ORIGINAL ARTICLE

Designing reality-based interfaces for experiential bio-design

Orit Shaer · Consuelo Valdes · Sirui Liu · Kara Lu ·
Kimberly Chang · Wendy Xu · Traci L. Haddock ·
Swapnil Bhatia · Douglas Densmore · Robert Kincaid

Abstract Reality-based interfaces (RBIs) such as table-top and tangible user interfaces draw upon ideas from embodied cognition to offer a more natural, intuitive, and accessible form of interaction that reduces the mental effort required to learn and operate computational systems. However, to date, little research has been devoted to investigating the strengths and limitations of applying reality-based interaction for promoting learning of complex scientific concepts at the college level. We propose that RBIs offer unique opportunities for enhancing college-level science education. This paper presents three main contributions: (1) design considerations and participatory design process for enhancing college-level science education through reality-based interaction, (2) reflections on the design, implementation, and validation of two case studies—RBIs for learning synthetic biology, and (3) discussion of opportunities and challenges for advancing learning of college-level sciences through next-generation interfaces.

O. Shaer (✉) · C. Valdes · S. Liu · K. Lu · K. Chang · W. Xu
Wellesley College, 106 Central St., Wellesley, MA, USA
e-mail: oshaer@wellesley.edu

C. Valdes
e-mail: cvaldes@wellesley.edu

S. Liu
e-mail: sliu@wellesley.edu

K. Lu
e-mail: klu2@wellesley.edu

W. Xu
e-mail: wxu2@wellesley.edu

T. L. Haddock · S. Bhatia · D. Densmore
Department of Electrical and Computer Engineering,
Boston University, Boston, MA, USA
e-mail: thaddock@bu.edu

S. Bhatia
e-mail: swapnilb@bu.edu

D. Densmore
e-mail: doug.d@bu.edu

R. Kincaid
Agilent Laboratories, Palo Alto, CA, USA
e-mail: robert_kincaid@agilent.com

1 Introduction

Over the past two decades, human–computer interaction (HCI) research has generated a broad range of interaction styles that move beyond the desktop into new physical and social contexts. Key areas of innovation have been table-top, tangible, and embodied user interfaces. These interaction styles share an important commonality: leveraging users' existing knowledge and skills of interaction with the real non-digital world. Thus, they are often unified under the umbrella of reality-based interfaces (RBIs) [42]. Building upon ideas from embodied cognition, RBIs offer a more natural, intuitive, and accessible form of interaction that reduces the mental effort required to learn and operate a computational system [42].

Given the potential of RBIs, numerous research prototypes have explored how these emerging interaction styles will impact education. Several studies have examined the effects of RBIs on learning, investigating the benefits and deficits of reality-based interaction in the contexts of formal and informal learning (e.g., [16, 20, 52, 60, 68]). However, most of these studies have focused on children.

To date, little research has been devoted to investigating the strengths and limitations of utilizing RBIs for communicating complex concepts to older learners at the high school or college levels. Our focus is on investigating the application of reality-based interaction for supporting college-level science education. In our work, we have explored the application of reality-based interaction for enhancing inquiry-based learning in data-intensive areas such as genomics [71, 74, 75], phylogeny [69] and phenology [79]. Our recent work, which we present in this paper, examines how reality-based interaction techniques can be applied to facilitate problem-driven learning and understanding in synthetic biology. We chose to focus on synthetic biology since it is a new area of research where interactive tools currently remain immature. Also, designing for problem-driven learning at the intersection of science and engineering can help move forward the theory and practice of educational interfaces, software, and technology.

Synthetic biology is an emerging research area that couples engineering and biology with the goal of building sophisticated biological circuits for novel applications [15]. For example, synthetic biology is used in the development of low-cost drugs for Malaria [52], in the creation of toxin and explosive compound sensing bacteria [45], and in the production of energy from bacteria [44]. The bottlenecks and challenges along the path to realizing the full potential of this field are formidable and numerous. For one, synthetic biology designs are currently implemented using a complex ad-hoc process that limits their scale and complexity [84]. As a result, undergraduate students in synthetic biology typically have limited opportunity to develop design competencies [53]. Providing students with opportunities to develop synthetic biology projects poses a challenge due to the cost and skills required for using biological technologies. Synthetic biology solutions have the potential to impact public policy decisions as well as environmental and personal choices. Thereby, in addition to training future scientists, it is important to make core concepts of synthetic biology accessible and understandable to non-scientists. This goal is often challenged by the limited access to biological technologies.

In this paper, we present two case studies of applying reality-based interaction for learning in synthetic biology. Using these case studies as a starting point, we discuss how ideas from reality-based interaction can be applied to facilitate problem-driven learning and understanding of college-level science.

Our contribution in this work is threefold. First, we describe a set of design considerations and a participatory design process for facilitating problem-driven learning in synthetic biology through reality-based interaction. Second, we reflect on the design, implementation, and validation of two case studies of RBIs for synthetic biology: (1) MoClo Planner—a multi-touch interface for collaborative bio-design; (2) SynFlo—a tangible and embodied interface for communicating core synthetic biology concepts to non-scientists. Finally, drawing on our described experiences, we discuss opportunities and challenges for advancing learning in college-level sciences through reality-based interaction.

We begin by revisiting reality-based interaction and core ideas of embodied cognition, followed by a brief survey of RBIs for scientific discovery and education, and design frameworks for RBI. We also survey related work on bioinformatics tools for bio-design.

2 Background

2.1 Reality-based interaction

RBI is a descriptive framework [42] that highlights salient commonalities of emerging interaction styles that diverge from the traditional window, icon, menu, pointing device (WIMP) interaction style.

RBIs draw strength by building on users' preexisting knowledge of the real, non-digital world to a much greater extent than before. In particular, they leverage four aspects of interaction with the non-digital world:

- *Naïve physics* The informal human perception of basic physical principles such as gravity, friction, velocity, the persistence of objects, and relative scale.
- *Body awareness and skills* The familiarity and understanding that people have of their own bodies. This includes proprioception, range of motion, and the ability to coordinate movement of multiple limbs.
- *Social awareness and skills* The general awareness that people have of the presence of others and of their skills of social interaction, including verbal and nonverbal communication, the ability to exchange physical objects and work with others to collaborate on a task.
- Finally, *environment awareness and skills*—the physical presence that people have in their spatial environment and their ability to navigate in and alter their environment.

The RBI framework suggests that basing interaction on preexisting real-world knowledge and skills may reduce the mental effort required to operate a system [42]. This reduction might speed up learning and encourage exploration because users do not need to learn interface-specific skills.

While RBI has been developed for a broad range of application domains, relatively little research has been devoted to investigating RBI in the context of scientific

discovery and higher-education. Following, we describe some RBI systems that illustrate the potential of supporting scientific discovery and education.

2.2 Embodied cognition and scientific thinking

RBI is based on ideas from embodied cognition, which holds that the body, physical activity, and the environment play significant roles in cognitive processes [14, 83].

Here, we describe three ideas from embodied cognition that are of particular importance when designing for scientific discovery and learning:

- *Coupling space and meaning* One strategy for reducing cognitive workload is to make use of the environment in strategic ways [83]—leaving information in the physical environment; for example, using spatial configurations, rather than taking time to fully encode it. Actions such as arranging objects, annotating them, and counting them all recruit external elements to decrease mental load. RBIs often allow users to easily construct meaningful spatial configurations as well as to store information artifacts, so they can be readily accessed when needed—reducing load from short-term memory.
- *Thinking through action* Various studies have demonstrated how physical artifacts support cognition by serving as "thinking props". Probably, most well-known are Kirsh's [46, 47] investigations of epistemic actions, which are not functional but help explore options and support memory. Thus, epistemic actions can reduce the complexity of activities. Interfaces that make epistemic actions such as pointing, turning, and arranging easily support cognition.
- *Bridging across representations* External representations (e.g., models, diagrams, notations) support the mind in constructing new knowledge and solving problems [65]. Scientists often use external artifacts to support their reasoning process [54, 55]. One famous example is the physical model of DNA built by Watson and Crick, which played an important role in discovering its structure [66]. There are many different ways in which RBIs can employ external representations: some application domains have inherent geometrical or topological representations; other domains have representational conventions.

