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Specifying task allocation in automotive wire harness assembly stations for Human-Robot Collaboration

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ABSTRACT

Wire harness assembly is normally a manual assembly process that poses ergonomic challenges. As a consequence of the rapidly expanding electrification of vehicles and transportation systems, the demand for wire harnesses can be expected to grow radically, further increasing assembly operator challenges. Thus, automating this assembly process is highly prioritised by production engineers. The rapid development of industrial robot technology has enabled more human-robot collaboration possibilities, simplifying the automation of wire harness process tasks. However, successful automation applications involving humans require efficient and safe allocation of tasks between humans and technology. Unfortunately, present assembly system design methods may be obsolete and insufficient in light of the capabilities of emerging automation technologies such as collaborative robots. This paper presents a design and specification methodology for human-centred manufacturing systems and focuses on collaborative assembly operations in complex production systems. A case study on human-robot collaboration provides an application example from a wire-harness collaborative assembly process. The proposed design methodology combines hierarchical task analysis with assessments of cognitive and physical Levels of Automation (LoA_c and LoA_p). The assessments are then followed by evaluations of the Levels of human-robot Collaboration (LoC) and the Levels of operator Skill requirements (LoSr) respectively. A task allocation matrix supports the identification of possible combinations of automation and collaboration solutions for a human-centred and collaborative wire harness assembly process. System designers and integrators may utilise the design and specification methodology to identify the potential and extent of human-robot collaboration in collaborative manufacturing assembly operations.

1. Introduction

Technologies such as *collaborative robots (cobots)* have been proposed (Vicentini, 2021; Cohen et al. 2022) as tools to empower the assembly worker. Cobots have the potential to assist in several existing *Wire Harness (WH)* assembly tasks and mitigate work-related health problems such as musculoskeletal disorders. While collaborative robots can work nearby human operators, it is crucial to have an optimal division of tasks between the human operators and the cobot for fast, successful, and productive collaborative assembly operations.

Present methods like the ones offered by Simões et al. (2022), Li et al. (2023), and Faccio, Granata, and Minto (2023) to analyse the need and potential for collaborative robot applications generally focus on the physical interaction between robots and humans. However, expanding the analyses through advanced task allocation methodologies would enable a higher precision in the specifications of the frequently dynamic distribution of cognitive and physical tasks between humans and automation systems (e.g., robots and augmenting technologies).

The rapid spread and upscaling of collaborative robot installations have been anticipated for several years (Cohen et al., 2022; IFR, 2022) but have yet to materialise to any great extent. One reason is a lack of "killer applications" where the widespread increase of safety, productivity, and superior workplaces resulting from the use of collaborative robots is demonstrated. One such application area is the exponentially increasing electrification and smartification of vehicles. This includes the deployment of added vehicle functionality, such as autopilots, lane detection, obstacle detection, and camera monitoring of the car's surroundings. Thus, a broad range of emerging electrical components needs

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to be assembled, many of which are related to the safety–critical functions of the *Electrical Vehicle (EV)* and its passengers. Consequently, quality aspects of EV manufacturing, for instance, its *Wire Harness Assembly (WHA),* are vital for their drivers and passengers requiring EVs to be assembled with zero defects. Further, the costs of correction of a defective wire harness assembly are very high, since it is performed during the early stages of a car's final assembly process. In summary, ensuring wire harness assembly quality and adequately designing the assembly workstations is essential for the automotive industry.

A *wire harness* is a group of selected cables widely used in automotive vehicles for various purposes. Wire harnesses are typically used to control power windows, automatic engine control, camera systems, and proximity sensors controlled by the mainframe computer in an automotive vehicle. Wire harnesses are often delivered from sub-suppliers as pre-kitted components, including elective plugs (male/female), and then installed in, for example, EVs. Unfortunately, wire harness assembly is a repetitive, strenuous, unergonomic, and tedious manual assembly process during the final assembly (Nguyen, Kuhn, & Franke, 2021). High-voltage cables are typically stiff and heavy, thus requiring high (human) muscle force during manual handling and connection. Consequently, wire harness assembly significantly contributes to musculoskeletal disorders among assembly operators (Trommnau et al., 2019; Nguyen, Kuhn, & Franke, 2021).

Much can be gained regarding improved work situations in WHA by increasing appropriate levels of automation. Examples of highly automated sub-tasks and the deployment of industrial robots for partial automation in WHA can frequently be found in the literature (Hermansson, Bohlin, Carlson, & Söderberg, 2013; Trommnau, Frommknecht, Siegert, Wößner, & Bauernhansl, 2020). However, given the complexity of WHA, even advanced and expensive automation solutions are often inferior to human assembly work, due to space and speed limitations in terms of quality and productivity. But the rapid evolution and increasing performance of collaborative robots may present elegant and efficient opportunities for WHA. To automate tasks using collaborative robots a few assessments are necessary, including extensive analysis of human-robot task allocation; assessments of automation levels; and identification of human-robot collaboration levels, combined being used as a tool to design collaborative workstations with a proper balance of tasks to be done by humans and robots. Attempts have been made to automate wire harness assembly tasks by focusing on path-finding for robots (Hermansson et al., 2013). The use of collaborative robots in manufacturing wire harnesses is reviewed in detail by Navas-Reascos et al. (2022). This article focuses on the assembly of wire harnesses in electric or hybrid vehicles.

To increase the precision, quality, and speed of an assembly system design, workstation designers or production developers should use prescriptive design tools, but these are presently scarce. While the design perspective for manufacturing wire harnesses was studied by Palomba et al. (2021), the assembly of wire harnesses into vehicles needs a similar approach. A core problem is that models and methods for assessing and designing collaborative robot applications are often descriptive and less valuable "analyses-after-the-fact". Therefore, the main question and concern of this paper are how a method for the prescriptive design of human-robot collaboration in an assembly process should be structured to provide efficient guidance to manufacturing systems and workstation designers while meeting needs and requirements from the operators' side. The technical specification for robot path planning and optimisation, normally the consecutive step after task allocation, is not included in the scope of this article.

2. Background

This section introduces the concepts used to develop the proposed design and specification methodology for human-robot collaborative applications.

