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Deliverable 5.1
LIVE LABS design of experiments and plans for implementation

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Versions

Revision	Date	Author	Organisation	Description
001	1/05/2022	Philip Long	IMR	Initial Document Preparation, document outline and Draft Table of Contents
002	16/05/2022	Aayush Jain	IMR/TU Dublin	Live Lab 1 outline of IMR cell in direct human robot collaboration, implementation and experimental plan
003	26/05/2022	Ammar Abbas	SCCH/ PoliTo / TU Dublin	Live Lab 3 description at Yokogawa and PoliTO with other ESRs and collaborative task division.
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Executive summary

This deliverable contains information about the design of experiments and plans for implementation of the Live Labs. Within the framework of the CISC project three Live Labs are proposed:

- **Live Lab 1-** *Human robot collaboration:* Live Lab 1 is divided into three different scenarios located in IMR's pilot factory in Mullingar and in the Faculty of Engineering, University of Kragujevac. This Live Lab will focus on how operators can better interact with robots at various different control levels. The efficiency and safety of these operations will be studied and data concerning human factors, such as attention and comfort etc., collected.
- **Live Lab 2-** *Augmenting Human performance:* Live Lab 2 is focused on manufacturing operations in a large-scale automotive plant. The project will collect data during manufacturing and model the human operator's performance versus task complexity. The objective is to exploit this data to enable optimization of human performance while simultaneously predicting anomalies and scheduling maintenance events.
- **Live Lab 3**- *Assisting Human decision-making:* Live Lab 3 is divided into two different scenarios, firstly utilizing data obtained from a real control room in Yokogawa's facility servicing the Oil and Gas industry and secondly data collection and exploitation from a controllable simulated environment developed by POLITO (Politecnico di Torino). The objective is to explore alarm flooding events, i.e., when multiple alarms occur simultaneously and how to predict such events and how to ensure the human operator is not overwhelmed.

This deliverable describes experimental setup for each LIVELABs the project implementation and the role of the researchers within each LIVELAB.

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1. Introduction

Maintaining optimal human and system performance is a major concern in Industry 4.0, particularly for safety-critical applications. Failure in the proper integration between automation, intelligent systems and the operators has resulted before in disastrous consequences, where the poor design of the system has led to a reduction of the operator's vigilance, reduction of situational awareness, information overload and/or loss of ability to manually control the system. It is then paramount for this new stage of collaborative intelligence in industry to prioritize the human-system interaction and communication to increase awareness of each other's actions and intentions. Indeed, this shift towards a human-centric approach complements existing industry 4.0 methods and contributes to the European Commission's vision of Industry 5.0, i.e. a manufacturing eco-system that brings benefits to industry, workers and the broader society.

Within the CISC project, different levels of interaction are studied through the use of Live labs. The Live labs are a means to validate research in near-real environments and ensure that the ESRs are exposed to real-world problems. There are multiple Live labs within the project which can be divided into three main classes. First, researchers will focus on direct human robot interaction. In this scenario, the human will oversee or teach a robot to complete a task. CISC will study the programming methods and aim to optimize this teaching process to improve task efficiency and human ergonomics. Secondly, researchers will focus on exploiting the data from a human executed manufacturing process. To do this efficiently, human performance will be modelled considering task complexity. The data generated during the manufacturing process can then be used to improve human performance and signal potential failures and maintenance events. Finally, researchers will study control room tasks, where humans must oversee complex and critical operations. CISC will show how machine learning and data analysis can alleviate stress, predict overloading scenarios and thus aid allow human operators to make judicious decisions under stressful conditions.

In all three scenarios, the human operator remains a central component responsible for the high-level cognitive actions. The CISC project will aim to amplify an operator's capabilities while maintaining a level of safety and ergonomics. This deliverable will outline the three LIVELABs central to the CISC project. The components, location and activity are described, and research implementation and experiment design are outlined. Each ESR has the opportunity to validate their algorithms/ approach across all LIVELABS however their methods/ approaches are typically tailored to a single main experiment. Table 1 shows, each ESRs associated LIVELAB and the proposed research topic.

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Table 1: Summary of ESR and their interaction with different LIVE LABS

ESR #	ESR name	Live Lab1 – Human Robotic Collaboration **IMR/FINK**	Live Lab2 – Augmenting Human Performance **IVECO**	Live Lab3 - Assisting Human decision-making **YOKOGAWA/POLITO**
1	**Houda Briwa**			Building a model for human performance prediction in critical scenarios using a Bayesian network (case of alarm floods in the control room) preceded by designing an experiment for HRA (Human Reliability assessment) data collection.
2	**Devesh Jawla**		Anomaly prediction and predictive maintenance using machine learning techniques	
3	**Joseph Mietkiewicz**			Predicting trips and critical scenarios using Bayesian Network (BN) to help decision making for a human operator. Compare data-driven BN, expert knowledge and data, and purely expert knowledge BN for online prediction.
4	**Chidera Winifred Amazu**			Process safety data modelling for human-in-the-loop configurations in process control
5	**Ammar Abbas**			process control optimization with alarm reduction and prioritization in an online human-in-the-loop setting using deep reinforcement learning.
6	**Milos Pusica**			Designed an experiment for evaluation of impact of simple/complicated visual assembly line instructions on operator's mental workload.
7	**Carlo Caiazzo**	Human ergonomics and task partitioning in human robot collaboration tasks		
8	**Ines Ramos**	Real-time interface adaption for human-in-the-loop telerobot operations		
9	**Doaa Almhaithawi**			Using latent spaces to explore security challenging such as intrusion detection and pattern recognition
10	**Naira Lopez Cañellas**	Legal and Ethical Implications of Collecting and Analysing the Output of Real-Time Data-Gathering Devices in the Workplace	Legal and Ethical Implications of Collecting and Analysing the Output of Real-Time Data-Gathering Devices in the Workplace	Legal and Ethical Implications of Collecting and Analysing the Output of Real-Time Data-Gathering Devices in the Workplace
11	**Carlos Albarrán Morillo**		Design experiments in a real automotive sector line work environment for Human-machine performance monitoring and prediction	
12	**Aayush Jain**	Programming from demonstration for fast robot programming. Human assistance during anomaly detection.		
13	**Shakra Mehak**	Safety and certification during human demonstrations and corrections of robot tasks		
14	**Andres Alonso Perez**			Apply wavelet transform series to model operator’s mental workload by processing and analysing signals recorded from wearable sensors such as electroencephalograms (EEG).

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2. Live Lab 1: Human Robot Collaboration (IMR & FINK)

2.1. Objective

The goal of this Live Lab is to investigate how humans and robots can cooperate to amplify each other's capabilities and how to optimize the interface and environment such that the human's comfort and safety is prioritized. This Live Lab is situated in IMR's facility in Mullingar with an additional study located in the Faculty of Engineering, University of Kragujevac.

