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TYPOLOGY DEVELOPMENT FOR SYNTHETIC CHEMISTRY SUB-TASKS: TOWARDS HUMAN-ROBOT COLLABORATION TASK DESIGN IN THE WET LAB

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ABSTRACT

Chemical manufacturing is a growing field that contributes to many industries and employs tens of thousands of researchers in wet labs. Automation tools for synthetic chemistry are of interest not only for their potential impact on efficiency and productivity, but also on human resources and safety, since synthetic chemistry poses a number of occupational risks and is largely inaccessible to researchers with physical disabilities. Currently, most automation tools for synthetic chemistry are either designed to perform highly specialized tasks or they are designed as closed-loop systems with minimal interaction between human and machine during a synthesis procedure. We are pursuing an alternative, human-centered approach to robotic tools for synthetic chemistry, in which general-purpose collaborative robots (cobots) offer diverse forms of support to human researchers in the lab. In order to design frameworks for productive scientist-cobot collaborations, we need a deep understanding of the task space in synthetic chemistry labs and the impact of these various activities on the researchers. Based on observations and surveys from a group of experimental scientists, we have identified and analyzed 10 manual tasks commonly performed by researchers in the wet lab, each of which may be broken down into a sequence of sub-tasks. We conducted an in-depth analysis of the two most frequently performed sub-tasks: liquids dispensing and solids handling. Through subcoding, we identified 40 liquid dispensing typologies and 18 solid handling typologies, and evaluated the burden associated with each of these sub-tasks using the NASA TLX. These data will be of value for the design of human-centered automation tools that support, rather than displace, researchers performing manual tasks in the lab, in order to foster a safer and more accessible lab environment.

Keywords: Human-Centered Design, Human-Robot Collaboration, Experimental Science, Synthetic Chemistry, Typology

1. INTRODUCTION

More than 80,000 chemists work in the United States [1], where the chemical manufacturing industry is expected to grow by 6.5% between 2016 and 2026 [2]. Approximately 10 million new chemical compounds are developed each year [3], contributing to innovation in medicine, materials science, energy, cosmetics, and many other fields [4]. These novel chemical compounds are usually synthesized manually by scientists in the chemical wet lab, who face substantial physical and cognitive burden and risks in their occupations.

Experimental chemistry necessitates time-intensive and physically-demanding labor, can be detrimental to the scientists' health, and is inaccessible for those who are physically disabled or chronically ill. Researchers are exposed to a wide variety of chemicals, many of which may be hazardous. Despite the installation of chemical fume hoods, participation in mandatory chemical safety training, and use of personal protective equipment (PPE) [5], tens of thousands of injuries take place in the field of chemical manufacturing annually [6]. According to the United States Department of Labor (USDOL), more than 190,000 illnesses and 50,000 deaths are related to chemical exposure of workers annually [7]. In the past few decades, multiple deaths have occurred from accidents in university chemistry research laboratories [8, 9], which started a movement within the community to strengthen their safety training protocols [10]. According to the Laboratory Incidents Report by the United States Chemical Safety and Hazard Investigation Board, however, not much has changed even after implementation of additional safety measures and increased awareness of laboratory safety [11]. Accidents are continuing to take place in the chemistry lab [12–14] and laboratory safety is an ongoing issue that is yet to be resolved. Furthermore, labs are not designed for scientists who are physically disabled, chronically ill, and neurodivergent [15]. Chemistry labs typically do not have wheelchair access and lab benches and chemical fume hoods are set at a fixed height. Some experimental procedures require multiple hours of standing and operation of certain lab instruments are physically challenging [15].

We hypothesize that appropriately designed collaborative robots (cobots) may relieve physical and cognitive burdens for researchers while making these jobs safer and more accessible. Since this human-centered approach to the merger of robotics and chemistry will demand an intimate knowledge of the diverse, complex tasks performed by experimental scientists, we are conducting observational studies of scientists in the workplace.

In this paper, we analyze ten tasks that were commonly performed by scientists being observed during regular work days in the wet lab. The operational definition for *task* is a standard protocol followed during chemical synthesis to facilitate a compositional (chemical or physical) change in materials. A task is completed through a sequence of *sub-tasks*, defined as the actions the researcher performs. Using a mixed-methods approach, we conducted (1) a comprehensive task analysis to understand the nature of the work experimental scientists do in the chemistry wet lab during chemical synthesis, and (2) a survey-based analysis of the burden levels associated with the two most commonly performed sub-tasks. This knowledge provides a foundation for designing human-robot collaboration tasks in the chemistry wet lab that will foster a safer and accessible environment, while increasing research efficiency and augmenting scientists' performance.

