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Turning experiments into objects: the cognitive processes involved in the design of a lab-on-a-chip device

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Abstract

Background: More and more, modern engineers design miniature devices that integrate complex activities involving many steps, people and equipment--- a micro-fluidic 'lab-on-a-chip' device being a good example. The design of such devices is cognitively demanding, and requires the generation of multiple model representations, which are used, in an iterative fashion, to analyze and improve prototype designs.

Purpose: The study reported here addressed two questions: How are various representations and prototypes used in the iterative design and building of a micro-fluidic 'lab-on-a-chip' device in a systems biology laboratory? In this design process, what cognitive functions did the representations serve?

Design/Method: This case study was build using mixed methods. We utilized the standard ethnographic methods of participant observation, open-ended interviewing of participants and artifact collection in an integrated systems biology research lab. Data were analyzed using open and axial coding. In addition, we used cognitive historical analysis in which we collect and analyze data from traditional historical sources (publications, grant proposals, laboratory notebooks, and technological artifacts) to recover how the salient representational, methodological, and reasoning practices have been developed and used by the researchers.

Results: The device design involved complex interactions among mental models, computational models, building and testing prototypes, using tagging and visualizations to query and validate the prototypes as well as the computational models, and integrating all these together to meet stringent experimental and fabrication constraints. Integration takes place across many different kinds of representations. The building of external representations helps not just to offload cognitive load, it also helps add detail to the mental model and constrain it.

Conclusions: Representational fluency and flexibility are required manage the complexity of modern bioengineered devices. To support the development of such fluency and flexibility, engineering students need to understand the function of such representations, which has implication for new models of learning.

1. Introduction

This paper reports on an extended case study of situated design or "design in the wild." More specifically, we focus on the role representational systems played in the design and development of a complex bioengineered artifact. More and more, engineers are developing micro-fluidic 'lab-on-a-chip' devices, which bring together in a single apparatus, a number of complex scientific activities executed by researchers in biology laboratories. These devices are often developed to improve the accuracy and quality of measurement as well as increase the number of possible measurements. The design of such devices requires a reasoning process that translates the goals and actions of intentional agents (researchers executing a complex lab routine) into mechanical procedures that can be accomplished by the device. The design also needs to take into account the constraints presented by the biological material (such as cell damage, contamination risk, etc.), the constraints imposed by the process of fabricating the device, and the research questions the device is seeking to address. Thus, the designer's reasoning process is highly complex and requires the generation of multiple external representations that are used in an iterative fashion to analyze and improve prototype designs. Here we have tried to explore and understand this process in a single case study, which chronicles how a bioengineering graduate student solved the problem of collecting time series data needed to develop a mathematical model of cell signaling.

This targeted investigation is part of a much larger, multi-year study of reasoning, problem solving, and learning in interdisciplinary research laboratories. A major objective of this body of work is to develop new models for engineering education that are informed by work and learning practices found in authentic sites of engineering and science (Osbeck, Nersessian, Malone, & Newstetter, 2011). In our *translational* approach, we investigate, through immersive engagement with real sites of work and learning *(in vivo* sites), the situated, socio-cognitive practices that engineers use to reason and problem-solve day-to-day. We then translate study findings into design principles (Brown, 1992; Brown & Campione, 1994) for classrooms *(in vitro* sites). This translational approach has been used in the design of an introductory course in engineering problem solving in biomedical engineering (W. Newstetter, Khalaf, & Xi, 2012; W. C. Newstetter, 2005) and of instructional laboratories (W. Newstetter, Behravesh, Nersessian, & Fasse, 2010). In both cases, the course design phase was preceded by an immersive, ethnographic phase, where we made a deep dive into the ways of working and learning in authentic work settings, seeking to eventually achieve a better fidelity between the classroom and the world of engineering practice.

This paper follows a four-part format. In the following section, we situate our work in prior relevant studies of design practice and cognition. In part two, we trace the emergent, iterative, and parallel representational practices employed by the designer of a microfluidic ‘lab-on-a-chip’ device, illuminating how representations at each stage served important functions for the researcher as she progressed towards a final design. In the third section, we step back and examine the possible cognitive mechanisms involved in this process. In particular, we examine how the researcher builds a distributed cognitive system through her representational practices. Finally, we extract from this case study implications both for engineering classrooms and for PIs who mentor advanced engineering students.

2. Designing engineers: A review

Researchers have long had an interest in the process of engineering design—how one moves into a design space, makes progress under conditions of uncertainty and constraint until finally, a design solution is reached. Thus, over the years, the design process has been investigated in a variety of ways. Bucciarelli discovered in his ethnographic studies of engineering design firms that design is essentially a “social process” in which incongruent understandings or “object worlds” among design team members need to be negotiated and aligned in the design process (L.L. Bucciarelli, 1988; L. L. Bucciarelli, 1996). Others have conducted think-aloud protocol studies focused on differences between novice and expert designers suggesting progressive learning pathways towards expert practice (C. Atman, Chimka, Bursic, & Nachtmann, 1999; C. J. Atman et al., 2007; Ball, Ormerod, & Morley, 2003; Cardella, Atman, & Adams, 2006; Purcell & Gero, 1998). In a normative approach to determining “good” design practices, Mehalik and Schunn (Mehalik & Schunn, 2006) conducted a meta-analysis of forty empirical studies of design to identify “high frequency” design elements or stages, one of these being graphical representation. While initially identified by the authors as an essential design activity, in the meta-analysis, it turned out to be only a moderately frequent element or a Tier 3 activity. A possible explanation for this finding is that only 50% of the articles reviewed described engineering design processes. In another review of the role of design in engineering education, Dym et al. (Dym, Agogino, Eris, Frey, & Leifer, 2005) discussed sketching and its functioning as another "language" or representation for exploring alternative solutions, enabling the generation of new ideas, compensating for the constraints of short-term memory, and facilitating problem-solving (Schutze, Sachse, & Romer, 2003; Ullman, Wood, & Craig, 1990). Further, it has been demonstrated that better design outcomes correlate with the quality and quantity of graphical representations (Song & Agogino, 2004; Yang, 2003). These previous studies establish the importance of graphical representation and strongly suggest the need to continue investigating such practices in-the-wild while also extending the notion of "representation" beyond sketching to the various representational systems utilized by practicing engineers in the pursuit of design solutions. Also strongly suggested is the importance of developing such representational capabilities in engineering students. In this study we take an important next step by investigating the situated, multi-variant representational systems designed and employed by a graduate student research engineer in pursuit of an optimal design solution.

3. Research design

Our investigations over the last twelve years have been designed to answer two larger questions: 1) How do practicing research engineers conduct their work and; 2) How does the lab environment continuously support learning? A subset of the first question includes questions specifically focused on representational systems: 1) How and when do engineers use representational systems in their laboratory work? 2) Which systems do they use and how do they decide on those systems? 3) What cognitive functions do these representational systems serve? To answer these questions, we have recently been conducting a two-year mixed methods investigation of a systems biology lab (Lab C) at a leading research university. This lab[1]was identified as a research site because of the multidisciplinary approaches the lab uses to investigate signaling in the context of the biochemical environment of the cell, with a focus on oxidation and reduction reactions. To develop this context-based understanding of signaling, the lab develops mathematical models and also does wet lab experimentation in parallel, to gain

[1] With funding from NSF we have been investigating cognitive and learning practices in interdisciplinary research settings for twelve years. During this time, we have collected ethnographic data in a tissue engineering lab, a neuroengineering lab, a bio-robotics lab, and currently in two integrative systems biology labs. This article focuses on one researcher in one of the labs, but the distributed cognitive practices described here are just as prevalent in the other labs we have investigated.

insight into the parameter settings for the models. As this study attests, they also engage in engineering design and fabrication when needed.

Given our research focus on situated socio-cognitive practices and learning ecologies, we conducted an extended ethnography employing the standard methods of participant observation, informant interviewing, and artifact collection. We observed researchers as they conducted their work on the bench tops, as they used instruments, devices, and equipment; we attended lab meetings, which were audio-taped to compliment the field notes; we sat in on PhD proposals and the weekly journal club. Field notes were collected by two team members of different genders, age and disciplinary backgrounds (industrial design and public policy), which afforded the collection of differing but complimentary data. We collected and analyzed relevant artifacts including published lab papers and dissertation proposals. Altogether, we collected fifty-two interviews (fully transcribed) and audiotaped fifteen lab meetings and two joint meetings with another integrative systems biology lab. We also used unstructured interviewing with the lab members and collaborators outside of the lab. At present eighteen percent of the transcribed interviews are fully coded.