2.2. Description

Human-Robot collaboration has been shown to improve ergonomics on factory floors while allowing a higher level of flexibility in production. However, the current robot programming interfaces require domain expertise. Moreover, robots' response for every possible event needs to be configured in advance which makes them hard to reprogram. Therefore, more intuitive methods of programming are desirable for instance by demonstration. Such systems could allow a non-expert to intuitively program robots on-the-go, without explicitly coding each detail. This would in turn allows a user to guide the robot through a task which the robot can then repeat either through mimicry or, using more advanced algorithms to extract underlying task primitives.

Although much effort has been put towards demonstrating compelling results in the laboratory, such methods are still not widely used in industrial applications. The main challenges in this field are the automatic learning of task representations and adaptability of the learned tasks in an uncertain environment, where each task can be expressed as a series of primitive action components. Additionally, in order to facilitate the widespread use of such technologies, it is imperative to consider human factors including ergonomics, stress and comfort level but additionally legal and certification challenges. Within the Live Lab 1 environment there are two human robot collaboration stations. First a dual arm collaborative robot cell, shown in Figure 1 and secondly a teleoperation cell shown in Figure 2. Each scenario is equipped with a range of human factors sensors to evaluate the effects of the robot instruction on the human user. The objective of the Live Lab is thus two-fold, first explore innovative methods of robot programming and second ensure that the developed methods are human centred and there exists a mean towards certification of such methods in the future.

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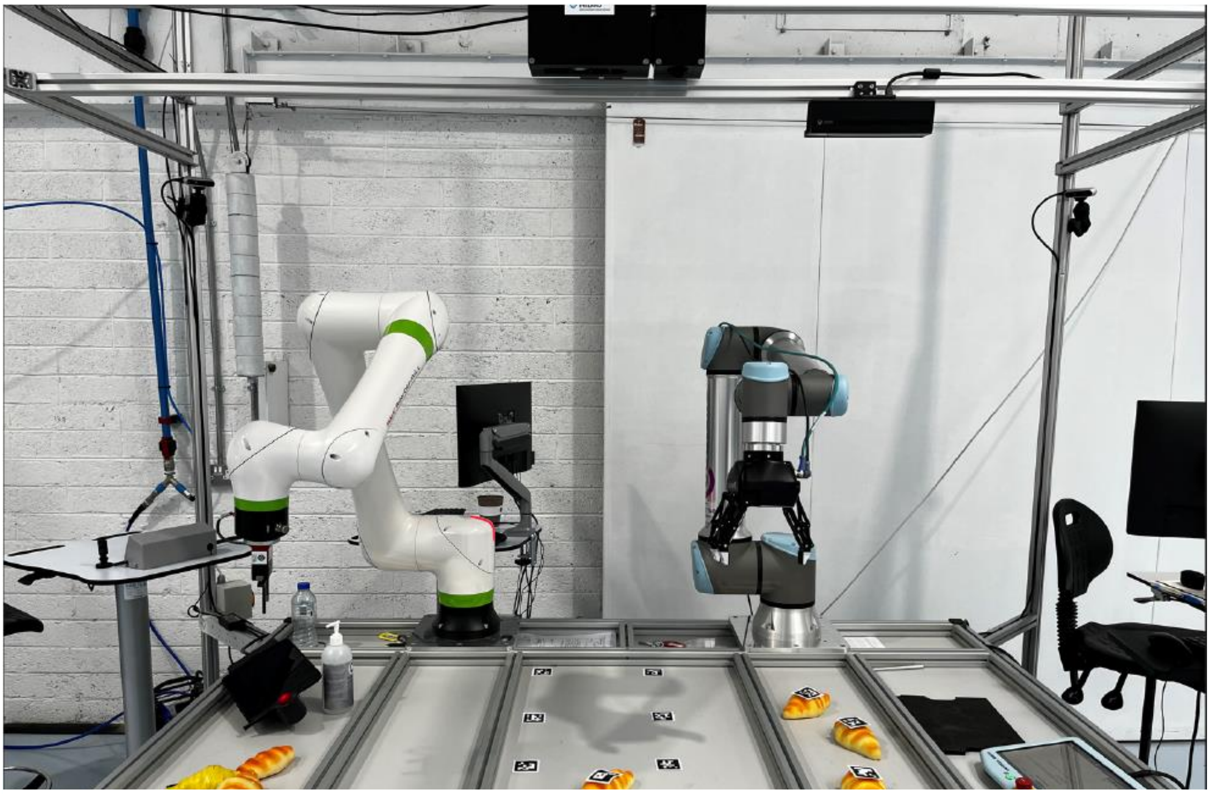

Figure 1: Livelab1: Direct Human robot collaboration cell, featuring two collaborative manipulators a FANUC CRx10 and UR10e each equipped with grippers, and a top down RGB-D camera.

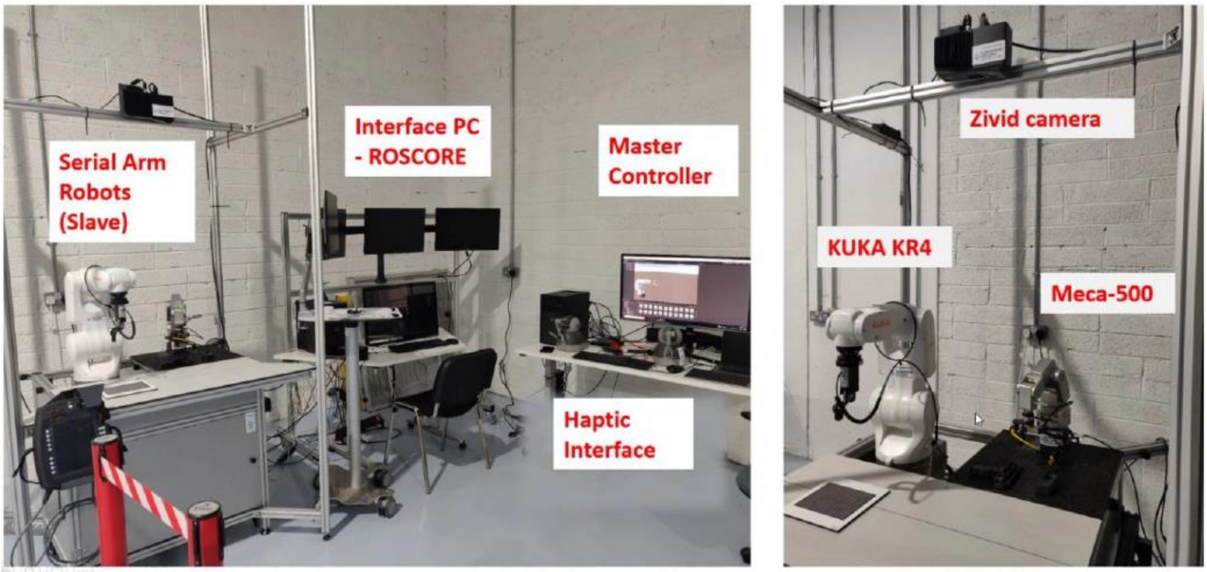

Figure 2: Live Lab1: Teleoperation or human-in-the-loop control consisting of two separate stations. Input station, 2 haptic input devices an eye-tracker and a digital representation of the remote robot cell. Output side, two industrial robots a top-down vision system, a set of USB mini-cameras and force sensors at the end of the robots' arm.