2. BACKGROUND

In various manufacturing industries, automation has been used as a tool to increase worker safety by reducing physical fatigue from repetitive, manual labor while increasing productivity, efficiency, and profit. The use of automation technologies is expected to reduce the difficulty of physically burdensome tasks, which in turn will increase diversity and inclusion in the workplace [16, 17]. Due to the labor-intensive nature and complexity of experimental science, laboratory automation technologies have been developed to eliminate scientists' exposure to toxic chemicals, relieve them from repetitive tasks, and enable faster completion of reactions [18].

Many chemistry automation tools are benchtop units tailored for one specific task such as high-throughput experimentation [19], liquid handling [20–22], extraction [23], or synthesis of specific classes of compounds, such as peptides [24] or oligonucleotides [25]. General-purpose automation units require a more complex set of capabilities to enhance the speed and/or efficiency of reactions [26–29], build new structures through iteration [30], or develop pharmaceutical compounds [31]. These end-to-end automated synthesis units comprise fully of automated modules such as in-line reactors and analytical processing units in order to perform real-time synthesis monitoring and self-optimization [32–48]. Machine learning algorithms are also in development to automate synthesis planning and optimization of reaction parameters [49–53]. One recent study reported a free-roaming robot that autonomously optimized reactions and executed experiments at a faster rate than human chemists [54].

While these end-to-end automation tools for chemical synthesis may potentially benefit productivity, safety, reproducibility, and/or labor costs in chemical manufacturing, they also come with some key limitations. Commercially available robots of this kind are very costly, whereas custom-built systems place large demands on time, labor, and specialized expertise. Fully automated units typically cannot be paused for manual intervention or modification of reaction parameters once a reaction has started [29], which may be counterproductive in syntheses at earlier stages of R&D. Full automation may also impede the discovery of new knowledge due to the lack of publicly available data [53] and algorithm limitations [43, 44, 54]. Chemical synthesis is an iterative process that is labor- and time-intensive [40], requiring advanced experimental skills, a deep understanding of theory, and human intuition [55, 56]; the expertise and dexterity of human scientists are still pivotal for experimental science. Therefore, full automation of chemical synthesis remains extremely challenging, which is why most synthetic chemistry labs around the world continue to lack end-to-end synthesis automation tools.

Little consideration has yet been given to collaborative robots (cobots) in the context of synthetic chemistry. Cobots, designed to work safely alongside humans, are more adaptable, user-friendly, and affordable, and have been widely used in industries including the automotive [57, 58], material handling [59, 60], automated inspection [61], and healthcare [62, 63]. Although commercial cobots have been used in previous laboratory automation studies [54, 64], they have not yet involved real-time human-robot collaboration in the wet lab. One recent work conducted a Wizard of Oz study to investigate how a cobot could support scientists by performing "non-value adding tasks" [65].

We envision that appropriately designed cobots could relieve scientists of physical and cognitive burdens and help increase the safety and accessibility of wet lab research. A human-centered approach is encouraged in human-robot interaction (HRI) studies [66, 67] to optimize and evaluate the interaction between robots/cobots and humans [68] and to ensure that the introduction of the robot is well accepted [65]. In order to ensure effectiveness and acceptance in the synthetic chemistry lab, user-centered studies must be conducted to fully understand the needs of the researchers to inform the early design phase of human-robot collaboration tasks.

3. METHODOLOGY

To establish a comprehensive understanding of synthetic chemistry tasks, we employed a mixed-methods research approach. Data were collected using direct observations and surveys.

3.1 Data Collection

We recruited four scientists through expert sampling. All participants are adults (ages 18 or older), work regularly in a synthetic chemistry wet lab at a large American R1 university, and have more than one year of chemistry wet lab research experience. Participants self-reported their chemistry wet lab research experience level as 1-3 years (2), 3-5 years (1), and > 5 years (1). This protocol was reviewed and approved by the university IRB (Protocol #23-0346).

