White Paper

Results of National Association of Manufacturers (NAM) member interviews around ML and AI

September 23, 2020

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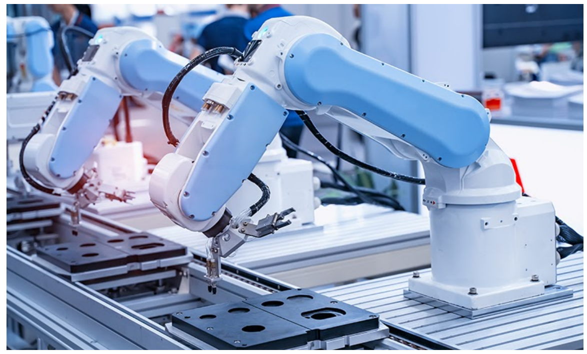
1. BACKGROUND AND PURPOSE



As automation technologies, sensor hardware, network connectivity, and computing power become more accessible to companies, the manufacturing industry is preparing for change. Machine Learning (ML) and Artificial Intelligence (AI) have enormous potential to turn huge pools of accumulated sensor and operational data into useful insight at all levels, from business intelligence to equipment configuration. Mass network connectivity allows this information to be collected from ubiquitous sensors and acted upon in real time. Access to computing power in the cloud makes processing this data both possible and affordable. Robotics and control automation technologies close the loop, allowing these informational insights to translate back into coordinated physical action on the factory floor. To emphasize the extent of such a change, proponents of this vision liken it to a fourth industrial revolution: Industry 4.0.

This framing puts technology in the spotlight, and indeed technology is both enabling and driving the change. In practice, however, the transition from “Industry 3.0” to “Industry 4.0” is heavily dependent upon the skills of the workforce. What knowledge and skills do workers need to see this transition through? What skills will allow them to thrive both during and after it? Who needs which skills? These answers are contingent, of course, on the paths companies have charted for themselves toward an AI future. But if a sectoral “Industry 4.0” transformation is under way in the United States, it has been far from overnight. Where are manufacturers really at in their adoption of ML and AI technologies? What are their goals? What obstacles are standing in their way? And how can the American workforce be best prepared to help both companies and workers succeed?

This paper shares the results of Carnegie Mellon Robotics Academy’s (CMRA) interviews with six companies that range from AI technology vendors to manufacturers. The interviews were conducted as part of an NSF Convergence Accelerator-funded research project called *Rapid Dissemination of AI Microcredentials through Hands-on Industrial Robotics Education* (RD-AIM-HIRE) to design and scale new methods of training to meet the technical workforce demands of the near future, especially where current systems were not working well.

The RD-AIM-HIRE team used a purposive (“corner”) sampling method to arrange a small number of semi-structured interviews, in collaboration with the nonprofit Manufacturing Institute, with manufacturers and manufacturing-related companies. These companies were selected to be of different sizes, in different sub-sectors, and have experienced different degrees of success with ML and AI at the time. The interviews focused on building an understanding of ML/AI applications companies were/had/were interested in pursuing, the nature of the internal apparatus (e.g. department) that conducted ML/AI work, barriers they had encountered to success in ML/AI adoption, and the workforce needs they anticipated around ML/AI over the course of the next few years.

1.1. Methodology

With the help of the Manufacturing Institute's (MI) Center for Manufacturing Research, companies in MI's network were contacted to ask if they were willing to partake in an interview that would take 30 minutes to an hour. Initial sampling criteria were to include vendors of AI technologies, and companies of different sizes that had active or past ML/AI efforts (successful or unsuccessful). Ultimately, no small manufacturers were included because we were unable to locate any with current or near-future plans for implementing AI technologies.

Individual interviewees were employees of each company with knowledge of the company's floor operations, current technology used in the manufacturing process, plans for their workforce, and plans (if any) of their use of AI. Most companies connected us to heads of operations, Chief Technology Officers, floor managers, or combinations of individuals in those roles.

Companies spanned the following sectors:

- Robotics
- Power
- Heavy Electrical Equipment
- Automation Technology
- Automotive Components
- Aluminum Products
- Inks and Coatings

AI Technology vendors were involved in:

- AI Intelligence Solutions
- IIoT Solutions

Interviewed individuals held the following positions:

- Head of Digital
- Digital Team Staff
- R&D Operations Manager
- R&D Operations Staff
- Chief Information Officer (CIO)
- Chief Digital Officer
- Senior Advisor

Two interviewers from the Carnegie Mellon Robotics Academy were present on each call, along with a representative from MI who had made the initial connection, and the interviewee(s). Interviews were conducted online through Microsoft Teams, following a semi-structured interview protocol. Interviews were not recorded. Instead, both interviewers took notes in real-time and frequently asked interviewees to confirm summaries of what they had said.