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Figure 3: Human Robot Collaboration Station in University of Kragujevac

2.3. Implementation & Design of Experiments

2.3.1. Direct Human Robot Collaboration

The aim of this experiment is to develop a framework for learning human actions and skills through demonstration to reduce the task definition time for collaborative flexible assembly lines. Furthermore, an anomaly detection method to identify the uncertainties in the assembly process and adaptable robot behaviours will be studied. Factory set-up for testing and validation that emulates one-off manual tasks will be designed. Lastly, the scenario will be evaluated and iterated based on ergonomic and safety certification factors.

In IMR, the UR10 robot arm equipped with a gravity compensation controller is used for this study. Gravity compensation enables us to use this collaborative robot for kinesthetic task teaching of the task from human demonstrations. The robot is equipped with a Robotiq 3-Finger Adaptive Robot Gripper with continuous grasp capabilities. A Microsoft Kinect v2 RGB-D camera is mounted above the robot and is used as a vision sensor that provides information about the workspace and tracks the object's current state on the table.

As shown in Figure 4, the proposed case study is organised into three main phases: the human-robot collaboration (HRC) phase, the learning phase and the execution phase. The perception modules, which sense the robot's internal state and object information, is run in parallel to other modules throughout the three phases.

During the HRC phase, the actions for each type of object are demonstrated via *kinesthetic* teaching by the human teacher. Time series data from the perception module during the demonstrations is recorded and stored in a dataset. The dataset is composed of end-effector pose, joint angles, gripper position, object pose and zone status. To test the working hypothesis, industrial scenarios of pick and place and assembly task are selected. The current focus of the experiments is on pick and place tasks where a single demonstration is used for each object type to learn the actions.

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Each robotic task can be decomposed into a sequence of sub-tasks and in turn each sub-task corresponds to a unique action. When these actions are performed sequentially, they can replicate the demonstrated task. To learn these sequences, a high-level learning module uses the collected data, where each task is segmented into actions and labelled with the corresponding object ID. Dynamic movement primitives (DMP) are used as a trajectory encoder in the low-level learning module. The segmented data for each action is converted to a DMP and stored with the same object ID. The execution phase is responsible for the adaptation and implementation of the stored action. If any object in the current frame matches an object stored in the database, the real-time execution module is activated. After object identification, the high-level objective of “what actions to initiate?” calls the previously learned actions and sequences. Now, the low-level objective “how to perform these actions?” is adapted by modifying the learned DMP based on current start and goal positions. Finally, the computed trajectories from each DMP are executed in the learned sequence to perform the task.

As the learned model is deployed to perform these tasks, there is a possibility of running into anomalies or changes in the environment. In these situations, the learned model needs to adapt to the situation and get back to normal working condition. In certain situations, it might require human intervention or feedback to correct its behaviour or adapt the model. Therefore, the current focus is on studying how human supervision and autonomous anomaly detection can be used to identify the need for corrective demonstrations. Furthermore, we will focus on how the learned model can adapt to the new environment with minimal corrective demonstration or human feedback

The method and modalities of human instructed teaching leads to several additional questions, which using the setups both in IMR and in the Faculty of Engineering, University of Kragujevac, the CISC project will aim to answer. For instance, what are the physiological data to take into account for the physical ergonomic assessment? How to plan and optimize the usage of resources for the tasks? How to manage occupational risks for health and safety of operators? What is the best strategy to timely communicate the important work-related information to the worker?

CISC will take a Human-Centred Design (HCD) approach to making the system usable by focusing on the requirements and needs of the operator, applying safety, ergonomics/human factors principles and techniques. In this regard, in the Live Lab at the Faculty of Engineering, University of Kragujevac (Serbia), an innovative hybrid modular workstation is designed respecting the anthropometric, safety, and ergonomic requirements. The workstation is equipped with a PC touch-screen, industrial computer, adjustable work chair, homogeneous LED lighting, and audio system to simulate the real work environment. Additionally, the workstation can be implemented with a cobot modular unit to conduct HRC experiments. The designed workstation represents the laboratory infrastructure for conducting neuroergonomic experiments and studying the behaviour of operators at the workplace. This study will initially be undertaken at Faculty of Engineering, University of Kragujevac’s human robot collaboration station shown in Figure 3 before being adapted to the cell at IMR which will validate the methods generality.

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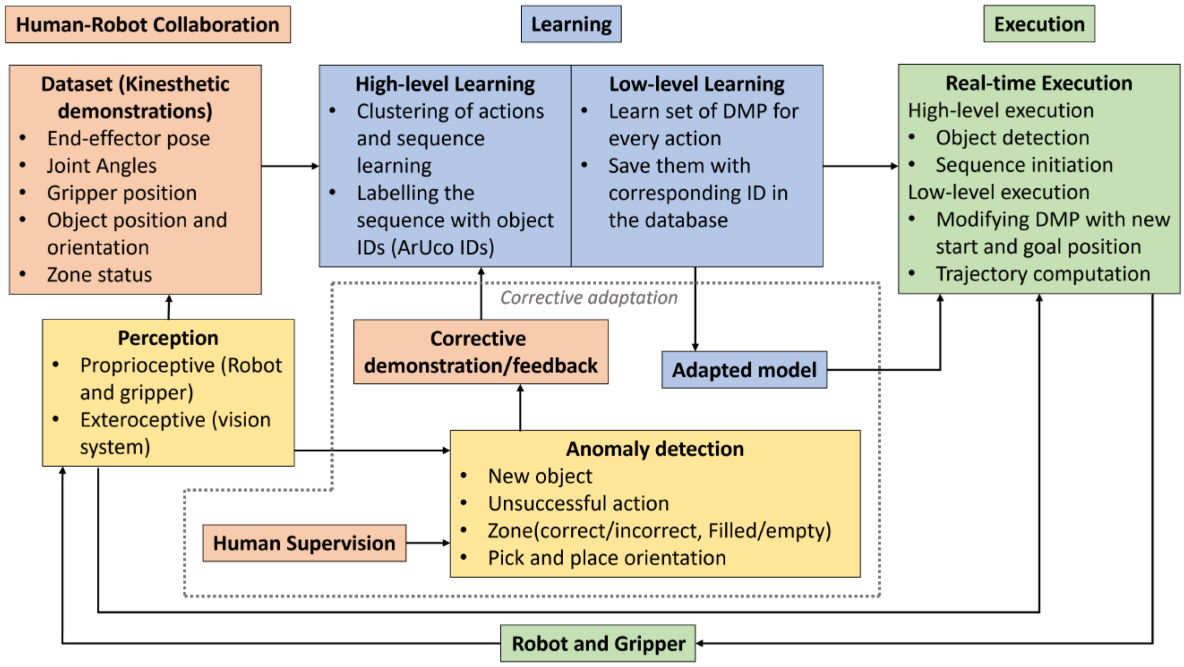