2.3 Reality-based interfaces for scientific discovery and education

Brooks et al. [25] developed the first haptic display for scientific visualization to investigate docking positions for drugs. Gillet et al. [36] presented a tangible user interface for molecular biology that used augmented reality technology to view 3D molecular models. Schkolne et al. [67] developed an immersive tangible interface for the design of DNA molecules. While these systems highlight potential benefits of RBIs for scientists, they focus on the representation of objects with inherent physical structure. We are interested in a broader use case, where abstract information is represented and manipulated.

A few systems were developed to facilitate collaboration among scientists across large multi-touch displays. We-Space [82] integrates a large data wall with a multi-touch table and personal laptops. TeamTag [63] allows biodiversity researchers to browse digital photographs. However, these systems target expert scientists rather than novices and are not aimed for learning new concepts.

The eLabBench [77, 78] is a tabletop system supporting experimental research in synthetic biology laboratories, which provides users with situated access to heterogeneous information in the lab. While eLabBench was designed to enhance the work of a single expert user, we are interested in supporting collaborative learning while promoting the development of scientific thinking.

Finally, several RBI systems have illustrated the potential to support science education. Most relevant to our work are augmented chemistry [34]—a tangible user interface for chemistry education and PhyloGenie [69]—a tabletop interface for collaborative learning of phylogeny through a guided activity. While these interfaces allow users to interact with a well-defined data set, we are interested in the development of interfaces that promote open-ended hands-on inquiry. Involv [40] and DeepTree [24] are tabletop interfaces for exploring the Encyclopedia of Life that share our challenge of creating effective interaction techniques for large data spaces. However, they aim at informal science learning settings, which are different from the formal college-level laboratory settings, which we target.

GreenTouch [79] is a collaborative environment for engaging undergraduate students in phylogeny research, which consists of a mobile application for data collection and a tabletop interface for exploratory analysis. G-nome Surfer is a tabletop interface for collaborative exploration of genomic information [71, 74, 75]. These works highlight how students collaborate around a tabletop to conduct an open-ended inquiry and illustrate that tabletop interaction supports high-level reasoning and hypothesis forming. In this paper, we go beyond hypothesis forming and exploratory analysis and delve into the design and specification of new biological systems.

2.4 Design frameworks for reality-based interfaces

There are several frameworks that inform the design of RBIs by specifying concepts and their relations and

providing design considerations (e.g., [34, 41, 42, 72]). Some frameworks focus on the design of learning environments [15, 51, 59, 60]; however, these typically target young learners. The Tangible Learning Design Framework [17] is a comprehensive explanatory framework that highlights design aspects important for learning and provides guidelines based on cognitive and learning theories. Our design, which we describe in the Sect. 5, draws on the concepts and guidelines provided by these frameworks.

3 Related work

Our work on supporting learning in synthetic biology needs to also be contextualized within the area of bioinformatics tools for synthetic biology.

Biologists often use a variety of existing bioinformatics tools in order to retrieve, compare, and study genomic sequences. Several studies indicate that current bioinformatics tools show severe limitations in supporting users to gain deep insights [23, 43, 65].

Current software tools in synthetic biology can be classified into two broad categories: software for wetware tasks and software for design and planning tasks. Each category may be further divided by user level: beginner, intermediate, and advanced. Following, we discuss each of these categories:

A majority of the current software tools in synthetic biology support design and planning and are intended for users with intermediate to advanced skills. Software tools such as Geneious [1] and Ape [2] are popular desktop tools for viewing and editing DNA sequences. Other software tools (e.g., Genome Compiler [3] and Vector Express [4]) work between the sequence and part level of abstraction allowing manual composition of genetic designs. Various primer design tools allow sequence-level engineering of biological parts based on biophysical constraints (e.g., [11, 64]). GenoCAD [26] and Eugene [22] supports the constrained combinatorial specification of biological designs. Cello [35] and the Proto BioCompiler [19] are tools for programmable functional specification of biological designs.

A number of tools exist to support the curation of biological parts and designs. Repositories such as the MIT Parts Registry [5] and Clotho [84] enable users to save DNA sequences associated with biological designs. Other software tools such as TinkerCell [28] and iBioSim [6] support the modeling and simulation of biological designs. The goal of the Synthetic Biology Open Language [2] consortium is to standardize formats for exchange of data and designs in synthetic biology.

Fewer software tools exist for wetware automation. Par–Par [50] and Puppeteer [80] are two platforms for wetlab protocol automation using liquid-handling robots for synthetic biology. OpenWetware is a web-based repository of biological protocols used by synthetic biology labs around the world. Many software solutions exist for lab sample information tracking and digitization of the lab notebook [62]. In addition, vendor-specific software exists for each programmable instrument used in synthetic biology labs such as flow cytometers, photospectrometric DNA quantifiers, electronic microscopes, and imaging systems.

While the majority of these software tools are aimed at users with advanced knowledge and skills, a few websites target novice users in synthetic biology. The Biobuilder website [7] offers animations and activities for teaching and learning synthetic biology. The iGEM competition [8] offers resources for undergraduates to learn basic concepts and participate in synthetic biology projects. The Learning Trails project is a new framework under construction for self-learning synthetic biology in an open forum with community-created content [13]. The DIYBio group [9] advances local community-driven practice of synthetic biology aimed at the layperson. While informative, these resources are rarely interactive. Our goal is to utilize reality-based interaction to promote experiential, hands-on, learning of synthetic biology concepts by novice users.

4 Designing for learning in synthetic biology

Our goal was to utilize reality-based interaction to develop problem-driven learning environments for synthetic biology. In this section, we discuss the audience, process, and design requirements that we considered.

4.1 Audience and learning goals

At least three distinct user groups are involved in the learning of introductory synthetic biology. Each is marked by unique needs and learning goals:

First, *undergraduate biological engineering students* are future scientists early in their career. A core synthetic biology curriculum includes the following learning goals [48]:

L1 designing biological systems in skillful and responsible ways;
L2 defining, specifying, and (whenever possible) implementing biological designs;
L3 defining the values, culture, and safety practices of the field

However, synthetic biology students have limited opportunity to develop design competencies and even fewer chances to implement their designed projects [53]. This can be attributed to four factors: (1) the vast amount of

disparate information required to characterize biological systems; (2) the limited knowledge of how biological parts interact; (3) the lack of mature computational tools for the design and assembly of biological systems; and (4) the cost and availability of biological technologies.

Second, iGEM teams consisting of students participating in the International Genetically Engineered Machine Competition (iGEM). The competition provides a project-based research experience driven by real-world problems, in which interdisciplinary teams of undergraduates learn by engaging in synthetic biology research. Students use a kit of standard biological parts and new parts of their own design, to build biological systems. Alternatively, teams competing in the software track develop tools for synthetic biologists. Learning goals for iGEM students [53] include L1, L2, and L3. In addition, students are expected to:

L4   Engage in actual practices of biological engineers
L5   Gain competency and confidence in laboratory techniques

Third, *outreach students* are enrolled in programs that span the divide between novices and traditional students. For synthetic biology programs, this audience typically consists of high school students. Learning goals for this audience include:

L6   Grasp foundational ideas in synthetic biology
L7   Recognize the excitement, promise, and risks of cutting-edge research

An important goal for this audience is to make ideas accessible through playful and entertaining formats. A major challenge is the limited access to wet lab environments and biological technologies. Thus, hands-on learning experiences in synthetic biology are rare in the context of outreach programs.

