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Identifying the Contributors of Intrinsic, Extraneous, and Germane Load in Human-Robot Collaboration Through Interview Questions

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ABSTRACT

A significant challenge in human-robot collaboration (HRC) is managing the emergent cognitive workload of the human operator. Current research focuses on understanding the overall cognitive workload rather than its individual components, which include intrinsic, extraneous, and germane cognitive loads. Understanding these components is important for developing HRC tasks that enhance human cognition. In this study, twelve participants participated in an HRC pick-and-place task under high and low cognitive workload. Following the task, semi-structured interviews were conducted to identify the contributors to cognitive workload. The intrinsic workload was primarily affected by the robot's speed, the need to multitask, and the learning curve associated with the robot's navigation and design. Regarding the extraneous workload, a central theme was the robot's speed, which triggered distractions for the operator. Finally, the germane load was characterized by the following themes: acquiring knowledge for HRC tasks and enhancing multitasking capabilities such as hand-eye coordination. These results highlight that different aspects of robot design, task design, and task execution contribute uniquely to the overall cognitive workload. Recognizing these contributors is important for optimizing human-robot collaboration, improving efficiency, and reducing the operator's cognitive burden.

Keywords: Human-robot collaboration, Cognitive workload, Qualitative analysis

INTRODUCTION

One of the aims of Industry 5.0 is the enhancement of human capabilities in manufacturing settings (Xu et al., 2021; Leng et al., 2022). Human-robot collaboration, where the precision of robots combined with the creativity of humans, can lead to more efficient and safer manufacturing processes (Leng et al., 2022). However, successful human-robot collaboration requires communication between humans and robots, decision-making, planning, coordination of collaborative tasks, and error handling. These cognitive processes can complicate the collaborative task and increase the cognitive workload of the human operator. Previous research has shown that a high cognitive workload is linked to decreased performance (Biondi et al., 2021). Monitoring and understanding the cognitive state of a human is important for improving human-robot collaboration. The cognitive workload is characterized by three different types: intrinsic, extraneous, and germane workload. The task's difficulty is influenced by the information needed to be processed and the user's existing knowledge (Sweller, 1994; Moreno and Park, 2010). Extraneous workload represents the cognitive effort imposed by environmental, instructional, and presentation factors. For example, distractions, irrelevant information, confusing guidance, or information during the task can lead to an extraneous workload. Germene load refers to the cognitive effort required to process and integrate new information into long-term memory (Paas et al., 2003). The cognitive processes involved include information organization, connecting task demands to prior knowledge, and constructing mental models to grasp complex concepts. Current research in HRC focuses on understanding and quantifying the cognitive workload imposed during the task utilizing objective and subjective measures. Various studies have demonstrated that physiological measures can act as a surrogate of cognitive workload (Casali and Wierwille, 1984; Charles and Nixon, 2019). The physiological measures that capture the change in cognitive workload can be represented as a function of the autonomic nervous system. Subjective measurements of mental effort allow participants to evaluate numerous channels of demand. Self-report surveys, like the Multiple Resource Questionnaire (Boles et al., 2007) and the NASA Task Load Index (Hart and Staveland, 1988), are examples of subjective metrics. Objective and subjective measures can identify cognitive workload states. However, these measures cannot distinguish the specific influence of each workload type (intrinsic, extraneous, and germane) on cognitive workload development. Each cognitive workload type uniquely contributes to cognitive processing; therefore, assessing them is important for understanding workload dynamics and optimizing task design in HRC. For this reason, we conducted a human-subject study where participants completed a collaborative task with a robot under low and high cognitive workload states. At the end of the task, participants completed a semi-structured interview. We conducted a qualitative analysis of participants' responses and identified key contributors and themes associated with each type of cognitive load. The findings of this study have the potential to advance cognitive workload assessment and task execution in human-robot collaboration by implementing a qualitative interview protocol that systematically differentiates between intrinsic, extraneous, and germane cognitive load.