Figure 4: Proposed System overview for learning from demonstration

This type of collaboration enables the operator and industrial robot to perform tasks within a predefined work area; this ability to work collaboratively is anticipated to increase productivity but raises safety concerns due to the increased likelihood of hazardous situations arising due to the proximity of humans and industrial robots. Developing collaborative applications requires a commitment to safety. As such ESRs will conduct a study concerning the **design level risk assessment** in accordance with the working modules of Pilz, Ireland. The objective is to optimize the HRC safety criteria in relation to industrial safety standards. Currently ESR 13 is attending 2 weeks CMSE (Machinery Safety Expert) Training organized by Pilz, Ireland to understand the process of CE marking and risk assessments for industrial applications. In particular, the ESR will focus on certification process within existing HRC standards and the necessary adaptations to these standards which would facilitate fluid human robot collaboration while still maintaining the necessary safety standards

2.3.2. Teleoperation

With the recent advances in wearable technology, it is now possible to monitor the operator's internal state, through changes in their physiological signals. Intelligence systems can then be made aware of the operator's state, not only to avoid critical situations of degraded performance, but to act proactively and adapt the automation level, the interface or interaction mode to the operator's needs to achieve optimal system performance.

In teleoperation of robots, where the operator is remotely located, the challenge lays in the reduced operator's situational awareness and lack of information to make sound decisions. This is therefore an appropriate case study to assess states of degraded performance using wearable sensor technology and collect a dataset to train a deep learning model to predict performance-related operator's states, based on the recorded physiological signals.

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This Live Lab is conducted at IMR's facilities in Mullingar in conjunction with two industry partners from the medical device manufacturing industry. In both cases, the partners are interested in teleoperation as a means to increase yield rate of product and operator ergonomics. The medical device manufacturing industry requires precise assembly tasks and the manipulation of complex objects. These operations are difficult to accomplish and indeed even program using standard robotic tools. Consequently, many medical device companies struggle to locate system integrators willing to automate a task for a reasonable budget. Additionally, since many materials are deformable, task parameters vary, leading to proposed automated solutions which are inflexible and rely on complex jigs and fixtures. The resulting solutions are applicable to a narrow class of assembly tasks. Maintaining this type of manufacturing in a high-cost society has become a priority and thus there is an urgent need for a class of adaptable automated solutions. In this particular use-case of telerobots there is no major safety concerns, however parallels can be drawn with other safety-critical applications, such as the use of telerobots for surgery, for military missions or rescue activities.

The preliminary experimental hypothesis is that human-machine interface and interaction haptic and visual factors can affect the cognitive/mental state of the operator and consequently the teleoperation task performance (schema illustrating the experimental hypothesis shown in Figure 2). A pilot study needs to be conducted first to determine what interface and interaction conditions affect operator mental state and performance. The following experiments' objective is then to use the designed interface/feedback conditions, validated in the pilot study, to induce performance-related internal states, such as mind wandering, effort withdrawal, perseveration, inattentional blindness and deafness, while the operator is performing a fine manipulation task and the physiological signals are being monitored by wearable devices (portable EEG device from mBrainTrain, eye-tracking using Tobii pro device installed in the interface screen and galvanic skin response measured with a wireless Shimmer device). The induced states will be validated with subjective measures gathered through questionnaires and objective metrics/indicators computed from the recorded physiological signals and task-related measures.

The case study goal is two-fold: the first is to identify and validate different telerobot interface factors and how they affect the operator internal state and performance, and the second is to create a dataset by collecting multi-modal data from participants while they perform a real telerobot task and while different performance-related internal states are evoked and assessed. The dataset will then be used to train a deep learning model to differentiate between these hidden internal states using multi-modal body-signals, with the goal to build a model that can be used to provide control input for real-time interface adaptation (adapt haptic, visual and auditory interface to the operator state) or during the interface design process of a system.

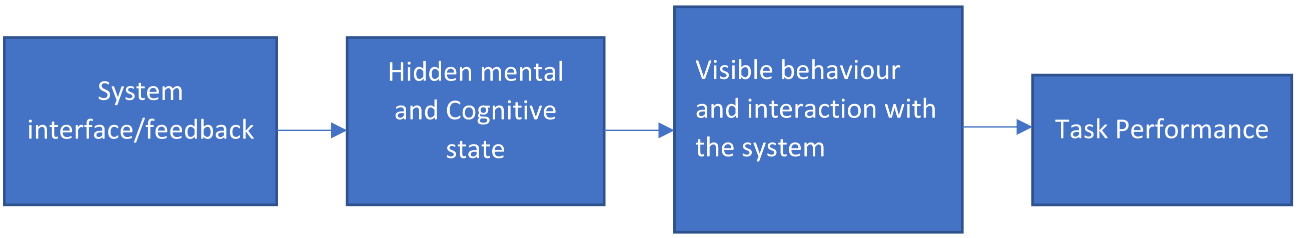

Figure 5: Experimental Hypothesis Scheme

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3. Live Lab 2: Making the Automotive Factory floor safer (IVECO)

3.1. Objective

The goal of Live Lab 2 is to demonstrate how data can be exploited to enable predictive maintenance and fault detection in human-in-the-loop operations within an industrial environment. This Live Lab is situated in IVECO's facility in Suzzarra, Italy, and transferrable to the IVECO's facility in Valladolid Spain.

3.2. Description

The manufacturing field is a sector still widely based on human operations, despite increasing automation. The automotive sector, for instance, is based on assembly lines, where the automation process is becoming more and more complex. Different operators contribute to assembly products, which call for different operational capabilities and a multi-faceted approach for analysing critical-safety procedures and making technological decisions.

IVECO is an automotive company where production systems are based on assembly lines that require the interaction between highly automated workstations and highly trained human resources. The researchers here will test human-in-the–loop-automation performance in the context of different workstations.

Human Factors (HF) is a critical component for employers' safety. A practical way to assess human performance modelling as the reliability of individuals to perform a specific duty, can help identifying critical scenarios in manufacturing plans. When an operator has enough capabilities to perform a complex given task, the probability of accident or error is reduced. According to the kind of tasks involved in the assembly line, the CISC project will devise and use the so called "ability corner" where empirical testing can be carried out to assess a set of measurable capabilities for the Human-automation interaction such as Manual skills, Memory and Physical skill, The tests have to represents or simulate frequent operations close to the ones performed in the assembly line. While on the other end the real sensory data from the machinery interaction (such as welding operations) performance will also be collected (parts completed without errors, unsafe conditions etc.).