Other audiences such as teachers, policy makers, and citizen scientists, may also express interest in learning synthetic biology. Kuznetsov [49] explored the development of artifacts for supporting DIYbio citizen scientists. Our focus is on formal and experiential learning.

4.2 Design strategy

Considering the complexity of synthetic biology, its evolving nature, and the diverse audiences involved, our design strategy combines rigorous user-centered and participatory design methods. Figure 1 illustrates our design strategy, which consists of three core aspects:

4.2.1 "Renaissance team"

Cox [32] introduced the term "Renaissance team" to describe a multidisciplinary team focused on solving visualization problems. Our "renaissance team" consists of 14 faculty and students with expertise in synthetic biology, biological engineering, computer science, HCI, information visualization, and science education. We took several

Fig. 1 Combining rigorous user-centered and participatory design methods
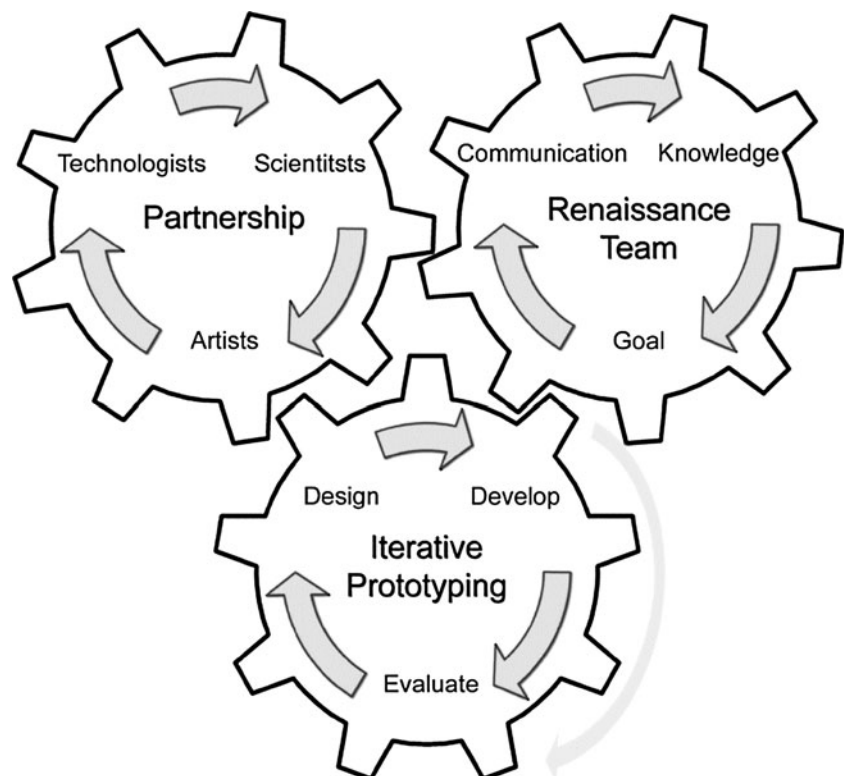
Fig. 2 Working with a "Renaissance Team": collaborative sense making and ideation (*left*), establishing common knowledge base through interdisciplinary boot camp (*right*)

steps (along with continuous coordination and coaching) to ensure that the team works together effectively: establishing a common knowledge base through a 2-week-long "boot camp" (see Fig. 2) and pursuing a passionate goal for the team—presenting the project as an entry in the iGEM contest, a focal event for the synthetic biology community.

4.2.2 Partnership and immersion

We established design partnerships with educators and researchers in the synthetic biology community including: 16 college students and five investigators from two research laboratories (in MIT and Boston University); a leading educator in synthetic biology (MIT), which chairs the BioBuilder educational foundation [7]; and an industry expert in bioinformatics. We met with our partners on a frequent basis throughout the development process. Our partners participated in every stage of the project from interviews and observations, to collaborative sense making and ideation, to the development and refinement of multiple prototypes, and final evaluations.

We began the project by interviewing our design partners. Interviews were semi-structured and lasted about an hour. We met with our partners at their work place, conducting one-on-one interviews with investigators and educators, and meeting with undergraduate student researchers in small groups. During the interviews, we asked our partners to educate us about their educational and research goals, their work practices, and the computational tools they use. We collected data by recording the interviews, taking pictures of the various work environments, collecting relevant work samples, and saving screen captures of participants' computers as they were demonstrating various tasks. We analyzed this data by identifying common high-level tasks and themes. We then met with our partners for a 2-day-long workshop. In the first day, we refined and validated our user study findings and distilled

design implications and requirements for supporting learning in synthetic biology. The following day was dedicated to brainstorming activities—breaking into smaller teams to collaboratively propose and design interactive applications for promoting experiential learning in synthetic biology. Next steps included weekly meetings with our design partners in which we discussed and tested various prototypes in increasing fidelity. We also conducted observations at our design partners' work place and interviewed additional users. Finally, we conducted a day-long workshop with our design partners and other users in which we presented and discussed the strengths and limitations of our functional prototypes and prospects for future work.

Beyond this traditional model of participatory design, we also sought to *immerse* in educational activities of the larger synthetic biology community. To accomplish this goal, we created an iGEM team comprised of our undergraduate student researchers and advised by the senior researchers on our team. Our team competed in the Software Division track of the contest. Participating in iGEM allowed us to become a part of this vibrant community and provided us with a unique perspective on the issues facing future scientists in this field.

4.2.3 Iterative prototyping

We created a large range of prototypes in increasing fidelity. In early stages, low-fidelity prototypes promoted common understanding and fostered dialog and exploration. Later, we used video and semi-functional prototypes to investigate particular designs. We conducted microstudies, testing the usability of particular features through a series of prototypes and then conducted formal studies that examined the usability and usefulness of an interface.

Following, we describe the design requirements, which we identified as a result of the participatory process described above.

4.3 Design requirements

4.3.1 R1: Facilitating constructivist learning

The constructivist approach, which views learning as an active process where learners construct new ideas and are active constructors of new knowledge [59], is particularly suitable to learning on the frontiers of science [56]. In synthetic biology, iGEM team members actively construct understanding and knowledge as they work to solve real-world problems. The constructivist approach is also applied in introductory project-based synthetic biology courses [48]. Software tools for promoting learning in synthetic biology are thereby required to support open inquiry and knowledge building, which are essential for constructivist learning. Realty-based interfaces can support constructivist learning by providing means for actively interacting and sharing content while exploiting sensory and motor processes, which are important for scientific thinking [37].

4.3.2 R2: Fostering collaboration

Synthetic biology research is often multidisciplinary and highly collaborative. The complex nature of the problems and the current state of the field in which much is still unknown, promote the distribution of problem solving activities and knowledge across a community of researchers. Often, even advanced practitioners in this field (e.g., graduate students and post-docs) are vacillating between expert and novice roles on various aspects of a project. Thus, collaboration, particularly in early stages of a project, is essential for tackling difficult problems and for dividing a project into sub-problems (e.g., planning the assembly of a medium-size library of biological parts). Such collaboration is typically based on face-to-face research meetings, email exchange, shared databases, and side-by-side work on a computer. iGEM teams and student project teams operate in a similar way—collaboration and communication are often the key for project success. Hence, software tools for learning in synthetic biology are required to support and foster collaboration, allowing users to share knowledge and artifacts, divide problems into sub-problems, and work together in an effective manner. This suggests that RBIs, which provide support for face-to-face collaboration, may be suitable for supporting learning in synthetic biology.

