Chapter 6. Terry

This third interview chapter is based on the first interview we conducted, which took place before we had gathered our technological partners and our "ensemble" of humans and robots (Salvo & Sherrill, 2024) to automatically transcribe the interview. Consequently, the structure of this chapter differs from the previous interview chapters, as we relied solely on notes taken during the interview and our recollections, rather than a transcript. The interview is reconstructed but is no more a construction than the previous two. Our participant, Terry, allows for reflection both on a senior strategic thinker's perspective and a view into healthcare automation and use of AI. Finally, while Terry's use, integration, and reliance on AI differs from other participants, the themes of ethics, application, displacement, and expertise are all still present in his articulation of AI and machine learning.

Throughout this section, we utilize an extended example, in Burke's rhetorical language, a *representative anecdote* to help explain complicated systems precisely and concisely (1969). It grew from our experience of explaining concepts to each other clearly and quickly, extending a moment of mutual understanding among Terry, Michael, and John during the interview. We use a pizza metaphor because customizability is the heart of an effective pizza shop and return customers rely on consistency and timeliness to develop habits. We both have noted that the major national chains have adopted similar software for their phone ordering apps, and our readers are likely familiar enough with both the promises and failures of these systems to transfer understanding from the seeming simplicity and ubiquity of ordering pizza to ordering a customizable medical kit from Labcorp. The extended pizza shop references are meant to be clarifying given parallels with user experiences using systems designed for mass customization as well as when producing for mass customization; simply skip them if they are superfluous to your understanding.

Interview 3: Terry at Labcorp

In Chapter 6, the third and final interview chapter, we describe our conversation with Terry, a high-level manager at Labcorp. Labcorp is an American company that produces medical testing supplies and is among the world's leading clinical lab testing providers. Although not a technical communicator by title, in practice, Terry manages teams of technical experts and mediates between a variety of audiences, and he recognizes the value of effective professional writing. Given Terry's experience, we believe that this third interview will help bridge important conversations about the changing nature of writing in an age of generative AI and generations-old conversations about workplace automation. After all, our work towards this book grew out of conversations about Autodesk's Project

Dreamcatcher using generative AI to "imagine" (generate) designs that could be fabricated with additive manufacturing techniques, nearly five years before ChatGPT's public release, in the realm of bicycles, cars, planes, and user experience. With this context in mind, we wish to cue readers' attention to moments in Terry's interview which will be familiar to technical and professional writers: discussions of augmenting human labor and the associated challenges with creating and managing consistent communication in collaborative environments, making changes to existing large-scale systems, management practices, and the importance of technical communication in facilitating infrastructural and personnel changes.

Terry's career, prior to and during his time at Labcorp, has given him extensive management experience and technical expertise in robotic systems and automation. In Terry's twenty years of experience before working at Labcorp, Terry worked as project manager for an automotive components manufacturing company in Northern Lower Michigan before it was purchased by a major U.S. battery technology company. After that incorporation, Terry worked as engineering manager for the battery tech company, overseeing the production of components and assemblies used in manufacturing across North America.

After several years, Terry moved to a different automation company located just a few miles away, which focused on advanced automation systems. This company produced automated assembly systems for a variety of industries around the world: automated assemblies that were used to manufacture and assemble vehicles, hot water heater tanks, windows, high-end blenders, cereal, and even dental floss containers. In other words, Terry was involved in the development and implementation of automated robotic systems that could produce highly specialized components for niche industries, e.g., a proprietary lead-screw, as well as everyday consumer goods used around the world. Terry advanced from being project manager, to proposal manager, and finally to engineering director, i.e., head of robotics, before he began his position at Labcorp.

Like our other interviewees, Terry's career has given him insight into managing teams working with specialized systems, and familiarity with the infrastructure that supports and extends the labor of those teams. Terry's ability to succeed in management roles has depended on his ability to describe, propose, and oversee the development of multi-million dollar production lines, while understanding the complex relationships between the proposed automated systems, human operators, documentation, and the actual material goods that these human-machine systems produce—often within global supply chains. In other words, professional and technical writing is essential to Terry's work.