The CISC project will exploit data such to aid help IVECO in predictive maintenance and fault/anomaly detection and predictive maintenance will be performed using IoT (Internet of Things) sensor data, where we can use ML techniques to predict any faults and or schedule maintenance work in order to reduce losses and increase efficiency. If they require a fault detection mechanism, ML techniques will be utilized and, since these are rare in occurrence, active learning could provide an optimal and novel solution. By using Bayesian neural networks, we would also be able to offer credible predictions. Fault detection data could be in the form of human sensor data, or it could be IoT sensor data from machinery which are safety critical in nature.

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Figure 6: Live Lab 2, IVECO's facility in Italy

3.3. Implementation and Design of Experiments

3.3.1. Evaluating Human Performance

Human performance (HP) modelling can be described as the result of an interaction between the level of skill demanded to achieve a given job in a working place with the capabilities of the employees assigned to it. In particular we will be working off assumptions displayed in the literature (Leva et al. 2016, Comberti et al. 2018, Leva et al. 2022) that human performance could be represented as directly dependent on two macro-factors:

1. Task Complexity (TC): assessed through Mental Workload (MW) and Physical Workload (PW), both associated to each activity identified and analysed in the assembly line.

2. Human Capability (HC): it represents the skills of workers under the actual working states, including the physical, mental and cognitive abilities of each employee.

It is applied this framework to assembly line work, the HC component can be grounded in three quantifiable capabilities: Memory, Manual and Physical skills assessed using the “ability corners”. The TC is estimated by assessing the observable variables related to Mental and Physical Workload and expressed in terms of indices harmonized in a Likert scale. The HP model results are addressed using a matching index matrix that compared the required aptitudes for each workstation with the harmonized recorded skillsets of each worker. The final goal is to provide a framework to better match workstation task requirement to operator capabilities so as to minimise error and inform a risk assessment for manufacturing errors and unsafe conditions that is currently quite static and generic

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Human Capability, as mentioned in the previous section represents the total amount of resources that a worker can offer to execute tasks under given environmental working condition. Literature suggests a large set of human skills that could be solicited by performing manual a task but considering the purpose of the project and the operational need a set of three abilities have been considered as solicited by tasks composing the assembly line. In particular, the human abilities that have been considered were:

- Manual: skills like precision, manual handling and coordination are solicited continuously during an assembly task.
- Physical: the skill of maintaining a constant performance during the shift and coping with pace.
- Memory: remembering the sequence of operations and parts to be assembled can differs considerably from task to task.

These variables have been related to the results of four empirical tests, the so-called ability corner performed by the operators (form more details see Comberti et al. 2018, Leva et al 2022) . Tests have been designed to simulate frequents operations close to the ones performed in the assembly line and to be more linked to human skill tests have to be performed by operators during the working activity. This operation was done with the technical support of a plant work analyst and line supervisor. The fourth test defined were:

• Precision test: it consists in moving an iron stick along a not linear contour without touching the borders. This test is related to the manual precision required in many tasks where workers have to assembly components avoiding impact. The number of errors were recorded during this test.

• Both-Hands test: The Work-organisation of the plant promoted the simultaneous use of both hands to perform the task. This was done to minimize the time required to complete the task and minimize the number of operator movements. Both-Hands test measures the ability of a worker to use both hands to perform simple actions. Time and precision of coordinate movements were recorded.

• Methodology test: During this test, the worker has to decide and complete a set of simple assembly steps with small parts. Time and errors were recorded.

• Memory test: sequences of geometric schemes were shown to the worker for a few seconds. The worker was then asked to replicate them on a desktop. The time to complete the task and its accuracy were recorded during this test.

Test execution involved the operators of the line directly. To minimize the disturbance to the plant activity, a training area was set nearby to the assembly line selected as a case study. In this area, the four tests were located. The campaign of the tests has been anticipated by a single session during which the operator received a profound explanation of the project, and they could freely try the four tests. This was done to limit any surprise effects on the operator performance. The tests were planned to minimize the impact on the working activity of the assembly line itself, and the average time of execution was between 10-12 minutes. To perform the tests, each worker was given a short break, for the time strictly necessary, and replaced by a substitute as it usually happens for any temporary absence. This configuration allowed the tests to be repeated 3 times during the whole shift for all the

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workers. All test results showed good discrimination of workers skills highlighting a wide range of variation in performances.

Figure 7: Assessment of human capabilities for live lab 2 (from Comberti et al. 2018)

3.3.2. Fault detection

The recent technological advances in various fields, including artificial intelligence (AI), allow enriching the human performance modelling. Since the dawn of the era of modern computers, some tasks, particularly repetitive ones, are best performed by machines. However, nowadays, more than that is demanded. The emerging technologies aim to improve operator safety, performance, and well-being and enhance the capabilities of the work-station-operator interaction. As a result, operators will have to acquire a broader range of specific skills. They will have more and more often to combine traditional task-associated expertise with computer science one.

Some initial research questions can be formulated that may feed the paradigm transformation. Which additional technological advances could be added to analysis the human performance in safety-critical scenarios, and how? Which are the pros and cons of these ongoing advances from the human performance point of view? Are all the devices or methods suitable to apply into the automotive sector? How can the data for assessing the operator's abilities and task complexity be collected? How could this approach be improved? Exploring the literature will be the first step to comprehend how the human performance model could be enhanced and deployed within safety-critical systems.

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A framework similar to this will be proposed in Live Lab 2. Managing the working environment reduces the probability of quality issues and human errors thus more attractive to an employer. On the other hand, many sensors collect data from the shop floor in the automotive sector. The information about the workstation counts for understanding the human performance. Machinery downtime and servicing could be reduced considerably if intelligent systems predicted maintenance needs. There are two relevant concerns for the automotive industry that could be addressed using ML/AI techniques, namely, predictive maintenance and anomaly detection:

• Predictive maintenance: Timely maintenance of in-service equipment is needed to increase safety and efficiency. Predictive Maintenance monitors the condition of equipment and uses machine learning for the definition of actual state and forecasting future states. This approach differs from preventive maintenance, which relies on statistical expected lifetimes of equipment, in order to predict when maintenance is required. This approach offers cost savings over preventive maintenance because maintenance is performed only when warranted. In addition to improved productivity, this approach uses fault detection to reduce waste production and prevent accidents.

• Anomaly Detection: This technique deals with the identification of abnormal data points which deviate significantly from the usual data. Its applications are numerous, and in the context of industry and IoT, it is used to identify safety-critical scenarios, for example, detecting the malfunction of equipment in production assembly or detecting faulty products coming out of an assembly. For IoT and Sensor Time-Series Data, anomaly detection uses AL, through uncertainty sampling. For example, suppose a highly imbalanced data with 999 regular events and only one abnormal event. In that case, the algorithm provides a label for this one abnormal event. There are usually only very few key events that require human attention in a very long time series. Here, AL and anomaly detection detect anomalies and learn about these critical events rather than the complete time series.

