Safety First: Developing a Model of Expertise in Collaborative Robotics

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Abstract. Rapid advances in technology also come with increased training needs for people who engineer and interact with these technologies. One such technology is collaborative robots, *cobots*, which are designed to be safer and easier to use than their traditional robotic counterparts. However, there have been few studies of how people use cobots and even fewer identifying what a user must know to properly set up and effectively use cobots for their manufacturing processes. In this study, we interviewed nine experts in robots and automation in manufacturing settings. We employ a quantitative ethnographic approach to gain qualitative insights into the cultural practices of robotics experts and corroborate these stories with quantitative warrants. Both quantitative and qualitative analyses revealed that experts put safety first when designing and monitoring cobot applications. This study improves our understanding of expert problem-solving in collaborative robotics, defines an expert model that can serve as a basis for the development of an authentic learning technology, and illustrates a useful method for modeling expertise in vocational settings.

Keywords: Collaborative robots · Epistemic frame theory · Epistemic network analysis · Epistemography · Quantitative ethnography

1 Introduction

Rapid advances in technology also come with increased training needs for people who engineer and interact with these technologies. In manufacturing, there is an increase in the automation of repetitive tasks using robots, however, there is also a shortage of workers trained to perform such operations [1]. One robotics technology that is becoming increasingly common in both industrial production and even in maker spaces is collaborative robots. While traditional robots are machines that are programmed to perform a task automatically, collaborative robots, or cobots, are robot systems designed with embedded safety measure that allow them to work with and around workers. Both robots and cobots engage in automation routines, however, the advantage of cobots include their affordability, increased safety, flexible and changeable applications, and easier and scaffolded programming routines [2].

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Nevertheless, there have been few studies of how people use cobots and even fewer identifying what a user must know to properly set up and effectively use cobots for their manufacturing processes. Our long-term goal is to design an authentic learning technology that can teach new and returning users how to use cobots like experts do. But in order to design such a learning environment, we must first identify the critical components of expertise in this emerging area. Therefore, we employ a quantitative ethnographic methodology to enable both qualitative and quantitative representations of what it means to think like an expert in cobots.

In this ethnography, we investigate how experts in implementing and using cobots approach the adoption, integration, and monitoring of collaborative robots in manufacturing settings. Subsequently, we employ a quantitative ethnographic methodology to examine what it means to think like a cobotics expert.

2 Theory

In recent years, the Learning Sciences community has been conducting more research with robots including investigating collaboration in robotics teams [3], engaging students with educational robots [4], as well as teaching students how to program robots [5]. While each of these studies provides insights into educational uses of robots, there is little understanding of how robots are used in authentic settings and less focus on the affordances and uses of the robot itself. Therefore, this study seeks to learn more about robotic automation used in industrial settings and focus on two types of robot: traditional and collaborative.

Traditional robots are powerful and programmed machines that are automated to complete repetitive tasks. Commonly, traditional robots are used on production lines, such as those that manufacture automobiles, to perform routine and high-volume processes [2]. For example, many traditional robotic arms engage in *pick-and-place* applications, where a part is moved from one place to another, or *machine-tending*, where a machine, such as a lathe, is loaded and unloaded.

Robots are used in such contexts because they are faster and more reliable than human workers, and also because they can perform tasks likely to result in injury if performed by humans [6]. But because traditional robots are fast and powerful, like many of the machines they interface with, they must be isolated from human workers to ensure safety. This is often accomplished with caged work cells or other measures to isolate the robots from humans engaged in other parts of the production process.

Whereas traditional robots are fast, powerful, and isolated, cobots are designed with improved safety features that allow them to be deployed without traditional caging and isolation [2]. Cobots are also used in routine and repetitive tasks but are designed to safely work with and around humans. Cobots may work around and in partnership with human workers because they are equipped with embedded safety sensors (i.e. power- and force-limiters) and are built to have rounded components that reduce the risk of operator harm. Consequently, cobots operate at lower speeds and forces in case of an unintentional collision with the human, but they can be incorporated in automation processes without isolation or caging. Cobots were designed with other affordances that allow for varying levels of collaborative interactions with humans including simplified programming, “ease of use,” and opportunities for flexible and rapid deployment [7, 8].

Both robots and cobots work with humans in manufacturing settings, however, there are a range of different human-robot collaboration levels. Christiernen [7] outlines four progressively more collaborative levels of human-collaborative interaction: no collaboration, start and stop, interactive, and collaborative. The first level, no collaboration, describes traditional robot activities that occur while physically separated from humans. The next three levels describe increasingly collaborative applications that move from asynchronous work, to synchronous work in the same physical space, and finally to the human and robot jointly working on same task.