Broadly consistent with the aims of grounded theory, we have been approaching interpretive coding analytically and inductively (Glaser & Strauss, 1967; Strauss & Corbin, 1998) enabling core categories (and eventually "theory") to emerge from the data and remain grounded in it, while being guided by our initial research questions. Coding began with weekly collaborative meetings by at least two research group members. A small sample of interviews was analyzed progressively line-by-line from beginning to end, with the aim of providing an initial description for most if not all passages in the interview. A description and code was recorded only when both researchers were in full agreement about its fit and relevance to the passage and, initially, there was no attempt to minimize the number of coding categories. Initial codes were presented in our full research group meetings (all had read the transcripts in advance) and codes were discussed until there was agreement. Descriptions and codes were revisited throughout the process in keeping with new discussion on the text as well as new observations in the laboratories. Axial coding aimed at continuous refinement and verification of the categories and connections between them. Codes were analyzed for conceptual similarities, overlap, and distinction and were grouped together under super-ordinate headings, and so forth, until no further reductions could be made. Altogether the team identified 127 codes organized into 16 superordinate categories.

In addition, we used cognitive-historical analysis (Nersessian, 1995) in which we collected and analyzed data from traditional historical sources (publications, grant proposals, laboratory notebooks, and technological artifacts) to recover how the salient representational, methodological, and reasoning practices have been developed and used by the researchers. We sought out the daily and diachronic dimensions of the research by tracing the intersecting trajectories of the human and technological components of the laboratory, conceived as an *evolving cognitive-cultural system* (Nersessian, 2006) from both historical records and ethnographic data. We used these combined data to understand both the nature of cognition and of learning in these settings. This novel combination of methods has enabled developing thick descriptions and analytical insights that capture the dynamics of inquiry characteristic of research laboratories. [2]

The case study reported here was developed and triangulated from several data sources. These include: field observations and notes of the design work unfolding on the bench top, informal, unstructured interviews of C10 (a lab member), lab meetings and the PPTs used by C10 for her presentations, two posters created by C10 for conferences, and two of C10's publications as well as her Masters thesis that reported on this work.

4.The design of a lab-on-a-chip device

4.1 The design problem

A central problem in developing mathematical models of cell signaling is the availability of time-series data, which are difficult to collect, as signaling events happen very quickly, sometimes within 20 seconds of stimulating the cell. To get an accurate picture of the signaling

[2] Our own interdisciplinary research group comprises Ph.D. level researchers with expertise in ethnography, qualitative methods, linguistics, psychology, philosophy and history of science, cognitive science, and learning sciences. Student researchers (graduate and undergraduate) have come from programs in cognitive science, intelligent systems, human-centered computing, and public policy. All members of the team received apprenticeship training in ethnography, qualitative methods, and cognitive-historical analysis.

process, measurements have to be made every half minute to one minute, which is challenging for a human experimenter, particularly if the measurement samples have to be uniform across all the time points. To overcome this problem, Lab C decided to develop a micro-fluidic (lab-on-a-chip) device, which would automate the stimulation of the cell and the collection of cell samples at different time-points. The automation would improve data collection, particularly for early signaling events that occur right after stimulation, and signaling events that occur in quick succession, thus providing cleaner and richer data for modeling.

The specific problem the lab wanted to investigate using the device was to quantify senescence (the aging of the cell, leading to an inability to replicate) in T cells, particularly which biomarkers change in correlation with the age. Since T cells collected from human donors immediately begin to age rapidly, they are only available in extremely limited quantities and can be used for experiments for only a few days. One of the advantages provided by the micro-fluidic device is that it would need only a limited number of cells for an experiment compared to bench-top methods.

To investigate senescence with this approach, the T cells need to be stimulated (mixed well with a reagent) causing different proteins to form in the cells (as a result of the signaling process) and then measured at many time-points within the first few minutes after stimulation, ranging from twenty seconds to twenty minutes. These measurements can be done at both the population level (a certain number of cells) and at the single cell level. The measurement of proteins itself is not done in the micro-fluidic device, but separately, using sophisticated biological instruments. The device freezes the cells' internal state at different time points by quenching the biochemical reactions in the cell. This is done by lysing the stimulated cells (adding a reagent that breaks open the cells; creating population samples) and fixing the stimulated cells (adding formalin; creating single cell samples). The measurement of proteins is then done offline on these samples, whose internal states are frozen at different time points in the signaling process.

Thus the device needed to automate three processes; 1) stimulating the cells (by mixing with stimulant), 2) freezing the cells internal state by lysing (by mixing with lysis buffer) half of the samples and fixing (by mixing with formalin) the other half, and 3) doing this at precisely the right moments (as defined by the desired time points). In the initial stage of the design, only lysing was considered, fixing was added towards the end of the design.

One of the early design decisions (made before C10 joined the lab) was to have a modular design, one module for the mixing process (roughly) and another for the freezing process. The two modules would be connected by tubing of different lengths, so that the liquid (stimulated cells in media) in each tube would take different amounts of time to reach the second module, where the biochemical reactions in the cells are then quenched. The varying tube lengths thus function as an analogue for different time points. The final design is shown in figure 1.

[Insert Figure 1 here]

4.2 The design process

The design of the device was developed in collaboration with another lab. In this case study, we report only the design changes and decisions involving one Lab C member (C10), a graduate student in bioengineering whom we followed closely. C10 has an undergraduate background in electrical engineering (this was her MS project), and she joined the lab with a good understanding of design and fabrication of microelectronic chips. The same techniques are used to create micro-fluidic devices. The device was created by specifying the structure of the channels (through which the liquid containing the cells would flow) using CAD software, and then fabricating this channel design using PDMS (a polymer commonly used in microfluidics). The resulting chip has very narrow channels instead of circuits, and the liquid containing the cells is pumped through these channels using a syringe pump.

The device was developed in an iterative and parallel fashion, with different facets of the device being revised repeatedly. A variety of representations were created and used throughout the design process – sometimes in parallel. In the following description, for the sake of clarity, we outline the evolution of the device using a sequential narrative of different problems. However, it is important to keep in mind that these design problems were never separate, and the device was built and experiments run using it as a whole unit, not as separate modules.

When C10 joined the lab, the research group had settled already on using a herringbone mixer (HBM) design both for mixing the cells and stimulant in the first module and also for the mixing needed for lysing in the second module. In our first interview with her, C10 noted: *"There were several rounds of the device [design]. So the first device for the first module was like this* [referring to an image] *– and all of these had herringbones – and* [member of collaborating lab] *designed it – and to be honest, I really don't know why."* The herringbone design involved creating grooves similar to fish bones (see figure 2a) on the top of the channel, which interrupt the flow of the liquids in a way that the two liquids (say, cells-in-media and the stimulant) folded into each other, thus getting mixed well.

However, for the design, the flow rate was as important as the mixing:

> *Another thing that is important in the design is the flow rate...because if you use too high a flow rate, then the cells get sheared...Imagine I put you in a tunnel and very fast I have liquids going other directions than you do, so you would shear -- and the other reason if you go too slow … then the time you spent in this region [referring to mixing image on computer] … it's big, right? …. You want the cells to go as fast as possible. In your body, when it encounters that, boom, and that's it – so you want to reproduce this thing. So these were two of the design principles – the volume and the mixing time.*

In initial experiments, C10 was part of investigations into how the geometry of the herringbone structure contributed to mixing, particularly how many cycles (one cycle corresponds to twelve herring bones in sequence) would be required to fully mix two liquids of different viscosity and/or density. This was done by developing computational fluid dynamics models (using COMSOL, a finite element analysis software for creating equation based models) of the folding of liquids with different viscosities and densities, comparing the model's output with the output of the mixer when using similar liquids, and then adjusting the HBM design and the length of the mixing channel to optimize the mixing. Confocal microscopy was used to qualitatively analyze the mixing throughout the mixing channel (figure 2c). Using analytical imaging software, C10 was able to quantify the mixing of the liquids through the channel to verify when the fluids were mixed well enough. These images allowed comparisons between the model output (figure 2b) and mixer output (figure 2c). A water and sucrose mixture tagged with dyes was used to examine the effects of viscosity and density mismatch between the two fluids.

[Insert Figure 2 here]

From the mixer, the mixed fluids moved to a splitter, which split the flow into the different tubes, the analogues for different time points: *"…and it is completely modular…so if you want to look at other types of time points, you change the flow rate or you change the tube size."* One of the problems with using tubing was that to achieve different time points, different lengths and diameters of tubing were used, resulting in pressure drop differences across them. *"The smaller tubing will have a lower resistance than the longer tubings and so that the flow rate will go faster there."* The different flow rates in each tubing led to an uneven amount of sample volume collected at their outputs. If the samples were dramatically uneven, they could not be used for the experiments. Figure 3 shows the tubing of different lengths, cut and laid out on C 10's work surface. The different lengths of tubing provide a physical representation of resistance and flow rate.

[Insert Figure 3 here]

To overcome this uneven splitting problem, pressure drop channels (PDCs) were added to the end of the tube outputs located in the second module. The PDCs acted like large 'resistors' that increase the overall resistance of the system so much that they virtually equalized the pressure differences associated with the different tubes: *"This is just a way to control to make sure that the liquid would go at the same speed everywhere."* C10 created a MATLAB program that mathematically modeled components of the device, allowing her to investigate possible geometries for the PDC by varying with its cross-sectional dimensions and length. As she noted, *"So, then basically what we could do was like play with the numbers here, like so this was for the first module (pointing to the MATLAB code]. That's the length, that's the height."* By comparing its calculated pressure drop with the largest pressure drop calculated for the tubing, she was able to create a PDC that reduced the pressure drop differences in the tubing to within 1%, evening out the fluid outputs.