4.3.3 R3: Supporting community standards

Standardization is essential for the growth and maturity of the synthetic biology discipline. Sharing data, parts, and techniques across different laboratories is challenging without the use of clear standards. Likewise, sharing designs is difficult without the use of a standard notation. The push for standardization mainly aims to help facilitate understanding and data sharing across laboratories. Software tools for biological design are thereby required to support efforts toward standardization. Several data models and specification languages are emerging as standards for software tools in the field including Clotho [84], the Synthetic Biology Open Language (SBOL) [76], and Eugene [22]. From the perspective of learning, supporting standards is important in order to allow users to share their bio-designs and to progress from novices to experts.

4.3.4 R4: Enabling an integrated and flexible workflow

To gain insight into and to design complex biological systems, synthetic biologists often explore several data sets, each one handled with a special tool. There are two general approaches to biological design [22]: Bottom–Up Design, which begins with low-level parts and then creates devices, and Top–Down Design that begins by specifying devices and then instantiating parts [20]. Software tools for biological designs are required to support both approaches through flexible workflow that integrates data and tools in a nonlinear manner. From a learning perspective, it is important to allow students to manage complexity while experiencing the flexible thinking that characterizes authentic problem solving.

5 Case studies

Following, we describe two case studies for RBIs for learning in synthetic biology that were informed by the process, goals, and requirements discussed above. We presented these systems as demos in ITS '12 [30, 51], here we describe them in detail. For each interface, we discuss the design rationale we followed to meet the learning goals and requirements we outlined above.

Fig. 3 MoClo Planner: users using separate workspaces to divide the work for part selection and module assembly

5.1 MoClo Planner

The MoClo Planner is a collaborative, multi-touch bio-design tool that simplifies the information gathering, design, and specification of complex biological constructs using the Modular Cloning (MoClo) method.

MoClo [81] is a hierarchical DNA construction method that allows for the assembly of multi-gene constructs from biological parts in a one–pot reaction. MoClo is a cutting-edge experimental method that facilitates and expedites the assembly of novel biological designs. However, it is an intricate multi-step process, which to date, does not have adequate computational support. Thus, current MoClo design practices involve a combination of web-based databases, tools, and spreadsheets in order to retrieve, store, and organize the information required for MoClo design. This process is time consuming, error-prone, and is difficult for novices to understand (i.e., college students).

Our MoClo Planner application was designed to allow students to gain experiential knowledge in the design and specification of biological systems (L1, L2). The application provides an interactive visualization of the MoClo process, allowing users to design and specify novel biological systems from existing parts (R1). MoClo Planner is implemented using a multi-touch vertical surface (Microsoft PixelSense [12]). Our decision to use a *vertical* interactive surface was informed by current work practices of our users, which typically collaborate through side-by-side

work on the whiteboard or a shared screen (Fig. 3). We also considered the limited real estate of research labs. We chose to use a multi-touch surface to facilitate collaboration through multiple entry points and opportunities for equitable input.

5.1.1 Design

We designed MoClo Planner to visualize the hierarchical MoClo design process. We visualize the steps of the process using three layered workspaces, each layer corresponds to a level of the MoClo design process and is represented by a "shutter", a vertical sliding panel. We used the metaphor of a shutter because it implies that a particular workspace can be open, partially open, or closed at any given time.

In Level 0, the application allows users to browse a collection of biological parts. Upon demand the application generates a data sheet characterizing a part's behavior, retrieving its DNA and RNA sequences, and displaying PubMed and iGEM abstracts related to that part. Users can select parts of interest and save them into the next, Level 1, shutter. Figure 4 shows the Level 0 workspace.

Parts that were saved by users into Level 1 are automatically organized according to their function. In this level, users design transcription units from the basic parts selected in Level 0. The design of transcription units must satisfy constraints that are expressed to users through a template. The application enables users to automatically or

Fig. 4 Level 0 workspace enables users to browse the registry of biological parts. Here a data sheet and several publication abstracts for a particular part are presented over search results
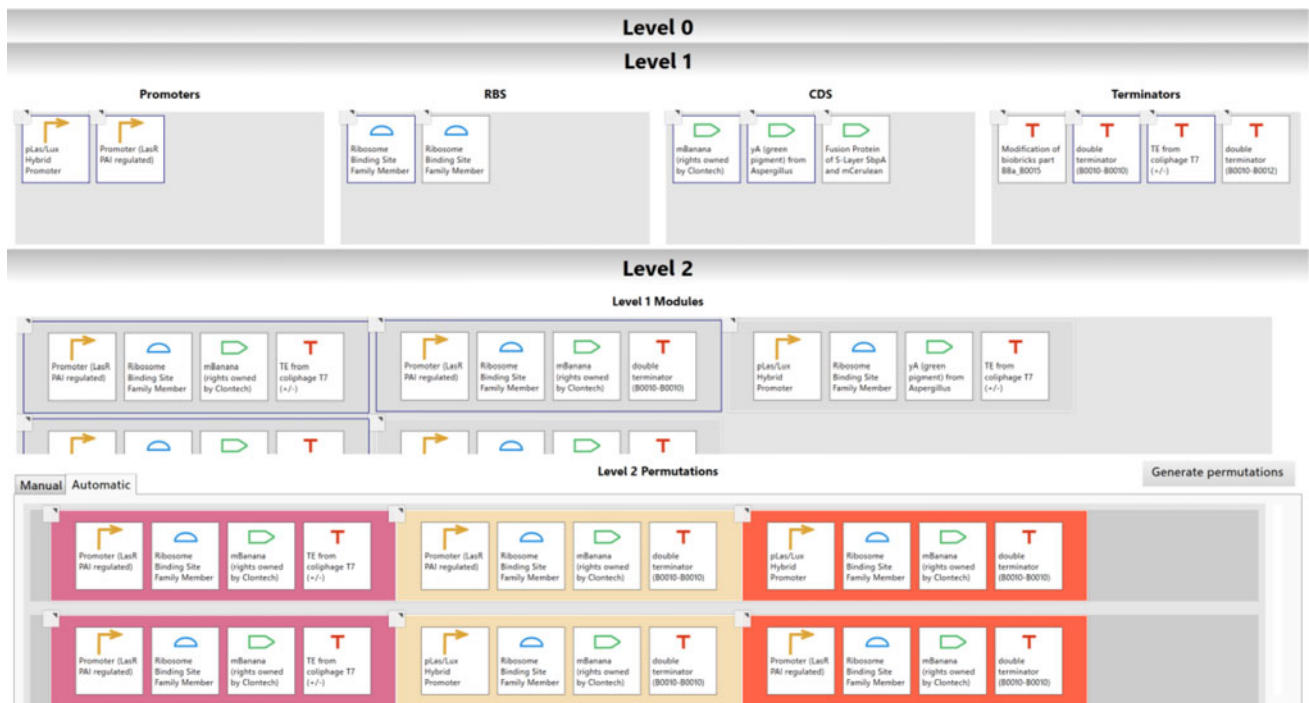
Fig. 5 Two or more workspaces can be used simultaneously. Here, Level 1 workspace displays selected parts while Level 2 displays transcription units and permutations

manually create constraint-based permutations of selected parts. Users can then select those transcription units of interest and drag them to the next level. Figure 5 shows transcription units created in Level 1 saved into the next level.