Our prior work found that the most common use of cobots by experts in manufacturing was as an "uncaged robot," where cobots were implemented in simple, less collaborative ways but without safety caging [9]. Experts in this study emphasized how traditional robots are faster and more powerful that cobots but are also expensive because they require physical barriers, safety sensors, and programming by engineers. Experts stated that cobots were often used to lower cost and reduce space requirements for simple automation tasks. This study found that the affordances of removing unwieldy and expensive physical barriers was worth the tradeoff in performance for many implementers and companies. At the same time, many common applications for cobots did not use this machine in collaborative, flexible, or synchronous ways promised by cobot designers. That is, cobots were often used like a traditional robot either with no collaboration or start and stop processes [7]. While our previous work focused on understanding how cobots were used, we build on this work in the current project to build an expert model of how experts think about and solve automation problems using cobots in automation.

Researchers have asserted that complex thinking and expertise is characterized by relationships among domain relevant cognitive and social elements, not the isolated accumulation of these elements [10, 11]. Similarly, diSessa [12] describes how novices have "knowledge-in-pieces," unlike experts who display deep and systematic understanding regarding the connections between these disciplinary pieces. Based on these ideas, Shaffer [13] characterizes learning as developing an *epistemic frame*, which is a pattern of associations among knowledge, skills, and other cognitive elements that characterize groups of people who share similar ways of understanding, examining, and problem-solving. Importantly, epistemic frame theory provides a way to view expertise as the relationship between, and not simply the accumulation of, domain elements. Epistemic frame theory has been used to characterize frame elements in a variety of professional contexts including urban planning [14] and biomedical engineering [15], as well as to develop practice-based learning environments based on those elements [16].

To learn more about cobotics experts, we conducted an *epistemography*: an ethnographic analysis of a profession through the lens of epistemic frame theory [17]. An epistemography allows a researcher to observe and describe the components of the epistemic frame for a particular community of practice. Epistemographies have been used to studying professional practica of journalists [17] and urban planners [14]. However, we draw on this method to observe and analyze a profession during, interviews, demonstrations, and factory tours. In particular, we observed the features of and relationships among the epistemic frame for cobotics experts in manufacturing and automation.

The incorporation of cobots is well underway, but we have little sense of how experts understand cobots, how people are trained in cobotic work, and what the implications of the shift are for a range of issues. Therefore, to analyze the epistemic frame of cobot use, we employ a *quantitative ethnographic approach* [18] to gain qualitative insights into the cultural practices of robotics experts and corroborate these stories with statistical warrants. In this epistemography, we interviewed experts in cobot use in manufacturing settings. We then conducted a qualitative analysis of the interviews to identify and understand the key elements of a cobotics experts epistemic frame, and importantly, how these elements are connected to one another. Once key elements were identified, the structure of connections between these elements can be represented as a network of relationships using epistemic network analysis (ENA) [22]. ENA is particularly well-suited to evaluate expert discourse because it can model the structure of relationships between frame elements. This results in a visual representation of the structure, a mathematical model of the structure, and a way to compare the quantified data with its underlying qualitative data. After assessing the epistemic frames of all using ENA, we compared these results to the qualitative findings. Finally, we use the ENA results to reinvestigate the different instantiations and underpinnings of cobot epistemic frames.

3 Methods

3.1 Setting and Participants

Participants ($N = 9$, all male) were from six different institutions including automation sales, manufacturing, and a regional technical college. See Table 1 for a summary of participants, occupations, and organizations. No other demographic information was collected about the participants.

Table 1. Summary of participant employment.

Participant	Occupation	Company	Interview type
P1	Applications Engineer	Automation Sales	Individual
P2	Instructor	Technical College – Robotics and Automation	Individual
P3	Automation Manager	Manufacturing Enterprise	Group A
P4	Application Engineer	Manufacturing Enterprise	Group A
P5	Automation Technician	Automation Sales 2	Group B
P6	Automation Manager	Automation Sales 2	Group B and C
P7	Applications Engineer	Manufacturing Enterprise 2	Group C
P8	Operator	Manufacturing Enterprise 2	Group C
P9	Applications Engineer	Automation Sales 3	Individual

All interviews were conducted at the participants job site and followed an open-ended interviewing approach. Overall, we conducted six interviews in both individual and group settings depending on the availability of participants at the job site and asked questions designed to elicit the expert's ideas about their epistemic frame of collaborative robotics. Each interview lasted approximately one hour. After each interview, the researchers discussed the visit and revised questions for subsequent interviews.