[Insert Figure 4 here]

The PDCs were initially designed as rectilinear channels folded in a zigzag pattern (see figure 4d) since the PDCs needed to be long and thin but had to fit in the small footprint of the device. The zigzag pattern was thought to be a good way to fit a long thin channel in the small space of the device: *"And the cells, they were turning, and the reason was that, it was to keep space to not have fifteen millimeters lost."* This decision would lead to problems when cells were introduced. Initially, the designs of the device were being tested using only fluids.

Once the fluids were mixing well and the distributions became even across the different tubes, the device was tested using Jurkat cells, an analogue to the T cells that were to be used later in the study. The cells behaved differently from fluids in the device. The distribution in the fluid case was fairly even, but in the case of the cells, the distribution (measured as the number of cells in each output) was highly uneven. It was hypothesized that the problem arose from the splitter design. A COMSOL simulation was used to visualize the streamlines and fluid velocities within the splitter. Using the simulation and long-exposure photography to capture the flow of cells in the splitter, it was determined that the geometry of the splitter was causing the uneven distribution. The splitter was then redesigned based on a bifurcating structure to create symmetry: *"Then we wanted to have it completely symmetric because we thought that because we had ten that the cell distribution was bad."* The channels were split three times, producing eight outputs (figure 5b). The original splitter had ten outputs but it was based on a somewhat arbitrary decision to make the time-points range from thirty seconds to five minutes (with time points every thirty seconds). In the redesign, it was decided that eight time points were enough for the senescence study. The output distribution became more symmetrical but remained significantly uneven. Not sure how to fix the problem, C10 generated three different design variations and tested them at the same time (figure 5c) and settled on a variation that produced the most even cell distribution (figure 5d).

[Insert Figure 5 here]

The use of cells for testing the device also revealed another problem. The cells were getting stressed in the zigzag turns of the PDCs: *"That's exactly the story. If you don't have cells, it's almost perfect. You put cells, nothing works anymore*." In testing with T cells, it was found that the T cells were larger than Jurkat cells and they tended to get stuck in the PDCs. C10 tried widening the channels to accommodate the bigger size of the T cells, which required lengthening them as well to conserve the pressure drop*: "The problem is if I make them bigger, they stay in the device longer. Then you are screwed with your mixing time – it's so small."* It was also discovered that some of the cells were getting torn and clogging the device. A variety of redesigns were tried (figure 6a-f), culminating in the spiral model, which emerged during a lab meeting discussing the clogging problem. As C10 recounted, the PDC needed to be redesigned to avoid cell stress and clogging, which led to quite a different design:

“Yeah, the shape, I just changed the shape for the cells not to be stuck on the corners cause they didn’t like the corners. And so sometimes they would get lysed cause they would see, on the corners the cells like see more force, because the cells are, liquid turns and so the cells are so, so that more force around them, so that they weren’t very happy. So I didn’t want like to make them turn ninety degrees too often, so that’s why I changed it this way [figure 5g], so that they only turn once.”

[Insert Figure 6 here]

Figure 7 (a picture we took of a worksheet located on the microfluidics bench top) provides a good representation of how C10 worked with the completed device. This analysis was for determining where each tubing should be inserted into the device during its operation. It provides an illustration of how she brought together knowledge generated by the MATAB code (the lengths of the tubing and the pressure drops), experimentally determined knowledge about the optimal flow rate for the best distribution, the experimental constraints of the time points, and knowledge about the design architecture and performance of the device. C10 used this sheet to bring all these factors together in to determine the optimal arrangement of the tubing. One interesting feature of this representation is that it shows how C10 still had to carefully tweak the balancing of the pressure differences between the different lengths of tubing, despite the addition of the pressure drop channels to the final device design.

[Insert Figure 7 here]

Starting at the top left with “0.5”, “1”, “1.5” down to “7” is a list of all of the time points (in minutes) being used in the device. The next column to the right of this maps the lengths of tubing (in centimeters) that correspond to these time points. Notice that the length of the 1-minute time point is longer than the 1.5-minute time point. This is because the diameters of the first two tubes are smaller than the rest, as noted by “PE2.” The rest of the tubing is “PE3” diameter. The third column contains another set of lengths (in centimeters) that is just slightly different from the second column. Its inscription inside of a box suggests perhaps more updated measurements. At the bottom of this column is “@ 38uL/min.” This indicates that these are the dimensions that work with a flow rate of 38 microliters per minute, a parameter that is controlled with the microfluidics pump. The last column, on the far right, is a list of the corresponding pressure drops (in Pascals) of the tubing. C10 selected the time points to use and calculated the following numbers using the MATLAB model she created.

The sketch below is a representation of the first module in the device. The time points are mapped to outlets. Notice that they are in a seemingly random order. But just below each of these time points, there is another line of numbers. These numbers are the pressure drops mapped to each of these time points. And below this on the left, these numbers are aligned into two columns and totaled at the bottom. The two columns represent the numbers on the left side of the centerline (actually drawn on the diagram) and on the right side. They have been totaled to see if this arrangement is approximately balanced (the balance helps to even out the output distributions). After the calculation and comparison was done, the order of the tubing was revised; the .25Pa and .33Pa tubes were switched. She did not update her calculations on this sheet of paper. Possibly she tried other arrangements and perhaps other methods to find the best order, but we did not capture these processes.

5. Cognitive processes involved in the design

The description in Section 4 shows that the process of building the device was neither completely top-down (built from an explicit blueprint) nor completely bottom-up (built by trial-and-error). A complex design such as the microfluidic device cannot be built from a blueprint, since it would require conceiving *a priori* of all possible design constraints, device features, and their interactions. The fully bottom-up approach is similarly not feasible, since it would require building and testing a large number of prototypes to evaluate the different design constraints, device features and their interactions.

For complex designs, the designing and building processes take a middle path between these two extremes, with some aspects of the design envisioned (usually rough initial designs), and some aspects tested by building prototypes (mostly to improve the initial designs). As we have seen in the case of the microfluidic design process, however, the process is not completely arbitrary. It involved C10 actively developing an optimal strategy, which we argue, minimizes the cognitive load involved in conceiving of all the constraints, features, and interactions, while also minimizing the physical effort and use of resources. In this section, we address the question: What are the cognitive mechanisms that allow this optimization to be achieved?

We will first examine the lab-on-a-chip design case from a process point of view and argue that this optimization is achieved by distributing the cognitive load to the environment, particularly using external representations. This strategy is best captured by *distributed cognition*, a theoretical framework in cognitive science that we discuss below. We will then examine the design case from the point of view of the coupling between the external representations and C10's mental modeling processes.

5.1 Distributed cognition

Distributed Cognition (DC) is a theoretical framework used to describe and analyze task environments where humans interact with complex machinery, such as airline cockpits, naval ships, and nuclear power plants (Hutchins, 1995a, 1995b).This model of cognition is suited to studying cognitive processes in complex (usually technical and scientific) environments, particularly environments where external representations are used. The primary unit of analysis in DC is a distributed socio-technical system. This system consists of people working individually or together to accomplish a task, and the artifacts/machinery that perform cognitive functions in the process. The people and artifacts are described, respectively, as agents and nodes of this extended system. The behavior of the system is considered to arise from the interaction between external (artifact) and internal (human) representational structures. Within this framework, to understand how problem solving is achieved requires examining the generation, manipulation, and propagation of the salient representations in the system in accomplishing cognitive work.

A standard example of external representational structures in DC is the use of speed bugs in a cockpit (Hutchins, 1995a). Speed bugs are physical tabs that can be moved over the airspeed indicator to mark critical settings for a particular flight. When landing an aircraft, pilots have to adjust the speed at which they lose altitude, based on the weight of the aircraft for that particular flight. Before the design of the bugs, this calculation was done by pilots using a chart and calculations in memory while executing the landing operation. With the bugs, once these markers are set between two critical speed values (based on the weight of the aircraft for a particular flight), instead of doing a numerical comparison of the current airspeed and wing configuration with critical speeds stored in memory or a chart, pilots simply glance at the dial to see where the speed-indicating needle is in relation to the bug position.

This external representation allows pilots to "read off" the current speed in relation to permissible speeds using perception and calibrate their actions in response to the perceived speeds. The speed bugs (an external artifact) thus lower pilots' cognitive load at a critical time period (landing) by cutting down on calculations and replacing these complex cognitive operations with a perceptual operation. The setting of the speed bugs also leads to a public structure, which is shared by everyone in the cockpit. This results in the coordination of expectations and actions between the pilots. These two roles of the speed bug – *lowering cognitive load and promoting coordination* – cannot be understood without considering the human's internal cognitive processes and the artifact as forming a distributed cognitive system.

As with most of the research contributing to the development of the DC framework thus far, the speed bug case focuses on the human's role in coordinating external representations and does not consider the nature of the human representations in the system. Further, DC analyses typically focus on how external representations are used and not on *how they are created*. For engineering problem solving these issues need to be addressed.