3.1.1 Direct Observations. Observations were conducted in the laboratories where participants worked routinely. A total of seven steps in six different syntheses were performed by the four participants during observation. We were present during the observations to record analytic memos electronically and ensure full video capture of the procedures. All seven steps were recorded using a webcam (Logitech C922 HD stream webcam) that was secured at the top of the chemical fume hood using a magnet or duct tape, or clamped on the side of the fume hood using a 3-prong clamp, to provide an overhead view of the experiments being conducted inside the fume hood. The placement of the webcam was determined based on the individual fume hood setup and primary workspace inside the fume hood.

3.1.2 Surveys. We administered the NASA Task Load Index (TLX) without modification to assess self-reported burden for each task performed. The NASA TLX determines perceived burden through six sub-scales: mental demand (mental and perceptual activity required, such as thinking, deciding, calculating, remembering, looking, and searching), physical demand (physical activity required, such as pushing, pulling, turning, controlling, and activating), temporal demand (time pressure from the rate or pace at which the task was performed), performance (satisfaction with performance), effort (mental and physical effort involved in accomplishing the task), and frustration (feeling insecure, discouraged, irritated, stressed, and annoyed versus secure, gratified, content, relaxed, and complacent) [69]. Each sub-scale is ranked on a 20-point scale, where higher rankings mean higher perceived burden. This method has been used in various contexts to assess self-reported cognitive load while performing activities and tasks [70–73]. It is also the second most frequently used survey in HRI studies [74], enabling a direct comparison with future studies in human-robot collaboration in the chemistry wet lab.

In addition to the unmodified NASA TLX, free-response questions developed for this research were included as optional survey responses. All participants were asked to submit a survey on specific tasks after the completion of the day's experiments. These surveys were provided to the participants via web hyperlink or QR code and the participants were given an unlimited amount of time to submit their responses.

3.2 Data Analysis

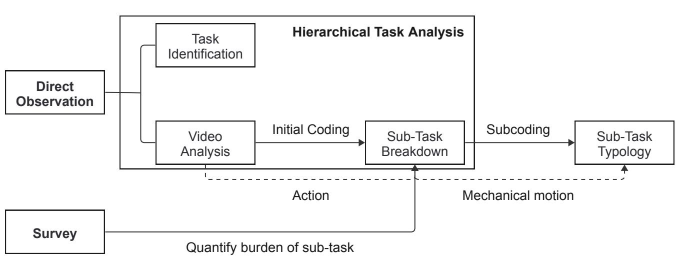


FIGURE 1: DATA ANALYSIS METHODS.

We performed a hierarchical task analysis (HTA), which is a method used to learn how a user performs a task by identifying the goals and tasks of a system and further analyzing these tasks by breaking them down into sub-goals and understanding their sequence [75]. HTA has been used as a method for task allocation and human-computer interface design [75]. We expect that HTA can also be used as a tool for designing collaborative tasks for human-robot collaboration in the chemistry wet lab.

Tasks involved in synthetic chemistry were identified through direct observations and analytical memos. These tasks were further analyzed using computer-aided qualitative data analysis performed in ATLAS.ti 23. The videos recorded during direct observations were coded using an initial coding method [76] that aided in breaking the tasks down into sub-tasks. During the initial coding process, we found that there were variations within these sub-tasks. Subcoding [76] was employed to further specify these sub-tasks, which served as the basis for typology development. A summary of data analysis methods are shown in Figure 1.

TABLE 1: SUMMARY OF 10 OBSERVED TASKS WITH THEIR OCCURRENCE FREQUENCIES AND AVERAGE DURATIONS (MINUTES:SECONDS).

Task	Frequency	Average Duration
Run Chemical Reaction	8	24:10 ± 26:34 (active) 43 ± 33 hrs (passive)
Gravity Filtration	2	02:05 (active) 04:46 (passive)
Syringe Filtration	1	06:41 (active) 00:00 (passive)
Vacuum Filtration	7	07:59 ± 06:18 (active) 20:40 ± 13:42 (passive)
Column Chromatography	2	31:50 (active) 00:00 (passive)
Dialysis	3	20:01 ± 11:05 (active) 72 hrs (passive)
Extraction	2	20:41 (active) 05:30 (passive)
Rotary Evaporation	8	20:07 ± 11:47 (active) 00:00 (passive)
Vacuum Dry	3	< 01:00 (active) overnight (passive)
Lyophilization	3	14:58 ± 11:12 (active) 72 hrs (passive)

4. RESULTS

Through direct observations, we identified 10 distinct tasks performed by researchers during routine synthesis procedures in the wet lab. These tasks were broken down into sub-tasks through initial coding of video recordings, which were further divided into sub-task typologies through subcoding. Follow-up surveys provided information on self-reported burden while performing these tasks.