2.1. Task allocation in manufacturing systems

Automation as a means to augment and gradually replace physical or cognitive human work has always been a major factor in advancing industrial competitiveness. In the context of *human-robot collaboration,* it is relevant to note that while robotic capabilities are exponentially evolving due to their intrinsic integration with computer technology; general human capabilities, apart from individual skills, more or less seized to evolve thousands of years ago. Thus, ground-breaking research from, e.g., 1950–60s aerospace research, and 1980–90s human-centred computer interaction technologies is often quite valid and often gravely under-appreciated in technical development. This article aims to avoid the common duplication of previous research.

Task, or function, allocation aims to break down large tasks or operations into sub-operations or sub-tasks, often referred to as tasks and functions. Such sub-tasks are then allocated to a human operator or a machine (e.g., a robot), depending on the requirements and capabilities needed to complete the overall task sequence successfully. The successful use of specialization and task allocation is not new. Taylorism and time measurements in the early 1900s complemented electricity as a driver of the second industrial revolution. In 1951, Fitts and Chapanis (Fitts, 1951) proposed a pragmatic scheme describing human and technological strengths and weaknesses that should be considered when designing military or aerospace products. Fitts' list or the MABA-MABA model ("Men Are Better At – Machines Are Better At") recommends task allocation based on the ability of machines and humans (see Table 1), this list still has high practical validity, even in the era of advance digitalisation (De Winter & Dodou, 2014).

Although Table 1 is a good starting point for allocating tasks and functions between humans and machines, the proposed list pits humans against machines and is quite static and limited when a dynamic interaction is required. Higher levels of automation increase the need to ensure the resilience of technological capabilities and competencies, while lower levels of automation rely on individual human abilities of, for example, shop-floor operators (Li et al. 2022). Such comparisons make little sense, as both humans and machines have different intrinsic capabilities (Jordan, 1963). Humans are more flexible, better at responding to uncertainties, and comfortable with unstructured, dynamic environments. Machines are physically stronger and more accurate in comparison with humans.

To overcome this comparison, Price (1985) proposed a task allocation decision matrix based on the performance of humans and machines, suggesting that some tasks are better suited for machines while others are better suited for humans. This methodology is in line with that proposed by Fitts but might be too complex to use when the human and machine need to collaborate on a task. Instead of complete task division, Parasuraman, Mouloua, and Molloy (1996) proposed a solution of allocating automated tasks to humans for a short time before returning

Table 1
Fitts' List (Fitts, 1951), The "MABA-MABA List".

Humans surpass machines in the:	Machines surpass humans in the:
Ability to detect small amounts of visual or acoustic energy.	Ability to respond quickly to control signals and to apply great force smoothly and precisely.
Ability to perceive patterns of light or sound.	Ability to perform repetitive, routine tasks.
Ability to improvise and use flexible procedures.	Ability to store information briefly and then erase it completely.
Ability to store very large amounts of information for long periods and to recall relevant facts at the appropriate time.	Ability to reason deductively.
Ability to reason inductively.	Ability to handle highly complex operations, many different things at once.
Ability to exercise judgment.	

them to automation. This solution can work in task allocations where a human operator has a supervisory role. Still, in tasks where collaboration is required, the use of similar approaches can be challenging and can lead to confusion and frustration on the operator's behalf. It is vital to instil an appropriate level of trust in automation, neither too much nor too little (Parasuraman & Riley, 1997). Sheridan (1997) highlights that task allocation in human–machine collaboration is not about allocating independent tasks to humans and machines, since tasks as rarely independent. In seven different steps presented by Sheridan (1997), it is proposed to conduct an overall task analysis followed by task allocation in a way so that complex tasks can be performed by humans and repetitive tasks can be performed by machines.

The ten-level scale presented in Table 2 can also be used to identify the maximum possible automation for a task. The use of *Hierarchical Task Analysis (HTA)* in task allocation from a human-centred perspective was explained by Stanton (2006). Since the human mind prefers large chunks of information, such as pictures and patterns, and not details, tasks should not be finely divided into smaller elements, where human attention and cognition require arbitrary partition. This is also situation-dependent, and not all available information is necessary if the human is expected to recall task instructions from memory (Li et al., 2022; Mattsson, 2018). Still, the focus should be on sharing the specific tasks where humans and machines take turns in performing a task. This type of allocation is explained in detail in task allocation based on supervisory control (Sheridan, 1997).

2.2. Levels of Automation (LoA)

Serious problems due to failures of human–machine systems have been well documented (Hollnagel, 2004). Many problems link to the status of the human operators, including vigilance decrements, loss of situational awareness, and complacency with the underlying factor being human-out-of-the-loop (Kaber and Endsley, 2004). This does not mean that work tasks should be easy; tasks should be challenging but within the abilities and capabilities of the human operators and should be adequately supported with an appropriate level of support (Rouse, Geddes, & Curry, 1987; Csikszentmihalyi and Csikzentmihaly, 1990).

Table 2
Levels of Automation by Sheridan and Verplank presented in (Vagia, Transeth, and Fjerdingen 2016).

Level of Autonomy	Description	Explanation
1	Fully manual control.	The computer offers no assistance.
2	The computer offers a complete set of decision/action alternatives.	Several options are provided to the human who decides.
3	The computer narrows the selection down to a few.	Human still has to decide.
4	The computer suggests one alternative.	Human decides amongst suggestions.
5	The computer executes that suggestion if the human approves.	Human approval is needed for execution.
6	The computer allows the human a restricted time to veto before automatic execution.	Limited time for veto given to the human.
7	The computer executes automatically and then necessarily informs the human.	No human interference, just information at the end.
8	The computer informs the human only if asked.	Human gets information only if asks.
9	The computer informs the human only if it decides to.	The computer decides whether to give information.
10	Fully autonomous control.	The computer decides everything and acts autonomously, ignoring the human.

Several approaches have been presented to overcome the traditional division of tasks. *Levels of Automation* (LoA) is one such approach, focusing on redefining the assignment of humans and machines with an integrated team approach that keeps humans and machines involved in system operations (Draper, 1995). LoA refers to the different levels of task allocation and performance interactions maintained between humans and machines in controlling a complex system (Billings, 1991; Kaber, 1996).

While the different degrees of automation proposed by Sheridan (1997) discuss automation in terms of autonomy, information sensing, control, and execution, the levels of automation define the assignment of system control between humans and machines, narrowing down to what degree humans and machines are involved in the operation of a system (Kaber and Endsley, 2004).