A major reason we invited Terry to participate in our research was because of his extensive experience with automated hardware: robots. Bridget and Kate both work for companies providing digital services and software, which have rapidly integrated generative AI and other forms of AI into their workflows. For many professional writers and aspiring students, software (writing interfaces in particular) and digital production is familiar territory. But when envisioning this book, we knew that many professional writers encounter hardware in their daily work at companies producing physical goods. Further, we understand AI as an extension of histories of automation that predate computers, much as we understand digital writing through a history of analog production. The physicality of the systems that Terry describes play an important role in grounding discourse surrounding AI in *meatspace* rather than in the cyberspace realm of sci-fi and virtual systems. Terry works closely with robotic systems and physical materials such as test tubes and medical samples, drawing attention to the parts of automated systems that interface between digital infrastructures of databases and programmed machines, as well as their associated physical constraints. At the same time, due to the scale of operations at Labcorp—including multi-million-dollar production lines and international operations—Terry's experiences managing large collaborative assemblages of people and machines parallel many of the experiences Bridget and Kate described standardizing writing and user experiences across teams within large organizations.

Across all three interviews, one clear constant has emerged: for rhetorically complex tasks, as well as tasks that require human dexterity, human labor remains essential in an age of generative AI. Artificial intelligence is best suited to strengthen and extend human work with limited exceptions, one of which we examine in this final interview: automated plasma cutting and assembly of joists in the Pacific Northwest. In particular, this final interview draws attention to relationships among (and distinctions between) AI-based systems, physical labor, and human labor, drawing from Knowles' concept of *rhetorical load sharing* to situate these sometimes overlapping relationships.

Labcorp is one of the largest suppliers of medical testing kits in the world, providing both standard and custom kits to businesses, hospitals, and individual customers, while also processing and testing millions of samples each year. Our interviewee, Terry, has over two decades of experience in the automation industry—spanning PLC (programmable logic controller), robotics, and automation—and has played a crucial role in managing and improving Labcorp's automated systems over the past three years. As Terry described, Labcorp is a $12 billion biotech company. Labcorp succeeds through implementing advanced automation processes that use industry-leading technologies, while also employing human thinking labor in production and testing. This final section describes how Labcorp has automated kit production and testing, illustrates potential opportunities to integrate AI into the process, and highlights practical challenges that limit the speed of advances at an industrial scale.

Listening to Terry during the interview, I (John) scrambled to both take notes and quietly Google terms and many acronyms for the various machines and processes that he encounters daily. Though I was initially overwhelmed with his rapid-fire expertise, Terry's detailed descriptions were followed with clear explanations of how each system worked in simple terms, as well as an explanation of why each new layer of information was important to understand. What was initially overwhelming became a testament to Terry's years of experience, and his ability, as he put it, to both "do" as well as "lead and teach." Terry's expertise relied not only on his ability to design and manage advanced automation systems, but also his ability to clearly explain how they work, their limitations and advantages, and *why* they're important. Terry recognizes the importance of this skill, as he explains later in this section regarding training employees who can "lead and teach." As Mya Poe et al., argued in their study of writing instruction at MIT, "Engineers who don't write well end up working for engineers who do write well" (Poe et al., 2010, p. 1). Terry is an engineer who writes and explains well, and as a manager, mentors his employees in how to become better writers and leaders.

Custom Medical Testing Kits, with Extra Pepperoni

To understand the present and near future of AI applications in optimizing the industrial assembly processes that produce medical testing kits, this chapter uses the familiar metaphor of ordering and assembling a pizza. For both local pizza restaurants and international chains, the ability to offer different combinations of standard ingredients is founded on optimized human labor and appropriately configured pizza assembly stations. There are important parallels regarding user experience, mass customization, and common business challenges between assembling pizzas and the advanced automated assembly of medical testing kits—and subsequent optimization of that process—which we discuss throughout this chapter.

The menu at a typical pizza place has multiple premade options, e.g., Supreme, Hawaiian, Meat Lovers, etc., available in different sizes and priced accordingly. These premade configurations of toppings based on common customer preferences simplify the ordering process for both consumers and workers, and sometimes highlight unique or novel configurations (e.g., a Bee Sting or Taco Supreme). They also streamline the assembly of pizzas and purchase of ingredients by limiting available options. But, most pizza places also offer a "build your own" option, depending on the configuration of ingredients, business model, and restaurant infrastructure. These different configurations afford different advantages and limitations. Pizza by the slice offers far less customizability for consumers, if any, but doesn't require buying a whole pizza if a snack or a quick lunch is the goal. For the business, selling by the slice limits the variability of production and can streamline the production process. Similarly, a "hot and ready" pizza offers customers zero customizability, but offers the advantage of speed to consumers and consistency to the business. It is the mass production of a single pizza variety, albeit with human labor. Of course, there is also the DIY option of making pizza at home, offering the least automation, but the greatest customizability.

