Skill and Knowledge Sharing in Cyber-Augmented Collaborative Physical Work Systems with HUB-CI

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PRISM Center and School of IE, Purdue University

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ABSTRACT

Recent advancements of manufacturing systems and supply networks towards Cyber-Augmented Collaborative Physical System (CCPS) necessitate skill and knowledge sharing model in a human-robot collaborative e-Work environment. Previous research on skill and knowledge sharing has mostly ignored the need to share knowledge with skills. It was also limited on how such helpful, collaborative augmentation can be enabled by the huge amount of data availability, and collaborative intelligence analytics. Such augmentation is further enabled by emerging, sophisticated computing resources, including machine learning, virtual/augmented reality, and hardware such as wearables, sensors, and IoT/IoS. This research aims to explore the state of the art of skill and knowledge sharing in manufacturing systems, and highlight the key areas and future research directions of the topic. A variety of case studies are also presented, particularly related to augmented reality and HUB-CI as the key enablers for skill and knowledge sharing.

Keywords: Augmented Reality, Collaborative Intelligence Augmentation, Cyber-Augmented Collaboration, Cyber Physical System, HUB-CI, Skill and Knowledge Sharing

Table of Acronyms and their definitions

No	Abbreviation	Definition
1	AI	Artificial Intelligence
2	AR	Augmented Reality
3	ARS	Agricultural Robotics System
4	CAD	Computer-Aided Design
5	CC-Management	Cyber-Augmented Collaborative Management
6	CCPS	Cyber-Augmented Collaborative (e-Work with) Physical System
7	CCT	Collaborative Control Theory
8	CC-Work	Cyber-Augmented Collaborative Work
9	CNC	Computer Numerical Control
10	CPS	Cyber-Physical System
11	CRISP-DM	Cross-Industry Standard Process for Data Mining
12	CRP	Collaboration Requirement Planning
13	CTR	Collaborative Telerobotics
14	CSCD	Computer-Supported Collaborative Design
15	DCSP	Demand-Capacity Sharing Protocols
16	ERP	Enterprise resource planning
17	GUI	Graphical User Interface
18	HITL	Human In The Loop perspective
19	HITN	Human In The Network perspective

No	Abbreviation	Definition
20	HRI	Human-Robot Interface
21	HUB-CI	HUB of Collaborative Intelligence, or a network of such HUBs
22	ICT	Information and Communications Technology
23	IoS	Internet of Services which leverage data from IoT/IIoT
24	IoT, IIoT	Internet of Thinks, also known as Industrial Internet of Things
25	TTC	Time to Complete (collaborative tasks executed by humans and robots)

1. Collaboration automation in a Cyber-Augmented Collaborative Physical System (CCPS)

In the collaborative work and factories of the future (Moghaddam & Nof, 2015, 2017) multiple systems, including humans as participants and as clients, are designed to work together, and cooperate towards accomplishing given objectives, collaboration and integration are necessary. With highly variable job and task requirements in modern work, and highly variable levels of preparedness of workers and robots under such conditions, a major concern of researchers of future work and factories has been: How to share skills and knowledge, as soon as needed, with workers and robots dynamically. CCT, the Collaborative Control Theory, aims to optimize such collaboration and integration. The purpose of this research is to address the sharing of skills and knowledge among the human participants.

What do we mean by skills and knowledge, and why it is necessary to share them online, just as needed and when they are needed? As an illustration, consider a baking work case: A baker needs *skills* of baking, e.g., best practice of ingredients preparation, measuring and mixing; and *knowledge*: details of the cake to bake, its ingredients, specifications of the mixer and oven available, and ongoing process status of the equipment and tools. While skill and knowledge sharing can be helpful to novice bakers, they become essential and mandatory for preparing and enabling human workers most effectively, when they work, or e-Work with a network of automation and robotics work agents.

Four layers of e-Work CPS, which we define as cyber-augmented collaborative work with physical systems, or for short, Cyber-Augmented Collaborative Physical Systems (CCPS), are defined as follows: 1. Cyber; 2. Physical items & systems; 3. Networking; and 4. CC-Work and CC-Management (CC: Cyber-Collaborative). Each layer is described as follows:

- **Cyber Layer**: An interdependent network of information systems infrastructures, including the Internet, telecommunications networks, computer systems, embedded processors, and controllers.
- **Physical Items and Systems**: The physical part of a CCPS includes sensors, actuators, radio-frequency modules for communication, and any other hardware to support CCPS function and provide the interface.
- **Networking**: Interconnectivity between computational elements (data repository, algorithms, AI) and computerized physical entities (CNC machines, robots, sensors) in the CCPS. Networking includes the IoT/IoS.
- **CC-Work and CC-Management**: Any task and management practices that are executed with cyber-augmented collaborative, or cyber-collaborative support means.

2. Skill in Cyber-collaborative Physical System

A widely acceptable taxonomy for objective assessment in the cognitive domain is termed Bloom's Taxonomy *(Bloom et al., 1964)*. The taxonomy is divided based on an ordinal scale of cognitive ability. The categories for the cognitive domain and illustrative action words for each level are presented in Table 1.

Table 1 The Definition and Action Words of Bloom's Taxonomy

No	Category	Definition	Illustrative Action Words
1	Knowledge	The ability to repeat information verbatim	to list; to state;
2	Comprehension	The ability to demonstrate understanding of terms and concepts	to explain; to interpret; to describe
3	Application	The ability to implement learned information to solve a problem	to calculate; to solve; to utilize; to execute
4	Analysis	The ability to dismantle a structure into its elements and formulate explanations based on a theory, or mathematical or logical models for a certain observed phenomenon	to derive; to explain; to interpret; to infer
5	Synthesis	The ability to create and combine elements with a high degree of novelty	to formulate; to make up; to design; to integrate
6	Evaluation	The ability to select and justify a set of selections from other alternatives	to determine; to select; to critique; to assess

Different cognitive-based taxonomies have been developed following Bloom's Taxonomy. RECAP model (Imrie, 1995) adopted Bloom's taxonomy and simplified it into a two-tier structure for both in-course and end-course assessments, related to two levels of learning, as presented in Table 2.