3.2 Data Sources and Analysis

Interviews were recorded and transcribed to provide a detailed record of interactions and were segmented by sentence for the subsequent analysis. We conducted a *grounded analysis* [19] of expert interviews to find meaningful patterns of values, behaviors, and skills. We focused our analysis on identifying common ways experts considered the planning, implementation, and monitoring of cobots in factory settings. First, we read each sentence of the transcript, discussed each interview, and conducted open coding to generate an initial set of qualitative codes that represented common and repeating elements from the expert discourse associated with cobots. We then conducted axial coding by reviewing the data and refining our codes. After reaching saturation, we describe a final set of codes that represent the epistemic frame of cobot expertise (see Table 2).

To code the transcripts, we developed an automated coding scheme that used regular expression matching. We used the *nCoder* webkit [20] to develop automated classifiers for each of the codes in Table 2 and then tested for inter-rater reliability between the human rater and automated classifier. For each code, we achieved a kappa greater than 0.9 and rho was less than 0.05. Rho is a Monte Carlo rejective method that tests the generalizability of a given Kappa to the rest of the data [21]. After validating each code, we applied the automated classifiers to the data set to code the data.

To measure expertise across experts, we used Epistemic Network Analysis (ENA; described in detail elsewhere: Shaffer, Collier, & Ruis, 2016) to identify and model the connections between expert frame elements. ENA measures connections by quantifying the co-occurrence of expert codes within a defined segment of data. In this case, we used a *moving window* [23] of four utterances to measure connections between codes that were within four utterances of one another. Codes that occurred outside of this window were not considered connected. Subsequently, ENA creates two coordinated representations for each unit including the *weighted network graph*, which visualizes these connections as network graphs where the nodes correspond to the codes and edges reflect the relative frequency of the connection between two codes, and a *plotted point*. Thus, we can quantify and visualize the structure of connections among elements of cobot expertise and compare differences across experts, making it possible to characterize an epistemic frame within and across experts. After using ENA, we revisited the qualitative data to further investigate key connections between elements.

4 Results

Our analysis of expert interviews revealed insights into the epistemic frame of expert setup and usage of collaborative robots in manufacturing environments. Our initial review of the interviews revealed that safety was the first and most important consideration

Table 2. Epistemic frame codes from expert discourse about cobots.

Name	Definition	Examples
Application	Referring to the automation task	"Some of the applications that started out with collaborative robots have been machine tending"
Integration	Referring to the process of incorporating a robot and other machinery into a production system	"I guess technology's evolved as well as the mindset behind how to implement and integrate the technology"
Operator	Referring to the employees that initiate or control the cobots and other machines on the factory floor	"Our operators need to know how to edit programs; I don't think every operator needs to know how to edit programs"
Performance factors	Referring to cobot attributes such as payload, cycle time, or speed	"They're also not able to be used for high-speed application, higher pay-load applications"
Programming	Referring to coding, programs, or operating interfaces	"Knowing how to edit the program would be…my biggest concern is knowing how to edit this thing"
Reliability	Referring to errors in cobot operation	"If it hits somebody and then faults out, that's not gonna autorecover"
Safety	Referring to risk assessment for human and cobot interactions	"The way that safety works, is that it's based off of risk assessment"
Trajectory	Referring to the points and/or motion paths of cobot movement	"I always push them to just get a rough program done, your picks and your places"

among elements of cobot implementation, and that in balancing cobots' limited capabilities with their benefits of cost, flexibility and safety, the limited capabilities were often seen as an insurmountable barrier.

4.1 Safety

Safety was core to every expert's perspective. In our interviews, we found that experts considered safety and risk assessment throughout the adoption, integration, implementation, and monitoring of cobots in automation. For example, P9 considered safety as a priority when he stated, "I truly do believe that robots regardless if they're traditional or collaborative, you can't have either of those without an understanding of safety." In such a statement, the expert prioritizes safety for all robots, regardless of the type. This safety prioritization was consistently applied across all experts but implemented in different ways. In the next section, we will present the various ways that experts describe safety of the cobot as a system, safety through sensors, and safety through collaboration.

Safety of the Cobot as a System. One major safety consideration is the safety of the cobot as a system. To ensure safe collaboration, risk assessments of robots must consider the robot, task, and workpiece as a complete system. Nonetheless, experts also stated "the biggest challenge for a collaborative robot is ensuring the entire system is collaborative" (P5). Cobots are manufactured to be collaborative by removing common pinch points and embedding force-sensing capabilities. Another expert, P1, explained how one component of the cobot system could negate those reduced safety affordances, "If your tooling that you're mounting at the end of the arms has sharp points on it and it could be maybe at any level with a person's body, you would definitely have to have some kind of safeguard." While a cobot may be considered collaborative in design, if the system (i.e. relationship between the cobot, task, and part) is not fully collaborative, then the cobot no longer meets the reduced safety rules and must be caged and treated like a traditional robot. In this way, experts must continually assess the interaction between components and processes of the cobot system to make a complete risk assessment.