First, as we have argued elsewhere (Nersessian, 2008; Nersessian, 2009) our data on how researchers think and reason provide substantial evidence that the mental representations they use in problem solving have a model-like structure. That is, they are organized representations customarily referred to as "mental models." Additionally, we have argued that a range of data on scientific reasoning, mental modeling, mental animation, mental spatial simulation, and embodied mental representation in the cognitive sciences supports the hypothesis that mental models can be manipulated by simulation–what we call "simulative model-based reasoning" (Christensen & Schunn, 2007; Nersessian, 2002; Nersessian, 2008; Trickett & Trafton, 2007). From a DC perspective, simulations are preformed through a coupling between mental models and external representations (Chandrasekharan, 2009; Nersessian, 2009)

Second, Hutchins has argued that humans build their cognitive powers by building external environments (Hutchins 1995b). However, little attention has been directed to the processes through which people build representational environments, thereby creating distributed cognitive systems. Engineering sciences provide fertile ground for examining these processes as much of frontier research involves building the external representational structures that provide the environments through which thinking and reasoning take place. Hollan, Hutchins, and Kirsh –

three founders of the DC perspective – have argued for a set of core principles which includes: a) "people establish and coordinate different types of structure in their environment" and b) "people off-load cognitive effort to the environment whenever practical" (Hollan, Hutchins, & Kirsh, 2000 p.181). Our analysis of C10's representational practices focuses on these two principles. It establishes how an individual researcher offloaded the cognitive effort of a design task by creating and coordinating representational structures. In this case, C10 and the representational artifacts comprise the cognitive system that accomplishes the task of designing the micro-fluidic device.

In the case of designing the micro-fluidic device and sophisticated design tasks in general, the task of mentally envisioning all design constraints and device features and their interactions is cognitively impossible due to its complexity. The alternate solution – generating and testing many variations of prototypes iteratively – is tedious and expensive. Our case shows how a middle-path between these approaches is developed, using four strategies that work in combination, all based on the generation of external representations that help *transfer cognitive load* to the environment.

Simulating: Developing external models that simulate a large number of possible scenarios and using these model scenarios to infer a viable structure for prototypes.

Visualizing: Numerous drawings make explicit the designer's mental models of how the device seeks to achieve the design objectives. There are many analyses of such drawings (e.g. Purcell & Gero, 1998), so we will not go into these in detail here. In relation to these drawings, the behavior of the prototype is also visualized using imaging techniques and graphical representations of the output of the device.

Tagging: This is the strategy of marking prototypes in a way that they can reveal their behavior/properties. Just as with the speed bug, tagging allows the designer read off the relevant behavior/properties visually and, thus, to bypass complex inference processes while evaluating the design. While tagging is an obvious and commonplace cognitive strategy in everyday life, it is a complex problem in biological experimentation, as biological tags need to meet many experimental constraints.

Interrogating: Once built, a prototype *also* serves as a representation. This is because apart from testing the prototype to see if the design constraints are met, it is possible to make changes to the prototype, and examine the resulting behavior. This helps in revising the designer's mental model of the problem and also isolating problems. For such probing-by-changing (interrogation of the device) to be possible, the design needs to be modular so that different variations of device features can be examined in relation to the design constraints. Modularity is often considered part of good design practice, but this is usually recommended from an engineering/manufacturing standpoint (Clark & Baldwin, 2000). From a cognitive standpoint, modularity contributes to the use of the prototype as an external representation, and thus shifts the cognitive load to the environment. A modular prototype can be 'probed' by altering different components and using different configurations, and this probing can help the designer to understand the problem better, isolate sub-problems, and sometimes it helps in revising the very way the problem is conceptualized.

The design of the microfluidic device exhibits all these cognitive load-reduction strategies. To understand how and when these strategies help lower cognitive load, we will examine one component of the design process in detail: the design of the herringbones.=

5.1.1 The design of the herringbones

As stated earlier, the herringbone design for quickly and efficiently mixing the fluids was chosen from a set of alternatives before C10 joined the group. Once chosen, C10 needed to know the relationship between: 1) the geometrical features of the herringbone structure, and 2) the level of mixing of liquids that result from the fluids passing through a given geometrical structure.

One possible way to do this is would be to build many different herringbone structures, evaluate the mixing for each using some measurement, and then iterate until the optimal mixing is achieved for a specific set of fluids. Note that the iterations would involve changing the geometrical structure and this would require the designer to think about how the mixing would be affected by a particular change. This, in turn, is based on developing a mental model of how the mixing is affected by the current geometry and fluid properties. This process would be cognitively demanding, tedious, and would require a high degree of physical effort and resources. Also, the design produced by such a trial-and-error approach would be very specific, suitable only for a given set of liquids or flow rates and not easily varied to suit other conditions.

Instead of such a trial-and-error approach, C10 developed a model using a computational fluid dynamics software (COMSOL), which allowed her to capture the pattern of flow for different channel geometries, for different liquids. The results of this model were compared against actual flow patterns in prototype channels, where water and sucrose were used to simulate viscosity. A fluorescent tag was added to the liquids to track the level of mixing. Confocal microscope images of the flow were then compared against the flow patterns generated by the model's visualization, to establish the level of correspondence between the model's output and actual output. Once a good correspondence was established, the validated model was used to generate and test different possible geometries. The model geometries that produced the desired mixing most quickly were built and tested. In addition to lowering the number of built prototypes, the COMSOL showed in clear terms the level of mixing achieved and the time taken, and the model's visualizations were used for this purpose in related publications.

The design process made use of the first three externalization strategies outlined above, simulating, visualizing and tagging. These, in combination, made C10's inferring the relation between mixing and geometry cognitively tractable and also lowered the number of prototypes developed. Once validated, the COMSOL model worked as what could be called an "external imagination," allowing C10 to simulate and visualize many variations and combinations of geometries and liquid properties. The tagging of the liquid (in the prototype) with the dye allowed her to read off the level of mixing visually, instead of inferring it indirectly. The tagging also allowed capturing the level of mixing using the confocal microscope images, which, in turn, enabled an explicit comparison between this image and the model's output, as well as C10's visual impression. Note that to vary the herringbone geometry using COMSOL, C10 needs to have a mental representation of the mixing process and she mentions thinking of the herringbones as "folding" the liquids. But her mental model is now *coupled* (Kirsh, 2010; Nersessian, 2008; Nersessian, 2009) with the computational model's output allowing the two to work as an integrated system, particularly with the tagged liquids and the resulting visualization. This coupled distributed cognitive system helped C10 arrive at a fine-tuned, adaptable and optimal design, with minimal prototyping. The coupling between internal and external representations arises from a strategy of actively generating external representations to lower cognitive load. The actual techniques used to externalize processing (modeling, tagging, visualizing and interrogating) will vary across design situations, but the underlying externalization strategy is the same for other situations.

5.2 Simulative model-based reasoning (SMBR)

The above analysis focuses on the general design strategy, specifically the process of offloading cognitive processes to external representations, which is applicable across many types of designs. The DC analysis does not address the cognitive mechanism that helps C10 imagine her particular design problem or how this mechanism is related to the offloading of cognitive processes to the world. In other words, we have not yet discussed the nature of her mental representations and the cognitive mechanism involved in processing the content, or the way the mechanism integrates the external representations with C10's mental representations. For this we need to bring the notion of *simulative model-based reasoning* (Nersessian, 2002) into the analysis.

The central problem in the design of the device is translating experimental procedures executed by researchers, in such a way that these procedures are executed by the device, but more efficiently. The researchers' experimental procedures involve actions, which are dynamic, but the device is static. The dynamic component is replicated using the flow of media through the device, and the effects of the researchers' experimental procedures (mixing, freezing) are recreated by manipulating the flow. *Flow* is thus the central component of the designer's mental representation.

It is fairly straightforward to imagine mixing being recreated by manipulating flow and freezing being recreated by combining the cell media with lysing/fixing reagents. However, replicating the different time points of measurement using flow requires a *conceptual shift*. C10's use of different lengths of tubing (figure 3) to recreate lengths of time involves a rather radical representational transformation (time to space), and this transformation drove all later revisions to the device. Instead of waiting a certain amount of time before quenching the reaction – which would be the procedure followed by a human experimenter – the *device transforms different time periods into different distances* flowed by the liquid. This is a novel transformation of the problem space, and it allows the researchers to conceive the entire design in terms of fluid dynamics. Critically, this unifying mechanism makes it easier for the designer to integrate the imagined flow process with the outputs of the external representations.

A *mental model* is the best way to characterize C10's internal representation of how media flows through the device. Since the flow process involves a combination of both dynamic and static features, imagining it requires integrating simulation and imagery, and a mental model is the cognitive process that supports this integration. Mental modeling allows both dynamic and static features to be manipulated in the mind, and the nature of this manipulation is considered to have correspondences with a built model. But the mental model is more abstract than the external built model in the sense that the features need not be (often cannot be) as specific as in external model. In the beginning phase of this design process, C10's mental model was likely quite generic, since the features and the nature of flow were not known. The building of the prototypes, the computational model, the external representations, and the testing using different fluids, gradually added more specificity to the mental model, both in terms of features as well as of the nature of the flow. The building of external representations thus helps not just to offload cognitive load, it also helps add detail to the mental model and constrain it (see also Kirsh 2010).