4.1 Task Identification

Through direct observations and analytical memos, we identified the following 10 tasks: (1) running a chemical reaction

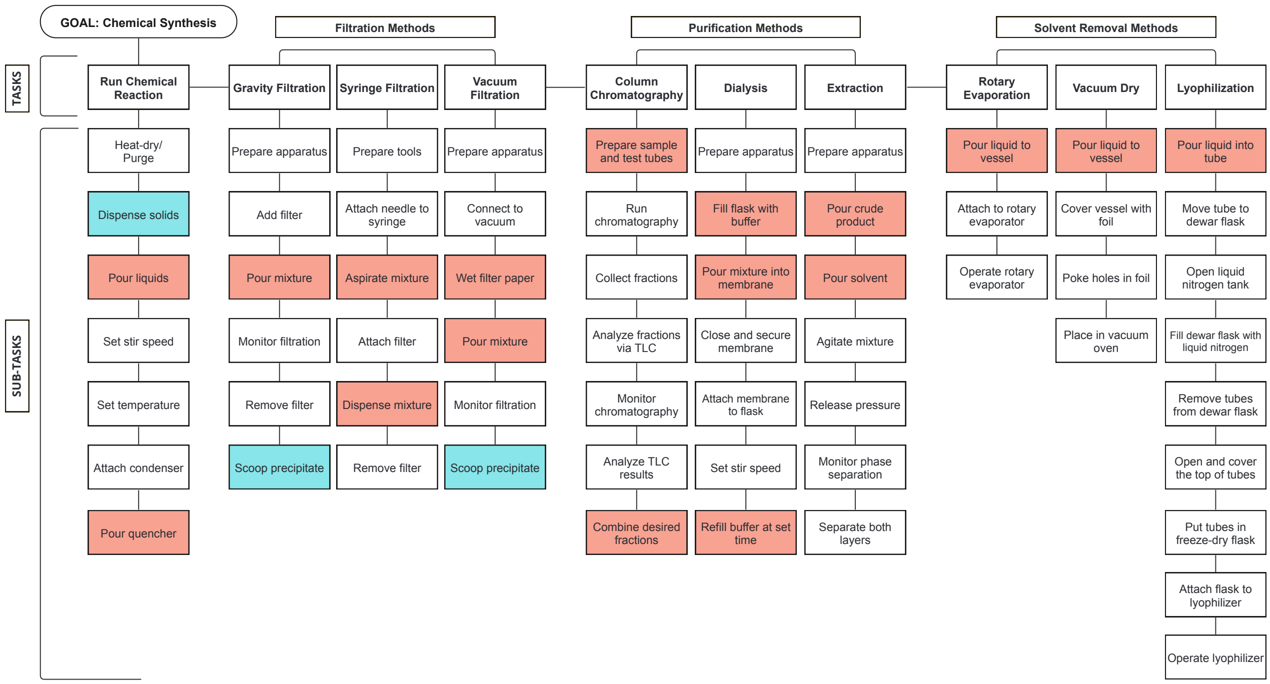


FIGURE 2: HIERARCHICAL TASK ANALYSIS DIAGRAM OF 10 OBSERVED TASKS PERFORMED BY SCIENTISTS DURING CHEMICAL SYNTHESIS. SUB-TASKS INVOLVING LIQUID DISPENSING ARE IN RED BOXES AND THOSE INVOLVING SOLID HANDLING ARE IN BLUE BOXES. DISASSEMBLING AN APPARATUS AND CLEANING UP WERE OMITTED IN THIS DIAGRAM.

(from preparing raw chemicals to work-up of a chemical reaction), (2) gravity filtration, (3) syringe filtration, (4) vacuum filtration, (5) column chromatography, (6) dialysis, (7) extraction, (8) rotary evaporation, (9) vacuum dry, and (10) lyophilization. The occurrence frequency and the average time taken to perform each task are summarized in Table 1. The average task durations are divided into active and passive times. During active times, scientists make changes to the experimental system through physical manipulation of glassware and tools, or closely monitor the experimental process to intervene when necessary. During passive times, the experimental apparatus is left unattended.