Finally, in Level 2 users can create more complex constructs that consist of a series of transcription units. Again, users can create constraint-based permutations so that all possible constructs can be considered. Figure 5 illustrates permutations created in Level 2.

On each of the levels, users can launch a primer designer, which allows users to convert constructs into concrete genetic elements by generating primers and protocols to facilitate assembly in the lab. Figure 6 shows users interacting with the primer designer feature.

The application allows users to move backward and forward between levels, keeping one or multiple shutters open at any given time. Leveraging this fluid interaction, users can iterate on their design, go back to select additional parts, or trace previous design decisions (R4).

The design of MoClo Planner draws on RBI principles [42] and guidelines provided by the Tangible Learning Design Framework [17]. MoClo Planner uses reality-based metaphors such as shutters to visualize a complex hierarchical process and organize large amounts of information. It has been shown that using a conceptual metaphor that is based on image schemas to structure interaction may bootstrap learning of abstract concepts [17]. The
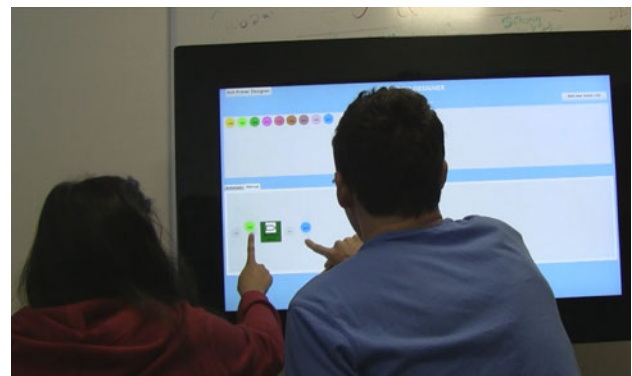

Fig. 6 Users collaborate while using MoClo Planner for designing primers

organization of the interface using separate "shutters" allows users to use the environment to explore and store information while transitioning back and forward between different stages of the experimental process (R4). The use of multi-touch input enables users to manipulate biological parts across different stages of the MoClo process using spatial and direct interaction, which could engage the connection between the hand, the eye, and the brain to support users' conceptual understanding and facilitate "thinking through action" (R1). Also, the use of spatial and physical interaction can reduce cognitive workload [83] and trigger reflection [17]. Finally, MoClo Planner draws upon users' social skills to afford collaborative interaction

(R2), which in turn can promote learning [58]. For example, the system provides multiple points of entry by presenting multiple graphical elements (i.e., biological parts) that could be manipulated in parallel across different shutters.

5.1.2 Implementation

The MoClo planner is implemented on the Microsoft PixelSense device using Microsoft Surface SDK 2.0 written in C#. Information is drawn from the MIT Registry of Biological Parts, PubMed, and the iGEM archive. We use the synthetic biology domain specific description languages Eugene and SBOL for validating and specifying new designs (R3).

5.1.3 Evaluation

We evaluated MoClo Planner using a tiered method [75] with 24 users. Our first study with 12 undergraduate biology students (all female, age 18–23), focused on the *usability* of the system. Our second study with 10 iGEM students (5 female, age 18–26) and 2 instructors (all female, age 27–33), focused on the *usefulness* of the system.

The *usability* study focused on four dimensions: functionality, learnability, performance, and errors. It was conducted in our lab. We randomly assigned users to work in dyads (overall 6 dyads). Prior to the session, we handed users brief reading materials about synthetic biology and the MoClo process (no written or oral tutorial about the system was given). Then, we asked each dyad to use the MoClo Planner to create at least two different multi-gene constructs from a given set of biological parts. This task was selected since it mirrors a real-world research task often conducted by iGEM teams. Users documented their progress, findings, and answered task-related questions on a task form. We collected data through observations and videotaped all sessions. Following the session, we debriefed each dyad.

We found that all users were able to complete the task successfully (typically with some difficulty that was resolved through collaborative work). On average, dyads spent 42:50 min working on the task (SD 13:13). Dyads' answers on the task form indicate that they understood the MoClo process as well as concepts such as permutations and fusion sites. We observed that user understood the "shutter" metaphor and were able to easily transition back and forth between stages of the MoClo process. These findings indicate good learnability and performance as well as show that the interface facilitates a flexible and integrated workflow (R4).

In terms of functionality and errors, the study highlighted several problems that led to a design iteration in

which we modified the keyword search, added color coding per construct and per part category, added information to the Level 0 data sheet, and redesigned the primer design feature to provide users with more control.

Following this design iteration, we conducted an additional study with 12 participants (10 iGEM students, 2 iGEM instructors; 7 female), which focused on *usefulness.* In particular, we investigated performance, engagement, and collaboration. We conducted the study in the users' work environment. We asked users to work in dyads to complete the experimental task: design and specify two different multi-gene constructs from the biological parts they had been using in their lab. This task was chosen since it mirrors real-world research task of iGEM teams, which is typically carried out with the help of an instructor using various ad-hoc computational tools. Users documented their progress and answered task-related questions on the task form. We collected data through observations and videotaped all sessions. Following the session, users filled questionnaires.

All 5 student dyads were able to complete the task successfully within an average time of 45:32 min (SD = 10:47). In their post-task questionnaire, users indicated that they gained a good understanding of the MoClo process (5.20 on a scale of 7, SD = 1.03) and were confident in their designs (5 on a scale of 7, SD = 1.5). Through discourse analysis we found that all 5 student dyads used MoClo process terminology (e.g., CDS, RBS, permutation, fusion site, promoter, primer) with a mean of 7.2 MoClo terminology utterances per dyad. The instructors' dyad used MoClo terminology in 32 utterances. We also found evidence for peer teaching within dyads, which is an indicator of autonomous and effective collaborative learning. Taken together, these findings provide evidence that students were able to use the system to successfully define and specify new biological designs (L2) while building design competency (L1).

Our design aimed to reduce the mental workload associated with operating the interface (i.e., syntactic load) while also reducing the load associated directly with designing complex biological constructs (i.e., task load). We used the NASA TLX [38] post-task questionnaire to measure subjective task workload. We found that, on average, students rated their task success (i.e., performance) as moderate (3.90 SD = 1.45) as well as their mental demand and effort (3.8 SD = 1.03, 3.9 SD = 1.45, 4 SD = 1.63). These results are positive considering the high intrinsic task load. Users rated physical and temporal demand as moderately low. We also asked users about frustration levels which they rated as moderate (3.9, SD = 1.45). We observed that one cause for frustration was the oversensitivity of the Microsoft PixelSense device. Users also reported that the complexity of the interface was