For each of the experts, the system and application are dynamic. Multiple experts talked about how safety "depends on the application" (P1), "depends on what kind of part you're moving" (P4), and "depends on the brand and how you program it" (P5). In another example, P3 warns about end of arm tool choice, "Well and, I guess we made the point too that it's collaborative until, what are you putting at the end of that arm? You can't have a pneumatic gripper jaw with sharp sides to it, I mean that basically becomes a knife." In a similar case, P5 warns about the part type and states, 'I could buy a collaborative robot, but if I'm moving around steak knives, it's no longer collaborative, so there's no point to using a collaborative robot." In other words, assessment of cobot system safety must consider the relationship between cobot, end of arm tools, and part in each application. As P5 said above, the cobot is only safe when the "entire system is collaborative." As a consequence, a robot is only deemed collaborative if that system can be safely operated around a human. In this way, an expert's epistemic frame for cobots is largely defined by assessing the safety of a cobot through a whole system lens, where individual aspects of the cobot interaction can undermine the safety features inherent in the cobot design.

Safety Through Cooperation. Most commonly, experts set up applications where humans and robots work in close proximity but with low interaction between human and robot. In these cases, the cobot was set up for one application where workers may set up the inputs for a process and then proceed to other activities while the application is running. In the following example, two experts discuss the factors for the set up and operation of a cobot operation,

> "We have like inserts and…it's expensive to get things oriented and aligned where you want…so we'll do that as the operator instead of having this automatic feeder, we'll have an operator just…load it, but we want to be able to load the insert to whatever that robot needs *without really getting in the way*…So, typically they'll be doing some other tasks, like, 'Oh, it's been fifteen minutes, I better put some inserts here so that it keeps running.' So we want to make sure that's in a nice location for the operator, too" (emphasis added).

At first, P3 describes the cost and positioning factors associated with inputs and pallets. He further elaborates by considering the multiple jobs an operator may have in the field. While it is important to consider the specific application, these experts also highlight the broader goals and automation activities that engineers and operators may be a part of. P3 goes on to say that an operator will check back in on the process and see if it is time for him to interact with the process. In this example, P3 uses this human, robot, and system interaction to make sure designs are both safe and convenient for the people that operate them. Importantly, though, the operator mostly interacts with the cobot by setting up, starting, checking on, and/or ending the process and then trying to avoid "getting in the way." Rarely are the operators working synchronously or dynamically with the cobot. Notably, this interaction is much more like cooperation where each entity completes a component separately to complete a joint process, in contrast to collaboration where the human and robot would work together on a joint task.

After the statements above, one interviewer asked, "So not only do you have to program the robot, you also have to design the human interaction?" The other expert in the group interview, P4, responded that,

> "Since we do mold swaps so much, you're machine here (one location), UR always working here (a second location), you might be doing a mold swap over here (a third location), so you need to be able to stay out of their way, as well. Keep it up tight against the press, so you don't interfere with them."

In this conversation, P4 extends his collaborators ideas by highlighting how the different locations affect operator workflow and safety. Here, P4 considers the movement of the operator and the requirements that the operator himself stay clear of certain machine actions. Importantly, it is the onus of the operator to "stay out of their way" indicating that the robot movement gains priority status in the cell. Instead of programming movements that are properly safe and collaborative, the operator should not "interfere with them." And so, while P3 and P4 were two of the experts that described more collaborative interactions than other experts, they too try to keep the cobot and operator separated. The above examples also highlight the need to see the robot and human as components in a bigger line or process, yet the separation between operator and robot task persists in part to improve safety in cases which safety measures may fail. That is to say that an expert epistemic frame considers when and if operators engage in cooperative tasks with cobots.