4.2 Sub-Task Breakdown

All 10 tasks were broken down into sub-tasks through initial coding [76]. Sub-tasks were defined by the actions performed to complete a task, such as "pour liquid," "dispense solid," and "turn knob to set stir speed/temperature." These sub-tasks were sequentially ordered to describe how the observed tasks were completed. The results, summarized in Figure 2, revealed two sub-tasks that occur with particularly high frequency: (1) liquid dispensing (red boxes in Figure 2) occurred at least once in all 10 tasks and was performed 613 times and (2) solid handling (blue boxes in Figure 2) occurred in 3 out of the 10 tasks and was performed 121 times.

4.3 Development of a Sub-Task Typology

During the initial coding process, we observed variations within the codes that led to the development of a sub-task typology. These variations were caused by the manipulation of different glassware and tools, which was added to the primary codes as subcodes [76]. We will refer to the glassware or tool being held directly as the "grasped tool," and the vessel the liquids and solids were transferred into as the "target vessel." Through subcoding, we identified 40 typologies for liquid dispensing and 18 typologies for solid handling from 17 grasped tools and 13 target vessels. For each typology, the distribution of sub-task completion times is illustrated in Figure 3 for liquid dispensing and Figure 4 for solid handling. Typologies are ordered from the most to least frequently occurring typology and the black squares represent the mean.

Figure 3 shows that the squirt bottle was used the most frequently, with a total of 141 occurrences. This is due to the fact that the squirt bottle was used to dispense solvents during experiments and was the primary vessel used for rinsing soiled glassware with solvents, such as acetone and isopropyl alcohol. Because used glassware are rinsed multiple times during each experiment, the occurrence frequency is significantly high. Similarly, the Pasteur pipet was used for liquid transfer during experiments and glassware rinsing, causing it to be the second most frequently occurring typology, with 113 occurrences. The box plot for the Pasteur pipet has the widest distribution (range = 61.30 s) and displays many outliers. This is likely the result of the Pasteur pipet being used not only for transferring liquid reagents and rinsing soiled glassware, where the liquids could be dispensed quickly, but also for drop-wise addition of liquids, which was a slow process.

The 18 typologies for solid handling are shown in Figure 4. The performance duration for transferring solids from a centrifuge tube to a vial using a spatula had the largest range of 51.29 s and an outlier at 65.63 s. According to our observations,