Table 2 RECAP-based cognitive domain taxonomies

Tier	Skill Level	Bloom's Category	Assessment Level
1	Recall; Comprehension; Application	Knowledge; Comprehension; Application	Essential skills are assessed by objective-based, structured, short questions and answers survey
2	Problem-solving skills	Analysis; Synthesis; Evaluation	Advanced problem-solving skills are assessed by case-study questions and other criterion-referenced or norm-referenced assessments

For a cyber-physical manufacturing system, a taxonomy of job complexity, required skills, examples of role, and technical requirements has been developed (Krachtt, 2019). Their taxonomy is presented in Table 3:

Table 3 Skill Taxonomy for a Cyber-Physical Manufacturing System

Job Complexity	Required Skill	Roles	Technical Knowledge Requirement
Entry Level	Resource management, social, and context skills	Order Pickers	AR devices, RFID, mobile ICT
		Sub Assemblers	ERP Systems, AR devices
		Data Clerks	Data Analytics in CPS
		Lift Operators	Material handling, RFID, Mobile ICT
		Manual Operator	AR Devices, RFID
Mid Level	Resource Management,	Robotics Operator	Automation, AI, AR devices, CPS, SMOs
		Materials Lead	Data Analytics in CPS, AI, AR, simulations

Job Complexity	Required Skill	Roles	Technical Knowledge Requirement
	Social, Content, Cognitive, and Technical skills	Machine Operators	Automation, AR devices, SMOs, IIoT*, ICT
		Welder	Automation, IIoT*, AR, ICT
		Production Analyst	Data Analytics in CPS, SMOs, IIoT, CPS, ICT, simulations
Advanced Level	Resource Management, Social, Content, Cognitive, Technical, and Process, System skills	Automation Technician	Automation, AR devices, AI, CPS, SMOs, ICT
		Systems Tester	IIoT, IoT, AI, AR devices, CPS, ICT, SMOs
		Systems Integrator	CPS, IIoT*, AR devices, ICT, SMOs
		Machine Programmer	SMOs, IIoT*, CPS, ICT, big data

* We note that IIoT, Industrial Internet of Things, always requires an IoS, Internet of Services, that are designed to intelligently utilize the data and signals obtained by the IIoT; and international standards exist for both.

3. Case studies of Skill Sharing to enable Collaboration automation

3.1 AR-enabled Skill and Knowledge Sharing

This section presents recent advances in augmented reality (AR), particularly on how it enables skill and knowledge sharing (see Acknowledgment). The first study (A. Villanueva et al., 2022), Collab-AR, is developed to facilitate and improve collaboration in Tangible AR (TAR) with a customized haptics feedback. In terms of time to complete the experiment: AR+Haptics (M=60.8 mins, SD=4.26), Zoom + Physical Components (M=81.2 mins, SD=4.71). The decrease in time (25.2%) was statistically significant between conditions ($p<0.05$), due to the combined use of haptics and voice, as opposed to voice-only.

Another form of enabling technology is wearables. One study (Paredes et al., 2021) proposed a wearables taxonomy; a database of research, tutorials, aesthetic approaches, concepts, and patents; and CHIMERA, an online interface that provides visual and taxonomic connections to the growing database. The wearables taxonomy consists of categories, elements, and grouping types. There are 4 categories: function, fabrication, materials, and body zones; and 5 grouping types: research, tutorials, aesthetic approaches, concept designs, and patents. The database consists of 842 resources which are published between the year 2010 and 2020. CHIMERA is validated across three groups: 24 participants conducting a multidisciplinary design task, a group of wearable experts, and students in a wearable class. In instances where the CCPS requires a highly-specific form of collaborative skill and knowledge sharing, wearables customization becomes essential. One study (Paredes, Reddy, et al., 2021) developed FabHandWear as a device capable of creating customized, functional, and manufacturable hand wearables. The system allows a user to fabricate functional prototype of wearables without special machinery, clean rooms, or tools. The system is validated by conducting wearable devices development by inexperienced users. The participants reported a mean NASA TLX score of 47.5 (SD=15.083), and a mean system usability score (SUS) of 70.42 (SD = 16.61), ensuring the FabHandWear's applicability.

In a skill and knowledge sharing instance, the primary role of AR is to augment the capabilities of a human in the loop. One notable research (T. Wang, Qian, He, Hu, et al., 2021), GesturAR, studied the taxonomy of human hand gestures as an input in AR, and processed into a hand interaction model which maps the gesture inputs to the reactions of the AR contents. The trigger-action AR allows visual programming and instantaneous results in AR. Five scenarios are developed to justify the proposed model: creating interactive objects, humanoid and robotic agents, augmenting in-door environment with tangible AR games, making immersive AR presentations, and interacting with entertaining virtual contents. The hand detection network accuracy and usability are evaluated as the performance metrics of the proposed design.

Skill and knowledge sharing also require object interaction and environmental manipulation. For instance, the integration of sensors, IoT devices, and human operators within a CCPS. One study (Chidambaram et al., 2021) proposed ProcessAR as an AR-based system capable of developing 2D/3D content that captures subject matter expert's (SMEs) environment object interactions in situ. ProcessAR locates and identifies different tools/objects through computer vision within the workspace when the author looks at them, and could be featured with 2D videos of detected objects and user-adaptive triggers. Compared to the baseline scenario, ProcessAR has a lower task time, better usability, particularly for novice users, and statistically significant reduction of the perceived workload both for expert and novice users.