Fig. 7 NASA TLX results from the MoClo Planner usefulness study along three additional dimensions of complexity, frustration, and enjoyment
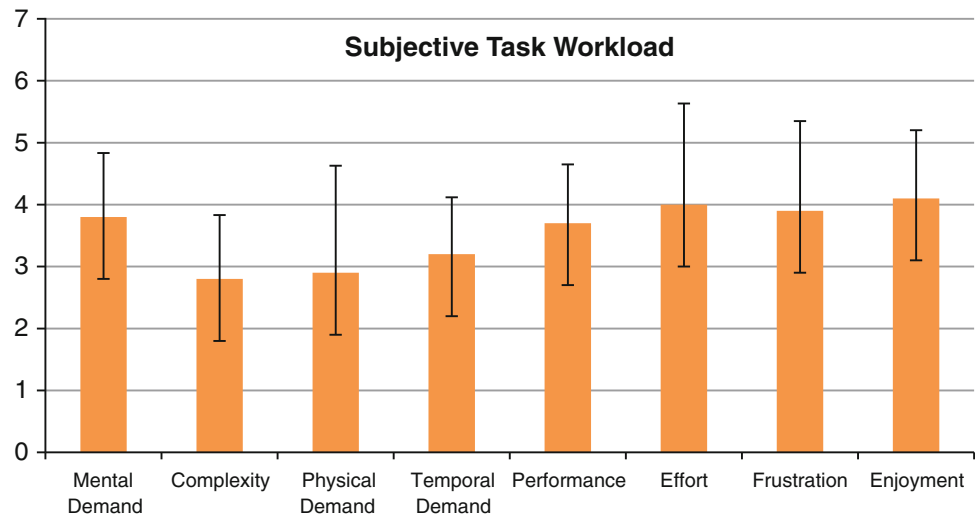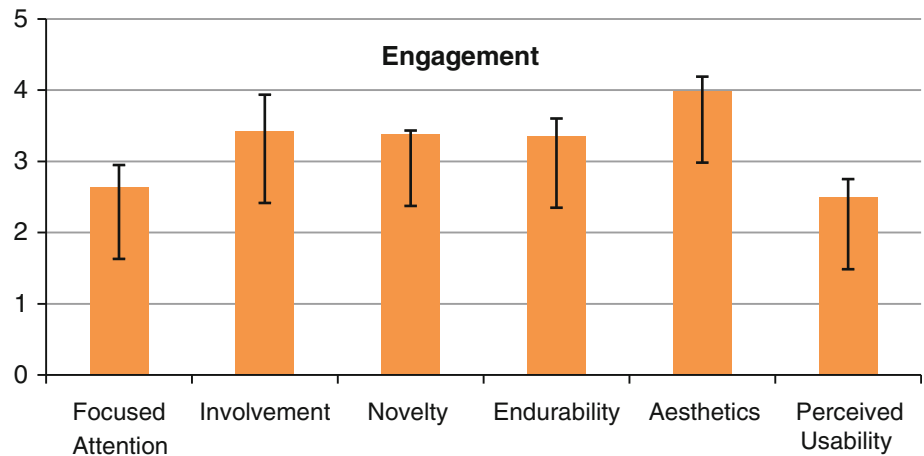

Fig. 8 Results of O'Brien's engagement questionnaire

moderately low (2.83, SD = 1.03) and that overall they enjoyed using the system (4.1 on a scale of 7, SD = 1.10). Figure 7 shows the results.

Several studies highlight a linkage between engagement and learning [27, 31, 61]. Thus, we were interested in gauging user engagement. We used O'Brien's multi-scale measure, which considers six attributes: perceived usability, esthetics, focused attention, felt involvement, novelty, and endurability. Figure 8 shows the results, indicating that involvement, novelty, endurability and esthetics were rated moderately high. These dimensions are important for supporting constructivist learning (R1). However, perceived usability and focused attention fell around neutral. The relatively high score for novelty might indicate some novelty effect. This needs to be further explored through a longitudinal study. We attribute the lower score of perceived usability to the frustration caused by the oversensitivity of the PixelSense device.

Considering the importance of collaboration for learning in the sciences [58], we also studied the nature of collaboration afforded by the MoClo Planner interface. We observed that in the beginning of a session often one user was unsure about trying out the new technology and thus waited until the partner took physical control of the system. When the timid user became comfortable with the technology, or was pushed into action due to their partner's inability to complete a task, they began interacting with the system. In two of the student dyads this resulted in turn-taking collaboration for the rest of the session, where both users participated physically and verbally. In the other three dyads, one user assumed the role of a driver (who participates both physically and verbally) for the rest of the session while the other participated as navigator (who guides the driver through verbal cues and "offline" gestures). Both collaboration styles resulted in effective, task-focused collaboration, which was mostly based on discussion and mutual agreement (R2).

Finally, in-depth interviews with the instructors' post-task completion revealed high satisfaction of the collaborative learning process mediated by the system and of the

integration with standards such as the Registry of Biological Parts, Eugene, and SBOL (R3). The instructors expressed their will and commitment to support future design iterations of this system with the goal of deploying it for longitudinal use by iGEM teams. Two areas of concern expressed by the instructors need to be addressed in future design iterations: integration with the Clotho data model, which handles all data generated by the wet lab, and support for lab automation which will provide fluid transition from specifications to physical assembly.

5.1.4 Future work

This study has several limitations that point toward future work. First, we studied one-time use rather than longitudinal use. Additional studies of longitudinal use are necessary in order to determine whether findings are affected by novelty. Also, we did not measure learning gains directly. Additional assessment instruments are required for measuring the system's effect on learning. We are planning to deploy MoClo Planner in a project-based synthetic biology course for a period of 4 weeks and are currently in the process of developing instruments for assessing the impact of the system on learning. We are continuing our design partnerships to further develop MoClo Planner. We are also working on integrating MoClo Planner with the Clotho data model and with an application that controls liquid-handling robots, which could automatically assemble biological designs.

5.2 SynFlo

SynFlo is an interactive installation for illustrating core concepts of synthetic biology for non-scientists (L6) and communicating the excitement and constraints of cutting-edge research (L7). This playful installation enables users to gain hands-on experiential learning of synthetic biology concepts when access to biological laboratory technologies is not possible or perhaps inappropriate.

5.2.1 Design

Our design goal for SynFlo is to help illustrate core concepts of synthetic biology for non-scientists. We focus on three core concepts: (1) abstraction—the representation of genetic materials as standard biological parts called BioBricks; (2) modularity—the construction of biological systems composed of reusable mix-and-match BioBricks; and (3) protocols—the use of predefined standardized laboratory procedures to ensure safety and successful replication of results. We also aim to provoke further inquiry about the everyday implications of synthetic biology while experiencing some of its excitement and constraints.

To accomplish these goals, SynFlo draws upon a well-known synthetic biology experiment called E. chromi [33], in which genetically engineered *Escherichia coli* bacteria act as biosensors, indicating the presence of certain environmental toxins. This experiment has four basic procedural tasks: (1) combining biological parts to create a genetic element capable of producing a particular color in response to the presence of a particular toxin; (2) inserting the selected BioBrick into a plasmid, a circular DNA strand that replicates independently from chromosomal DNA; (3) infusing *E. coli* bacteria with the engineered plasmids; and (4) deploying the modified bacteria into a testing environment.

SynFlo utilizes tangible and embodied interactions to allow users to experience a playful simulation of the E. chromi experimental process (R1). The system consists of triplets of Sifteo cubes, a tabletop computer (Microsoft PixelSense), and tangible objects that represent environmental toxins (see Fig. 9). Each triplet of Sifteo cubes consists of a BioBrick cube, a plasmid cube, and an *E. coli* bacterial cell.

We chose to use Sifteo cubes to implement the interaction with BioBricks because they support a variety of gestures including moving, shaking, flipping, rotating, and neighboring. We leverage these abilities to mimic physical aspects of laboratory work. In addition, the form factor of the cubes communicates modularity. We represent the testing environment using a tabletop computer. Multiple users can deploy modified *E. coli* into the surface and interact with the deployed bacteria through touch. Users can also add tangibles that represent different environmental toxins to the surface and observe their effects on the existing bacteria.