Safety Through Automation. In contrast to the above cooperative example, some experts viewed human and robot interaction in a different way. One of the goals of automation is to automate tasks that are repetitive and/or harmful for humans to engage in. For some experts, the safest way to use robots is without humans and therefore experts may design processes that keep humans separate from cobots. Two experts in particular, P2 and P5, believed that it was important to automate the easy tasks which would free up that person to engage in other tasks at the factory. These experts argued that companies "who automate are going to want to remove the operator" (P5). This is an important process to do in order to reduce "repetitive injuries" (P5) where "you have people doing [things] that's not very ergonomic" (P5). Likewise, P2 made statements throughout the interview indicating that he believed that automating work using traditional robots was more important than collaborative robots. During his courses, he teaches students primarily about traditional robots because he believes that is what is most important for students to learn to get good jobs in industry. In many cases, he believed that a "collaborative robot just couldn't keep up" and that it was just a "slow robot" (P2). Although he believes that cobots are important enough that he incorporates a cobot challenge into the coursework, he does so only during the final section of coursework. In each of these cases, the expert frame considered the safety of the worker as well as weighing the performance of the robot when thinking about what type of robot would be useful for a certain application.

4.2 Performance Tradeoffs for Cobots

While considering robot systems and applications helps make the work cell collaborative, there are important tradeoffs for these decisions. Experts often discussed how the application may require different capabilities for the robot. During one interview, P1 discussed that "if they need um fairly high throughput one of our robots…we have maybe a couple of robots that might work as far as reach goes and payload goes…but if they need the higher speeds that say, a collaborative robot might not be able to achieve, then we will talk about a traditional robot and then safeguarding that also." Like above, there is a dynamic relationship between robot system and application, and in this case, the experts consider other business goals, efficiency, and performance factors. P2 reflects, "so you've got a, um collaborative robot, co-bot um that is able to work without all of the guarding and next to somebody, but typically the cycle times…are lower." Here, P2 weighs the importance of reduced space requirements in comparison with how long it takes to finish a process. In another case, P6 considers the weight of the product when he says, "so depending on the weight of whatever product you're looking at, you might have to go into say the FANUC collaborative" which is a more powerful type of collaborative robot.

These examples show how experts consider how collaborative robots allow the removal of safeguarding in order to allow a cheaper and less bulky cobot that can more easily work with and around humans. On the other hand, cobots can be collaborative because they do not move as fast or powerfully as traditional robots. In other words, experts work to balance the collaborative benefits and performance tradeoffs for each task, which is an important perspective defining an expert's epistemic frame.

4.3 Epistemic Network Analysis

These qualitative results suggest that an expert epistemic frame depends on the interaction between safety principles, the ability and needs of the workers, the specific applications of cobots, and performance limitations of cobots. Within each application, experts attend to the cobot, programming, sensors, and human collaboration to ensure that the dynamic interactions between these moving components remains safe. When discussing each of these epistemic frame elements, experts switch back and forth between focusing on specific details of a cobot application and broader concerns about the risk of a cobot process. While all participants discussed their expertise in cobot implementation and integration, each expert described cobot use in different ways.

One of the goals of this project was to determine whether and how the qualitative stories we found generalize within the larger set of interviews. Therefore, we used ENA to investigate (1) the types of epistemic frame elements that experts discussed, and (2) how all experts make connections across these frame elements. ENA affords a method to see if the patterns identified in the grounded analysis occur as a systematic pattern across all units. Figure 1 shows an ENA representation of expert discourse when discussing collaborative robots. The figure shows the average plotted points (squares) for each expert, as well as the overall mean plotted point for all experts in the ENA space. The figure also shows an average discourse pattern for all experts, where the thickness and saturation of a connection indicates that experts frequently discussed these ideas together.

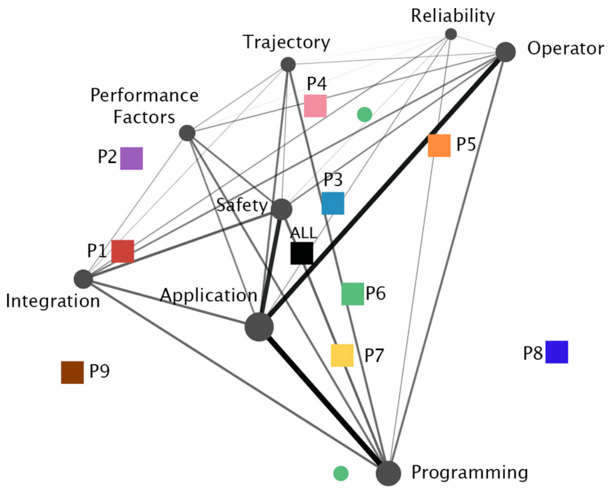

Fig. 1. Mean network points (squares) and overall mean network for the expert model of cobots. Thicker lines indicate higher relative frequency of a given connection between two expert codes.