A review by Vagia, Transeth, and Fjerdingen (2016) summarises useful taxonomies while Tsarouchi et al. (2016) highlight the challenges of task allocation in HRC. Ultimately, all taxonomies applicable in the context of human-robot collaboration divide levels of automation into two main categories: "cognitive" and "physical". Such a model is explained in detail by Frohm et al. (2008) and specifically for assembly by Dencker et al. (2009). A notable work on task allocation in the context of collaborative robots is a complexity-based task allocation method proposed by Malik and Bilberg (2019). The study highlights the common practice of using *gut feeling* in task allocation between humans and robots. This article presents an interesting assessment from a mathematical standpoint of using automation capability as a tool for task allocation. Antonelli and Bruno (2019) presented a task allocation in robotic and collaborative robot cells based on the dynamic allocation of tasks between humans and machines with the main purpose of overcoming disturbances or delays. The dynamic task allocation based on task length and precedence is an interesting approach. Though the production manager identifies tasks, the basis for task allocation is not quite clear. In another example of a design approach for assembly line balancing using collaborative robots and humans, Dalle, Mura, and Dini (2019) present an algorithm based on a generic ergonomic assessment to reduce ergonomic risks to operators. Though Dalle, Mura, and Dini (2019) provide an excellent tool for assessing ergonomic risks, task allocation between humans and robots remains unclear. The current article presents a design tool based on levels of automation for collaborative robots that can complement the aforementioned articles with the task allocation between humans and robots. Often, levels of collaboration are used as a starting tool in task allocation. But the levels of collaboration do not clarify the task allocation between humans and robots, for instance, the who-does-what issue. In the example from Fig. 1, the level of collaboration will change from sub-task to sub-task based on the allocation of tasks. Ideally, an operation will consist of different levels of collaboration from task to task.

2.3. Levels of Collaboration (LoC) and collaborative robot applications

Collaborative robots, commonly known as "cobots", are a type of industrial robot designed for direct interaction with humans in completing a task (Peshkin & Colgate, 1999). They are equipped with advanced sensors and actuators capable of detecting obstructions in the cobot's path. Traditional industrial robots face huge limitations, such as caged safety areas, less flexibility when moving between workstations, extended programming and verification processes for their application in final assembly, and a high degree of human operator involvement in assembly processes. With their safety features, such as fast and comparatively easy programming and verification, and their ability to work near human operators, cobots can overcome the challenges faced by traditional industrial robots (Ore et al., 2017). Besides taking over tedious and less ergonomically sound tasks, such as rapid or heavy pick-and-place operations, cobots may also be used for material handling, quality assurance, and verification processes. The ISO 10218 and ISO/TS 15066:2016 technical specification emphasise the external safety

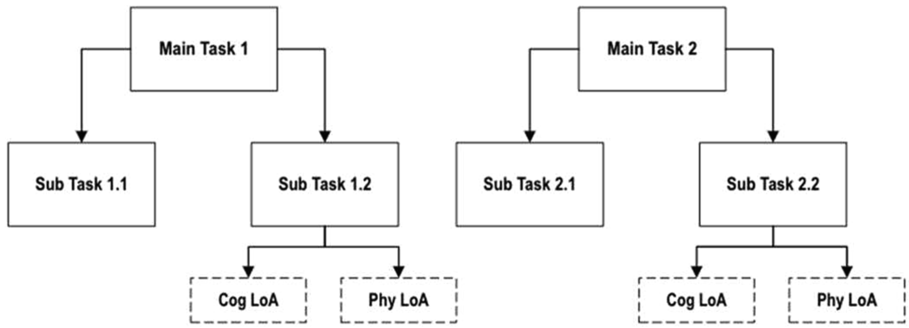

Fig. 1. Task allocation of an Operation consisting of Two Main Tasks, Broken Down into Sub-tasks, and Analysed from Physical and Cognitive Level of Automation Perspectives.

features required when using a collaborative robot. These standards also encamp human operators as an integral part of the functioning of collaborative robots. Thus, a collaborative robot application consists of a collaborative robot and a human operator supported by external safety measures such as infrared safety sensors, proximity sensors, and so on. The basis for using collaborative robot applications is to help human operators perform tasks that are otherwise challenging to accomplish using conventional automation solutions (Vicentini, 2021). The different levels of collaboration are shown in Fig. 2. These levels are explained further below (Bauer et al., 2016):

Cell: Traditional cage scenario where the robot is isolated in a cage.

Coexistence: Humans and robots work alongside each other without the presence of any cage though the workspace is not shared.

Synchronised: Humans and robots share the same workspace. Only one interaction partner, either human or robot, is actively working in the workspace.

Cooperation: A shared workspace where both humans and robots have tasks to perform. This task is not simultaneously performed at the same location as a product or component.

Collaboration: Humans and robots work simultaneously on the same product component.

2.4. Levels of task complexity and skill requirements

When deciding on the design of the workplace and allocation of tasks for a collaborative situation, it is assumed that the more complex the situation, the higher need for human integration and interaction in the workstation performance. This is in line with arguments by Bainbridge's "paradoxes of automation", i.e., the more automation that is applied, the more dependent the technical system becomes on the human operator(s) to solve the tasks that could not be sufficiently automated (Bainbridge, 1983). Based on Mattsson (2018), complexity in a manufacturing assembly is combined into three main areas: (i) station design, (ii) work variance, and (iii) disturbance handling. This can be further broken down into tools, layout design, product variants, and work content. Reducing task complexity has a positive impact on the quality of assembly operation, and cognitive automation is proven to be a helpful tool in reducing task complexity (Fast-Berglund et al., 2013). The proposed *CompleXity Index (CXI)* is a tool used for assessing complexity as perceived by operators (Falck et al., 2017). The tool can be used to analyse the complexity of a task. The higher the complexity of a task, the higher the requirements placed on the operator. Therefore, the operator will either need extended cognitive support or be subject to high skill requirements (Li et al., 2022). Specific requirements necessary for completing a particular task are identified during *Hierarchical Task Analysis (HTA)* and task allocation processes. The necessary skills required for completing a task can be identified based on the cognitive and physical requirements of a specific task. The levels of skills proficiency presented below are outlined based on the *European Qualification Framework (EQF)*. The proficiency levels for skills listed below are identified in the 2009 World Manufacturing Forum Report (WMF, 2019).