For IoT and Sensor data, we can perform anomaly detection and predictive maintenance using the following techniques:

• Active Learning (AL) for Anomaly Detection in IoT and Sensor Time-Series Data: A major challenge with anomaly detection is that by definition, anomalies are rare events, and so to train a data driven anomaly detection model it may be necessary to review and label a very large number of data points in order to identify a sufficient number of anomalous datapoints for the data driven anomaly detection model to be trained on. Active learning is based on the belief that comparable model performance can be achieved using a small, curated dataset as compared to a large dataset. Building on this belief, the goal of active learning is to reduce the cost of data labelling by attempting to select the most useful data points to label in order to achieve high model accuracy. The basic idea is to iteratively train models on a task using small amounts of labelled data, use the model performance on the data to inform the selection of new data points for labelling, and then label the selected data points and retrain the model using the extended training dataset. In essence, the model is used to inform the selection of the data that are presented to a human annotator/expert for labelling and that are then used to retrain the model. AL finds applications in the industry due to a need for a safety critical system, and an efficient system so that it is practical for use in the industry. A Bayesian Deep Active learning framework for example provides credible predictions and therefore sits well with our requirements of a safety critical system. Moreover, in contrast to a passive ML system, we need to actively make sure that our system does not miss any valuable data. AL ensures

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this by way of uncertainty sampling and diversity sampling that we address all the classes, for example, if we have data which is highly imbalance with 999 normal events and only 1 abnormal event, we need an algorithm which makes sure that we provide a label for this 1 abnormal event. Secondly, AL naturally makes a supervised learning agent much more efficient because we require fewer samples to train our agent. IoT and Sensor Time series data can be explored much more efficiently by AL because usually in a very long time series there are only very few key events which require human attention. Here our task then becomes AL and Anomaly detection, where we first detect anomalies and then learn about only these important events, rather than learning about the complete time series.

• Predictive maintenance using Reinforcement Learning (RL) and Active Learning: RL is a powerful technique used for decision making and predicting future states. It is based on the concept of training a model by rewarding correct predictions and penalizing incorrect predictions. For example, given a state of chess board, a RL algorithm could predict the best move to make. We can use reinforcement learning and AL to incorporate a human in the loop for predictive maintenance. Say, our RL algorithm predicts a certain part of a machine needs replacement then our system can alert a human that a part needs a replacement, however in the other case if the part in question does not need a replacement, then our AL algorithm can query the human and improve the RL agent from this feedback.

In addition to the above analysis, a set of future experiments will be proposed in the framework of

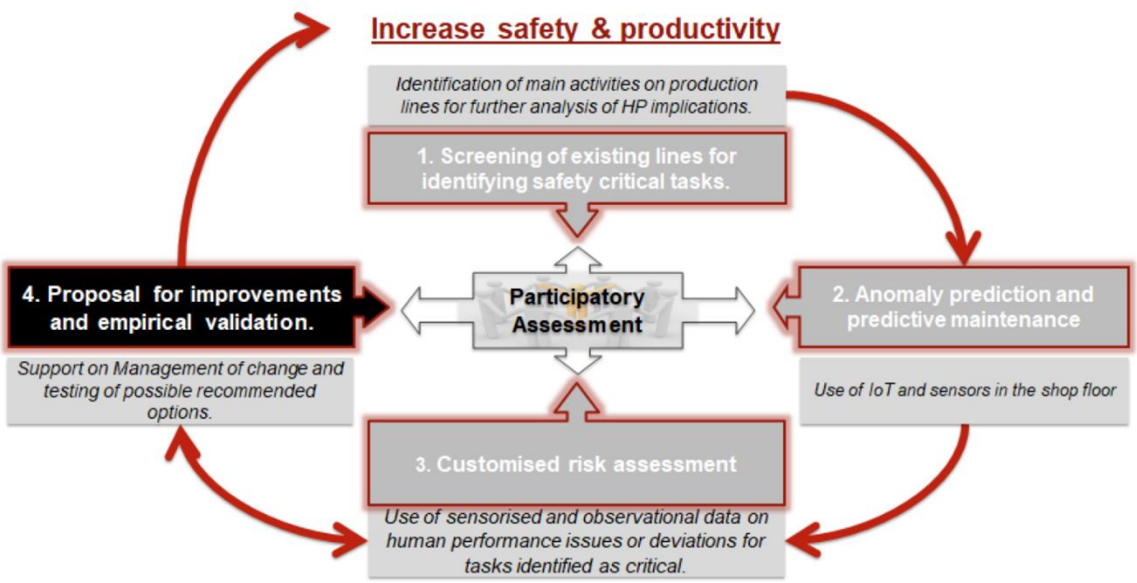

Figure 8: Enriching Human Performance through ML techniques adapted from Leva et al.2016

Live Lab 2. These experiments will collect IoT sensor data from a single or multiple machines which form a complete process (for example, one complete process would be robots spray painting the metal body of vehicle, this process is in itself complete when the painting has finished, one could then investigate for any defects in the paint job using ML and controlling for quality with the help of a human). Additionally, the so-called “ability corner” will be re-design and validated experimentally.

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4. Live Lab 3 Assisting Human decision-making (YOKOGAWA, POLITO)

4.1. Objective

The goal of Live Lab 3 is to demonstrate how data analysis and advanced control techniques can optimize the control for the process industry. This Live Lab is situated in Yokogawa's facility in the United Kingdom and additionally in POLITO's facility in Turin.

4.2. Description

Safety is of paramount importance in critical industries like the process and energy industries, for example, in oil and gas facilities. Several error sources have been identified to impact safety in these domains of which human error has been most consequential. However, studies have shown that human error is also as a result of their interaction with other systems and their environment. Indeed, while human operators are the key in a critical situation in the industry but 80 % of accidents in the industry is caused by human. In a critical situation, humans tend to use intuition over systematic evaluation and trade-offs. Sensible to cognitive biases (like recency bias, confirmation bias,…) and overload.

The Live Lab focuses on control room operations and human's situational awareness during stressful interventions i.e., alarms. Primarily this Live Lab will be based on Yokogawa's facility with a particular focus on risk monitoring in control runs. To facilitate the research, Yokogawa are providing a dataset with over 150,000 samples and 44 features, consisting of timestamps of alarm and alert events.

The Live Lab will also provide a simulated Distributed Control System (DCS) in a laboratory setting in POLITO in Turin. The system can accurately simulate a process plant and has the flexibility to allow different scenarios of normal operations, failures, and emergencies to be simulated through a scenario editor. The simulator is customisable to produce a range of scenarios and fit with different possible HMI and DCS environments. This empirical study aims to investigate the influence of both obvious and latent factors (human, organisation, and technical) during man-machine interaction and the consequence on human performance and safety. A case study on the production of formaldehyde in a chemical plant has been selected and simulated for this purpose. The facility produces around 10000 kg/h of 30% formaldehyde solution, operating the partial oxidation of methanol with air. The human-in-the-loop configurations in simulation is varied from a monitoring to both monitoring and control. Both normal and abnormal situations have been considered as well.