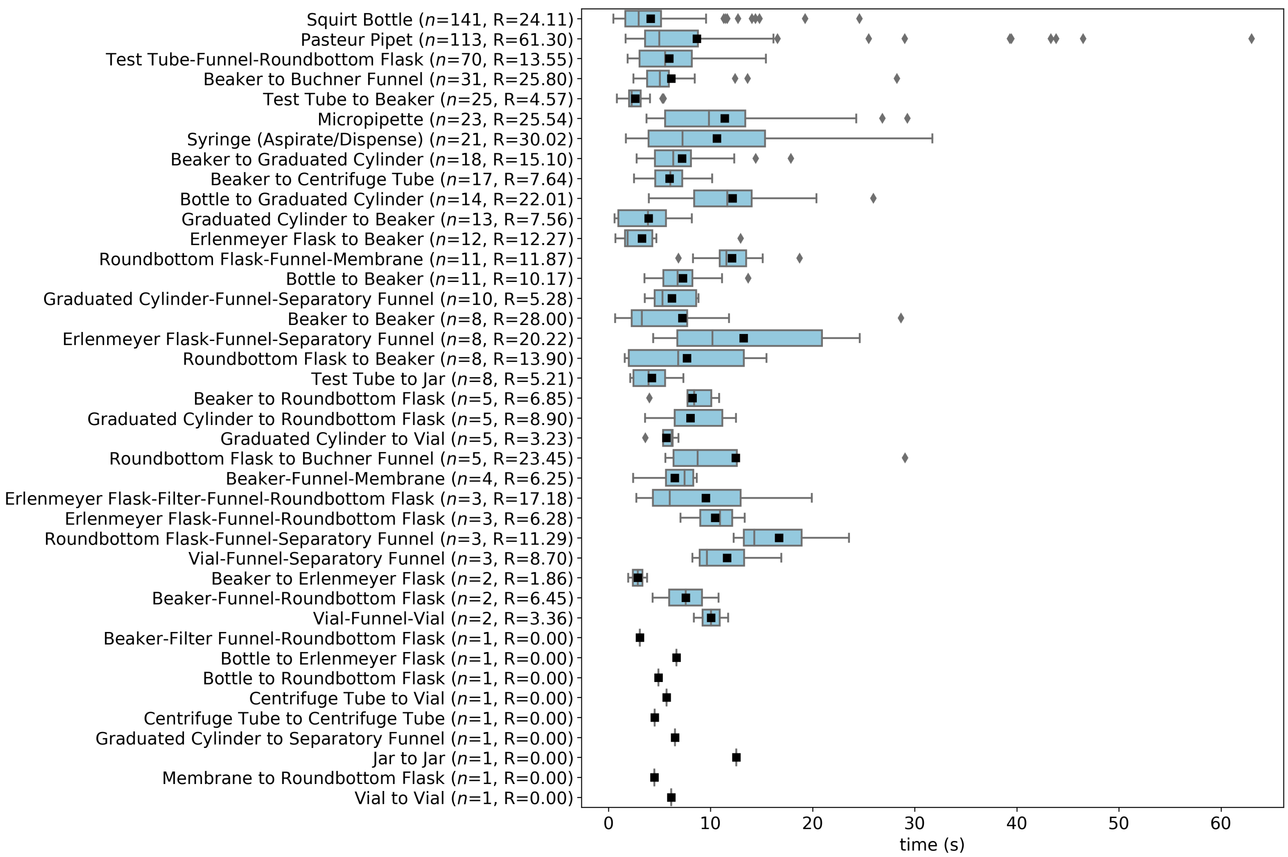


FIGURE 3: BOX PLOT OF SUB-TASK COMPLETION TIMES (IN SECONDS) FOR 40 LIQUID DISPENSING TYPOLOGIES. THE BLACK SQUARES REPRESENT THE MEAN, *n* IS THE OCCURRENCE FREQUENCY, AND R IS THE RANGE.

the solids stored inside centrifuge tubes for these procedures were sticky materials. This may have been the cause for the broad range of performance duration and extreme outlier. Solid handling is highly dependent on the physical and chemical properties of the solid being transferred, such as the granule size and hydrophilicity. These differences may have caused the broad distribution of performance duration in all typologies involving solid transfer.

4.3.1 Self-Reported Burden of Sub-Tasks. A total of 32 survey responses were collected. Out of the submitted responses, 84% of the free response questions were answered, and it took participants an average of 5 minutes and 19 seconds to complete one survey (with an outlier survey having taken 5 hours and 18 minutes).

17 out of the 32 responses discussed the difficulties of liquid and solid handling during various tasks. Results of these 17 responses (9 for liquid dispensing and 8 for solid handling) are shown in Figure 5, where the 6 NASA TLX sub-scales are listed along the y-axis and each cell color and value corresponds to the exact value submitted on a 20-point scale.

The survey results showed that for both liquid (Fig. 5a) and solid (Fig. 5b) handling, while mental demand, physical demand, and effort stayed ≤ 11, temporal demand, performance, and frustration ranked > 11 in multiple instances. Free response answers revealed that the high ranks of temporal demand, performance, and frustration were caused by the physical and chemical properties of the liquids and solids being used.

O_2-sensitive, H_2O-sensitive, or light-sensitive liquid reagents require quick transfer to avoid exposure to the atmosphere. This increased the level of temporal demand, as the participants felt rushed. This also contributed significantly to performance and frustration. Generally, participants were happy with their performance when liquids were transferred quickly without dripping or spilling, but were unhappy with their performance if they felt that the liquid transfer could have been quicker. Participants felt frustrated by the pressure to dispense the correct amount without spilling the chemical, while dispensing quickly to avoid exposure to the atmosphere. There was also a comment about the stress of dealing with hazardous chemicals.

Similarly, hydrophilic solids contributed to the temporal demand experienced during solid handling, as participants felt rushed to measure and dispense quickly to avoid exposure to the atmosphere. The low satisfaction with performance (correlated with higher values on the NASA TLX scale) was caused by the difficulties associated with reaching the exact target weight and dispensing the solids into the target vessel without spilling or having it stick to the side of the flask. The primary cause of frustration was going over the target weight. One participant described solid dispensing as a "tedious task."