Following SynFlo experimental protocol users choose a BioBrick from a library of biological parts that encode for a
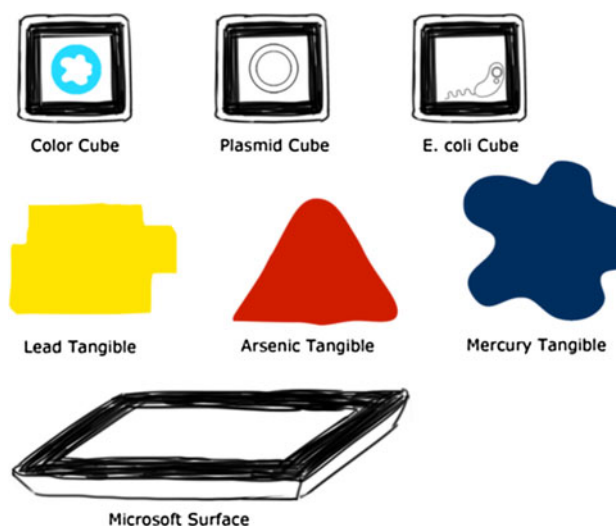
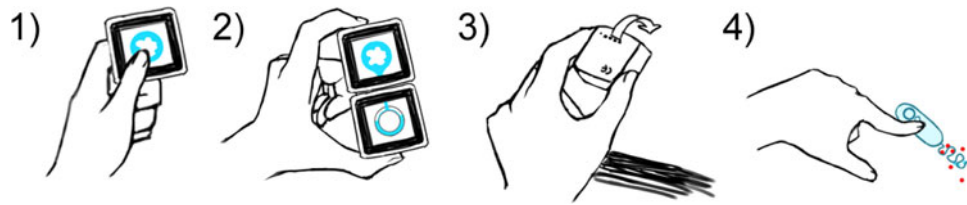**Fig. 9** The components of the SynFlo system

Fig. 10 The SynFlo experiment workflow: (*1*) Clicking through the BioBrick library; (*2*) shaking the DNA material into the plasmid cube; (*3*) flipping the *E. coli* to insert the plasmid into the *E. coli* and again

to introduce to the surface environment; (*4*) interacting with the *E. coli* in its testing environment
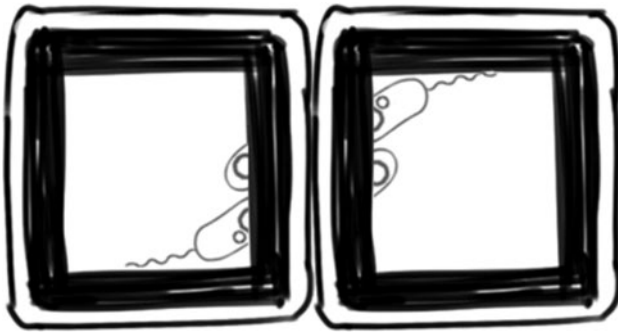

Fig. 11 *Escherichia coli* interact with each other by contaminating visiting *E. coli* cubes (*left*). Selecting a part from the BioBrick library (*right*)

particular color (see Fig. 10-1). Similar to the biologists performing the E. chromi experiment, users add the Bio-Brick to a plasmid and mix by vortexing (see Fig. 10-2). Then, just as a biologist would pipette, mix, and eject the newly-infused plasmid onto the waiting biological vessel, SynFlo allows the user to place the now colored plasmid cube next to the awaiting *E. coli* cube and then flip the plasmid cube as if pouring or pipetting into the *E. coli* (see Fig. 10-3). Finally, users can deploy their *E. coli* to the testing environment by placing the *E. coli* cube on the Microsoft PixelSense and flipping the cube. Users can then interact with the *E. coli* by adding tangibles to the surface that represent different environmental toxins (see Fig. 12); the modified *E. coli* sensitive to particular toxins will respond by changing their color. Touching the *E. coli* results in a color change (see Fig. 10-4). When two *E. coli* cubes are placed next to each other, there will be an incident of contamination (see Fig. 11).

The design of SynFlo draws on RBI [42] and the design guidelines provided by the Tangible Learning Design Framework [17]. SynFlo uses naive physics metaphors such as inertia, velocity, and gravity in the design of the interaction gestures. The use of simple visual and tangible representations for complex notions (e.g., biological parts, plasmids, and environmental toxins), and the choice of manipulation gestures that mimic physical aspects of laboratory work enables users to construct mental models that transforms abstract ideas into concrete (R1). Finally, like tangible interfaces in general,

SynFlo draws upon users' social skills to afford collaborative interaction (R2): the system provides multiple points of entry through multiple cubes and facilitates visibility of users' actions. The tabletop interface allows for multiple users to interact in parallel by presenting multiple graphical elements (*E. coli*) and tangibles (toxins).

5.2.2 Implementation

SynFlo uses Sifteo [10] 1.0 cubes. The current prototype of SynFlo supports up to 6 cubes. The interaction is programmed using the Sifteo SDK written in C#. The tabletop application is implemented on the Microsoft PixelSense using the Microsoft Surface 2.0 SDK. The communication between the Sifteo cubes and the PixelSense is implemented using client–server communication.

5.2.3 Evaluation

We evaluated SynFlo with high school students participating in a week-long, on-campus science outreach program. Our evaluation consisted of four sessions (total 18 students, 10 female, age 15–17) that were conducted in our lab. We collected data through observations and video recording of each session.

Students were first given a 10-min presentation explaining basic synthetic biology concepts, and then interacted with SynFlo for an average of 10:57 min (SD 06:27). Students were asked to complete a task: use a triplet of the Sifteo cubes to modify an *E. coli* so that it becomes a biosensor for a particular environmental toxin, and test it to verify that it indeed sensed that toxin. We chose this task because it represents the famous E. chromi experiment, thus requires users to complete a sequence of actions that mirrors a real-world synthetic biology lab protocol.

On average, users interacted with the Sifteo cubes for 01:35 (SD 00:30) and then moved on to interact with the tabletop interface where they touched the *E. coli* to introduce a mutation and tested its response to environmental toxins by adding tangibles to the environment. Users typically spent the rest of the session around the tabletop.

Fig. 12 Introducing red toxin into the testing environment (*left*), high school students collaborate as they select a biological part and insert the part into a plasmid (*right*)
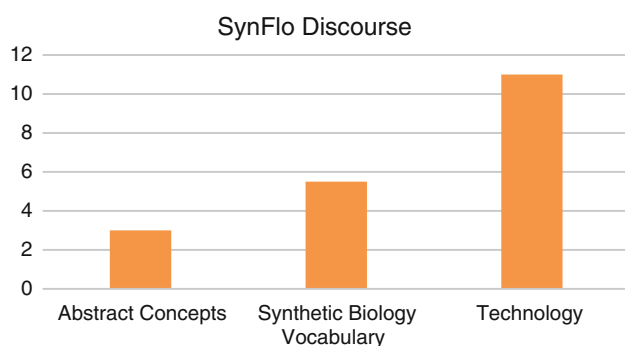

Fig. 13 Distribution of content-related utterances per category

Fig. 14 High school students interacting with SynFlo. Users collaborated by dividing the steps of the process and coming together at each step transition

Some users went back to create more modified *E. coli*. Since the system consists of only two triplets of Sifteo Cubes, users had to wait for their turn. During this time some users observed their peers, while others explored the tabletop environment. Overall, we found that the system facilitated a flexible and fluid workflow (R4).

In the first few minutes, users were fascinated by the technology and asked many questions. For example: "What kind of sensors do the cubes have? How does it know to do things…" Later in the session, users reflected on the connection between SynFlo and the synthetic biology concepts discussed: "[we're] designing and constructing new biology things. But it's hard to put into words 'cause we're seeing this new…" We used discourse analysis to quantify content-related utterances. We found that content-related utterances could be divided into three main categories: abstract concepts (e.g., modularity, synthetic biology, assembly process), synthetic biology vocabulary (e.g., plasmid, DNA, gene, *E. coli*), and technology-related utterances. Figure 13 shows the distribution of content-related utterances per category with an average of 4.5 users per session. The relatively high number of technology-related utterances might indicate a novelty effect. We intend to further address this issue in future studies.