A possible way of thinking about the design process would be to consider the prototypes and external representations as instantiations of an existing mental model. However, this description does not capture the design process of the device because of the way the prototypes and the external representations were used to identify and solve problems (such as the splitter design), and also to revise the mental model (to include features of the cell). The case study establishes that there was an *interactive process* between the internal and external representations, and they were integrated to form a distributed system that performed the reasoning processes. In this case, the final outcome of this simulative model-based reasoning is a novel object with features that support new experiments.

In this case study, the design of the device involved complex interactions among mental models, computational models (COMSOL, MATLAB), building and testing prototypes, using tagging and visualizations to query and validate the prototypes as well as the computational models, and integrating all these together to meet stringent experimental and fabrication constraints. Understanding this outcome requires examining how integration takes place across many different kinds of representations. We believe that this process of representational use and integration is not just an isolated case of simulative model-based reasoning, but rather emblematic more generally of sophisticated engineering design practice. Striking the middle path between following a fully formed blueprint and building bottom-up requires that the expert engineer find strategies for minimizing the cognitive load and the physical effort and time required. The interplay/interaction between device drawings, computational modeling and simulation, and provisional prototypes supports the progression from idea to a fully functional material artifact. While many have noted the importance of sketches, drawings and prototypes in advancing a design concept using think-aloud protocols and analysis, the complex integration of varied representational systems towards the development of a designed artifact has not been investigated "in the wild" from a cognitive perspective. This study is a first step towards a better understanding of the important cognitive processes that undergird the sophisticated design of complex interdisciplinary devices. The more we understand the authentic, situated cognitive reasoning and problem solving practices of expert engineers, the better we can design learning environments that support those practices.

6. Implications for engineering education

Overall our case study illuminated how a designing engineer distributes reasoning and problem solving over the span of a complex design task and uses simulative model-based reasoning to engage and solve local problems. Drilling down, we excavate three implications of this work for engineering education.

6.1 Promoting the concept of distributed cognition as an antidote to "all in the head"

If we consider the situated design practices of this researcher as a starting point for thinking about engineering learning, the salience of the distributed cognitive system is most striking. It is not the solo engineer making decisions in the head. Rather, it is the coupling of the mind with the emergent, iterative, and parallel representations that allows for trouble-shooting in route to a more optimal design solution. By building and manipulating the external model, the engineer is able to make inferences not possible without this distribution of cognitive work across the internal and the external representations. Thus, learning to be an engineer essentially means learning to embrace the need to develop and use external representations of all kinds from free body diagrams to physical prototypes to Matlab simulations as essential to the problem solving process generally and design specifically. It is this conception of problem solving and reasoning that we need to impart to engineering students.

But as any faculty member knows who has encountered student resistance to drawing diagrams as the prelude to doing the math, this understanding is not easy to come by. We contend that it is not laziness or a desire to plug-and-chug, but rather a failure of students to grasp the centrality of process of diagrammatic representation as the actual articulation of the problem and solution, which the mathematics then represents. We conjecture that this is because engineering students harbor naïve conceptions of thinking and learning as being solely in the head. To them, few things external are important or essential to problem solving other than mathematics because they have practiced this math-driven protocol repeatedly in prior schooling. This study of situated design clarifies why we need to bring our students to a revised understanding of learning and problem solving, an understanding that appreciates the boot-strapping value of distributing the complexity of cognitive tasks across internal and external representations. This is the cognitive practice of an engineer. This is why the free-body or circuit diagram is so emblematic of the engineering habit of the mind. Students need to understand that external representations and manipulations of the problem are not incidental. They need to understand that the community practice of leveraging multiple kinds of representations and provisional models fulfill at least three functions: 1) they allow you to manage complexity and detail that you cannot manage "in the head" alone; 2) they bootstrap new ideas and provide new ways of manipulating these ideas; and 3) they make it possible to run a cognitive process quicker and with greater precision (Kirsh, 2010). A major challenge for engineering faculty is to get students to understand the nature and the power of distributed cognition and simulative model-based reasoning.

Unfortunately, engineering textbooks perpetuate the false notion that the external representations (usually diagrams) are unimportant because these are generally provided to the student. The student task then becomes one of doing the math. More classroom activities need to focus attention on diagrammatic representations and computational simulations and their pivotal role in the reasoning and problem-solving process. One idea would be to give students several diagrams that they would need to map back to the problem prompt. Another would be for students to create a problem prompt from a free body diagram. Another still would be to give students a constrained design challenge and have them build a Matlab simulation and play with it to find an optimal design solution. We cannot simply assume students understand the value of external representations as cognitive tools. We need to more intentionally help them understand this.

6.2 Complex problems demand representational fluency and flexibility

Engineering classrooms should help students develop a repertoire of representational practices that can be flexibly utilized in problem solving. The more complex the problem, the more onerous the cognitive load, and the more the cognitive load, the more need to distribute the cognitive tasks to the environment. This is when the value of a diverse toolkit of representational strategies can become clear to a student. However, if the classroom task is constrained and relatively simple, there is no need to use or master diverse representational strategies. And of course, their value will not be evident. Unfortunately, the problems generally found in engineering classes, perhaps with the exception of the capstone course, rarely require more than one or two representational practices. Students therefore have few opportunities to see how representational chaining can be foundational to problem solving. From a classroom design standpoint, an instructor could decide on a series of representations that s/he wanted students to practice using, and then develop a set of specific complex problems that would benefit from those forms of cognitive distribution. Thus, the learning objective would not be focused on mastering content but rather on developing more expert-like representational skills while expanding the existing repertoire. This of course implies moving out of the textbook and into the realm of authentic real-world problems that are cognitively onerous and need fluency and flexibility in representational practices.

6.3 Visioning is afforded by modeling fluency and flexibility

Complex design problems invariably entail encountering snags or impasses when the immediate problem solution strategy fails. When this happens, the engineer needs to develop a trouble-shooting strategy that is targeted and efficient. In the case study, we see such impasses with the mixing and with the uneven splitting, as two examples. In each case, when the trouble was realized, the engineer developed a representational strategy, a kind of *cognitive partnering* capability (W. C. Newstetter, 2005; Osbeck & Nersessian, 2006) that allowed her to “see” into the space in a particularly targeted way that supported the troubleshooting. With the uneven mixing, developing a computational fluid dynamics model of the folding liquids allowed her to envision her impasse in a way that enabled her to address the problem. So representational fluency needs also be understood as a troubleshooting strategy, which is unfortunately not how engineering students might understand a computational fluid dynamics model. The reason for this is that although engineering students often practice developing mathematical and computational models for class assignments, it is doubtful that they come to understand the *envisioning* capability afforded by such approaches when faced with an impasse. For the most part, such practice is about mastering a concept for a test or fulfilling an assignment. Suppose an instructor were to present students with problems like uneven mixing in a device or cells clumping in a tube and then ask them to develop representational approaches for seeing into the space before actually going to the design and manufacturing stage? If we want students to understand the very sophisticated envisioning capabilities offered through flexible representations, they need practice identifying and harnessing such cognitive partners in the context of troubleshooting.

7. Conclusion

In this paper, we have reported on a case study of an engineer designing and building a novel lab-on-a-chip with the intent of highlighting the important function that representational fluency and flexibility played in troubleshooting and reaching a design solution. Moreover, we have offered a cognitive lens through which to understand the day-to-day activities of scoping and responding to a real world design problem. Distributed cognition and simulative model-based reasoning are two particularly significant cognitive theories relevant to unpacking how engineers reason and work. We think it is very important in the design of engineering learning environments to understand engineering as practiced both at the frontiers of science and also in industry, especially as more and more traditional lecture modes of delivery are being called into question. In our work, we are attempting to develop an integrative cognitive-socio-cultural account of such work. In this brief analysis, we illuminate the cognitive aspects of research design and problem solving to highlight the distribution of cognition across researchers and representations. If we can better understand how knowledge and skills are deployed in real world engineering problem solving, we can better identify design principles to assist us in the development of educational models that achieve greater between the two sites. This continues to be the goal in our translational approach to educational design.

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Figure Captions

FIGURE 1

An overview of the device consisting of Modules I and II (made in PDMS using soft-lithography) connected via tubings over varying length (generating time-points from thirty seconds to seven minutes). Image (a) shows the device set-up and running with colored fluids. Image (b) shows the stimulation mixing channel (the straight portion) and splitter (used to distribute the cells into the eight different tubings). Image (c) shows the pressure-drop channel (PDC) and (d) shows the quenching mixing channels for both the fixing operations (formalin) and the lysing operations (lysis buffer). All figures reprinted with permission of C10.