For both liquid and solid handling, one survey responded with 18 out of 20 for performance. These responses were sub-

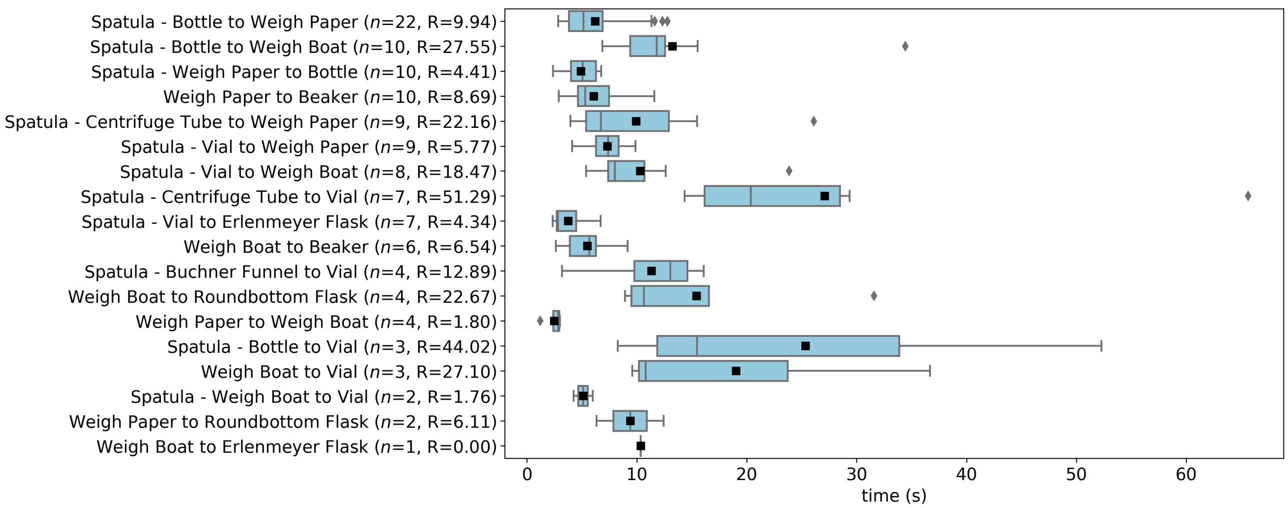
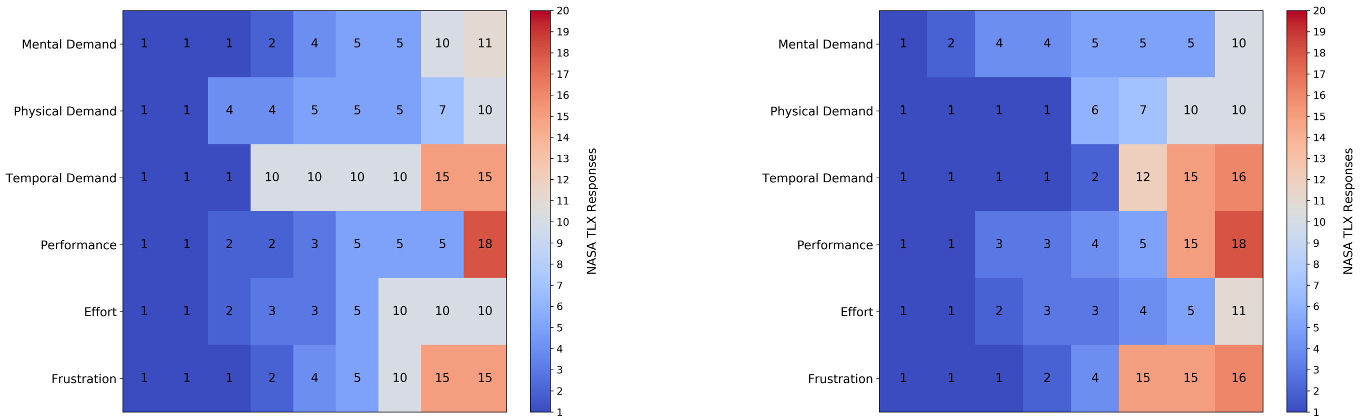


FIGURE 4: BOX PLOT OF SUB-TASK COMPLETION TIMES (IN SECONDS) FOR 18 SOLID HANDLING TYPOLOGIES. THE BLACK SQUARES REPRESENT THE MEAN, *n* IS THE OCCURRENCE FREQUENCY, AND R IS THE RANGE.