METHODS

Six male and six female college students, with an average age of 27.25 years and an age range of 6.75 years, participated in the study. All participants were required to sign a consent form before participating. The university's Institutional Review Board approved the study (IRBNO: 2023-593). Each participant received a $25 Amazon gift card as compensation for their participation in the study. The participants in this study used a joystick to control a UR3e (Universal Robots, DK) collaborative robot to pick up objects from a surface and place them in a bin. The participants performed the task under two levels of cognitive workload (low cognitive workload session and high cognitive workload session), with the order counterbalanced. The cognitive workload was manipulated by adding a secondary visual task, which required participants to simultaneously complete the pick-and-place and the peripheral detection tasks. The pick-and-place task was divided into picking and placing the object. Participants performed the task at six different speeds at each division (pick or place), ranging from 0.03 m/s to 0.08 m/s; the task was performed at all speed combinations for the pick and place states, resulting in 18 unique speed combinations. Each combination was repeated four times, resulting in 72 trials, with each trial lasting approximately one minute. At the end of the session, either low or high, depending on what was the last session, participants completed a semi-structured interview designed to understand the different types of cognitive workload involved in the task.

SEMI STRUCTURED INTERVIEWS

We conducted a semi-structured interview to gather insights into the three cognitive workload types involved in the HRC task. The semi-structured interview questions were designed by a Professor of Industrial Organizational Psychology. Intrinsic load questions intended to identify the cognitive effort required to perform the task and the interactions involved in the collaborative task. Extraneous workload questions focused on identifying how environmental factors interfere with the task and impact the user's performance. Germane load questions sought to understand how the knowledge gained from performing the task influences future task performance. The recorded interview questions for each participant were transcribed and reviewed for accuracy and readability. The participant's data was imported into NVivo. Thematic analysis served as the primary methodological framework for discovering insights within the text. This involved a coding process where text segments were tagged with descriptive labels representing underlying themes, concepts, or ideas. Finally, we performed a comparative analysis of coded segments across the low and high-cognitive data. The complete set of interview questions is presented in Appendix A.

RESULTS

Findings from this study revealed several thematic categories across the different types of cognitive load, i.e., intrinsic, extraneous, and germane load. We organize the results by three types of cognitive load, and under each section, we discuss the observations from the high and low cognitive workload scenarios.

Intrinsic Load

The study identified three main themes affecting intrinsic workload during the human-robot collaboration task: robot speed and multitasking, the learning curve of the task, and the design challenges. **Theme 1: Stopping or Slowing Down Due to Robot Speed and Multitasking**: Across both LCW and HCW, a primary contributor to intrinsic load was robot speed and multitasking. Additionally, participants reported slowing down or stopping because of high robot speed and multiple action items. Specifically, most participants (>80%) were likely to stop or slow down during HCW. The participants reported slowing down and stopping when the speed of the robot increased, and they had to multitask, especially during the initial stages. Specifically, participants in HCW commented: "*I had to stop to adjust them at the beginning because of the rotation of the arm of the robot.*" As mentioned, sometimes, the participant did not have to stop completely, and one commented: "*I definitely did have to slow down and stop to readjust when there was a lot going on.*" During LCW, 70% of the participants reported slowing down or stopping during the initial stages of the task and when the robot was functioning at high speed. However, the participants were more likely to slow rather than stop, and one participant explicitly mentioned: "*Sometimes, I forgot what I was doing and wanted to know how far away the robot was from the blocks.*" **Theme 2: Learning Curve and Performance**: Irrespective of the task load (LCW or HCW), all (100%) participants reported a learning curve in operating the robotic arm. However, all participants noted that they could improve their performance, and some reported that their perceived performance improved towards the end of the task. Specifically, one participant mentioned: "*I started to get pretty good at it in the end. Like I wasn't really moving the objects anymore; I was kind of over them centered. So that was really cool too, like see that I was getting better.*"Another participant mentioned that: "*Once it became an extension of your arm, once you understand the dimensions and the limitations of the robot arm, I think you could get faster with time.*" Overall, while all participants mentioned the challenges of familiarizing themselves with the system initially, they all reported an improvement in their perceived performance and further improvements through training. **Theme 3: Robot Design Challenge:** Finally, across both LCW and HCW, another contributor to intrinsic load was the design of the robot. Specifically, most respondents during HCW (>80%) and 70% during LCW reported issues with robot design challenges, such as joystick design, which controls the robotic arm, and gripper design, which controls the pick and place task. Specifically, one participant reported: "*It might just be a joystick design that the opening and close buttons I just feel should be close to one another. I don't know if it's possible on a joystick like that.*" Another participant mentioned a similar concern and suggested a redesign idea: "*I would actually say moving the button back to release on the thumb button. Just down the trigger grab, and the thumb releases it. It would make it a lot more efficient than bringing your thumb over to the right side.*" Another minor design challenge participant during the HCW and LCW scenarios raised during the HCW scenario was the gripper design, where the gripper was accurately grabbing the block. Specifically, one participant commented: "*The only thing that gets tricky is exact positioning. Sometimes, it's difficult to tell if you're coming down on a block, whether you're going to be around it or over it, and you need to* *pull it to adjust it spatially for it. So, the position of the gripper is to pick an object. I often see the shadows to locate the gripper*." Overall, we observed that the challenges increasing the intrinsic load across both HCW and LCWs are similar. However, the intensity and the effect of these contributors were significantly different across the two workloads (LCW and HCW) scenarios, where they were more prominent during HCW.