Questions that were asked during the interview included the following:

- Has your company adopted or investigated any technologies or equipment that make use of ML and AI? What parts of the business are using them?
- Does your company have a specific vision around ML and AI-based technologies currently?
- Picture your workforce company-wide 5 years from now. What would people need to know about ML and AI?
- Will there be employees displaced by the new technology or equipment? Do you have plans to reskill or upskill them? Does your company have a way of doing that today?

A full list of questions from the interview protocol can be found in the appendix.

1.2. Findings

1.2.1. Outlook and Vision for ML and AI

All the manufacturers we interviewed had similar views and expectations about the role and long-term potential for ML and AI in the abstract. All the interviewees were aware, and felt that others in their field were aware, that ML and AI would become valuable.

Awareness of the nature of ML as a data-heavy technique enabled by high computational power and network connectivity was ubiquitous. Manufacturers pointed out that even before AI, their equipment (and/or operators) have been collecting data such as temperature of equipment, estimated time taken, number of products created, and uptime, through, e.g. operational logs. They also know that the products that allow equipment to be connected (i.e. Internet of Things capability) were becoming increasingly inexpensive, and that ML/AI would allow this large set of data to be analyzed in real-time. They cited increases in computing power (i.e. cloud computing) as making integration of these technologies easier.

Short-term goals for ML were also relatively consistent. All the manufacturers in our sample framed a major goal of their analytics, ML, and AI efforts as finding ways to improve efficiency in the manufacturing process. In some cases, this meant smarter automated control of production equipment. In others, it meant improvements in operator interfaces to improve productivity, for example through natural language interfaces. Several manufacturers expected this direction of development to produce ML/AI systems that would eventually be trained to replace human operators for certain kinds of tasks, and strongly emphasized that their organizations had both plans and capability to retrain those workers for different positions.

Companies are on the same general page that ML and AI integration will be a long-term endeavor. One manufacturer of automotive parts said that they started just 3 years ago, but see that they're only starting to "scratch the surface of AI, Data Analytics, and Big Data". However, the concreteness of those longer term plans varied. While all the companies we interviewed had plans for Machine Learning in particular as a way of solving operational issues or increasing productivity, larger companies had invested more time and effort into preparing for entirely new categories of applications (e.g. novel applications of autonomous drones), as well as non-production applications like supply chain optimization.

The AI technology vendors we spoke to had, understandably, planned out to the farthest and broadest horizons. This was evident not only in the breadth of change they described, but also the specificity of language they used, differentiating strongly between terms like Industry 4.0, Machine Learning, Artificial Intelligence, Analytics, Automation, and Autonomy. The terms *automated* and *autonomous*, for instance were used more or less interchangeably by most of the manufacturers we spoke to, but was a brand-defining contrast for one the AI companies -- *automation*, according to them, is what people had been doing in programming machines to perform tasks; *autonomy* is a fundamentally different capability defined by the ability of autonomous systems to operate and improve themselves independently.

1.2.2. Adopting ML and AI

The AI technology vendors and consultants we interviewed pointed out that not all companies followed the same pathway to ML and AI technologies, but successful ones started with a specific, real problem to be solved, for which ML/AI was a good fit. The opposite approach -- searching for problems to solve with AI -- had not been productive for their manufacturing clients.

But identifying good ML/AI applications is difficult. Manufacturers are not technologists and don't know all the ways ML/AI can be applied. On top of that, ML/AI is not the best solution to every problem -- there are often much cheaper and simpler ways of getting the job done. It may be that this combination of barriers -- manufacturers' incomplete knowledge of AI's applications, and the fact that the "sweet spot" for ML/AI applications today is small to begin with -- explains why one technology vendor framed the main blockage as addressable through "customer education" (i.e. building solution awareness), while internal and external consultants spoke of the difficulty finding good matches between problems and AI solutions (i.e. the sweet spot problem).

