As a graduate pointed out, "*The interactions with the others in the different cohorts is very useful to network with a common cause/interest.*" Program participants were drawn from different business areas across the organization, thereby fostering a learning environment that was characterized by divergent viewpoints and a plurality of problems that many of them would never have been exposed to had they been in their functional silos.

5.3 Understanding That Data-Driven Solutions Can Unlock Business Value Is Important

Deep-rooted practices and entrenched routines can impede an organization's efforts to instill a data-driven culture. The problem is exacerbated by an inherent bias against new approaches as well as distrust of insights provided by AI/ML, particularly when they are counter to the intuition of the decision-maker. As a graduate remarked, "*Our traditional way of solving problems is always to identify the root cause for each problem that comes to the team.*" For example, before attending the program, a group of employees had been grappling with a problem that did not have an apparent solution. Following practices to which they were accustomed, the employees of the company delved deeper into an aspect they believed to be at the root of the problem. Subsequent interactions among the professors, employees, and the project sponsor during the program led to a more holistic, data-driven solution. The program has not only imparted skills and concepts that employees are now using effectively but it has also served as a catalyst for AI/ML projects that can reduce costs and/or increase revenues. There is increasing evidence that the success of data-driven approaches has inspired confidence among managers and increased their trust in these new ways of solving problems. The exposure to AI/ML has also opened their minds to possibilities (e.g., new types of problems) that would have been hard to conceive otherwise.

5.4 Talent Management Is Critical

The gap between the demand and supply of AI practitioners and data scientists is steadily widening, making the program participants prime targets for recruitment. The deep domain expertise that they possess, combined with their newly acquired AI/ML skills, makes them highly marketable. Therefore, it is important to establish incentives to retain such talent. Among other things, we observed a strong desire among program participants to be involved in challenging projects where they can utilize their newly acquired skills. It is important to create an environment where such employees are valued and given the freedom to express their ingenuity. In the case of Ericsson, many program graduates have advanced their careers by applying their new skills to challenging roles, reinforcing the value of their personal investment in the program. A manager noted, "*Some of the employees who achieved the certification have moved to other groups within Ericsson as a result of attaining their new skills.*"

5.5 Support From Senior Management and Project Sponsors Is a Driver of Success

We cannot overstate the importance of active participation and support of senior management and project sponsors during the program. Project sponsors need to be sensitive to the fact that participants are under considerable duress during the program, as they are expected to fulfill demanding course requirements and meet their project deadlines simultaneously. In addition, the constructive feedback and encouragement they provide motivate learning and help participants become reflective learners who think more deeply about how to apply the skills taught in class. Support of senior management should focus on motivation and goal setting rather than providing specific directions for completing tasks. A project sponsor strongly emphasized the following: "*The project sponsor should spend more time assisting the team in their quest and spend less time directing them to find a specific solution*."

5.6 Dissemination of AI/ML Skills and Data-Driven Decision-Making Culture

One of the objectives of the program was to establish an organization-wide, data-driven culture. This experience revealed that data science and AI have gained traction in Ericsson. Graduates of the program have taken the initiative to form special interest groups on AI that have fostered a climate for active knowledge exchange between Ericsson employees and AI/ML experts from industry and academia. They organize regular lunch-and-learn sessions that allow other Ericsson employees to learn about AI/ML skills and their application to relevant business problems. These sessions are quite popular and very well attended and have been instrumental in spreading AI/ML knowledge and skills throughout the organization.

Furthermore, graduates not only bring new expertise to their projects but have also become informal consultants to other teams, imparting their newly acquired knowledge and guiding team members in developing novel solutions. This has been confirmed by many graduates of the reskilling program. According to a graduate, "*I advise other teams' AI/ML projects which helps in diffusing what I have learned to teams that don't necessarily have deep AI/ML knowledge*." Another graduate asserted, "*I teach AI/ML concepts to my colleagues. I have been able to coach my manager on the importance of these new methodologies. I have also presented the projects to senior leaders in North America and other global regions to show what we can do with this new AI/ML technologies to solve our business problems*."