This model shows connections to SAFETY and to APPLICATION were common across all experts, which reinforces our qualitative interpretation of the interviews. The ENA model also identifies the common ways that experts describe their approaches to setting up robot systems for a specific application. For example, the two strongest connections in the mean network are between APPLICATION and OPERATOR and APPLICATION and PROGRAMMING. Each of these connections provides evidence that experts often consider the two actors in a cobot process: the worker initiating, monitoring, and ending the tasks, and the specific coding and logic that moves the robot through the task. These results support our grounded analyses and provide a quantitative warrant for our qualitative claims that an expert frame focuses on the dynamic interaction between safety and components of application.

These ENA results suggest that experts spend more time talking about specific details of how operators engage with a task and how implementers program the robot system within that task. In this case, ENA can identify that experts consider operators and programming less often than other relationships. It is equally important that through ENA we can see that not all experts discuss cobots in the same way. In the qualitative examples, P9 is very concerned about safety and frequently discussed ways to integrate sensors into each application. And the ENA space positions him farther to the left near APPLICATION, INTEGRATION, and SAFETY. On the other hand, P5 is to the right of the space because he more frequently discussed how the OPERATOR may need to restart a PROGRAM that had issues with RELIABILITY and experienced an error. In this way, ENA allows us to benefit from the variety of expert discourse and classify types of experts. Additionally, ENA affords identification of both expert and researcher blind spots.

However, these results also highlight important gaps in cobot use and additional pieces to the above stories. As researchers we were surprised at the weaker connections to operator, particularly from SAFETY and from PROGRAMMING. For example, as processes incorporate more collaborative interactions, cobot systems need to program for the operator as much as the application. After evaluating these network results, we as researchers dove deeper to learn why some connections were more prominent than we expected (i.e., OPERATOR & APPLICATION), while others were far less prominent than we hypothesized (i.e., OPERATOR and SAFETY or OPERATOR and PROGRAMMING). Based on our review of the literature and our previous work, we would have expected there to be more discussion about ways humans and cobots can safely collaborate, which guided our reevaluation of the qualitative data.

4.4 Challenges in Safety and Collaboration

After investigating our ENA model, we identified qualitative examples that may explain why certain connections were more or less frequent across all experts. Next, we explain how challenges in both safety and collaboration may help us understand these differences and inform future trainings for operators and implementers.

Safety Challenges. Because of the dynamic factors involved in creating safe manufacturing operations, employing good safety practices is still a challenge for experts. Even with the safety standards and physical and electronic barriers separating traditional and collaborative robots from humans, there are still instances of people using the machines unsafely. For example, P9 recounts "traditional robots have always been something that are very high speed. And it's something that you don't want to get yourself within their operational reach. (laughs briefly) Now there's many examples of where I can state people that uh still do that." And so, while traditional robot setups often have stricter rules separating humans from machines, operators may still try to bypass safety precautions in service of their work. For these reasons, P9 believes that,

> "to be honest, if there's weakness right now I think in the automation industry…it's the true understanding and knowledge on how to implement safety correctly. So people when they implement safety, they think if they're doing something and they're putting something there, it's deemed safe. And …that's not necessarily true" (P9).

Even though every expert in our study discusses safety, these conceptions of safety vary in scope, type, and depth as seen in the different positions of experts across the frame elements. Each expert expressed different ways they dealt with safety, although all consistently referenced safety throughout their interviews.

One barrier to safe deployment of all robots and cobots is safety training itself. Above, P9 finds safety to be the most important and yet weakest component in the automation industry. Similarly, P4 expresses this concern and reflects, "I know, from when I was in school, we didn't talk much about safety. At all, when it comes to control systems, so that might be something else that you can start integrating. That they can be aware of safety." Such statements suggest that both engineers and operators would benefit from more opportunities to think about and apply safety techniques in their day to day work.

These results have suggested that safety is the primary lens with which experts consider programming, integration, collaboration, and robot systems. However, this dynamic picture is further complicated and limited by the operator himself.

Collaboration Challenges. An interesting result from our reinvestigation of the qualitative data is how experts talk about operators. People are an important component in a collaborative robot interaction, however, expert attitudes towards the operators may affect how or if collaborative robots are used at all. Some experts see operator agency as an advantage while others see it as a liability. One engineer expressed his desire for more training and assistance for operators. He thought it is a benefit for his workload and for the applications when an operator is trained. For example, P7 says,

> "If [operator name] weren't trained, every time a new error came up that he'd never seen before…we'd just teach them how to reset it and they'd just mindlessly go through and hit the buttons they know to hit to reset it…but if he actually knows what the error means and he knows how to reset it, then he doesn't have to call us, wait for us to come out, reset it".

In this case, operator knowledge and agency would allow the operator to modify programs that could help save both the operator and engineer's time. Knowing how to understand problems would help both individuals.