FIGURE 2

Image (a) shows the first cycle of the mixing channel (consisting of six right-bias herring-bones followed by six left-bias herring-bones) overlaid with cross-sections generated by COMSOL. In the actual device, the herringbones were on the top of the channel, not the bottom as shown in the model. Images (b) and (c) compare the COMSOL model output (b) with experimental results (c) captured using confocal microscopy. C10 quantified mixing using imaging software to analyze the images.

FIGURE 3

Tubings cut and lain out on the table.

FIGURE 4

Image (a) shows the direct output of the initial splitter without any tubings attached. Graph (b) shows the output distribution of fluids with various tubing lengths before the first pressure drop channel (PDC) was implemented. Graph (c) shows the output distribution after the PDC was implemented. Design (d) shows the rectilinear zigzag geometry of the PDC.

FIGURE 5

Shows the evolution of the design of the splitter. When design (a) was tested with cells, the output distribution was found undesirable. A bifurcating design geometry was the first attempt to improve the distribution (b). The output distribution became more symmetrical, but remained significantly uneven. Not sure how to fix the problem, C10 generated three different design variations and tested at the same time (c). Design (d) was selected as the final design.

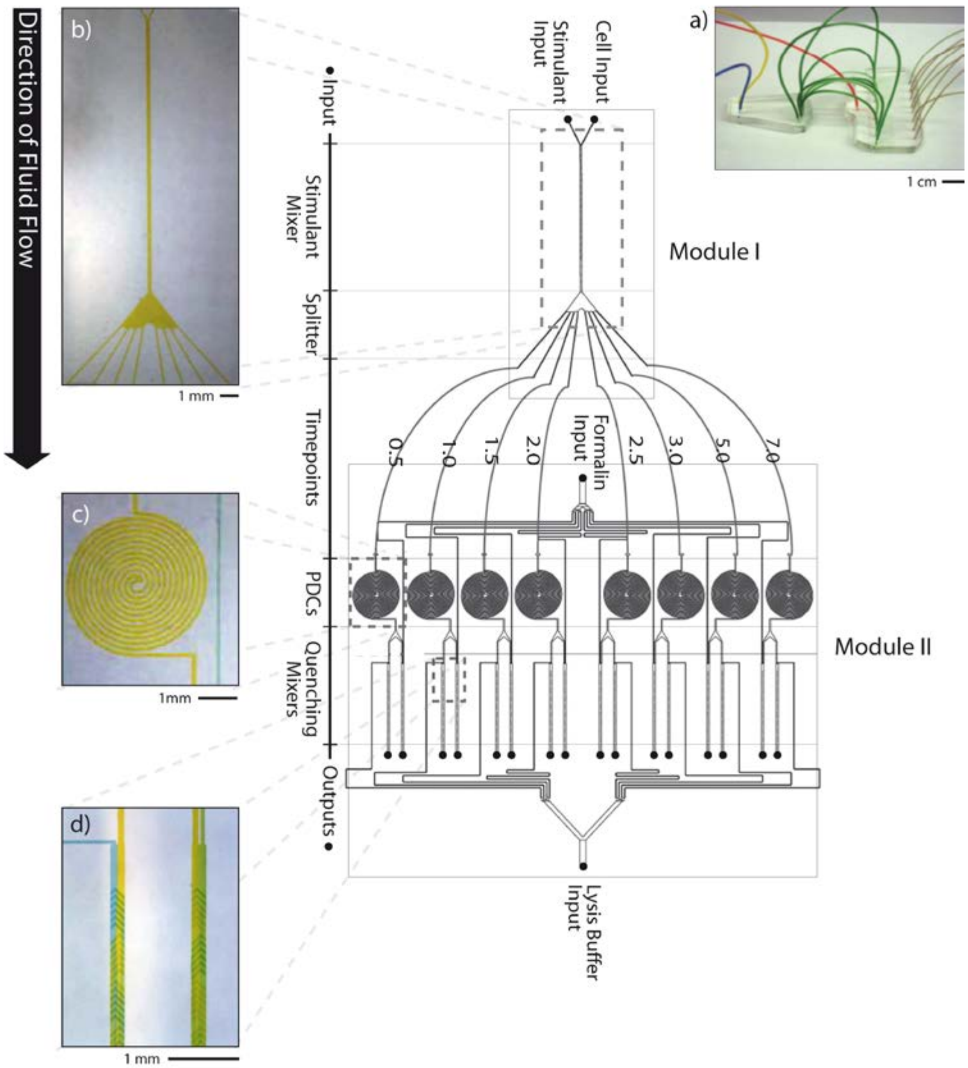
FIGURE 6

Shows the evolution of design of the pressure drop channels (PDCs). Design (a) was created to solve the uneven fluid distribution problem, prior to testing with cells. The PDCs were lengthened in response to the first cell trials (b). Later, when the fixing operation was added, a splitter was added immediately following the PDC (c). The PDCs were widened (and subsequently lengthened) to accommodate the T Cells (d). It was then discovered that the cells were consistently being destroyed in the PDCs and clogging the device. It was hypothesized that the large number of quick turns induced too much shear stress on the cells, causing them to break open. Design (f) was an attempt to reduce the number of turns the cells experienced. But the PDCs were still getting clogged. The next design eliminated the zigzag rectilinear geometry altogether (g). This became the final design.

FIGURE 7

A picture of a worksheet located on the microfluidics bench top. We highlight the different components of knowledge C10 brings together: knowledge generated by the MATAB code (the lengths of the tubing and the pressure drops), experimentally determined knowledge about the optimal flow rate for the best distribution, the experimental constraints of the time points, and knowledge about the design architecture and performance of the device.

FIGURE 1



Direction of Fluid Flow
a)
1 cm
b)
1 mm
c)
1mm
d)
1 mm
Input
Stimulant Mixer
Splitter
Timepoints
PDCs
Quenching Mixers
Outputs
Cell Input
Stimulant Input
Module I
Formalin Input
0.5
1.0
1.5
2.0
2.5
3.0
5.0
7.0
Module II
Lysis Buffer Input