Extraneous Load

The study identified one major theme related to extraneous workload: the impact of robot speed on operator distraction. **Theme: Robot Speed**: Across both LCW and HCW, very few participants reported extraneous distractions while performing their tasks. However, an interesting observation was that during both LCW and HCW, participants reported being distracted and paying attention to the environment when the robot was moving at low speeds. Overall, participants in the LCW scenario were slightly highly likely to be influenced by extraneous distractions during their tasks. One participant commented: "*There were definitely times that it was slow enough I could look at other stuff. I looked at your site and around somewhere else*." Overall, very few contributors added extraneous load to this experiment, which was expected as the study was conducted in a controlled environment. However, four participants reported that their personal devices, such as phones and watches, lead to an exraneous load. An interesting observation here is that participants were more likely to experience an extraneous load when the task at hand was less challenging.

Germane Load

The study identified three key themes related to germane load during Human-Robot Collaboration tasks: acquiring HRC knowledge, improving multitasking skills, and developing hand-eye coordination. **Theme 1: Knowledge of HRC**: During both the HCW and LCW scenarios, all participants (100%) reported gaining Human-Robot Collaboration (HRC) skills. Since all participants were novice users of robots, this observation was expected as germane load represents the mental effort dedicated to assimilating new information to their long-term memory and building mental models. One participant mentioned: "*How to use this joystick, but also learn to coordinate the robotic arm*." This observation can also be supported based on the theme noted in Intrinsic Load above (Learning Curve and Performance), where all participants reported they could improve their performance, and some reported that their perceived performance improved towards the end of the task, highlighting the germane load dedicated to learning HRC skills. **Theme 2: Multitasking Skills**: Another contributor to the germane load was the multitasking skills required during the HRC task. A high majority of participants (>80%) reported gaining multitasking skills during the HCW scenario, whereas only 50% reported gaining this skill during LCW. Specifically, respondents during HCW mentioned: "*Improved my multitasking skill where I had to use the left and right brain with the left clicker in my left hand and running the joystick in the right, kind of had to* *use a combination of that.*" This observation, where all participants reported gaining multitasking skills during HCW and very few gaining during LCW, is expected. As mentioned in the methods section, during the HCW scenario, a participant has to complete multiple tasks with varying speeds of the robotic arm. In contrast, during LCW, they have to complete only the pick-and-place task at varying speeds. **Theme 3: Hand-Eye Coordination**: Another primary skill that participants reported gaining during the experiment was hand-eye coordination skills. Specifically, 25% of the participants reported gaining hand-eye coordination skills during HCW and LCW. Specifically, participants reported: "*I feel like I gained hand-eye coordination skills by using this joystick, but also learning to coordinate the robotic arm.*" While hand-eye coordination is one of the primary skills required for multitasking (theme two above), only a few participants explicitly mentioned this as a contributor to the germane load.