An average U.S. grocery store provides all the ingredients necessary for making pizza: cheese, sauce, dough, and toppings. Each of these components are commonly available in different forms, e.g., shredded vs. block cheese, canned or squeezable sauce, premade dough or box mix, etc., and depending on the size of the store and the exact location, there may be more or less variety of choice, e.g., allergy-friendly, organic, ethically sourced, etc. For the average consumer, making pizza at home requires only a quick trip to one grocery store and a bit of labor in assembling and baking the pizza. But, the pizza can be fully customized to individual preferences and dietary needs.

Of course, when I'm making homemade pizza with anchovies, garlic, and chilies, there's the inevitable problem of what to do with the other half of the tinned fish. Somehow, the pizza never requires a whole container, and I've never simultaneously craved Caesar salad or spaghetti sauce while making pizza. Leftover cheese, pepperoni, and sauce even packaged in bulk don't pose the same issue given their more immediate versatility. Consequently, I often wish that I could purchase just the right amount of anchovies when I do crave them on my pizza. Many pizza places don't offer them on the menu, and I've yet to find anywhere that sells anchovies by the filet.[16] However, appropriately portioned anchovies would convince me to purchase a customized pizza kit. Even at a slightly higher price, avoiding anchovy waste and saving shopping time would add value for me.

In general, sourcing ingredients for a homemade pizza isn't a particularly laborious task, and anchovies are not a popular topping. But for most other applications, kits exist because someone with expertise has saved consumers time by gathering the necessary components and providing instructions or recommendations, offsetting the amount of expertise and labor required from the end user, while still requiring some labor for the actual assembly or use of said components. Kits, by nature, are designed and assembled to suit particular applications. Consequently, premade kits are inherently limited, at times being too specialized or at others too general that they become bloated. No single pizza configuration suits every taste. For someone who does not like anchovies, anchovies included in a kit with more popular toppings might still go to waste.

Ideally, a kit is assembled to suit the needs of a given situation, or at least balances flexibility with specialty to address situations that are likely to arise. Much like standard pizzas, standard kits are easier to mass produce, with their production even being automated. But customized kits can better serve consumers. This is an inherent tension between mass-produced and mass-customized goods: when is good enough actually good enough? This tension reveals a Goldilocks problem of price, components, and other constraints based on circumstances, as well as need. From a consumer standpoint, a customized kit that meets individual needs is ideal. From a user experience perspective, it's important to avoid overwhelming consumers with endless options for customization. Premade kits, much like a Supreme Pizza, serve as a starting point that helps to guide user decision making,

16. Even if such a market did exist, I'm not sure I would trust a business that sold individual anchovies.

allowing for tailoring for better fit rather than haute couture (from scratch). More advanced users, however, may want the convenience of an assembled kit without the limitations of one that is premade. After all, adding green olives and jalapeño to a Meat Lovers pizza, whether in kit or fully produced form, might offer the best possible user experience afforded by the pizza assembly system. Designing and optimizing industrial assembly systems for mass customization is challenging. As the following interview illustrates, AI is poised to improve the efficiency of automated assembly systems. However, human agents continue to play important roles in designing, configuring, and optimizing these systems, and in addressing associated challenges.

A Brief Overview of Labcorp's Automated Processes

During our interview with Terry about his work, Terry explained that there are two sides to Labcorp: production and testing. On the production side, Labcorp produces test kits for doctors who are conducting studies, for large biopharmaceutical studies, and for other types of testing (e.g., drug screening centers). On the testing side, Labcorp processes samples that have been collected with the kits (e.g., drug tests, genetic tests, COVID-19 tests, etc.). Labcorp operates on a massive scale. The company offers over 5,000 different tests, with approximately 540 million test kits ordered every year (Labcorp, 2023b). According to a 2019 press release, Labcorp "typically processes tests on more than 2.5 million patient specimens per week" (Labcorp). Terry oversees these largely automated processes. Among these processes, 75 percent of what Terry does involves the automation that builds the testing kits, while the other 25 percent of his time is taken up in the processes of assessing and redesigning automated testing processes.

On the production side, Terry explained that Labcorp runs 800 SKUs (stock keeping units) for test kits at their Indiana location. Of the kits assembled there, 25 of the kits are fully automated. For those automated kits, the process applies custom data from their database of kits and supplies, applies a label to appropriate test tube or other part, and puts the part in the kit. While Labcorp produces a variety of standard test kits, which are uniform across all orders, they do complete custom fulfilment as well. Standard kits and custom orders follow the same basic steps, with fulfilment starting from Labcorp's database. After the automatic part of the process, the order goes to 12 pick cells. There, human operators take the 160 most common SKUs and do more custom labeling for test kits. As Terry described, human operators label, "mostly things that aren't round [so, things that aren't test tubes], for example, urine bags." That is, solid objects of a standard shape and size are easier to automate, while squishy or amorphous parts are comparatively more complex, making it more efficient for humans to handle.