On the other hand, there were quite a few opinions about what operators should be allowed to do. P6 describes the variety of perspectives that he has experienced working with different companies. He recounts that, "we've had companies say that, 'We want a robot where we can literally let the operator change programs: speed it up, slow it down.' And I've been at facilities where you have to be a trained maintenance or automation technician to get the password to [be] allow[ed] to even unlock the teach pendant." Each of these examples illustrates the wide range of trust that the engineers at a company have for their operators. In some cases, experts even expressed some disdain for employees. P5 asserts that, "If you would ask most owners, they would like to have robots in there doing everything. They don't take smoke breaks, they don't call in sick, they don't intentionally try to sabotage your product if they're having a bad day or weren't treated fairly for X or Y reasons." Even the community college educator states that, "It's not like everybody can move up that pyramid of skills" (P2). And so, it may come as no surprise that P2 and P5 are the two experts that advocate for automation over collaboration to ensure safety and efficiency of work. These examples provide insight into why some experts may be more open to collaboration than others and provide explanations as to why the connections to the operator were less frequent across the entire sample. Some experts may have viewed operators simply as someone that starts and stops an application, treating the humans as one component in the system. Other experts envision a more dynamic role where the operator is an agent that can engage in coding and problem-solving. In either case, an expert frame would consider the interaction between application, cobot system, and operator.

5 Discussion

This study shows how the expert epistemic frame works to assess safety at different levels—from programming logic to the setup of a full automation line. Experts look for how safety depended on the dynamic interaction between the robot system, application, and human actions. These results suggest that experts put *safety first* when designing and implementing collaborative robot interactions.

The epistemic frame outlined in this study can also be used to support novices in learning how to use cobots as well as to support experts' ability to round out their robot expertise. Our future work will leverage the expert model to design and develop a cobot project-based learning simulation. This learning environment will engage students in an authentic cobot application while providing real-time and adaptive supports based on the epistemic frame outlined in this study. Learners will be able to enable components of the frame to see what an expert would see based on the epistemic frame, such as how to consider safety in conjunction with trajectories. We will also explore the design and function of different interface modalities (*i.e.,* teach pendant, desktop simulation, augmented reality) that afford user interactions with the system and how they affect learning the epistemic frame. In this way, a quantitative ethnographic analysis of expertise in a domain can be used to create curriculum and learning environments. Additionally, by creating a representation of expert knowledge through QE and ENA, we can also use the resulting ENA space to evaluate novices and compare their discourse with expert discourse.

This study also provides important methodological implications. When quantifying the qualitative, we must not lose sight of local meanings from discourse. Our analysis highlights the importance of closing the interpretive loop by both scaling our local understandings across the sample as well as investigating how statistical representations shed light on more specific patterns. As seen the two analyses, there were important differences in how experts accounted for safety and collaboration. Some experts addressed safety through fostering more collaborative interactions, while others made the application safer by removing the workers during operation. Future analyses would benefit from learning more about these perspectives and which is more common in the workplace. While the goal of the current study was to summarize all expert perspectives, further analyses could categorize experts based on their perspectives and consider the similarities and differences between these groups.

Our study is limited in both size and diversity of the sample, which would benefit from interviews with more operators, recruitment of female operators, and comparisons across different types of companies. During our data collection, we focused on interviewing implementers and engineers as experts but recognize the need for more understanding about operator uses and interactions with cobots.

However, in the end, this study improves our understanding of expert problem-solving in collaborative robotics, defines an expert model that can serve as a basis for the development of an authentic learning technology, and illustrates a useful method for modeling expertise.