In cases where object interaction and environmental manipulation occur on a physically small scale, one study (Adam et al., 2021) proposed a robust and multifunctional micromanipulation system with 3D micro-force sensing capabilities. In this system, multiple probes are actuated to achieve and simplify more complex manipulation tasks while providing force feedback to the user. A graphical user interface (GUI) was developed as a robust and comprehensive platform to intuitively control the entire system and its many capabilities. Furthermore, a VR system has been implemented to provide intuitive manipulation, and with the use of the force sensing probes, the user is able to select a maximum threshold force to keep the manipulation process safe. In order to validate its capabilities, several experiments were conducted: automatic contact detection, simple and complex caging applications (manipulation/assembly), and the test of VR capabilities. In terms of accuracy, caging manipulation has an error of 7.73% for polygonal parts and 8.78% for circular parts, in comparison with pushing application which has a 14.07% error.

Table 4 summarizes other projects related to AR-enabled skill and knowledge sharing for cyber-collaborative physical system:

Table 4 Summary of AR-enabled Skill and Knowledge Sharing in a CCPS

Title	Type of Augmented Reality	Metrics and Measurement	Features	Skill and Knowledge Modeling	Fields of Skill and Knowledge	Skill and Knowledge Sharing Instances
A Large-scale Annotated Mechanical Components Benchmark for Classification and Retrieval Tasks with Deep Neural Networks (Kim, Chi, et al., 2020)	Mechanical Components Benchmark (MCB) for annotating, defining, and benchmarking deep learning shape classifiers	mean accuracy over objects, average accuracy per class, F1-score and average precision (AP), and precision-recall curves	7 shape classification algorithms from point cloud, multi-view, and voxel grids 3D shape representations	The ability to view, annotate, classify and analyze the knowledge of mechanical components data	Computer vision	Could be implemented as AR-enabled knowledge-driven classification benchmark for mechanical parts
AdapTutAR: An Adaptive Tutoring System for Machine Tasks in Augmented Reality (G. Huang et al., 2021)	AR-based tutorial to better adapt to workers' diverse experiences and learning behaviors, with different levels of details (LoDs)	tutoring time, repeating times, testing time, and count of mistakes; user preference	Unity3D, backend server running web framework in Pythonbased on Tensorfow (v2.1) and SVM.	Skills are detailed into step- enabled Avatar, animated component, step expectation, and subtask description	General; laser-cutting machine	Tutors perform tasks; tasks are decoded by AR; AR is equipped by novice operators
First-Person View Hand Segmentation of Multi-Modal Hand Activity Video Dataset (Kim, Hu, et al., 2020)	Multi-modal video dataset generation based on hand thermal information	The mean Intersection over Union (IoU) between the two class based on manually-annotated labels	Modification of DeepLabV3+ with 3 modalities LWIR, RGB, and depth	Knowledge of left and right hands segmentation is based on "hands using tools" videos	Computer vision	Accurate and faster hand segmentation allows better hand tracking for operators
LightPaintAR: Assist Light Painting Photography with Augmented Reality (T. Wang, Qian, He, & Ramani, 2021)	AR for spatial reference to enable precise light sources movement	user evaluation (SUS) on accuracy and overall experience	Hololens 2 spatial tracking function, Lume Cube LED, Canon EOS M6ii EF-M 11-22mm lens	The skill to light-paint the words "CHI 2021" using the LED light	General Motoric Skill	Could be implemented for vision-based light-signal detection

Title	Type of Augmented Reality	Metrics and Measurement	Features	Skill and Knowledge Modeling	Fields of Skill and Knowledge	Skill and Knowledge Sharing Instances
Object Synthesis by Learning Part Geometry with Surface and Volumetric Representations (Kim et al., 2021)	Part Geometry Network (PG-Net) to simulate realistic objects for a robust feature descriptor, object reconstruction, and classification.	task convergence time, fitting time, and inference time; classification accuracy of PG-Net; reconstruction measures	TensorFlow deep learning framework on ModelNet datasets with a linear SVM for 3D classification benchmark	Knowledge is modeled as object synthesis based on AR-enabled multi-task and part geometry learning	3D object synthesis, and classification	Knowledge sharing could be implemented for AR-enabled CAD
RobotAR: An Augmented Reality Compatible Teleconsulting Robotics Toolkit for Augmented Makerspace Experiences (A. M. Villanueva et al., 2021)	AR for assessment, teaching, and learning	key competencies assessment and usability survey	phone-mounted robot platform; Unity 3D for the software	Skills are modeled as the ability to assemble electrical circuitry components kit	Electronics and circuitry	Skill sharing via AR and teleconsulting enables better students assessment and teaching
Towards modeling of human skilling for electrical circuitry using augmented reality applications (A. Villanueva et al., 2021)	AR-enabled assessment, teaching, and learning to implement an educational curriculum	the attainment of learning outcome of micro-skills	Micro-skills are aligned with the AR content using Q-matrix; they are classified into perceptual, cognitive, and motor types of skill	Skills are modeled as micro-skills, which are mapped into learning outcome	Electronics and circuitry	The model allows a feedback loop between the micro-skills, delivery method (full or partial), and learning outcomes attainment
VRFromX: From Scanned Reality to Interactive Virtual Experience with Human-in-the-Loop (Ipsita et al., 2021)	Do-It-Yourself (DIY) platform to create interactive virtual experiences	time required to finish each task; System Usability Scale (SUS)	Unity Engine in C# pre-loaded back-end neural networks; object classification is achieved by a PointNet	Skills are the VR-based ability to retrieve object, model behavior of virtual objects, and interact (weld virtually).	virtual Metal Inert Gas (MIG) Welding simulator	VRFromX enables worker to train and simulate welding in-situ

3.2 HUB-enabled Skill and knowledge Sharing

Multi-agent skill and knowledge sharing becomes critical in work and factories of the future. With an increasing degree of automation, remote operation, maintenance, reorganization and reconfiguration become objectives of the human-automation-robot skill sharing augmentation initiative. This section reviews previous research on the usage of hubs for collaborative intelligence (HUB-CI) for enabling skill and knowledge sharing in a CCPS.