Our interviewees did mention a few ways that manufacturers tended to get started with ML/AI projects in practice. Sometimes companies would notice a competitor's success and attempt to replicate it. Other times a consultant would identify problems as part of an overall improvement plan, and propose ML/AI solutions for some of them. In one case, a floor worker identified a potential application.

Many other challenges followed. Managers needed to buy into the solution, including the business case around it. Operators needed to learn how to use the system. Floor workers often did not trust that the new technology was safe. IT infrastructure was a major barrier. The solutions themselves needed to take all of these into account throughout design, development, and implementation. Successful completion of the work hinged on a complex interdisciplinary collaboration involving combined expertise in data science, industry knowledge, and a company's day-to-day operations. One interviewee emphasized the importance of a "translator" who could coordinate such work.

It makes sense, then, that the technology vendors and consultants we spoke to emphasized the attention that needed to be paid to ensuring the right convergence of "physical, digital, people, and process" were present to justify adoption of advanced technology in each instance, and also to the uniquely tailored solution that needed to be developed at each company.

1.2.3. Current state of ML and AI efforts

All of the manufacturers we interviewed had begun down the path of ML/AI implementation, investing in specific applications to solve concrete problems with solid business cases. They were, however, in vastly different stages of progress in solving their respective challenges. Some were just beginning to capture and clean up data, while others were several years into focused development efforts around specific applications such as quality control inspection. They also differed significantly in terms of the scope of transformation they intended to achieve.

Organizational approaches. Companies have adopted different approaches to organizing expertise and personnel related to their ML and AI efforts. The larger companies in our sample had set up internal ML/AI research and development units. These units worked in conjunction with other production units throughout the company to explore and develop solutions to specific problems in context. The prevalence of this approach among large companies was corroborated by an AI technology vendor, who pointed out that most of the work they were doing at present was with dedicated R&D groups at large companies, and that they had not yet engaged medium-sized companies without such labs.

The ML/AI research unit approach was cited as successful by both the companies and consultants, but was not without drawbacks. It is essentially the traditional interdisciplinary engineering project approach, in which subject matter experts in constituent domains -- here, generally an ML expert and a process engineer -- gather data on a problem of practice, construct a model, and refine it. Accordingly, the primary difficulties reported in interviews mirror those encountered by interdisciplinary engineering projects in general: for example, that the data scientist on a project had trained a model with an incomplete understanding of how some of the data fields were used day-to-day among floor operators.

The medium-sized companies we spoke to, as expected, did not have R&D departments, and had instead adopted a targeted homebrew approach in which they identified a specific series of inefficiencies in production operations they wished to solve, and brought in consultants to provide spot expertise. One company knew that it was sitting on a large quantity of historically accumulated data including thermal chamber status and uptime, and wanted to use that data to begin training an ML model that would automate key control processes on primary production equipment to increase its efficiency. However, once this development effort began, the company realized that their data was "dirty" -- the uptime entries included shutdowns due to scheduled maintenance, and they eventually found out that equipment operators had been inattentively pressing certain buttons to clear an intrusive on-screen dialog rather than logging events as expected. While these difficulties are certainly surmountable, this example serves as a reminder that while the in-house approach is strong in terms of application authenticity, expert consultants do not cover all the bases, and are not cost-effective to employ for labor-intensive processes such as data scrubbing.

1.2.4. ML/AI AND THE WORKFORCE

Our final series of questions focused on gathering employers' perspectives on the workforce needs and impact of ML and AI technologies over the next few years. As would be expected, interviewees' responses generally followed their companies' plans around ML and AI within that timeframe, and thus reflected a diverse set of efforts and directions.

A few common elements appeared among the responses. First, all the employers expressed a desire for all workers to acquire some level of familiarity with ML and AI. This included understanding the "boundary conditions" of what AI can and can't do; and to become familiar with the importance of data, particularly around collecting and using the RIGHT data. Second, there was a theme of proximity to data processes -- everyone would be working with data, or at least working with someone who did. Companies whose efforts included ML/AI teams stressed the importance of interdisciplinary collaboration in teams that now included a data scientist. One interviewee suggested that business schools and data science departments should collaborate more closely within higher education. Smaller employers wanted their existing engineers to expand their skillsets to include statistics and data science, and knowledge of the requisite tools. The smallest company we spoke to, whose efforts were being held up by data quality issues, was keenly aware that they needed their operators to log events correctly on the machinery. These skills were in addition to the ones generally mentioned by employers when asked about desired employee skills, e.g. critical thinking, problem solving, and STEM skills.