Managers in the organization have noticed the graduates' adoption of this new data-driven problem-solving approach. As a senior manager observed, "*The cohort graduates think differently now and are motivators for others to think differently. Their problem-solving approach is more proactive instead of reactive.*" He further added, "*Some cohort members have moved to new opportunities internally and are motivated to work on new problems and areas proactively.*" As mentioned earlier, such internal mobility within the organization has been a strategic effort by the company to better manage its AI/ML talents. This strategy has not only helped retain talents but also facilitated the spread AI/ML skills throughout the organization. This diffusion of AI/ML skills and knowledge through formal and informal channels has accelerated learning across the organization and fostered a data-driven mindset.

5.7 Further Industry Insights

Our analysis provided some additional insights that go beyond the effectiveness of the AI/ML reskilling programs. While AI/ML skills have been the focus of our attention, enterprise data management is a key to delivering business value through the application of these techniques (Roh et al., 2019). Graduates of the program became aware of the critical role of data organization and management, as evidenced by the following comments. According to a graduate, "*We found that data being collected by Ericsson is conducive for the display of dashboards. The data is not appropriate for AI/ML algorithms and prediction. Based on my new knowledge I am influencing how and what new data to collect in my organization with my management*." Another graduate stated, "*We have a lot of data in our organization, but now that I have learned how to use data for decision making, I find that I need a lot of subject matter experts to help me understand what this collected data means so that I can use it for solving our business problems.*" When employees understand the value of data and take proactive steps in data organization and management, it is likely to lead to better outcomes in creating business value using AI/ML technologies. This highlights the need to add a data management learning module to the AI/ML curriculum.

Another interesting finding is the role of the reskilling program in boosting employee morale. According to a senior manager, "*A surprising finding is that having people work on new areas (AI/ML) who have deep telecom experience really helps boost their morale. People learn new areas and implement something that is hot like AI/ML, and they feel very rewarded.*" Thus, an in-house reskilling program not only imparts new skills to employees but also can help them feel appreciated.

5.8 Insights for Academia

Effective collaboration and interaction with industry stakeholders are crucial for the success of reskilling initiatives. A key factor in achieving this success is tailoring the course content to the specific contexts in which it will be applied. While the foundational principles of training in AI/ML skills are broadly applicable, the practical use of these technologies is highly context-dependent. Customizing homework assignments, utilizing company-specific data, and designing projects within the organization's domain proved instrumental in maintaining student engagement with the course material and ensured that the company benefitted from student projects. Such customization also limited the enrollment in a class only to employees of Ericsson due to intellectual property protection policies.

To maximize the impact of reskilling efforts, instructors need to extend their engagement beyond traditional academic interactions with students and involve company management in course development, project selection and assignment design. Reskilling initiatives are often resource-intensive for organizations, and managers may hesitate to allocate employee time to formal training, favoring on-the-job learning instead (Whiting, 2020). Therefore, gaining managerial support is essential. This can be achieved by demonstrating the tangible benefits of reskilling and ensuring that coursework aligns with the organization's priorities. Selecting projects relevant to sponsoring managers and conducting regular reviews of proposed solutions foster sustained managerial engagement and underscore the value of the training program.

To sum up, the reskilling program has been very effective in not only imparting AI/ML skills to employees but also has resulted in fostering the diffusion of AI/ML expertise and promoting a data-driven decision-making culture within Ericsson. The fact that several traditional areas, such as business development, contract negotiations, and pre-sales, are beginning to use AI/ML techniques to quantify the tradeoff between risk and reward confirms this. Therefore, there seems to be growing acceptance of these technologies within the organization. Our findings and lessons learned are summarized in Table 2.