(a) NASA TLX responses for liquid dispensing.

(b) NASA TLX responses for solid handling.

FIGURE 5: NASA TLX RESPONSES FOR (a) LIQUID DISPENSING AND (b) SOLID HANDLING. THE 6 NASA TLX SUB-SCALES ARE LISTED ALONG THE Y-AXIS AND EACH CELL COLOR AND VALUE CORRESPONDS TO THE EXACT VALUE ON A 20-POINT SCALE, WHERE HIGHER RANKINGS MEAN HIGHER PERCEIVED BURDEN. 9 RESPONSES FOR LIQUID DISPENSING AND 8 RESPONSES FOR SOLID HANDLING WERE COLLECTED.

mitted by two different participants. According to the answers to the free response questions, the reason for such discontent in performance was from the feeling that they did not perform as well as they should have, as they commented: "I could have done this quicker" and "this measurement was imperfect."

5. DISCUSSIONS AND FUTURE WORK

In this paper, we presented 10 common wet lab tasks and their associated sequences of sub-tasks performed by scientists during synthesis procedures, as well as a method of identifying typologies for liquid and solid handling sub-tasks based on the grasped tool and the target vessel. The complexity of these sub-tasks are demonstrated by the diversity of their respective typologies, highlighting the challenges in perception and reasoning that a cobot for chemical synthesis would face.

Analyzing the most common sub-tasks of liquid and solid handling, we found several factors that introduce variations in difficulty and completion time. Regarding the grasped tool, three factors appear to contribute to variation in difficulty and procedural time. First, the diameter of the grasped tool determines the gripping diameter of the grasp. Second, the weight of the grasped tool will change the force required to pick it up from the surface. Third, the volume or mass of material influences how long it will take to complete the sub-task, where greater masses or volumes take longer to complete the sub-task. The target vessel also has three contributing factors. First, the shape of the target vessel determines how the grasped tool must be poured to avoid knocking over the target vessel. Second, the diameter of the target vessel opening will govern the level of precision required for successful material transfer, where higher precision requires more time to complete the transfer. Third, the location of the target vessel relative to the grasping tool will change how much the arm must move.

Consideration of these factors may provide avenues to enhance efficiency and reduce error rates in the two critical sub-tasks of liquid and solid handling. These typologies may also help contribute to the identification of (1) robotic platforms with suitable capabilities to provide useful support, (2) appropriate programming or training paradigms to enable cobot-scientist collaboration, and (3) additional tools (such as peripheral sensors or manipulators) that might be needed to equip a cobot with the faculties to provide maximum support and safety in the lab. In addition, it may provide insight for designing a novel cobot tailored for applications in chemistry research. Coupled with our survey data that reveals the level of burden experienced by the researchers in various tasks, these observational studies may help us prioritize which tasks will be most rewarding to researchers who have access to cobots in the wet lab.

The work presented in this paper is a part of a larger study that aims to develop a comprehensive "map" of the task space that researchers navigate routinely in the chemistry wet lab. In future work, we aim to expand the number and diversity of participants in our observation studies, identify more tasks and sub-task sequences, and synthesize the quantitative and qualitative data into a framework of decision-making and task-performance that will facilitate the design of human-robot collaboration tasks in the wet lab with commercially available cobots.

6. CONCLUSION

Using a mixed-methods approach, we have identified 10 tasks performed during chemical synthesis, divided these tasks into sequential sub-tasks, and developed a typology for the two most frequent sub-tasks: liquid dispensing and solid handling. The typology was developed based on the mechanical motions of the hands and arms, which were governed by the glassware and tools being grasped and the vessel into which the liquids and solids were transferred. We also used the NASA TLX and free-response survey questions to quantify self-reported burden experienced while performing these two sub-tasks. Through an analysis of survey responses, we found that self-reported burden was highly dependent on factors specific to each liquid or solid reagent, such as their physical and chemical properties and toxicity. Such a comprehensive analysis of tasks performed during chemical synthesis will help understand the scientists' needs in their workplace and contribute to the design of effective collaboration between human scientists and cobots in the lab in order to reduce the burden on scientists while increasing laboratory safety, research efficiency, and accessibility.

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