Interviewees had considerably different thoughts on the ongoing relationship between workers and AI. Some respondents were pursuing ML projects that would, e.g. automate routine quality control inspections of outgoing product. One company with an active project of this type believed that the corresponding job positions would be eliminated over time because the computer systems would be able to perform the task in its entirety once sufficiently trained. They expected to fully retrain displaced workers using their existing internal apparatus. Jobs such as engineering, they suggested, would change to take advantage of the continual insights provided by ML and AI information systems to become "much higher level". Data scientists, of course, would always be needed. This contrasts somewhat with a different manufacturer's expectation that the ML/AI augmentation would make the actual work of operating machines easier, but shift the emphasis of operators' skillsets and responsibilities to ensuring clean data input.

Domain expertise of, e.g. production systems, was mentioned by multiple interviewees as a fundamentally hard thing to replicate or replace. One of the AI technology companies had made this a cornerstone of their approach, designing a toolchain specifically to enable such domain experts to train fully autonomous AI agents quickly and efficiently.

1.3. Conclusion

Interviews of executives and technology officers from six medium and large manufacturers and tech vendors as part of an NSF Convergence Accelerator project surfaced several patterns in their plans and efforts around ML and AI.

- While all the interviewees understood and regarded ML and AI as valuable in the abstract, their goals and progress to date differed considerably. All the companies in the sample had begun work toward specific applications of ML around production efficiency. Larger companies and AI technology vendors had longer-term plans for broader changes involving ML and AI.
- Productive ML/AI efforts target specific, concrete problems. However, identifying good applications is challenging, as only some problems are appropriate, and considerable expertise is required to know when an ML/AI could yield a solution. Many other barriers also stymie ML/AI projects, including the need for a solid business case, IT infrastructure, and human trust of the new technology.
- A combination of expertise is needed to successfully implement an ML/AI project. Companies organized this expertise in different ways. Larger companies had AI-focused R&D units that worked with production units to solve problems. Interdisciplinary collaboration skills are critical for success under this approach. Smaller companies relied on consultants for ML/AI expertise in support of specific efforts, with staff engineers picking up the necessary knowledge and skills along the way. Semi-technical work such as data scrubbing caused problems under this arrangement, as it was too complex to do without training, but too labor-intensive to apply consultant hours toward.

- All employers believed all their employees would be working with data, or with someone who did, within 5-10 years. They therefore believed *all* their employees would benefit from a general understanding of ML/AI including what it can and can't do, and the importance of data and data quality. Furthermore, they expected that nearly all positions would be transformed to varying extents by ML and AI. Some positions would be eliminated entirely, with employees retrained to new functions. Domain expertise and interdisciplinary collaboration skills were expected to remain relevant and valuable throughout the transformation.

This material is based upon work supported by the National Science Foundation under Grant Number 1937063.

APPENDIX A

Semi-structured interview protocol

- **Your Company**
    - Tell me a little bit about your company's relationship to ML and AI.
    - Has your company adopted or investigated any technologies or equipment that make use of ML and AI? What parts of the business are using them?
        - If not, what factors led to the decision not to adopt them?
        - If yes, how did your company make the transition into using them?
    - Does your company have a specific vision around ML and AI-based technologies currently?
        - Are there any technologies you have your eye on next?
    - Picture your workforce company-wide 5 years from now. What would people need to know about ML and AI?
        - Do you foresee any need for entry-level technical staff to have knowledge of ML or AI? What kind of knowledge? What kind of staff?
    - Will there be employees displaced by the new technology or equipment? Do you have plans to reskill or upskill them? Does your company have a way of doing that today?
- **Your Customers (AI tech vendors only)**
    - What does a typical adoption and transition cycle look like for one of your customers?
    - What issues do customers most commonly encounter when attempting to adopt AI?
    - What have you seen derail the process? Are any of them workforce-related?
    - What about the potential customers who haven't made the decision to adopt? What issues do they have that are keeping them away from AI technology adoption?
    - How do your customers typically handle training or upskilling around the new technology?
    - Is there a customer or market segment that you think would open up "if only" more people knew…? [Something about AI, or how to do something, or a certain way of thinking…?]
- **Workforce**
    - Where do you see the biggest shortages of training in AI today? Where/when will people start to feel those?
    - If there were one thing you want people to know about the world of work a decade from now, what would it be?