Within this largely automated system, there are two different subsystems that make production happen: the PLC (Programmable Logic Controllers) robotics side—which is what Terry is most familiar with—and the systems database, warehouse management, and warehouse fulfilment (that is, tracking and managing where things are in the automated system).

Following production, and after test kits have gone out for use, samples are sent back to Labcorp for analysis. The returned samples must be sorted before testing can take place. Thanks to an automated system, Labcorp has the capacity to process over 15 million samples per year (Labcorp, 2022b, 00:18).[17] Terry drew our attention to a seemingly mundane part of this system: opening 14" x 14" boxes. He explained that there is significant demand for such systems, and that at the time of our interview, only two companies specialized in automatic box opening.

Automated box opening, in addition to being more efficient at opening boxes than multiple human workers, helps avoid cross-contamination and damage to samples. This reduces potential health risks for human workers who would otherwise have to carefully handle thousands of samples each shift.[18]

Though this example at Labcorp is routinized thanks to consistently sized 14" x 14" boxes, the machines used for box opening can be configured to analyze boxes in order to determine their shape and dimensions, optimizing a toolpath for cutting each unique box. Although AI is not required for driving such systems, its potential application brings attention to two important points: 1) AI is an extension of longstanding automation technologies which often shift the labor of mundane, tedious, or repetitive tasks towards more complex tasks. 2) Machine vision and machine learning could be applied to augment such systems, enabling the base robotic systems to handle slightly more complex tasks, e.g., opening boxes that have been deformed or damaged in shipping, but not yet soft bubble mailers or plastic bags that will likely require human dexterity.

In our interview with Terry, it became clear that while AI-based automation systems can be built from scratch, and do open new opportunities (and challenges) for advanced manufacturing and automation, AI is more commonly being used to gradually augment and enhance existing systems. Though some companies are in the process of building AI-driven systems from scratch, for many companies this is not a practical option compared with upgrading their existing systems over time. This is in large part a difference between upgrading software vs. hardware, as well as the scale of operations. One might wonder why some of the issues that Terry describes throughout the following sections couldn't be addressed during the initial design phase, or quickly fixed. However, the systems Terry described are not static, and many automated systems run constantly,

17. Labcorp provides a virtual tour of its kit production and sample analysis processes on its YouTube channel. Indy Central Lab – Kit Production: https://youtu.be/HNflxYeb-84 (2023a). Journey of a Sample through Our Central Lab: https://youtu.be/_l5nSzKAilY (2022a).

18. We extrapolated these numbers based on annual processing. If 15 million samples per year evenly divided (assuming a steady rate) is 41,000 samples per day, that yields approximately 1,700 samples per hour assuming 24/7 operation.

24 hours a day/7 days a week, and 365 days a year. Changing any part of the automated system means balancing decisions about potential downtime or reduced throughput during installation against potential gains. Does production halt to make a quick swap while losing hours, or even days of operation? How long will it take to ramp up production from a complete stop? Is it better to slow production while maintaining a steady trickle through the system? Or is it better to reroute some of the production through a different facility? Unlike upgrading software, in which a virtual system can be setup for development before updates are deployed and "go live," even deploying thoroughly tested hardware requires downtime for installation and troubleshooting. Virtual systems are not infallible, as demonstrated by the recent Crowdstrike update that interrupted computer systems globally (Baran, 2024). While simulation of analog systems is valuable, it cannot entirely prevent potentially catastrophic errors when applied in practice. A key difference is that virtual test builds or prototypes of physical systems cannot be easily replicated and deployed to a new site with a simple click, as is often the case with websites or virtual systems. Instead, implementing changes in physical systems involves more complex and gradual processes to ensure safety and functionality.

From Terry's perspective, at Labcorp, AI would have the greatest impact on system optimization. In the immediate future, its primary application would be at the database and systems level. In other words, it's more likely that AI would be used to optimize what goes into bubble mailers than to automate opening them. For now, consistently sized boxes are still the most efficient solution for receiving samples. However, Terry did share with us an example of an optimization problem directly related to hardware, and for which he could foresee AI helping manage.

AI as Optimization Tool

When producing test kits, each kit (regardless of its contents) is packaged in a white, 7" x 4" box. Like at many automated production facilities, kits are packaged along a conveyor system. Different pieces of the kit are added at each stage of the process, e.g., a standard box is placed on the conveyor, a label is applied, and the box moves along. Further along, a labeled test tube is added to the kit, and so on. In the system packaging the kits, there's a buffer on the conveyor that holds up to 1,200 kits. The buffer's purpose is to control the rate of flow of kits through the system, ensuring a smooth production rate as different parts of the system move faster or slower. This buffer is currently optimized via a program running on C# code—a standard piece of software, nothing AI-driven.