DISCUSSION

Four key takeaways of this study are: 1. Ergonomics, experience, and task complexity impact intrinsic load during human-robot collaboration. 2. Training and multitasking affect germane load during human-robot collaboration. 3. Overlapping nature of factors contributing to germane and intrinsic load. 4. Challenging tasks exert minimal extraneous load during human-robot collaboration.

Ergonomics, Experience, and Task Complexity Impact Intrinsic Load During Human-Robot Collaboration

Ergonomics: Participants in low and high cognitive workload sessions expressed concerns about the joystick design, more specifically regarding the position of the buttons for opening and closing the robotic gripper. The operation of the buttons required hand movements that affected the task efficiency. Research has investigated the integration of cognitive load theory in human-computer interaction (Oviatt, 2006; Hollender et al., 2010). Redesigning the joystick button to a more intuitive design can help the users learn to operate the robotic arm faster and reduce intrinsic workload. Another ergonomic issue the participants reported was the robotic gripper's position relative to the objects they had to pick up. Participants performed multiple adjustments to pick up the objects, which led to increased focus and intrinsic workload. A potential solution to such ergonomic challenges would be visual feedback through user interfaces accompanied by haptic and sensory input (Skulmowski et al., 2016). Creating more natural interactions that do not require cognitive recalibration makes designing robotic systems that reduce the intrinsic workload needs possible.

Experience: In both sessions, low and high participants experienced a learning curve to operate the robotic arm to pick and place the objects. However, time on the task positively affected the learning and participants' performance. This finding highlights the importance of training new users in collaborative tasks with robots. The challenge here is knowing what to train and how to train it. There are many taxonomies of good training principles. Still, they generally include some form of needs assessment, some form of learning context (i.e., attention to good instructional design, the basic principles of learning, and characteristics of the trainees and trainers), some evaluation of transfer of training (both positive and negative), and some form of training evaluation. From a cognitive load perspective, the ideal training outcome is two-fold: trainees learn all tasks contributing to germane load and practice skills and abilities that reduce intrinsic load. Usually, the short time allowed for training is often insufficient for an operator to develop a large degree of automaticity in critical tasks. Typically, the level of automaticity seen in experts (versus novices) is acquired not in training but on the job. Innovative approaches can be implemented to better train users to gain experience and reduce the cognitive burden of a collaborative task. One approach would be using augmented or virtual reality to train users to practice interaction (Kaplan et al., 2021)with reduced time and resources spent on real-world training.

Task Difficulty: Our research demonstrated that multitasking led to increased intrinsic workload. Participants in the high cognitive workload session performed two tasks simultaneously: the primary pick and place and the secondary peripheral detection task. This dual demand imposed cognitive challenges on the participants, especially at the beginning of the session, which led participants to slow or stop performing the task in order to cope with the cognitive demands. In the low cognitive workload session, participants did not report stopping, indicating less difficulty compared to the high cognitive workload. However, sometimes, slowing was necessary to meet the task needs. Previous research has shown that attentional overload and cognitively demanding tasks can cause stress, sensory overload, and errors, whereas attentional underload may result in boredom and reduced vigilance, and divided attention can lead to cognitive tunneling, narrowing perception to only the most salient information (Johannsen, 1979; Wickens and Alexander, 2009). It should also be mentioned that the time on the task also affected participants' performance; as participants became more familiar with the task and its demands, they could handle the intrinsic workload better and adapt to the task demands, suggesting a reduced workload.

Training and Multitasking Affect Germane Load During Human-Robot Collaboration

The results of our study showed that participants were able to develop skills. Participants reported hand-eye movement coordination and enhanced multitasking abilities, especially during the high cognitive workload. This finding suggests that the task facilitated learning and implies that experience is beneficial, as also reported in previous research (Haith and Krakauer, 2018). We should keep in mind that the germane load depends on the complexity of the task, and it varies based on task design and the human-robot interface design. Therefore, the task difficulty should be considered to accommodate different learning stages and maximize skill acquisition. Furthermore, the cognitive workload varies with the capabilities of humans (capacity of working memory, the amount and type of spatial ability, and other individual differences). Tasks and interfaces that present the human operator with too much information simultaneously, task designs that require high amounts of spatial processing, especially spatial transformations, and task and system designs that require high amounts of numerical or verbal processing can add to germane load sometimes beyond the capability of a given human operator.