The aforementioned aspects will link the control room operations simulations to the biometric data providing the opportunity to investigate adaptive "human in the loop" automation features, such as decision-making support and what real-time impact they have. These features will be defined in collaboration with a DCS equipment supplier (Yokogawa) who has a leading role in the committee for HMI for the International Society of Automation (ISA). By analysing the data from Yokogawa, the CISC project will:

- Help predict trips and critical scenarios using Bayesian Network (BN) to help decision making for a human operator (identify likely root causes for process deviations). Compare data-driven BN, expert knowledge and data, and purely expert knowledge BN for online prediction

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- Finding clusters of alarms to group them
- Apply reinforcement learning to classify alarms and help identify nuisance alarms and reclassify them also in terms of priority in an online setting
- Provide suggestions on response strategy (controllable variables) using reinforcement learning
- Predict human performance and reliability of human response to critical scenarios
- Help identify critical information and tasks to support situational awareness (trouble shooting strategy procedure and HMI support for them)

A number of researchers will collaborate on Live Lab 3 as shown in Figure 9**.**

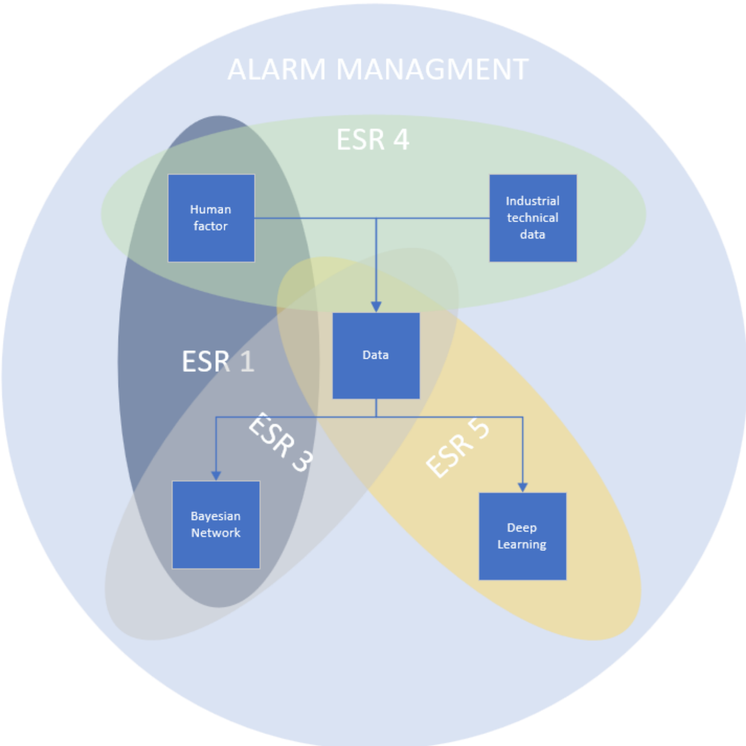

Figure 9: Breakdown of the roles of different researchers in Live Lab 3

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4.3. Case Study

The case study developed in collaboration with POLITO, focuses on a simulated chemical plant for the production of formaldehyde. The plant produces around 10000 kg/h of 30% formaldehyde solution, operating the partial oxidation of methanol with air. For this experiment a simulation of the plant has been done with some variations and optimisation. The plant is made of three sections**:**

1. Feed section: the systems here include, two nitrogen flow systems, a methanol tank, a methanol pump, a boiler, air and gas compressors, heater, piping, controllers, safety valves, indicators.
2. Heat and recovery section: three heat exchangers
3. Reaction and Separation Section: a reactor, controllers, alarms, sensor, rupture disk, piping, absorber

Hazardous events (process safety occurrences) considered include: depressurization of the methanol tank, air entrance in the methanol tank with the formation of a flammable atmosphere, the reactor overheating. The scenarios are broken down according to complexities (normal and abnormal situations) within the different plant sections, to vary 'task load' as a variable and observe its impact on performance alongside other variables as shown in Table 2.

Table 2: Safety related Scenarios in Live Lab 3

Section	Scenario	Assumption	Interface/Triggers /Stimulants	Operator
Feed1: Nitrogen flow	This scenario simulates a disturbance in the inflow of Nitrogen to the methanol tank as a result of a damage on one of the valves. Nitrogen is used to pressurize the liquid methanol in the storage tank. The hazardous event here includes a possible imploding of the tank and outflow of methanol.	Time delays switching from nitrogen system 1 to backup or switching not automated	Alarms	**Goal:** Ensure the right flow and dosage of Nitrogen and prevent hazardous event **Actions:** - switch to second nitrogen system
Feed2: Boiler and reactor	One of the possible scenarios here is preventing air entrance into the methanol tank and preventing the burning of the boiler. Pump/boiler: This could be as a result of damage or seal leakage on the methanol pump. The boiler continues its operation with an absence of fluid. Tank: It could also be a situation that already stems from the Nitrogen scenario. In this case pressure keep dropping due to unknown damage of second system thus triggering the safety valve and pressure recovery from atmosphere and emergency state activated. Also, potential air entrance to the methanol tank. In both cases the plant is out in emergency shutdown and possible explosion if ignited	system 2 does not function due to issue from lack of use	Pump power indication Pump level indication Pump flow indicator Nitrogen flow indicator Steam flow indicator	**Goal:** Avoid emergency state activation, prevent air entrance, prevent the burning of boiler. **Actions:** Switch to second nitrogen system Switch pump to manual Switch boiler to manual Communicate with field operator Change heater steam flow to manual and control it
Reactor and separation	A possible scenario here could be the overheating of the reactor and the high concentration of oxygen as a result of the previous scenario with depressurisation of methanol tank causing more %Vol of CO than required.	The alarms in the feed section are active. Participants build prior knowledge from initial scenarios Pump failure not present	Pressure controller (reactor steam press.) CAH05 and 06 (oxygen and methanol concentration) TAH07, TAHH07, D5 rupture disk.	**Goal:** prevent flammable atmosphere and the burning of the reactor **Actions:** Switch to second nitrogen system Switch pump to manual Switch boiler to manual Communicate with field operator Pressure controller (automation) Concentration control

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4.4. Implementation and Design of Experiments

The objective of this experiment is to understand the influence the different interactions between variables during human-machine and automation interaction have on operator performance and how this affects process safety. This would enable opportunities for a more holistic risk-based decision making on real-time support adaptation, process control optimisation and management of change (resources allocation, etc.)

There are four key aspects to evaluate and implement collaborative intelligent algorithm to safely augment human capabilities in a process control run. achieve this. First, to develop a model for a real time assessment of human performance in the context of a Human-machine interaction environment. Secondly, the safety data for Human-in loop configuration in process control must be modelled. Thirdly, methods for optimal decision-making process in safety-critical systems using Reinforcement Learning considering human-in-the-loop setting will be explored. Finally, Bayesian networks will be developed to assist human operators and recommend adaptive automation strategies.