- **Foundational:** The operator possesses basic cognitive and practical skills.

- **Intermediate:** The operator possesses a range of physical and cognitive skills.

- **Advanced:** The operator has comprehensive and specialised knowledge.

- **Expert:** The operator possesses highly specialised knowledge.

Based on these definitions, in the context of collaborative robots, the levels of skills are described below.

1. **No skills:** No skills are required of the operator.
2. **Foundational:** Basic cognitive and practical skills, such as stopping the robot in an emergency, are required.
3. **Intermediate:** Normal cognitive and practical skills, such as understanding the basic functioning of the robot, understanding the safety parameters, etc., are required.
4. **Advanced:** The operators should be able to read and understand data from sensors, for example, the sensor's indication to initiate or stop an operation.

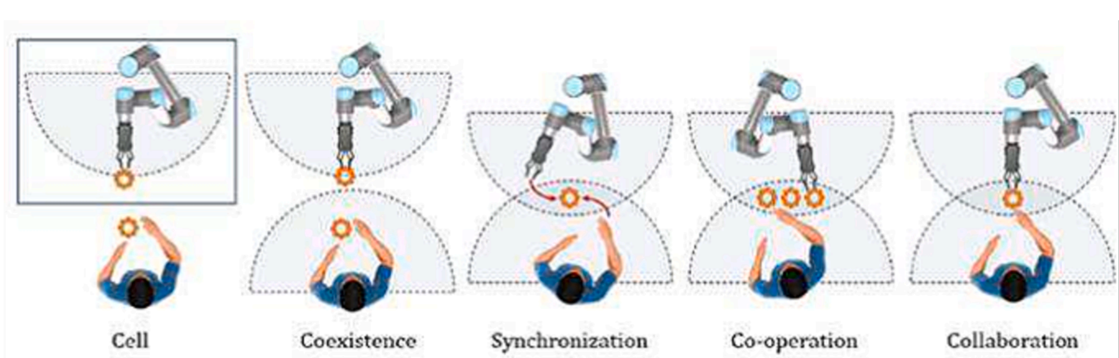

Fig. 2. Levels of Collaboration (LoC) as described by Bauer et al. (2016).

5. Expert: The operator should understand all parameters governing an HRC operation, such as the ability to read and understand data from the robotic system, PLC signals, etc.

3. Designing human-robot collaboration for manufacturing systems

The key objective of designing human-robot collaboration is to create a synergistic relationship between human operator and robot. The key objective of designing human-robot collaboration is to create a synergistic relationship between a human (operator) and a robot. This involves developing intuitive interfaces, and safety mechanisms that enable seamless interaction and cooperation. It also necessitates the consideration of ergonomic factors to ensure that the working environment is comfortable and ergonomically sound for both humans and robots. Human-robot collaboration can increase productivity by utilising the strengths of both humans and robots. Humans thrive on cognitive capacities, adaptability, and sophisticated decision-making, whereas robots excel at repeated activities, precision, and heavy lifting. Manufacturing systems can achieve greater efficiency, quality, and flexibility by using the specific characteristics of each. All these aspects are vital to be considered while designing a human-robot collaborative workstation.

3.1. Selection of levels of automation

Task allocation and Level of Collaboration (LoC) are complementary. To achieve an optimal LoC, one must conduct a thorough task allocation between the human (operator) and the robot. This allocation needs to be conducted in two dimensions, i.e., allocation of "cognitive" and "physical" tasks respectively. The LoA matrix presented in Table 3 is partly derived from the model proposed by Frohm et al. (2008) but modified to suit aspects of collaborative robots working in conjunction with the human operator. Frohm's et al. (2008) "cognitive" and "physical" levels of automation have in Table 3 been redefined to better reflect the technical development in the collaborative robotics area. This model is based on the concepts and methods of task and function allocation developed by Sheridan (1997), Sheridan (2000), and Kaber and Endsley (2004) as previously referenced. Fig. 3 shows a simplified overview of the matrix proposed in Table 3. The physical LoA for collaborative robot applications are presented on the X-axis, while the cognitive LoA for collaborative robot applications are presented on the Y-axis. The grey zone denotes a collaboration zone. The new matrix does not split tasks between robots and machines but rather between their physical and cognitive abilities. For human-robot collaboration, the physical abilities of humans and robots are obliviously different. Robots have physical advantages, e.g., carrying more loads repeatedly, with higher accuracy than humans. Further, a robot's cognitive abilities can be increased through vision systems and sensors and enhanced by advanced technologies such as machine learning and artificial intelligence.

Table 3
Levels of Automation (LoA) for Collaborative Robot Applications.

Levels of Cognitive Automation (LoA_c)	Levels of Physical Automation (LoA_p)
Totally manual (1) – The human creates his/her own understanding of the situation and task at hand and develops his/her course of action based on his/her previous experience and knowledge. No automation is not involved in decision-making. For example, operators use previous knowledge and experience.	**Totally manual (1)** – No use of a robot or any mechanical tool by humans to complete the physical task. For example, no used tool.
Basic task (2) – The human gets overall information on what to do or a proposal on how the task can be completed. For example, checklists and manuals.	**Basic task (2)** – The human or robot uses a flexible tool to complete a task. For example, the use of a multiple-purpose tool like an adjustable spanner or a gripper capable of picking-&-placing different sizes and shapes.
Instructions (3) – The human gets detailed instructions on how the task should be done. For example, assembly instructions.	**Instructions (3)** – The human or the robot uses a fixed tool to complete a task. For example, the use of a specialized gripper.
Supervision (4) – The human observes the automation performing the task and decides on intervention. For example, an Andon alert is triggered calling for human repair/fix intervention.	**Supervision (4)** – A robot self-selects the best possible solution for a given task and guides the operator in solving any issue if this occurs. For example, the use of an adjusting tool.
Totally Automatic (5) – All information and control are handled by automation. The operator is not involved. For example, autonomous manufacturing cells and smart workstations.	**Totally Automatic (5)** – The system handles all information and control by itself. For example, autonomous manufacturing cells and smart workstations.