We found that while we designed SynFlo to utilize gestures, which mimic physical actions performed in the lab (e.g., vortexing, pouring, and flipping), users did not always understand these metaphors. One possible way to help users to make the connection between the wet lab environment and the SynFlo elements is to embed the Sifteo cubes within more evocative tangibles that resemble lab instruments and afford such actions.

Overall, participants demonstrated high-engagement with the system: all users have successfully completed the task of creating a modified *E. coli* and deploying it. Users also had prolonged interactions with the tabletop interface. Overall, users exhibited effective collaboration (R2): sharing the tabletop surface while respecting territoriality as well as sharing the cubes—often passing them to those who had not tried them yet. Several students collaborated by dividing the task and sharing the cubes. For example, while one user was choosing a color, the other one was inserting the plasmid into the *E. coli* (see Figs. 12, 14).

5.2.4 Future work

This system and study have several limitations that point toward future work. First, we did not measure learning gains directly; additional assessment instruments are

required for measuring the impact on learning. Second, additional investigation is required for clarifying the presence and extent of a novelty effect. Third, the current form factor of the cubes does not afford the rich gestures representing wet lab protocols. We are currently redesigning the SynFlo tangibles to resemble scientific instruments. We plan to further evaluate the system by deploying it in a summer outreach program.

6 Discussion

While both case studies have limitations, findings indicate that in general, they were able to meet our learning goals and requirements. In particular, we identified four requirements: (1) facilitating constructivist learning, (2) fostering collaboration, (3) supporting community standards, and (4) enabling an integrated and flexible workflow. Our user studies showed that MoClo Planner facilitated experiential and collaborative learning of complex synthetic biology concepts through a flexible workflow that complies with emerging standards in Synthetic Biology. SynFlo allowed users to experience the excitement and constraints of cutting-edge research in synthetic biology through hands-on, collaborative, and playful interaction.

More broadly, our case studies demonstrate the potential of using RBI to facilitate problem-driven learning of complex scientific concepts. Taken together with current literature, these case studies illustrate four ways in which next-generation user interfaces can impact learning and understanding of advanced scientific concepts. Our case studies also highlight challenges for interaction designers. In the following, we describe these challenges and opportunities:

6.1 Providing rich representations of abstract and complex concepts

RBI enables users to manipulate rich physical and digital representations with their hands. For example, in MoClo Planner users explore the relationships among parts by arranging them upon the interaction surface and combining parts into complex biological constructs. The interactive surface of MoClo Planner allows for the comparison and analysis of data through parallel multi-touch interactions. In SynFlo, users manipulate representations of scientific data using various gestures and actions, which in turn represents the physical nature of biological laboratory techniques. Manipulating information through touch and gestures could potentially engage the connection between the hand, the eye, and the brain to support users' conceptual understanding [29].

A major challenge for interaction designers is to identify effective representations for abstract and complex concepts. This includes deciding which concepts should be represented in a digital form and which in a physical form as well as combining physical and digital representations so that they support powerful and expressive inquiry [73]. Reality-based metaphors could serve as a starting point. Additional design considerations include representing multiple scales of data while maintaining seamless transition across different levels of abstraction, representing domain concepts as well as process concepts, and facilitating the navigation of large data sets while maintaining context. It is also important to select representations that are consistent with standards and notations of a field.

6.2 Fostering engagement through affordance and autonomy

Several studies investigated the connection between engagement and learning [21, 27, 31, 61]. Other investigations indicate that the esthetic and affordance of tangible objects contribute to user engagement [18, 55, 68]. It has also been shown that engagement acts as a positive mediator for efficient collaborative learning [69]. Beyond affordance, another aspect of RBIs that could contribute to engagement is autonomy [61]. RBIs often provide learners with a collaborative environment where they could work with their peers to construct mental models through collaborative exploration with minimal instructor intervention.

In both of our case studies, users worked autonomously and exhibited relatively high levels of engagement. In the evaluation of MoClo Planner, we used O'Brien's multi-scale measure [57] to gauge levels of engagement. Our findings indicate that the dimensions of *esthetic*—the extent to which the system is attractive and sensory appealing, and *endurability*—the extent to which the experience is perceived as successful, were rated moderately high. We also found that the dimension of novelty was rated moderately high. While this can be attributed to the natural curiosity invoked by new technology, such ratings could also point toward a novelty effect—a temporary increase in engagement that would fade when users lose interest in the technology. A major challenge for interaction designers is to identify when increased student engagement points toward a novelty effect. This issue could be investigated through longitudinal studies and in-depth interviews.

Another challenge for deploying new technologies in the classroom was highlighted by the relatively low rating of the *perceived usability* dimension of the MoClo Planner, which we attribute to the frustration caused by the over-sensitivity of the PixelSense device. A major challenge for

deploying new technologies in the classroom is to ensure that the technology functions as expected.

6.3 Supporting effective collaboration

One of the known strengths of tangible and tabletop reality-based interaction styles is their support of co-located collaboration. Collaboration in crucial for scientific understanding as demonstrated by empirical studies [58] and by perspectives from embodied cognition view cognitive processes as socially distributed across members of a group [39].

Several factors support face-to-face collaboration in RBIs. First, affordances known from interaction with the real world lower the threshold for engaging with a system and thus increase the likelihood of users to actively contribute [41]. Second, multiple access points allow for simultaneous interaction [70]. Third, manual interaction with digital or physical objects is observable and has enhanced legibility, which in turn supports group awareness [41]. Finally, several studies indicate that territoriality is important for collaboration [43].

Both case studies support collaboration. MoClo Planner provides multiple access points through parallel workspaces. It allows users to reinforce their territory or share a particular workspace. SynFlo provides multiple access points through cubes and tangibles as well as through the tabletop interface. The interface enables users to divide the problem spatially and temporally so that users can assume different roles. For example, some users collaborated so that while one user selected a biological part, another added the plasmid to the bacterial cell.

One challenge for interaction designers is to support spatial and temporal multiplexing [70], allowing users to approach a problem by breaking it into smaller problems that could be distributed across different users, interaction objects, and addressed at different times. Designers should also provide multiple access points and ways to reinforce users' ownership of both physical objects and areas on top of an interactive surface.

6.4 Reducing mental workload by coupling space and meaning

RBIs often apply various strategies for reducing cognitive workload. For example, MoClo Planner allows users to easily structure and restructure spatial configurations of biological parts through direct touch in order to explore a solution space. Users can save spatial configurations for immediate access in one of the various workspaces. The interface enables users to open and close "shutters" as needed, facilitating incremental addition of complexity and seamless transition between layers of abstraction. Finally,

the interface hides information by encapsulating it in various digital objects, presenting required information upon request.

The challenge for designers is twofold: reducing the mental workload associated with operating an interface while providing support for complex tasks (i.e., syntactic load), as well as applying various strategies to reduce the load associated directly with solving problems (i.e., task load).

7 Conclusion

This paper presents three main contributions: (1) design considerations and participatory design process for enhancing college-level science education through reality-based interaction, (2) reflections on the design, implementation, and validation of two case studies of RBIs for learning synthetic biology, and (3) a set of opportunities and challenges for advancing learning in college-level sciences through reality-based interaction.

While the domain of synthetic biology provides the context for this work, the contributions of this paper are relevant to applying reality-based interaction to college-level science education in general. We also believe that designing for problem-driven learning of complex concepts at the frontier of science helps to move forward the theory and practice of educational interfaces, software, and technology.

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