HUB-CI focuses on improving human collaboration through e-collaboration tools and services. It significantly enhances synthesis and integration of knowledge and discoveries, as well as their sharing and delivery in a timely manner (Seok & Nof, 2011). Additionally, HUB-CI connects humans and robots for collaborative control of physical automation and assembly in manufacturing (Zhong & Nof, 2013). Multiple HUB-CIs can operate in a hub-to hub and multi-hub collaborations involving multiple networks. Recent advances of HUB-CI aim to optimize information flow, based on the current activity, physiological state, attained information, and unique attributes of each worker. The design framework is presented in the following diagram:

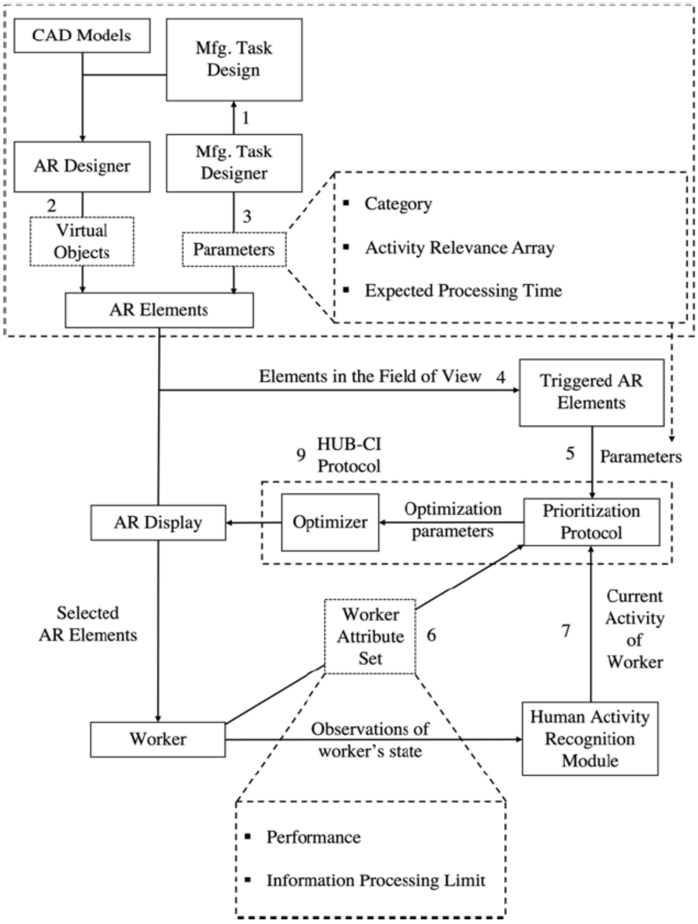
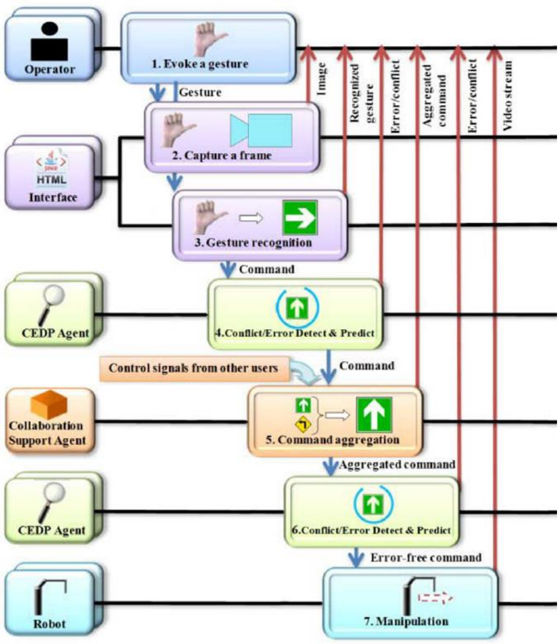


Figure 1 AR design framework with HUB-CI protocol *(Source: Moghaddam & Nof, 2022)*

3.2.1 Collaborative Telerobotics for Product Design and Testing

A study in Collaborative Telerobotics (CTR) developed a model where humans (experienced and novices in the work tasks) and robot execute initial stages of skill and knowledge sharing based on a HUB-CI model (Zhong et al., 2013). Robot agents operating under collaboration protocols through the HUB-CI carry out their actions according to the aggregated command received. In turn, human agents acquire feedback from the robots from either a video stream, or 3D arrows which indicate the aggregated command (speed and direction) in spheres alpha-blended in the video. The conceptual model and mathematical formulation are as follows:



$$X_{ij}(t) = \begin{cases} 1, & \text{if operator } i \text{ issues } C_j \text{ at } t \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

$$V(C_j, t) = \sum_{i=1}^{N} \left[W_{ij}(t) \cdot X_{ij}(t) \right] \quad (2)$$

$$\hat{C}(t) = \arg\max_{C_j} \left(V(C_j, t) \right) \quad (3)$$

$$E(\hat{C}(t)) = \begin{cases} 1, & \text{if } \hat{C}(t) \text{ is free of error} \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

$$S(C_j, \hat{C}(t)) = \begin{cases} 1, & \text{if } C_j = \hat{C}(t) \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