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References

1. National Academies of Sciences: Building America's skilled technical workforce. The National Academies Press, Washington, DC (2017). https://doi.org/https://doi.org/10.17226/23472
2. Faccio, M., Bottin, M., Rosati, G.: Collaborative and traditional robotic assembly: a comparison model. Int. J. Adv. Manufact. Technol. **102**(5–8), 1355–1372 (2019). https://doi.org/10.1007/s00170-018-03247-z
3. Elliott, C.H., Radke, S.C., Ma, J.M.: A focus on contribution towards product performance in collaborative design. In: Kay, J., Luckin, R. (eds.) Rethinking Learning in the Digital Age: Making the Learning Sciences Count, 13th International Conference of the Learning Sciences (ICLS) 2018, pp. 48–55. International Society of the Learning Sciences, London (2018)
4. Kim, Y., Marx, S., Pham, H., Nguyen, T.T.: Designing technology as a cultural broker for young children: challenges and opportunities. In: Kay, J., Luckin, R. (eds.) Rethinking Learning in the Digital Age: Making the Learning Sciences Count, 13th International Conference of the Learning Sciences (ICLS) 2018. pp. 88–95. International Society of the Learning Sciences, London (2018)
5. Starr, E.L., Reilly, J.M., Schneider, B.: Toward using multi-modal learning analytics to support and measure collaboration in co-located dyads. In: Kay, J., Luckin, R. (eds.) Rethinking Learning in the Digital Age: Making the Learning Sciences Count, 13th International Conference of the Learning Sciences (ICLS) 2018, pp. 448–455. International Society of the Learning Sciences, London (2018)
6. Hirschfeld, R.A., Aghazadeh, F., Chapleski, R.C.: Survey of robot safety in industry. Int. J. Hum. Factors Manuf. **3**, 369–379 (1993). https://doi.org/10.1002/hfm.4530030405
7. Christiernin, L.G.: How to describe interaction with a collaborative robot. In: ACM/IEEE International Conference on Human-Robot Interaction, pp. 93–94 (2017). https://doi.org/10.1145/3029798.3038325
8. Djuric, A.M., Urbanic, R.J., Rickli, J.L.: A framework for collaborative robot (CoBot) integration in advanced manufacturing systems. SAE Int. J. Mater. Manuf. **9**, 457–464 (2016)
9. Michaelis, J.E., Siebert-Evenstone, A., Shaffer, D.W., Mutlu, B.: Collaborative or Simply Uncaged? Understanding Human-Cobot Interactions in Automation, pp. 1–12 (2020). https://doi.org/10.1145/3313831.3376547
10. Chi, M.T.H., Feltovich, P.J., Glaser, R.: Categorization and representation of physics problems by experts and novices. Cogn. Sci. **5**, 121–152 (1981). https://doi.org/10.1207/s15516709cog0502_2

11. Bransford, J.D., Brown, A.L., Cocking, R.R.: How People Learn: Brain, Mind, Experience, and School. National Academies Press, Washington, DC (1999)
12. DiSessa, A.: Knowledge in pieces. Constructivism in the Computer Age, pp. 49–70 (1988). https://doi.org/10.1159/000342945
13. Shaffer, D.W.: How Computer Games Help Children Learn. Palgrave Macmillan, New York (2006).
14. Bagley, E.: Epistemography of an urban and regional planning practicum: appropriation in the face of resistance. WCER Working Paper (2010)
15. Arastoopour, G., Chesler, N.C., Shaffer, D.W.: Epistemic persistence: a simulation-based approach to increasing participation of women in engineering. J. Women Minor. Sci. Eng. **20**, 211–234 (2014). https://doi.org/10.1615/JWomenMinorScienEng.2014007317
16. Chesler, N.C., Ruis, A.R., Collier, W., Swiecki, Z., Arastoopour, G., Shaffer, D.W.: A novel paradigm for engineering education: virtual internships with individualized mentoring and assessment of engineering thinking. J. Biomech. Eng. **137**, 1–8 (2015). https://doi.org/10.1115/1.4029235.
17. Shaffer, D.W.: WCER Working Paper No. 2005-8 Epistemography and the Participant Structures of a Professional Practicum: A Story Behind the Story of Journalism 828. Cognition (2005)
18. Shaffer, D.W.: Quantitative Ethnography. Cathcart Press, Madison (2017)
19. Corbin, J., Strauss, A.: Grounded theory research: procedures, canons, and evaluative criteria. Qual. Sociol. **13**, 3–21 (1990)
20. Hinojosa, C., Siebert-Evenstone, A.L., Eagan, B.R., Swiecki, Z., Gleicher, M., Marquart, C.: nCoder (2019). https://app.n-coder.org/
21. Eagan, B.R., Rogers, B., Serlin, R., Ruis, A.R., Irgens, G.A., Shaffer, D.W.: Can we rely on IRR? Testing the assumptions of inter-rater reliability. In: CSCL 2017 Proceedings, pp. 529–532 (2017).
22. Shaffer, D.W., Collier, W., Ruis, A.R.R.: A tutorial on epistemic network analysis: analyzing the structure of connections in cognitive, social, and interaction data. J. Learn. Anal. **3**, 9–45 (2016). https://doi.org/10.18608/jla.2016.33.3
23. Siebert-Evenstone, A.L., Arastoopour Irgens, G., Collier, W., Swiecki, Z., Ruis, A.R., Williamson Shaffer, D.: In search of conversational grain size: Modelling semantic structure using moving stanza windows. J. Learn. Anal. **4**, 123–139 (2017). https://doi.org/10.18608/jla.2017.43.7