Approximately the top 20 percent of kits are fully automated in their production, meaning that machines place the required materials into each test kit box. For the majority of kits, workers transfer the contents of each kit from bin to kit box by hand. However, there's one current issue with the system that AI could help optimize. For the top 20 percent of kits, two machines run the same product ("CBD2") back to back. Currently, the system that runs those two stations assigns almost everything to the first machine, while the second machine is only running 15 percent of that product. To make production more efficient, Labcorp is working with their software vendor to configure that system to set a baseline of 50/50 distribution between the two machines. Though this might not seem like a complicated task, Terry posed a simple question that illustrates the underlying complexity: What if they want to add a third machine to the production line? With the current software, it's not possible to add machines. Labcorp wants the flexibility to add a machine (or more) and automatically adjust the division of automated labor. Doing so could free up 13 or more hours of time on the line. However, Labcorp's system for those kits is 20 years old and does not have the capacity to flexibly expand.

Human Limitations in Automated Systems

Terry recognizes the constraints and challenges of the current legacy system. The current software vendor designed and maintains the software that runs the kit assembly line. Labcorp has tried to hire different developers in the past. But Labcorp would lose access to experts familiar with their 20-year-old system. The vendor has a 20-year history developing and maintaining Labcorp's custom software. Further complicating the situation, the vendor sometimes pushes back asserting that it is difficult to develop legacy systems customized by Labcorp's internal programmer. AI could optimize hardware, but implementation would not be plug and play. It would likely require developing entirely new software.

As Terry explained, "What hamstrings us is that we just put in a new facility in Belgium … using the same [20-year-old] system." At first glance, a new facility seems like the perfect opportunity to develop a new, optimized, and fully automated system for preparing the top 20 percent of kits. However, in addition to the time required and cost of developing new software, backwards compatibility plays a role. Any new system would have to work with the current database of kits and parts, as that database is foundational for the entire operation—not just the fully automated systems producing the top 20 percent of kits. Another factor is the risk of putting a brand-new system on the other side of the world. As a concrete example of hamstringing with new systems, Terry described a $70 million dollar job with the potential to multiply that investment in expected earnings that didn't work out because Labcorp couldn't move away from their software vendor. Instead, a $15 million operation in Ohio proved less risky, being closer to Labcorp's established operations and the software vendor, albeit with comparatively less potential yield.

At this point in the interview, Michael noted that it was interesting that one of the limitations in all this automation is still the human. An experienced software vendor, and equally experienced internal developer, combined with a longstanding database significantly limited how Labcorp could develop new operations or upgrade existing systems. One of the ways that Terry personally responds to this challenge is by building the communication skills of employees to avoid siloing tacit knowledge of systems. Communicating knowledge to other employees and creating effective documentation helps make tacit knowledge communal. If only one employee has extensive knowledge of a system or process, and that knowledge is locked away in their mind, that employee potentially limits what the company can do in the future. As Terry explained, one of the challenges is that there are great "doers," who do exactly what they're told to do, and who do what's needed to the required specifications. But often, these employees are "Great doers but bad leaders and teachers." In response, Terry requires employees in management roles who are "great doers" to spend four hours each week explaining over the phone what they do to gain practice communicating their expertise. This weekly documentation practice helps makes knowledge available, shareable, and even *searchable* when written, and allows for action to be taken in the near and long term for strategic development. This challenge of making tacit knowledge explicit and communal shares similarities with the challenges of developing AI decision-making systems. Transparency is key: without the ability to explain the decision-making process, the system cannot be audited or verified.

However, this example of tacit knowledge also shows that human-powered systems are not immune to communication problems. After 20 years of customization and exclusive development, the software running Labcorp's test kit assembly system could become a black box due simply to employee changeover or a shift to a different vendor. Employees who can share their knowledge effectively and clearly explain the inner workings of automated systems are immensely valuable, and they play a foundational role in maintaining and developing advanced systems. Though generative AI systems like ChatGPT make it easier than ever to communicate complex information with skillful prompting, as the previous chapters have made clear and Johnson-Eilola et al., similarly argued, AI-generated text is not a substitute for effective, rhetorically fitting, technical communication by humans for the use of other humans (Johnson-Eilola et al., 2024). That said, generative AI systems can still extend the communicative capacity of "great doers" if they have the technical expertise necessary to identify technically problematic outputs. However, much like with Poe's "engineers who write well," employees who already possess technical *and* rhetorical expertise are better equipped to use generative AI effectively.