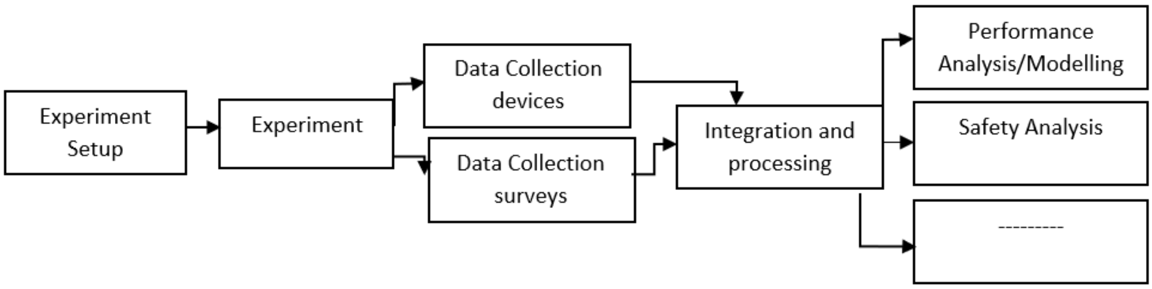

Figure 10: Experimental Implementation Plan

The researchers are provided preliminary alarm log data forming the first step in understanding the human's role in the automated system. Initially, the data will be analysed in order to cluster alarms this will reduce the overall number of alarms significantly reducing the possibility of cognitive overload. The data will then be analysed to investigate whether a trip can be predicted and whether a point of no return can be identified. Following from this, the researchers will conduct a set of operator interviews which will enable CISC to properly fill the open gaps from the analysis and on the data, while drafting a scenario(s) for the next phase of the project.

Experiments will be performed to test the hypothesis by collecting live data from operators in simulation and control room environments. These tools include graphical interfaces, eye trackers, EEGs, post and pre-experimental surveys and video recordings. The following potentially dependent variables have been hypothesized and are noted with the evaluation methods,

- Stress- Video recording, survey, log
- Trust – Surveys
- Situational awareness- Survey, Eye tracking
- Workload - Survey, Eye tracking, EEG, …)
- Time to complete (log)

Additionally, the following potentially independent variables have been hypothesized

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- Interface configurations
- Stimulants
- Task complexity
- Knowledge and Experience
- Operating procedure
- Room conditions
- Demographics
- Interaction

Three different experiments will be performed as outlined in Table 3.

Table 3: Scenarios for Live Lab 3

Scenario	Operator Role	Automation
Normal operation (Task complexity level 1)	Monitoring	Active
Abnormal process safety situation (Task complexity level 1)	Monitoring and control	Active
Abnormal process safety situation (Task complexity level 1)	Monitoring and control	Disabled

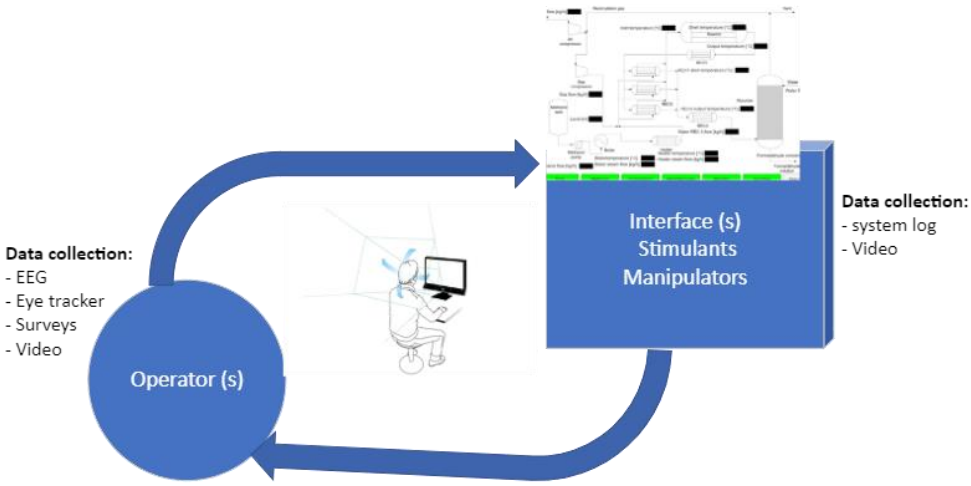

Figure 11: Schematic for Live Lab 3 experimental setup

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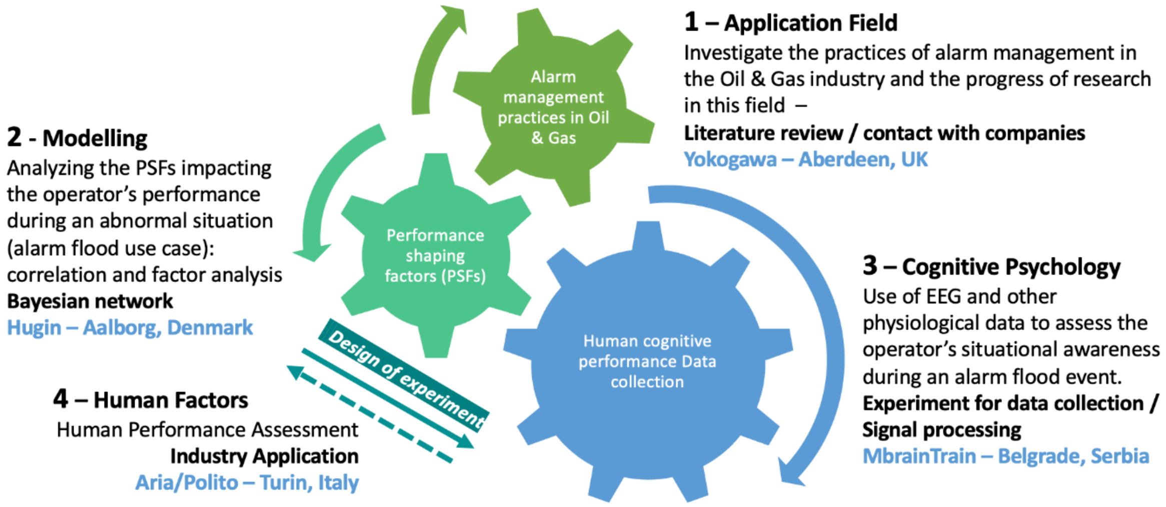

Figure 12: Live Lab 3 description of proposed experiments at Yokogawa's facility to monitor human situational awareness during alarm event.

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5. Conclusions

This deliverable contains information about the design of experiments and plans for implementation of the Live Labs. Three different Live Labs are proposed that include six different experimental scenarios in four different countries. Within all scenarios, humans are central to achieving an optimal system performance but until now the human factors are often a neglected component.

The researchers in the CISC project will be exposed to different problems relevant in diverse industries and within various working cultures demonstrating the importance of human centred design. The deliverable has outlined a detail design of each experimental setup. Additionally, the preliminary approaches which will be taken by the researchers are outlined and hypothesis detailed.

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