FIGURE 2

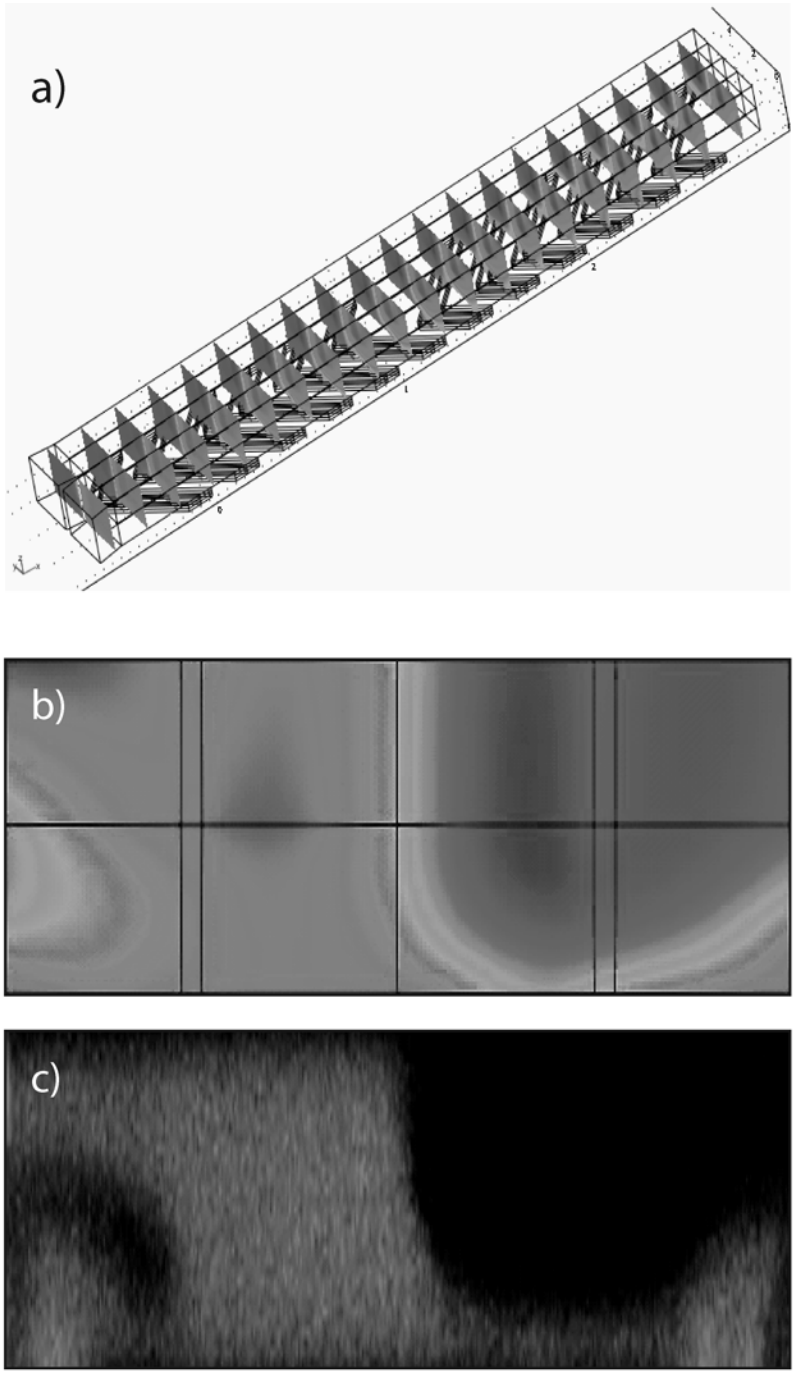


FIGURE 3

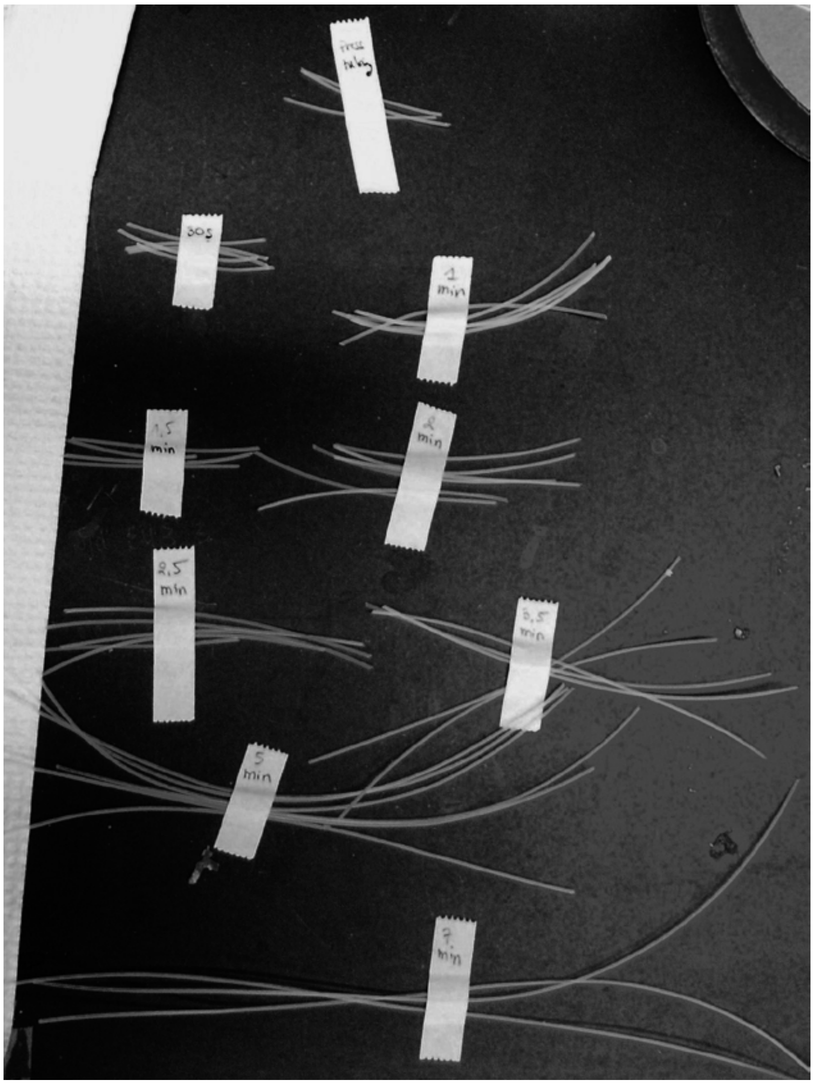


FIGURE 4

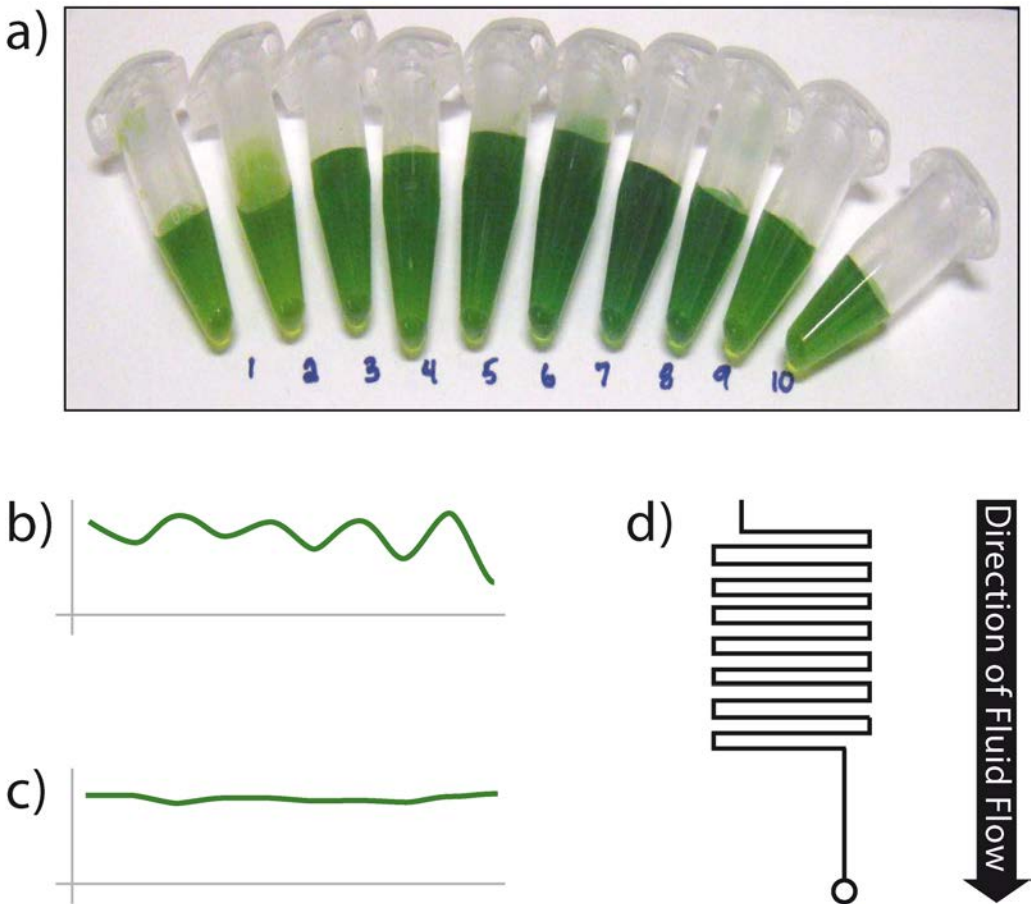


FIGURE 5

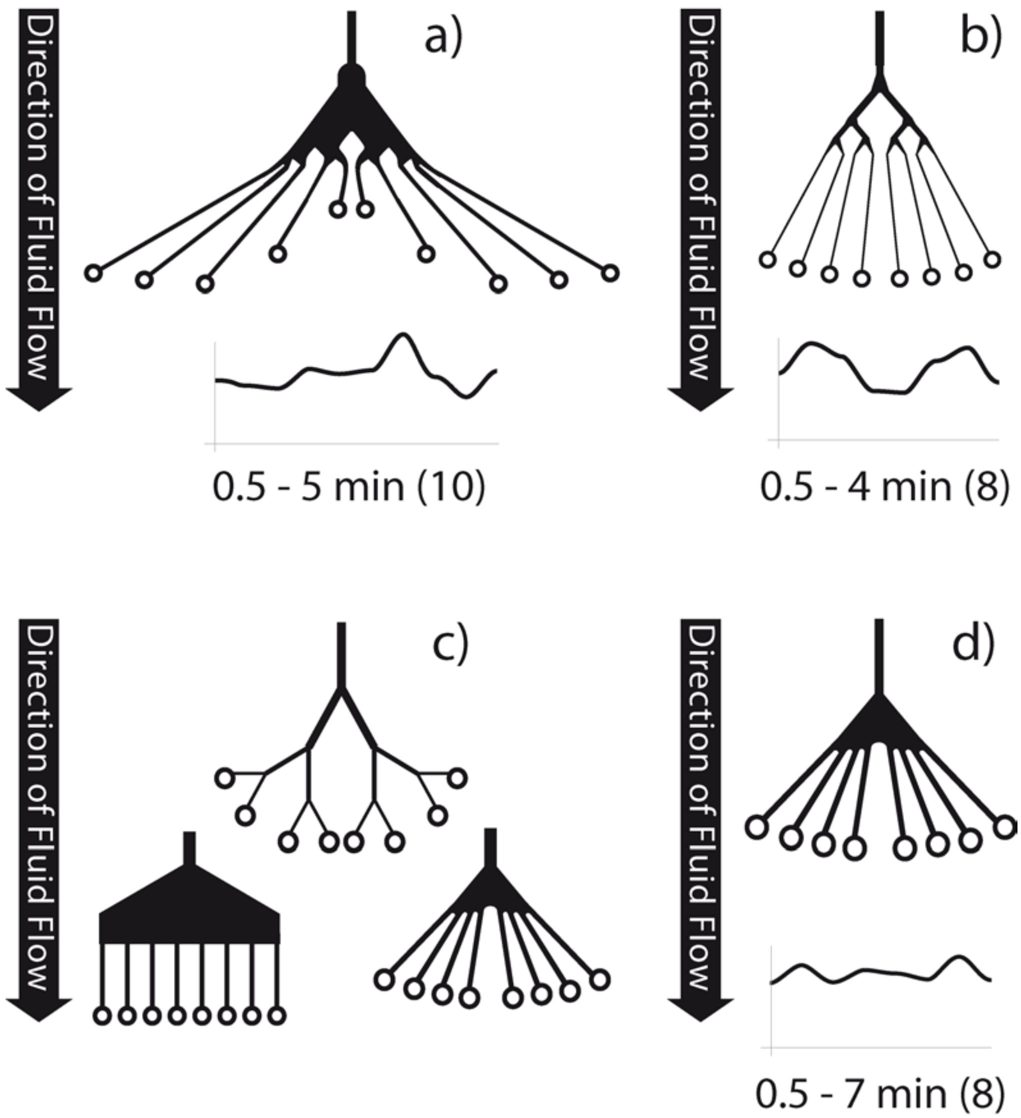

Direction of Fluid Flow
a)
0.5 - 5 min (10)
Direction of Fluid Flow
b)
0.5 - 4 min (8)
Direction of Fluid Flow
c)
Direction of Fluid Flow
d)
0.5 - 7 min (8)