Beyond communication challenges, there are practical inefficiencies which Terry identified that AI-driven optimization could more readily address in the kit assembly process. Kits are assembled in first-in-first-out (FIFO) order, meaning that at times, the entire assembly line is held up by a single kit waiting on a specific part to arrive at the work station. This doesn't create a significant delay on average, but as Terry explained, Labcorp has had days where the entire line was held up—not because of any mechanical problems, human workers, or other infrastructural breakdowns, but because of the mix of kits that required certain parts. Such delays are a problem of mass customization on linear assembly systems.

Again, imagine your preferred pizza chain. Pizzas run through the oven on a conveyor, baking in the sequence they've been ordered by customers and prepared to bake. Whether a customer places an order for two pepperoni pizzas or 20, the process is efficient because the mix of ingredients remains consistent and the fulfillment time is linear, relative to the volume of pizzas rather than the sequence in which they're assembled and baked. That is, completing 20 identical pizzas takes longer than completing two, but only because there are more pizzas to be made. Similarly, a mix of 10 pepperoni pizzas and 10 chicken pizzas takes a comparable amount of time to prepare as 20 pepperoni because the most popular toppings are within reach of the workers assembling each pizza. The sequence of assembly and baking can be optimized to prioritize pepperoni, chicken, or a mix, but the overall time required remains predictable. However, if a customer places an order for an anchovy pizza, which is then followed by an order of 10 pepperoni pizzas, the anchovy pizza at the front of the line might require a worker to grab a container of (rarely ordered) anchovies from the walk-in refrigerator, delaying the 10 other pizzas waiting unprepared. A pizza chain operating this way wouldn't stay in business long. Instead, another employee might begin assembling the pepperoni pizzas, or prepping base cheese pizzas to be topped. Or to prioritize a higher value order, the single anchovy pizza could be queued last despite being ordered first.

The flexibility of these potential solutions to a pizza jam, in response to unpredictable variance, is an advantage of human assembly. Workers can simply be assigned to different tasks or reconfigure the production process on the fly. This metaphor also helps explain why only the top 20 percent of Labcorp kits are fully automated. That said, Terry has been working towards a solution to the Labcorp equivalent of the pizza pile-up. He's designing what is called a "flex cell" to account for the anchovy pizzas of Labcorp test kits. When a test kit hits an assignment scanner (at the front of the assembly line), the scanner sends the kit ID up to the database. If the database sees demands for parts that are slotted into that flex cell, it sends the part (if it's available, based on the database) in advance before the kit gets to the assembly workstation so that the whole line isn't waiting on that one kit part. Essentially, the flex cell puts the order into a "work in process" status so that when the kit arrives at the workstation, the pre-fetched item can be added to a preassembly collection, what Labcorp and Terry call a "process cup." Each cup can prepare up to 20 items to be placed into custom kits. In terms of the pizza metaphor, if someone orders an anchovy pizza, the ordering system automatically checks the ingredients stock list, and anchovies are placed in a general-purpose cup placed near more popular ingredients, ready to be placed on the correct pizza in the baking cue without delaying any other pizzas. Although incorporating AI is not a requirement for improving the efficiency of such a system, machine learning could help analyze kit combinations and assign weights to kits that are more likely to cause significant delays or make extensive use of the flex cell to further optimize the system.

Here again, Terry is attempting to optimize the flow of production, balancing the potential downtime to implement such a system with improved efficiency. Unlike a system of human workers, reconfiguring an automated system of hardware would take downtime. Though optimizing the sequencing of kits could help somewhat, it cannot always address backups caused by unpredictable combinations of kit components. Similarly, humans can readily recognize when a slowdown is happening at a pizza place and figure out what caused it, whereas this type of analysis can be orders of magnitude more complex at Labcorp. The scale of customizations is a significant factor, but one which also creates an opportunity for an AI-driven solution, as human workers cannot readily identify in advance which combinations of thousands of items that can be included in thousands of kits are likely to create delays. But a system of flex cells, optimized based on machine analysis of millions of combinations of test kits and their production times, could significantly smooth production flow, recognizing slowdowns and reacting accordingly, at least for automated kits. Beyond reducing delays, these AI interventions would also take stress of tedious prepositioning off human workers and shift the burden on to the automated system.