3.2. Selection of level of collaboration

The current levels of collaboration are descriptive and applied to the entire operation instead of specific tasks (see Fig. 1). Based on the task allocation achieved using the *Levels of Automation (LoA) matrix* presented in Table 3 and visualised in Fig. 3, *Levels of Collaboration (LoC)* for each individual task, along with the corresponding skill requirements, can be visualised in Fig. 4. This mapping helps visualize different levels of collaboration for different tasks as well as the skills level for each task. Normally, the easiest task is allocated to the robot, while the most complex task is done by humans. This matrix aims to divide tasks not based on complexity but on the basic requirements necessary for completing a task based on the abilities of both humans and machines.

4. Wire harness assembly using human-robot collaboration

The application of the defined *Levels of Collaboration (LoC)* is exemplified using a wire harness assembly process. The reason for the use of wire harnesses is the complexity involved in assembling wire harnesses in a car using collaborative robots. Many factors, such as the safety of the operator and the location of the robot's tool central point TCP, need to be considered. Since the assembly of wire harnesses is carried out in an enclosed space inside the frame of a car, this complexity is further increased. This complexity can be reduced using a task allocation method. Task allocation also helps in dividing tasks between humans and robots in an efficient and meaningful way. The task breakdown of a wire harness assembly operation is described below. This breakdown of tasks is based on empirical data collected during

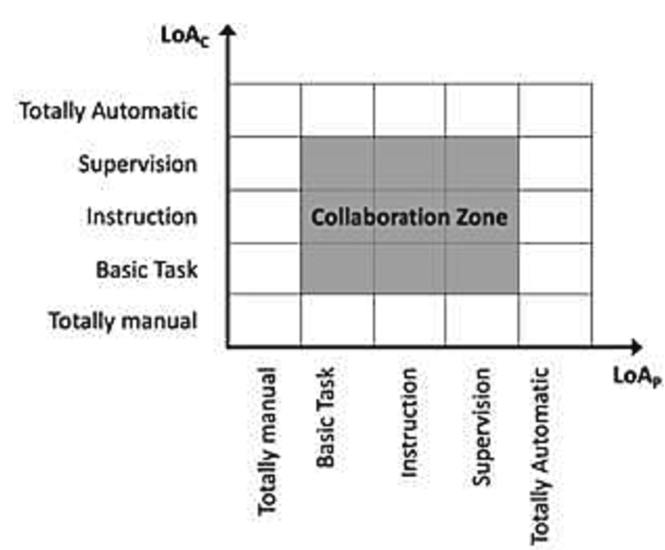

Fig. 3. Levels of Automation (LoA) Matrix for Collaborative Robot Applications.

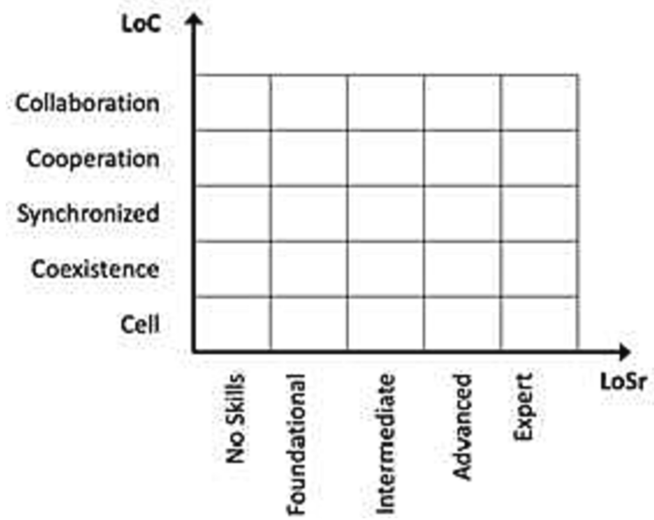

Fig. 4. Levels of Collaboration (LoC) & Levels of Skill Requirements (LoSr) Matrix for Collaborative Robot Applications.

visual inspection of the wire harness final assembly operation at Volvo Cars' final assembly plants in Gothenburg and Gent. Table 4 contains the task breakdown done using the *Hierarchical Task Analysis (HTA)* method. Tables 5 and 6 show the allocation of LoA, LoC, and LoSr, respectively. This allocation is visualised in Fig. 4 for LoA and Fig. 5 for LoC and LoSr.

Task 1: The *Wire Harnesses (WH)* are packed in plastic packages;

Table 4
WHA Task Breakdown and Description.

Task	Sub-task	Task	Cognitive Task	Physical Task
1	1.1	Open the WH plastic package	Ensure that the WH is not damaged while opening	Open the plastic packages using a tool
	1.2	Load the WH package on the metal pallet	Ensure the correct WH is loaded completely on the pallet	Drag the WH on the pallet using your own strength
2	2.1	Move the pallet inside the car	Decide on how to move the pallet so that it does not hit the car's body	Use the power lift to take the pallet inside
	2.2	Unload the WH from the pallet	Observe that the placing area is clear	Rotate the pallet by 90° using your own strength
	2.3	Move the pallet out of the car	Decide on how to move the pallet so that it does not hit the car-body	Use the power lift to take the pallet inside
3	3.1	Spread the WH	Decide which wire to pick up first, which direction to start	Use your own strength to spread the wire harness for aligning
	3.2	Align the wire harness for assembly	Decide on the best possible alignment positions	Ensure the location for placing the WH is correct
4	4	Plugin the wire harness sockets on Y-axis	Ensure the assembly is successful by verifying it	Insert the WH using your own strength at the required locations
	4.2	Plugin the wire harness sockets on the floor frame	Ensure the assembly is successful by verifying it	Insert the WH using your own strength at the required locations
	4.3	Visual quality inspection of the assembly	Ensure the assembly is successful by verifying it	Use of vision system for verification of correct assembly

Table 5
LoA Allocation in WHA.

Task	Sub-task	Task	LoA Cognitive	LoA Physical
1	1.1	Open the WH plastic package	2	2
	1.2	Load the WH package on the metal pallet	1	1
2	2.1	Move the pallet inside the car	3	1
	2.2	Unload the WH from the pallet	1	2
	2.3	Move the pallet out of the car	3	1
3	3.1	Spread the WH	2	2
	3.2	Align the wire harness for assembly	3	4
4	4.1	Plugin the wire harness sockets on Y-axis	4	4
	4.2	Plugin the wire harness sockets on the floor frame	3	3
	4.3	Visual quality inspection of the assembly	4	5

Table 6
LoC and LoSr Allocation in WHA.