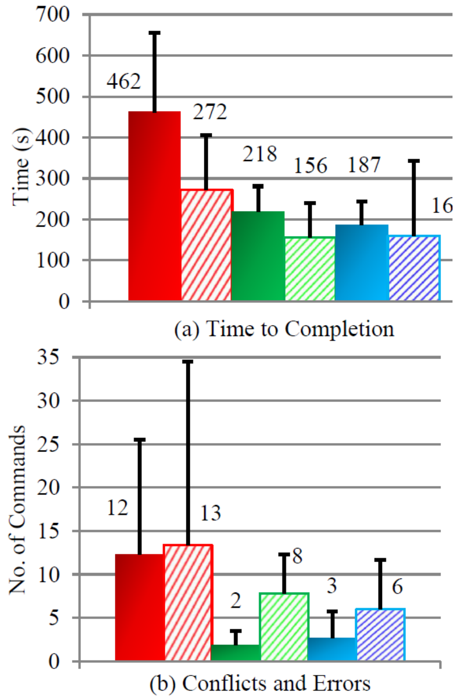
$$F_i(t) = \sum_{j=1}^{M} \left[X_{ij}(t) \cdot S(C_j, \hat{C}(t)) \right] \quad (6)$$

$$K_i(t) = \overline{XOR}(E(\hat{C}(t)), F_i(t)) \quad (7)$$

$$W_{ij}(t+1) = \frac{\sum_{\tau=t-p}^{t} K_i(\tau)}{\sum_{\tau=t-p}^{t} \sum_{j=1}^{M} X_{ij}(\tau)} \quad (8)$$

Figure 2 Collaborative Telerobotics Sequence Diagram and Co-tolerance of Error and Conflict Algorithm (Source: (Zhong et al., 2013))

Individual and collaborative experiments have been designed to evaluate the performance of CTR system implemented with HUB-CI model. Overall performance of the CTR system is determined by the time to complete (TTC) the given robotic task, the occurrence of conflict/error (CE) under each experiment, and its relationship to TTC. It is concluded that to achieve better performance, operators have to reduce errors and increase the frequency of error-free commands, as shown in Figure 2. The intuitive and logical observation can be achieved by more effective skill and knowledge sharing augmentation, provided by HUB-CI.



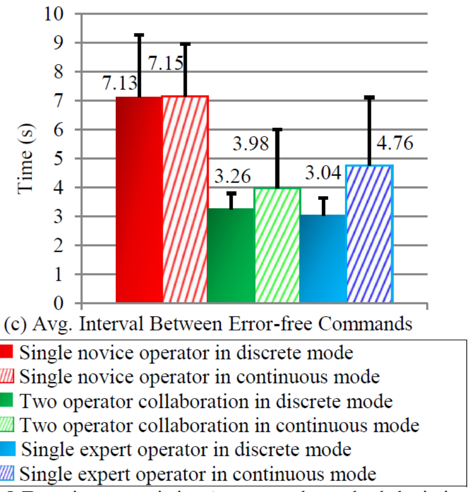


Fig. 5 Experiment statistics (means and standard deviations) (Adapted from Zhong *et al.*, 2013)

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	608682	304341	19.53	<.0001
Error	46	716802	15583		
Total	48	1325485			

Figure 3 Experimental Results in terms of e-Criteria and e-Measure of HUB-CI in CTR (Source: (Zhong et al., 2013)

3.2.2 Computer-Supported Collaborative, Integrated Life-Cycle Product Design

A second application of HUB-CI as an enabler for skill and knowledge sharing is described in a computer-supported collaborative design (CSCD) case study using CAD software (Zhong et al., 2014) . The HUB-CI environment is hosted on a server which can be accessed via Internet, and offers the following elements and capabilities to support CSCD:

1. Defining the tasks and e-Work requirements;
2. Storage in an online database;
3. Collaborative coding and electronics CAD;
4. Structured Co-Insights Management as an environment used for the conceptual design of the physical product;
5. Capability to network, which is responsible for checking conflicts and errors throughout the development cycle of a new product;
6. Electronic CAD as the tool that supports the required software development and hardware design;
7. The physical development, testing, and validation, which are accomplished at the robotic prototyping cell;
8. The telerobotic cell, which is built as one of the service resources available to designers through the HUB-CI environment;
9. The designers working at the interaction tier of the HUB-CI environment;
10. The coordinate system representation of collaboration which indicates the multidimensionality of the collaboration space.

As a proof of concept, the study (Zhong et al., 2014) implemented a pilot system for collaborative design and prototyping based on HUBzero package. The distributed designers were asked to build a digital voltmeter from ten LEDs, ten resistors, a potentiometer and an Arduino controller. The output voltage of this voltmeter should be understandable by human as a form of knowledge intelligence. The result of this study has shown that an integrated system with HUB-CI can effectively provide the functionality required during the product development lifecycle.