Overlapping Nature of Factors Contributing to Germane and Intrinsic Load

In the high cognitive workload, our task required high cognitive demands (a primary and secondary task), which increased the intrinsic workload and induced a germane load as participants exerted greater cognitive effort to manage the complexity of the high cognitive workload state. Intrinsic load was influenced by the complexity of learning to operate a robotic system, such as understanding the joystick controls. Germane load was influenced by the effort required to process and integrate new information and develop knowledge. These cognitive workload types often overlap. In our study, the user interface design affected both types of cognitive workload. This suggests that a nonintuitive user interface can add intrinsic workload and affect the germane workload as it will require increased cognitive demands. Therefore, the intersection of task complexity and the controls used in the user interface design are important to facilitate intrinsic and germane workload development to achieve effective learning and interaction with robotic systems.

Challenging Tasks Exert Minimal Extraneous Load During Human-Robot Collaboration

In our study, the extraneous load was minimal due to the controlled lab environment. However, our results indicate that the speed of the robotic arm affected the user's attention. Participants performing the task at lower speeds were more prone to distractions and sought additional stimuli from the surrounding environment, especially in low cognitive workload sessions. This finding suggests that the low speed of the robotic arm introduced unintended extraneous load and allowed participants' attention to be disrupted. Therefore, it is important to identify robot speeds that align with the task demands and engage the user with the task to avoid attention destruction and minimize extraneous workload.

CONCLUSION AND FUTURE WORK

In this study, we focused on identifying and understanding intrinsic, extraneous, and germane load contributors in a human-robot collaborative task. Participants performed a collaborative task with a robot at different levels of cognitive workload and speed. At the end of the task, participants participated in a semi-structured interview to gather insights about the development of the three types of workload: intrinsic, extraneous, and germane. The results of our qualitative analysis demonstrated that intrinsic workload was affected by the robot's speed, multitasking demands, and learning curve. Furthermore, our results showed that operating the robotic arm at a low speed created distractions that influenced the extraneous workload. Finally, the germane load contributed to skill development in human-robot collaboration, such as hand-eye coordination and multitasking abilities, particularly during high cognitive workload. Our future efforts will focus on improving ergonomic design in human-robot collaboration. Furthermore, we will explore the learning curve of operating a robotic arm and the skills acquired in human-robot collaboration through longitudinal studies. Additionally, we will focus on studies that include different user demographics to identify user needs based on the three different types of cognitive workload. These efforts will help us understand how to design robotic systems that enhance human performance while minimizing cognitive load, ultimately leading to more effective human-robot collaborations.

APPENDIX

A. Intrinsic Workload Questions

1. Do you ever have to stop and think about the units (i.e.,millimeters, inches) used in the task?
2. Are there parts of your task where you have to stop (or slow down) to think about it? For example, if you have to think about how the object being moved is oriented from the robot's point of view instead of your own point of view.
3. Are there parts of your task where you will probably get faster at them (and they'll become more automatic) as you get more practice and experience with the task?
4. Are your controls (including voice commands) easy to understand and use? Are there aspects of these controls that could be improved to make the task clearer or easier?
5. Is the information you're getting from the system easy to understand and use?
6. Are there things that could be improved to make the task clearer or easier?

B. Extraneous Workload Questions

1. Was there anything in the immediate work environment that distracted you from your task?
2. Were parts of the task sufficiently slow that you could look at other things in the environment (i.e., signs, lighting)?
3. Did you note any unusual noises during the task?

C. Germane Workload Questions

1. What knowledge/skills/abilities did you acquire as you were learning how to do the job?
2. Were there important tasks that you had to learn while you were actually doing the job?
3. Do you feel like you understand the goal of the task?
4. Was there more than one goal (e.g., quantity versus speed)? If so, how did you prioritize those goals?

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