Task	Sub-task	Task	Level of Collaboration	Level of Skill Req.
1	1.1	Open the WH plastic package	1	1
	1.2	Load the WH package on the metal pallet	1	1
2	2.1	Move the pallet inside the car	1	2
	2.2	Unload the WH from the pallet	1	1
	2.3	Move the pallet out of the car	1	2
3	3.1	Spread the WH	2	2
	3.2	Align the wire harness for assembly	4	4
4	4.1	Plugin the wire harness sockets on Y-axis	2	4
	4.2	Plugin the wire harness sockets on the floor frame	4	4
	4.3	Visual quality inspection of the assembly	2	5

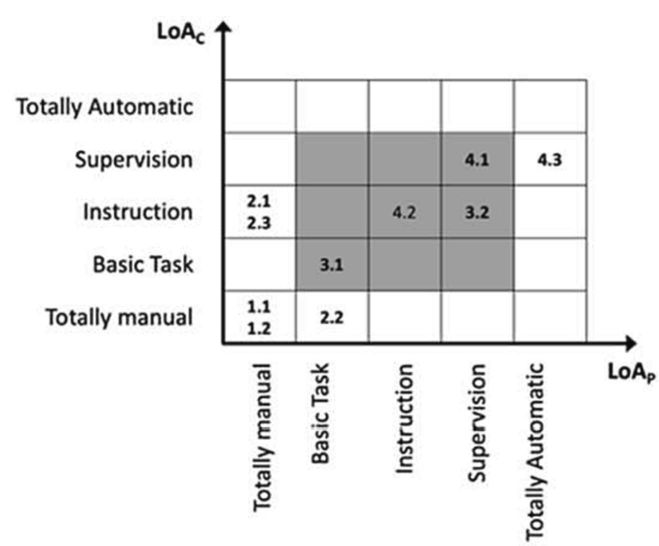

Fig. 5. Visualisation of LoA Allocation in WHA.

these packages are heated to soften the WH before they are cut open. These open packages are then loaded on a metal pallet.

Task 2: The metal pallet is moved inside the car by an operator with the help of a portable power lift. The pallet is then unloaded by lifting it up to 90°. Once the WHs are dropped in the car, the metal pallet is moved by the operator.

Task 3: The WH is untangled and spread on the floor of the car manually by operators. The plugging pins are aligned by the operators to their required positions. Operators often have to bend up to 50° to reach and place the WH.

Task 4: The operators start plugging in the WH in their designated areas which helps with their own muscle power. This is quite a strenuous and unergonomic task.

4.1. Selection of the levels of automation for a collaborative assembly process

The aim is to automate the WH assembly process, using collaborative robots. Thus, the allocation of LoA is based on maximising the use of collaborative robot applications. Based on our allocation of tasks using the matrix from Table 3, The LoA allocation presented in Table 5 signifies such. Since the table is acting as a design and evaluation tool, the focus is on the type of task as well as the requirement for successfully completing the task. LoA levels for wire harness assembly are presented in Fig. 5.

4.2. Selection of the level of collaboration and level of skills requirements for a collaborative assembly process

The allocation from Table 5 is then used to identify the levels of collaboration and skills presented in Table 6 and visualised in Fig. 6.

4.3. Integration of levels of automation (LoA), level of collaboration (LoC), and level of skills requirements (LoSr) for a collaborative assembly process

Task 1.1 of opening the packages is done by the operators, and they will need a hand tool to open the package. Since the requirements here would be a sharp tool, this cannot be a collaborative operation due to the risks. This operation does not require any skill level, so Level 1 is allocated to this task. An opened package of a wire harness is shown in Fig. 7. These mixed bundles of wires are too complex for a completely automated robotic operation.

Task 1.2 is to load the WH on the pallet. This task does not require any special tool or cognitive requirements. The operator will use their own muscle power. Thus, LoC and LoS requirements are set to 1 since no special needs are identified from LoA allocation.

Task 2.1 and **Task 2.3** is to move the pallet in and out of the car. A flexible tool (a lift) is readily available to move the pallet. Thus, the use of a flexible tool is devoted to this task (LoA_p 3). There are no special cognitive requirements other than not hitting the car, thus LoA_c 1. LoC is 1 since no special needs are identified, and LoSr requirements are set to 2. Since the lift is at risk of hitting the car, the operator needs to possess some basic physical and cognitive skills from LoA allocation.

Fig. 7. An Opened Wire Harness Package.

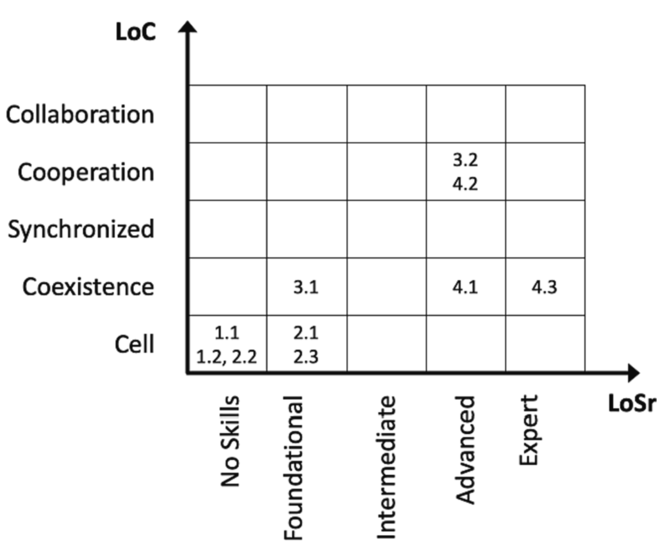

Fig. 6. Visualisation of LoC and LoSr Allocation in WHA.

Task 2.2 is to unload the WH in the car. There are no special cognitive demands thus LoA_c 1, but the pallet needs to be rotated by 90° for which a flexible tool is recommended, thus LoA_p 2. Since this is a simple task, the potential for LoC and LoSr is set to 1.