3.2.3 Cyber-Physical Agricultural Robotic System

A third implementation of HUB-CI is within the field of precision farming, specifically in Agricultural Robotics System (ARS). Automation systems for greenhouses deal with tasks such as climate control, seedling production, spraying, and harvesting, however, few research projects have been conducted to optimize human-robot collaboration in the ARS. The HUB-CI for ARS (Nair et al., 2019) aims to develop an agricultural robotic system for early disease detection of pepper plants in greenhouses. The scope revolves around greenhouse monitoring, detection, and responding tasks, detailed in the system's architecture (Figure 3 - Left)

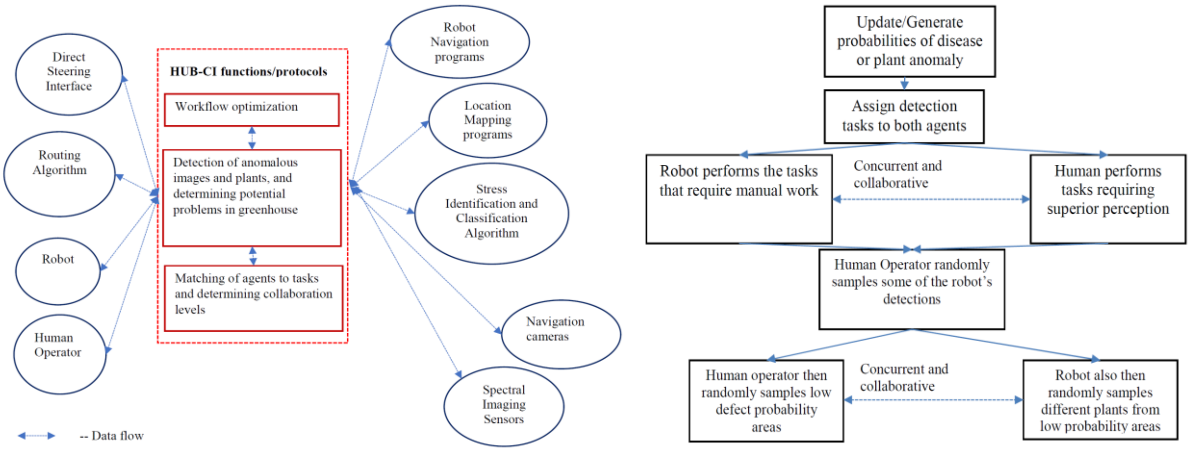


Figure 4 HUB-CI model for Greenhouse monitoring (Left) and Workflow diagram for HUB-CI Collaboration Strategy (Right) (Source: (Nair et al., 2019))

The workflow is presented in the diagram shown in Figure 3 (right). Specific CI tools developed for this purpose include: (1) spectral image segmentation for detecting and mapping to anomalies in growing pepper plants; (2) workflow/task administration protocols for managing/coordinating interactions between software, hardware, and human agents, engaged in the monitoring and detection, which would reliably lead to precise, responsive mitigation.

The study (Nair et al., 2019) experimented on how the HUB-CI improves human-robot skill sharing. Evidently, HUB CI yields significantly fewer errors and better early detection, improving the system efficiency by between 210% to 255% across 80 runs, compared to the system that does not implement decision support through HUB-CI. To simulate the remote operational nature of HUB-CI, commands were sent using Python and Robotic Operating System (ROS) programs via a Google Drive, between the PRISM lab in West Lafayette, Indiana, and the Volcani Institute agricultural robotic lab in Israel. Average lag time of remotely sent commands was 1.06 seconds across 2 different sets of runs of 30 minutes each. It is validated that HUB-CI yields significantly a higher quality of knowledge via collaborative workflow protocols, as indicated by fewer errors and better detection. The application enables precise monitoring for healthy growth of pepper plants in greenhouses.

3.2.4 Cyber-Collaborative Factory of the Future with Humans and Robots

The fourth case study (Dusadeerungsikul et al., 2019) is based on the implementation of collaboration requirement planning (CRP) for a HUB-CI within factories of the future. HUB-CI has been designed to comprise algorithms and protocols to improve the productivity and efficiency of a distributed system of networked agents via augmented collaboration. Multi-robot control in industry is a proven strategy of reducing production cost by having robots working faster and in parallel, with humans in the loop, leading to overall shorter processing time and higher flexibility.

The study (Dusadeerungsikul et al., 2019) developed and implemented two phases of CRP-H collaboration protocol: CRP-I (task assignment optimization) and CRP-II (agents schedule harmonization), These protocols are developed and validated in two test scenarios: A two-robot collaboration system with five tasks; and a two-robot-and-helper-robot collaboration system with 25 tasks. Simulation results indicate that under CRP-H, both operational cost and makespan of the production work are significantly reduced in both scenarios. The cost is slightly lower while average makespan of CRP-H is 45% less, compared to the baseline collaboration protocol scenario.

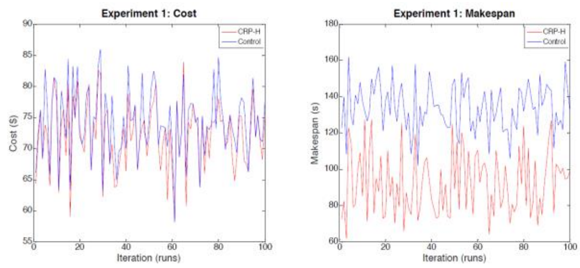


Fig. 3 Experiment 1: Operational cost (left), Makespan (right)

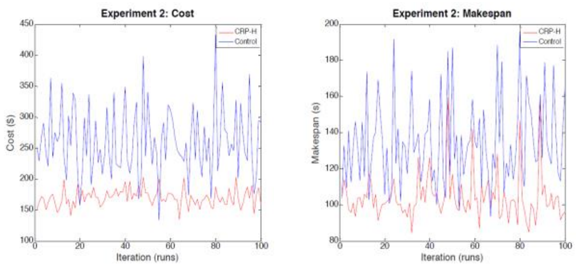


Fig. 4 Experiment 2: Operational cost (left), Makespan (right)

Table 1. Result of Experiment 1

	CRP-H	Control
Average operational cost ($)	72.07	74.21
SD of operation cost ($)	5.59	5.39
Average makespan (second)	92.30	134.00
SD of makespan (second)	17.04	12.72

Table 2. Result of Experiment 2

	CRP-H	Control
Average operational cost ($)	169.70	260.20
SD of operation cost ($)	13.71	53.97
Average makespan (second)	104.00	134.20
SD of makespan (second)	12.66	23.41

Figure 5 Experimental Results of CRP-H
(Source: (Dusadeerungsikul et al., 2019))

It has been validated that the new CRP-H protocol delivers superior performance in terms of operational cost and makespan, when compared to a system logic that randomly assigns tasks to robots and instructs random scheduling. The better operational cost comes from CRP-I which optimally assigned tasks to robot(s). Moreover, makespan is minimized because of CRP-II which can updates schedule real-time from IoT/IoS devices' information.