FIGURE 6

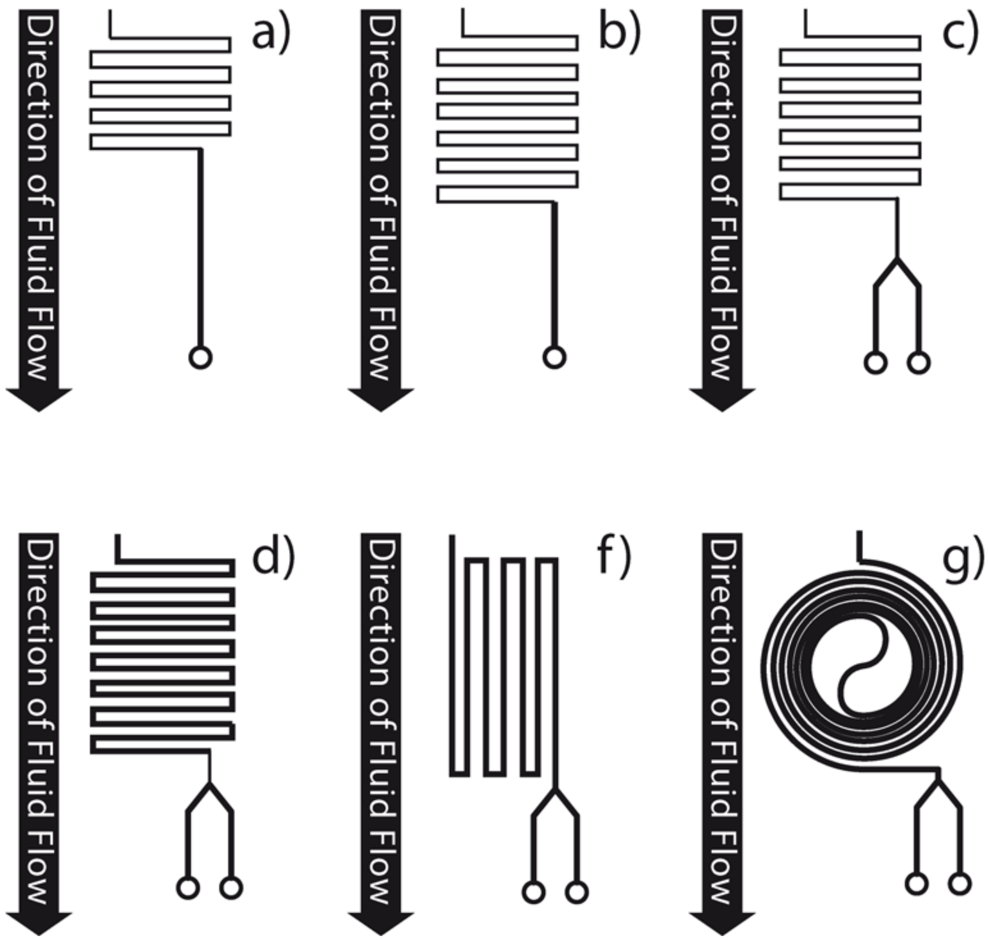
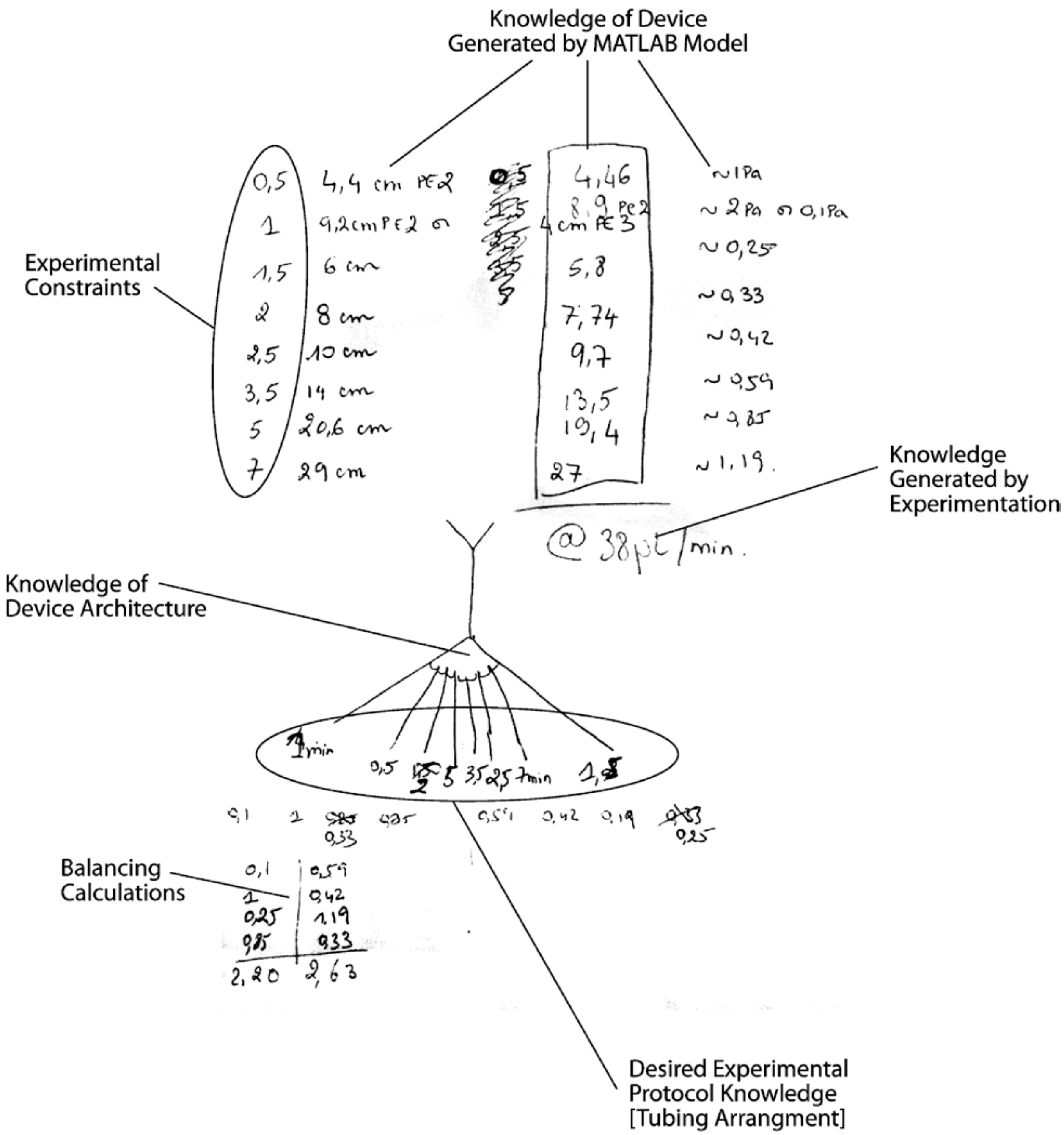

a)
b)
c)
d)
f)
g)
Direction of Fluid Flow
Direction of Fluid Flow
Direction of Fluid Flow
Direction of Fluid Flow
Direction of Fluid Flow
Direction of Fluid Flow

FIGURE 7


Knowledge of Device
Generated by MATLAB Model
Experimental
Constraints
0,5
1
1,5
2
2,5
3,5
5
7
4,4 cm PE2
9,2 cm PE2
6 cm
8 cm
10 cm
14 cm
20,6 cm
29 cm
4,46
8,9 PE2
4 cm PE3
5,8
7,74
9,7
13,5
19,4
27
~1Pa
~2 Pa
~0,25
~0,33
~0,42
~0,59
~1,19.
Knowledge
Generated by
Experimentation
@ 38µL/min.
Knowledge of
Device Architecture
Balancing
Calculations
2,20
2,63
Desired Experimental
Protocol Knowledge
[Tubing Arrangment]