Task 3.1 is to spread the WH inside the car. The cognitive demand is to identify the correct ends of WH for specific locations, which can be fulfilled by giving operators basic information and using the vision system to detect the correct WH to pick (LoA_c 2). The physical task is to spread the WH. Operators can use their own strength here, but since the aim is to automate the WHA as much as possible, this task is proposed to be done by a cobot with the help of flexible tools such as a two-finger or vacuum gripper (LoA_p 2). Since the task is to spread the WH, there is potential for HRC, as both humans and robots are capable of completing the task using appropriate tools. Coexisting level of collaboration (LoC 2) is determined to be best suited for this article as robots can spread the wire harness areas difficult for humans to reach, like the centre of the car, while humans spread WH on the edges, thereby reducing the ergonomic load. Since this task involves selecting the correct wire harness ends and bringing them to the correct locations, basic skills requirements are deemed sufficient (LoSr 2).

Task 3.2 is aligning, and **Task 4.2** is to plug the WH on the car floor. Here the operator needs information on where and how to plug WH. In an HRC scenario, the human operator will spread the harnesses until it is ergonomically challenging when the robot will take over the task for **Task 3.2;** for **Task 4.2,** since plugging the harnesses is an ergonomically challenging task, a robot is preferred to carry out most of the plugging operation with high force requirements while the humans will carry out the easy plugging operation. Since there are different shapes and sizes of wire harnesses, proper instructions need to be provided to the operators, thus LoA_c 3. In terms of robots, a collaborative robot with a good reach is desired. Apart from picking and placing, the robot self-selects the best paths, and should a problem occur, the robot should guide the operator to solve the issue (LoA_p 4). In terms of LoC, These operations have good potential for HRC. With the operator and the robot working together in the same working space, these tasks are best suited to work at a cooperation level of collaboration (LoC 4). Since this is quite a critical operation of aligning and plugging the correct WH, the LoSr requirements are also set to 5 as the operators are expected to have comprehensive and specialised knowledge about WHA and understand the instructions received from robots LoSr 4.

Task 4.1 is similar to **Task 4.2,** but the difference here is the assembly on the Y-axis of the car, i.e., the exact centre of the car. Operators need to bend up to 50° to reach some of the plugging sockets as shown in Fig. 9. Due to the high physical requirements and ergonomic risks of this task, it should be completely carried out by collaborative robots (LoA$_p$ 4), with the operator's role limited to the supervision (LoA$_c$ 4) of the operation. The LoC level best suited for this operation is 2 since there is no requirement and involvement of operators in this task unless called on by the robot. LoSr level is the same as for **Task 3.2** and **Task 4.2** as the operators are expected to have comprehensive and specialised knowledge about WHA and understand the instructions received from robots LoSr 4.

Task 4.3 is the visual inspection of the quality of operation; here the robot will verify the quality of the wire harness assembly and identify any defective assembly with the help of a vision system (LoA$_c$ 4). The operator's role again is limited to supervision, and the robot will carry out the entire task (LoA$_p$ 5) by best selecting the paths and rechecking and verifying for any missed locations during the inspection. Since the robot is doing the entire operation by itself and the operator is limited to the supervisor's role, LoC for this task is 2, i.e., coexistence. Since the operator needs to understand the reports generated by the robot and look for any deviations, the operator is expected to be an expert in WHA with the capability to identify and solve any issues. Thus, LoSr is set to 5.

Based on the classification, the process overview is presented in Fig. 8, it can be seen that there is good potential for human-robot collaboration. In terms of requirements, it is known that tasks with higher cognitive and physical requirements can be better handled by the robot, while tasks with low physical and cognitive requirements can be better done by humans. From the requirements specification, it is needed a robot that can reach all wire harness assembly locations inside the car and with a good vision system, and proper, clear instructions need to be provided to the operators.

5. Discussion

Our review of the field indicates that automation has historically proven to be cost-effectively and efficient in discrete manufacturing. When involving humans in an automated system, careful allocation of work tasks and the well-designed interaction between humans and complex machines becomes crucial, a conclusion drawn already in 1950s aerospace research and development and continuously reinforced since. The need for efficient and precise methods is obvious. Simulation tools are commonly used to validate HRC operations. Nonetheless, Tsarouchi et al. (2016) identified a noteworthy limitation of these tools,

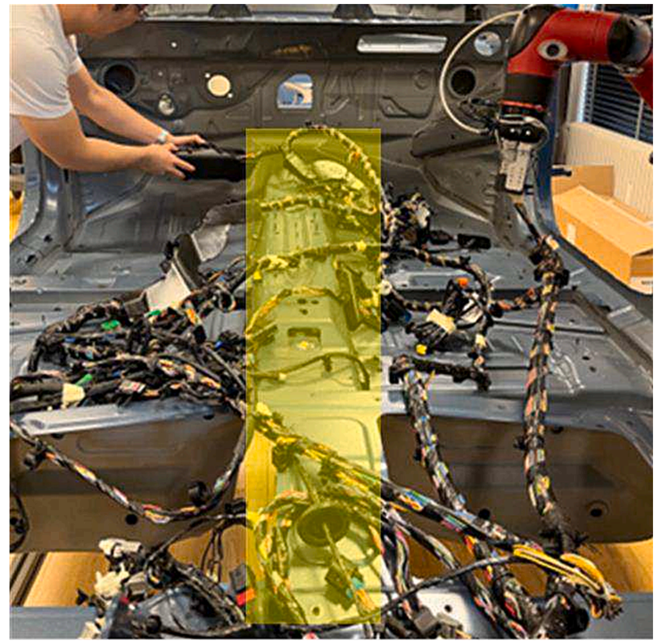

Fig. 9. Operator and a Robot Collaborating in a Wire Harness Assembly Process with Y-Axis Highlighted.

which is their failure to comprehensively analyse cooperative tasks involving humans and robots. Moreover, the process of testing and evaluating HRC operations using real robots and operators can be an expensive and time-consuming endeavour. By using appropriate task allocation methods in the design process of HRC operations, these challenges can be avoided (Tsarouchi et al., 2016; Malik and Bilberg (2019); Salunkhe et al., 2023).