3.3 Other Recently Researched Fields of Skill and Knowledge Sharing

Other recent research projects related to skill and knowledge sharing are summarized in Table 5:

Table 5 Summary of Other Related Research on Skill and Knowledge Sharing

No	Project Topic	Summary of the Approach	Relation to Skill and Knowledge Sharing
1	A novel social gamified collaboration platform enriched with shop-floor data and feedback for the improvement of the productivity, safety and engagement in factories (Lithoxoidou et al., 2020)	Gamified collaboration platform allows positive mood, engagement, and satisfaction, and increased human contact	Social enabler to skill sharing within a manufacturing enterprise
2	Affiliation/dissociation decision models in demand and capacity sharing collaborative network (Yoon & Nof, 2011)	DCSP through affiliation and dissociation decision to ensure effective demand fulfilment through collaboration	Collaborative resource sharing between collaborative network of enterprises
3	Automated assembly skill acquisition and implementation through human demonstration (Gu et al., 2018)	Portable Assembly Demonstration (PAD) system to train robots for simple assembly tasks	Human-robot skill sharing protocols
4	Big data analytics-based fault prediction for shop floor scheduling (Ji & Wang, 2017)	Big data analytics-based fault prediction model for shop floor scheduling	Knowledge sharing protocols for scheduling and maintenance operations
5	CausalWorld: A Robotic Manipulation Benchmark for Causal Structure and Transfer Learning (Ahmed et al., 2020)	benchmarking platform for reinforcement learning for pushing, picking, pick-and-place, and stacking	Simulation-based skill sharing protocols for robot arm manipulation
6	Collaborative capacity sharing among manufacturers on the same supply network horizontal layer for sustainable and balanced returns (Ahmed et al., 2020)	DCSP through horizontal (supplier) capacity sharing to ensure demand fulfilment through collaboration	Resource sharing between collaborative network of enterprises
7	Consultation length and no-show prediction for improving appointment scheduling efficiency at a cardiology clinic: A data analytics approach (Srinivas & Salah, 2021)	CRISP-DM data analytics for appointment scheduling optimization	Knowledge sharing protocols for scheduling operations
8	Demand and capacity sharing decisions and protocols in a	DCSP through information sharing to	Collaborative resource sharing between

No	Project Topic	Summary of the Approach	Relation to Skill and Knowledge Sharing
	collaborative network of enterprises (Srinivas & Salah, 2021)	ensure demand fulfilment through collaboration	collaborative network of enterprises
9	Human-Robot Cross-Training: Computational Formulation, Modeling and Evaluation of a Human Team Training Strategy (Nikolaidis & Shah, 2013)	The human-robot cross-training uses mutual adaptation process for learning fluency in joint-action	Human-robot skill sharing protocols
10	Human-Robot Teaming using Shared Mental Models (Nikolaidis & Shah, 2012)	Theoretical model of SMM, how it plans, assesses, and promotes HRI	Human-robot knowledge sharing protocols
11	Improved Human-Robot Team Performance Using Chaski, A Human-Inspired Plan Execution System (Nikolaidis & Shah, 2012)	A robot system capable of real-time workflow adaptation in a human-robot environment	Human-robot skill sharing protocols for a flexible collaborative workflow
12	Increasing Human Performance by Sharing Cognitive Load Using Brain-to-Brain Interface (Maksimenko et al., 2018)	Brain-to-Brain Interface allows workload-sharing and redistribution depending on current cognitive performance based on electrical brain activity	Human-to-human knowledge sharing protocols for a better teaming
13	Integrating representation learning and skill learning in a human-like intelligent agent (Li et al., 2015)	Deep feature learning SimStudent with transfer learning and feature focus to solve problems	Human-robot knowledge sharing protocols for a better tutoring system
14	Machine learning for predictive scheduling and resource allocation in large scale manufacturing systems (Morariu et al., 2020)	Cloud computing and machine learning for combined scheduling and maintenance optimization	Knowledge sharing protocols as an enabler of collaborative resource-sharing
15	Quantifying Task Similarity for Skill Generalisation in the Context of Human Motor Control (Sebastian et al., 2016)	Quantifying task similarity, learning, and transfer learning in motoric tasks	Skill sharing protocols in a sequential task assignment
16	Skill transfer support model based on deep learning (K.-J. Wang et al., 2021)	Skill transfer model aids new operator to execute tasks based on expert operators data, modeled with RNN and CNN	Human-to-human knowledge sharing protocols using machine learning
17	Towards Fully Autonomous Ultrasound Scanning Robot With Imitation Learning Based on Clinical Protocols (Y. Huang et al., 2021)	Imitation learning framework with One-Step Exploring (OSE) and Region of Attention (ROA) for Autonomous Ultrasound Scanning Robot	Human-robot skill sharing protocols for procedure-specified tasks
18	Virtual reality (VR) as a simulation modality for technical skills acquisition (Nassar et al., 2021)	VR as an enabler of skill acquisition and surgical simulation	Human-to-human skill sharing protocols for procedure-specified tasks

3.4 Emerging Research Challenges of Skill and Knowledge Sharing

3.4.1 Theoretical Research Challenges

Skill and knowledge sharing in production systems and supply networks is accomplished through the four layers of the cyber-collaborative physical system (CCPS), as illustrated in the figure below. Skill and knowledge sharing is preceded by a preliminary phase of skill and knowledge acquisition and documentation. The expert system developed in the first phase becomes the foundation of the next stage, the execution phase. In this second phase, the four layers of CCPS are streamlined and optimized to support the instance of skill and knowledge sharing. The outcome of skill and knowledge sharing is measured based on a set of performance metrics in the last stage, the evaluation phase.