Summary of Findings and Lessons Learned
Experiential Learning Environment Create an experiential learning environment that reinforces learning through application to ensure successful learning outcomes.
Cross-Disciplinary Teams Cross-disciplinary teams bring diverse perspectives to the learning environment. They also facilitate the rapid spread of AI/ML skills throughout the organization.
Data-Driven Approach Building confidence in a data-driven approach to problem-solving among employees and managers is critical for the adoption of AI/ML techniques within the organization.
Talent Management A talent management program that encourages employees with AI/ML skills to apply their newly acquired skills across departmental units - and rewards them for their contribution - enhances retention and benefits the organization.
Senior Management Support Support from senior managers and business unit managers is crucial to the success of the reskilling program and its participants.
Collaboration Is the Key to Success Collaboration among academics and industry stakeholders at every stage of the reskilling program—from planning to curriculum design to program delivery—is crucial for the success of the program.

Table 2. Summary of Findings and Lessons Learned

6. CONTRIBUTIONS AND FUTURE DIRECTION

Our study makes several contributions to research and practice. First, an experiential learning environment is paramount when an organization aims to reskill its workforce with a new technological tool such as AI/ML. Second, an organization must carefully select its student group, ensuring it includes individuals from diverse business areas who understand and believe in the power of new technologies (such as AI/ML) to drive business value. Moreover, it fosters a divergent learning environment with like-minded participants which would not have been possible otherwise. Third, management should incentivize participants in a way that encourages them to stay after acquiring new skills. They should also provide opportunities for them to use their acquired skills in new and exciting work opportunities. This helps safeguard management's investment in their employees and keeps the employees motivated. Another key to success is the role of project sponsors: they need to have patience and provide the necessary resources for students to experiment instead of giving specific work assignments. Finally, these reskilling efforts led to the spread of AI/ML skills to other employees within the organization.

For academic staff and industry practitioners, we provide a methodology template that can be successfully followed to reskill the workforce in new technologies. It also provides a model of collaboration between industry and academia to address the ongoing demand for reskilling driven by rapid technology obsolescence. The implementation of the experiential learning environment is technology-agnostic and can be applied to any future revolutions in digital technologies.

Our study is not without its limitations. While it provides strong evidence supporting the efficacy of the learn-ideate-apply-reflect model in reskilling the workforce within a single firm, the case study design limits the findings to this specific context. Future research conducted in diverse organizational settings and incorporating surveys could provide deeper insights into the model's effectiveness, yielding more generalizable results.

Another promising avenue for future research involves adapting our template, with creative modifications, for application in traditional university classroom settings. Although challenges may arise due to the diverse backgrounds of students, certain elements of our methodology could be applied. Students from particular industries, such as retail, can benefit from the course customization strategies proposed in this paper for learning AI/ML skills.

7. CONCLUSIONS

By all accounts, rapid digitalization is transforming businesses in ways that arguably contradict the management principles that have been the foundation of organizations for decades. AI and ML are at the heart of this revolution. Building an AI-powered organization, a necessity rather than an option in a hypercompetitive business environment, is not a trivial endeavor. In addition to the acquisition of new talent and the reskilling of the existing workforce, major shifts in mindset and culture facilitated by senior management are critical for success.

In this paper, we demonstrate the importance of an experiential learning-based approach to reskill employees in AI/ML skills. The takeaways that we articulate are invaluable to companies that are inevitably embarking on the journey of infusing a data-driven ethos to unlock business value. Our experience confirms the widely-held belief that senior management should be the catalyst for large-scale changes within firms. Furthermore, fostering an environment conducive to active experimentation and reflective practice while undergoing training can accelerate learning and spread a data-driven mentality throughout the enterprise. Above all, the active engagement of faculty members and their collaboration with employees, senior management, and project sponsors engenders a generative, "double loop" learning environment in which prevailing assumptions are continually questioned, and novel problem-solving approaches are explored. Finally, our study demonstrates how industry and academia can successfully collaborate to develop an AI/ML skilled workforce.

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