The methodology presented in this paper aims to generate specifications for human-robot collaborative workstations based on hierarchical task analysis, where the division of these tasks between humans and robots is based on levels of automation and levels of collaboration, that will be required to engineer human-robot collaborative workstations. This process is visualised in Fig. 10. This tool aims to provide help in selecting support tools required for a collaborative workstation. The selection of tools, such as collaborative robots, and grippers, as the requirements for operations and operator support, will be based on the engineering choices/capabilities/costs, etc. The inclusion of the level of collaboration and task complexity matrix is used to identify the complexity of tasks and the levels of collaboration for the respective

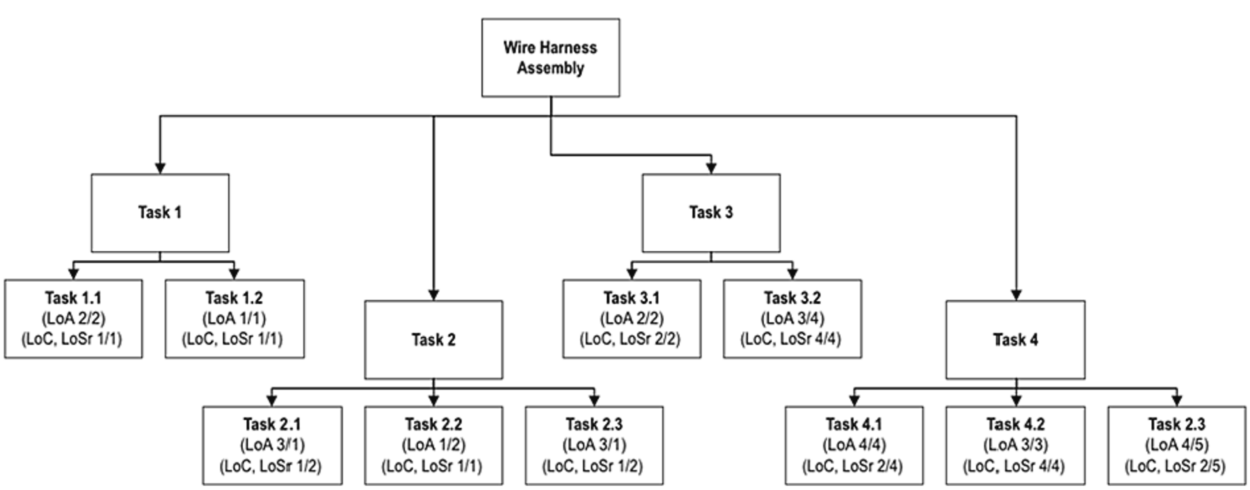

Fig. 8. HTA Wire Harness Assembly Process Overview.

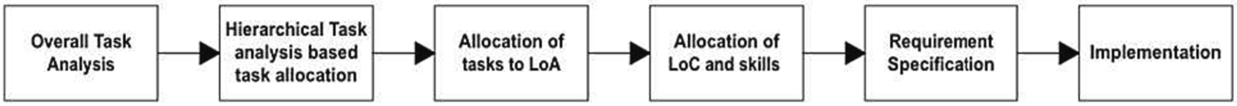

Fig. 10. Visualisation of the Complete Process in WHA using HRC.

tasks. This information, along with the information from task breakdowns, should be used to categorise risk factors, such as appropriate support tools and instructions to be used by operators for completing complex tasks and enhanced safety zones for tasks with high levels of collaboration.

In human-robot collaborative workstations, the cognitive aspects and requirements are often looked at from the operator's perspective. But these cognitive requirements can be shifted to automation with the help of modern vision systems and sensors that can fully identify and understand their surroundings. In the context of wire harness assembly, the requirements of looking for the correct assembly of wire harnesses can be easily carried out by vision systems. Such vision systems, combined with computer vision and machine learning, can provide up to 100% correct identification of a successful or unsuccessful operation.

Task allocation is important in human-robot collaboration; with the help of task allocation, tasks can be identified and divided between humans and robots. Such an approach also helps reduce the allocation of repetitive tasks to robots and complex tasks to machines based on prejudiced opinions. Instead, the tasks are allocated based on the capability of the robot or human to do the task successfully and in an economically friendly way.

Allocating an entire operation and a specific level of collaboration also limits how much humans and robots can be involved in an operation or even in completing a specific task. Instead, it is the task that should be allocated the levels of collaboration and not the operation. Ideally, each operation should go through different levels of collaboration as each task has different requirements from a machine and a human in a human-robot collaborative workstation. It is common that the higher the level of collaboration, the higher will be the task complexity. Suppose a complex task is looked at from just the levels of collaboration perspective. In that case, the underlying subtasks, which can be easily handled at different levels of collaboration, have a good chance of being overlooked, and the entire operation can be deemed as impossible for human-robot collaboration. But with, focusing on tasks and then using task allocations to identify the levels of collaboration helps in designing human-robot collaborative workstations with proper levels of collaboration based on the complexity of tasks and the requirements from an operational perspective.

6. Conclusions and future work

In this article, a methodology for task and levels of collaboration allocation in a human-robot collaborative workstation was presented, using well-established methods such as *Task Allocation (TA), Levels of Automation (LoA),* and *Levels of Collaboration (LoC)* for identifying a proper balance of tasks and collaboration between humans and the robots, primarily in a manufacturing context. The new LoA matrix for HRC presented in this article provides a proper balance of tasks based on the required capabilities of the task. The LoA matrix is then used to identify the levels of collaboration and skills required to complete the task. The visual matrices for LoA and LoC are used as an overview of the entire operation to the user.

Human-robot collaboration research is rapidly evolving and expanding, especially in the technological area, as collaborative robots become smarter with the help of advanced technologies such as machine learning-powered vision systems and artificial intelligence. This article contributes to both technical and human aspects, specifically by combining cognitive and physical LoA with the levels of collaboration and skills required to complete a given task.

The presented design tool aims at assisting system designers in creating workstations where humans and robots should collaborate actively. Though the article focuses on using this new model in developing a human-robot collaborative workstation for an automotive wire harness assembly, the proposed model can be generically applied to any design process for developing complex human-robot collaborative workstations. The tool is aimed at reducing the complexity involved in human-robot collaboration. The focus of this article has been on developing the model rather than analysis of the impact of this model on the quality and performance of an operation. This is the next step in this research process. The continuing study of automating wire harness assembly processes provides an ideal venue for design tool testing. Future studies will involve examination and impact research of the design tool's performance in collaborative robot workstations.

CRediT authorship contribution statement

Omkar Salunkhe: Conceptualization, Methodology, Validation, Supervision, Investigation, Writing – original draft. **Johan Stahre:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition. **David Romero:** Conceptualization, Methodology, Validation, Writing – original draft. **Dan Li:** Writing – review & editing, Investigation. **Björn Johansson:** Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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