A Fully Automated, Dynamic System

Near the end of our interview, Terry briefly described a fully automated system at another company which used machine vision extensively. Though Terry was not certain whether the system yet incorporated machine learning or other forms of AI, machine vision and image recognition are closely related and are increasingly common applications of traditional AI, as demonstrated through Bridget's interview.

Terry's decades of experience in the automation industry make this example particularly significant: this was the closest example of a potentially AI-driven and fully-automated production system that came to Terry's mind. This is not to say that AI is not being widely implemented across a range of industries, but rather to highlight that in most cases, AI is still augmenting existing systems. The previous example of Labcorp's hesitation to build a new system in a different country given the potential risks—resulting in large part from compatibility issues with customized software—highlights the complications that arise when building new systems for a stable company. Terry's expertise and our research suggest that integrating AI into existing systems, rather than the creation of entirely new systems from scratch, is the more prevalent approach. As such, this example serves to illustrate the potential to combine off-the-shelf components with machine learning to build a highly-automated system with minimal human input beyond the initial programming and setup. We juxtapose automated beam production with the necessity for human labor in medical test kit assembly here, in this final interview chapter, to demonstrate a single example of (potentially, plausibly) AI-based automation replacing human labor rather than the augmentation prevalent throughout our interviews.

The company Terry described manufactures joists for industrial applications in the Pacific Northwest. This context is significant because of frequent earthquakes. In most areas of the United States, floors and ceilings can be connected directly to steel beams or webbed steel structures. Joists can be manufactured from steel (or wood, for primarily non-industrial applications) and then shipped. Buildings in most of the US rarely, if ever, experience potentially destructive vibrations, and thus aren't constructed to withstand earthquakes. However, as Terry explained, in the Pacific Northwest, joists need two inches of wood between the top of the joists and the ceiling. Consequently, construction workers screw materials into wood-topped joists rather than into steel joists directly.

Efficiently creating steel joists with wooden tops requires surprising precision. For the Pacific Northwest, the manufacturing process begins where it ends for most of the country: with a 70-foot steel joist. The joist is flipped into position so that holes can be plasma cut in precise locations. In theory, this might seem like a straightforward process. Simply place each 70-foot beam in exactly the same position each time and cut. Small variations in the precise dimensions of each beam due to manufacturing tolerances, warping during transportation, and the precision of the machine that is positioning the beam all impact the placement of holes. This precision matters though. Computer-controlled plasma cutters can operate with sub-millimeter precision while cutting at temperatures hotter than the sun's surface. Each joist measures approximately 21,336 millimeters, and once manufactured, all joists need to consistently align throughout the construction process.

To ensure the accuracy of each individual cut, the system Terry described was "completely parametric," meaning that it dynamically adjusted to specified parameters (e.g., a beam slightly shorter at one end would still have holes cut in the correct location relative to the shorter length). When entering the work area, each beam would be precisely laser scanned to find the end of the joist and top of the joist. From that point on, everything was dynamically adjusted to figure out pathfinding for the plasma cutter. That is, based on the laser scanned dimensions, the system automatically determined where to plasma cut each hole, the most efficient path for each cut, and each transit between cuts, for every unique beam. Further down the line, a 2D camera would automatically identify and precisely pinpoint the center of the holes, and then translate those coordinates to a robot that screws a screw into each hole. There is an additional complication to contend with: Joists flex based on length. So, the calculations for hole placement were *also* adjusted based on the flex of each joist to accurately position holes and screws for each beam.

This system used commonly available industrial components, such as laser scanners, 2D cameras with machine vision, and plasma cutters, to create a dynamic and efficient solution to address a regional need. Advances primarily in software, rather than hardware, enable creation of more advanced and dynamic systems that enhance the capabilities of hardware that has existed for decades.

Manufacturing joists for the Pacific Northwest is a clear example of an automated system replacing, rather than augmenting, human labor. Though laborious, measuring/sensing, cutting, and fastening screws is tedious and a repetitive task that can be readily automated. These are not highly complex or nuanced tasks that demand manual human labor, and represent the opposite end of the automation spectrum (Armstrong et al., 2023). Perhaps someday, Labcorp will develop a similarly advanced AI-driven system capable of identifying and dynamically placing kit components without human workers for all but the most complex or unusual kits, using a combination of more advanced software and minor changes in hardware. Though that future is closer than ever before with advances in AI, it will likely remain more cost effective to employ humans to label, grab, and pack parts, in addition to the humans responsible for designing, programming, maintaining, and managing automated systems. Regardless of who or what is packaging kits, AI-driven inventory systems will likely yield more efficient packing in the immediate future.