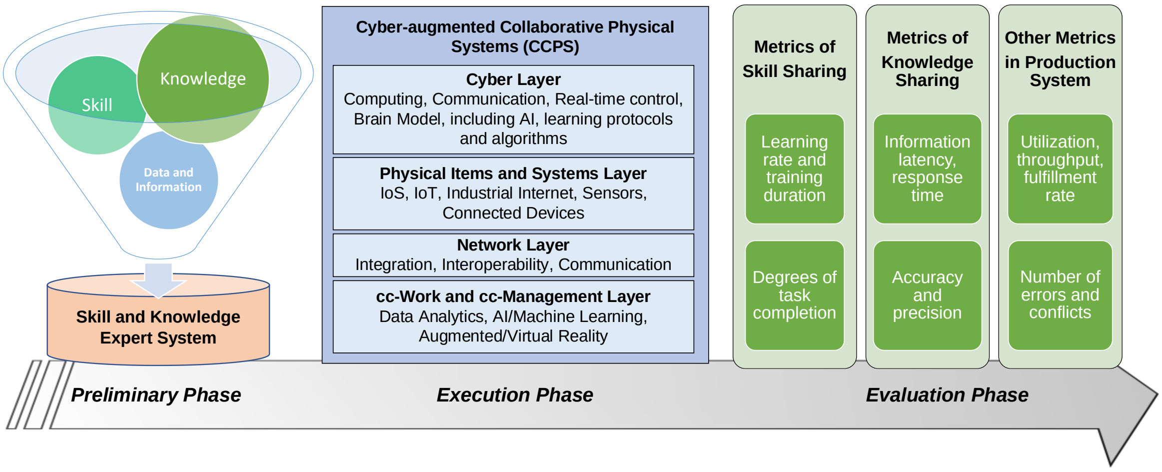


Figure 6 The Framework of Skill and Knowledge Sharing in CCPS

- Previous research has mainly focused on generating preliminary working systems of skill and knowledge sharing models. Some common developments include teaching robots to perform procedural tasks; guiding novice operators to execute a particular task using augmentation and wearables; and other applications in which the focus is put on developing a contextualized system, where instances of skill and knowledge sharing occur. The key finding of the previous studies is that skill and knowledge sharing occurs in various case studies, and is enabled by a wide range of tools, varying from machine learning, data analytics, industrial internet of things (IIoT) and virtual/augmented reality (VR/AR/XR).
- In terms of performance metrics, the effectivity of the working system is mostly measured by a usability survey, where human subjects are given a set of questionnaires to fill, and the options are formulated in Likert scale, or a similar scale. Despite their quantified nature, most of the surveys do not include objective assessments of the production system's or supply network's performance. Therefore, the framework defined here and shown in Fig. ?? above is able to measure the effectivity of skill and knowledge sharing into three different sub-metrics to deepen our understanding of the outcomes. The benefits of skill and knowledge sharing should be extended and related to general production systems and supply networks metrics, such as throughput, error reduction, conflict resolution, and on-time delivery.
- Previous research has only partially, not fully addressed the dynamic execution of skill and knowledge sharing under integrated, operational system conditions. Recent advances of automation have modeled human as an integral element in a smart

manufacturing systems and supply networks, which is the human in the loop (HITL) perspective. As key decision making participants in the systems' network, human agents must be fully equipped and augmented with the necessary, timely skills and knowledge. The augmentation process should be streamlined so that the training and preparation duration is minimal. In cases where this time duration can be reduced, optimize and harmonized dynamic skill and knowledge sharing must be implemented.

- Further research is needed to address the three above emerging challenges in order to enable concurrent, optimized, and harmonized intelligence sharing in a skill and knowledge sharing CCPS. For this purpose, the HITL focus will have to expand to the NITN, Human in the network scale.

3.4.2 Future Research Plan

The emerging areas of research and major open questions about challenges concerning the field of Skill and Knowledge Sharing can be summarized in the following directions:

- *HUB-CI for information flow optimization*, which optimizes and harmonizes the collaborative intelligence of agents in a workflow by controlling data and information flow between them. This application of HUB-CI is particularly advantageous in cases where Augmented Reality (AR) and its variants are being used as tools for skill and knowledge sharing.
- *Learning protocols in the skill and knowledge sharing* (SaKS), which streamline the data exchange process for faster transmission. As the latency and coherence are maintained, SaKS can be organized and managed dynamically.
- *Machine learning-based ontology for SaKS taxonomy,* which provides an adaptive, interpretable definitions of basic concepts and the relationships between skill and knowledge. With the rising level of intelligence of computing resources, this subject will extend the classification that Bloom's Taxonomy and its derivatives provide, and improve researchers' understanding with contextual and iterative definitions of skill and knowledge.
- *Other collaborative augmentations*, which are related to physical wearables, augmented/extended reality and online, and real-time analytic systems based on the collaborative intelligence.

Several on-going PRISM and PGRN research projects are already addressing these challenging directions.

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