Summarizing Terry's Interview

Not coincidentally, Michael's power went out during the first 10 minutes of our Zoom interview with Terry. As frightening as automated systems may seem, whether it's their potential to replace human labor or shape our realities, the power can still shut off. The infrastructure for automation, and the human participants involved in creating and sustaining automated systems, still break down. When least expected, things go wrong. In these moments, human adaptability and expertise remain as important as ever. Michael was able to improvise, communicating with me on his phone via 5G connection until he could connect to the video call. In the worst case, even interviewing across the Atlantic, we were prepared to establish a second video call to have everyone in the same meeting across layers of fallible infrastructure.

As demonstrated through Terry's interview, as well as Bridget's and Kate's, AI systems are enhancing the ability of many expert and non-expert workers to produce content and do their jobs more efficiently, both augmenting their labor and at times replacing human labor. But the rhetorically complex ability to analyze and explain problems, to design or articulate fitting solutions, and understand the consequences of the available responses remain important human labor.

At the time of our interview with Terry early in 2023, ChatGPT was still in its initial public release with version 3.5. Now, ChatGPT-4o is available in limited capacity for free, and a paid subscription offers even greater access. By the time this finished manuscript is available, it is plausible that ChatGPT 5 will be public, pending an official release date announcement by OpenAI. With each new iteration, ChatGPT produces better output, despite its inherent limitations as a generative LLM system. It still hallucinates, produces horrible recipes and poems, ignores software versioning when providing troubleshooting guidance, contains the same biases present in training data, and only ever ultimately produces an average of what it has been trained on. However, out of curiosity, I prompted ChatGPT to address the situation that Michael and I had faced. What to do when the power suddenly goes out before a Zoom meeting?

ChatGPT successfully generated the same steps that Michael and I ultimately worked through. Of course, this is not a particularly novel scenario. Most worthwhile texts on research methods and conducting interviews will explain the importance of having multiple backup methods and recording options. ChatGPT was surely trained on such sources. Most video calling platforms also automatically provide a phone number to participate in a meeting for accessibility reasons. Despite understanding that the training data likely included this information, Michael and I were both surprised that ChatGPT had generated such usable output in the same order we had considered. In discussing this unexpected output, we assumed that although ChatGPT could generate usable output, we knew that it did not actually comprehend the underlying rationale or rhetorical significance of this communication. As a test, we prompted ChatGPT to explain the rhetorical situation. To our surprise, while we know that ChatGPT does not actually understand or comprehend the rhetorical situation, it faked that human understanding surprisingly well, accurately outlining the audience, exigence, and constraints of the situation along with a brief explanation for each. In response, thinking that surely ChatGPT would struggle to explain the "why" behind the list of steps, I prompted, "Why is it important that the participant who lost power communicate that information?" Surprised again by the resulting output, I generated more prompts, hoping to find a clear point at which ChatGPT's performance deteriorated.

> "How can the outcomes of the person who lost power be judged or evaluated?"
>
> "How might that person's actions impact their relationship with the other two meeting particpiants[sic]?"

In response to these prompts and several others, ChatGPT produced effective output (the full output is available as an appendix). None of the prompts that we had anticipated would pose a challenge did. The AI-generated output was remarkably useful, nuanced, and human. Clearly, the development from 3.5 to 4o (according to OpenAI, the "o" is "for 'omni'") was a significant improvement. Somewhat frustrated, I finally prompted ChatGPT as follows:

"What questions might ChatGPT struggle to address effectively regarding this particular rhetorical situation?"

> In summary, while ChatGPT can provide general insights and suggest possible actions and outcomes, it may struggle with questions requiring deep personal insights, specific technical details, real-time decision-making processes, insider knowledge, subtle

> interpersonal dynamics, and subjective interpretations that are unique to the individuals involved in the rhetorical situation.

To elaborate, ChatGPT, much like the very efficient test-tube grabbing robots, struggles with more fluid constructions. For now, humans are still better than the average robot at grasping pliable bags than rigid and consistently shaped test tubes, though specialty applications are an exception. But that is not an inherently bad thing nor something to be feared by default. We, as technical communicators, should remain critically aware of the limitations of AI as well as its affordances. The examples we have described throughout this book show both, but our primary purpose throughout has been to identify the current state of AI's applications in professional writing contexts, and realistically consider what this may mean when preparing future professional writers. A workplace in which the top 20 percent of writing tasks are fully automated does not seem fictional in 2025. The remaining 80 percent of tasks may rely heavily on automated tools to be more efficient, but are made possible through human input and critical decision-making. Inevitably, some of the most complex and nuanced communication tasks will still require fully manual control to construct a rhetorically fitting and effective response.