

Characterizing the Role of Modeling in Innovation*

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Modeling is a core skill for engineering students and a pervasive feature of the engineering curriculum. Engineering students engage in modeling anytime they use an equation, flow chart, force diagram, or any other representation of some physical phenomena regardless of discipline. In this way modeling relates to both design process and analysis; however, students do not always recognize the full and nuanced ways that these two interact. This paper reports results from our research that is exploring the role that computational, analytical, and modeling abilities play in innovation, in the context of engineering design education. Our study reports results on faculty and students' conceptions on the role of modeling in design. Specifically, our study sheds light on the variations in how faculty and students describe how to model a design idea or solution, and the different ways each group perceives how models can be useful/helpful in the design process. Our findings indicate that students recognize the descriptive value of physical models but mention the more abstract mathematical or predictive nature of modeling less often. In addition, we found significant differences between students and faculty responses in providing mathematics or theory as an approach to modeling a design solution.

Keywords: modeling; conceptions; design; adaptive expertise

1. Introduction

This paper reports results from our research that is exploring the role that computational, analytical, and modeling abilities play in innovation. Society's most pressing technological needs such as national security, public health, and environmental sustainability, require substantial subject matter knowledge to develop realistic solutions to meet these needs. Engineering solutions to modern technological needs require foundational analytic skills and facility with modern computational tools and methods, which are at the core of modeling. As educators/researchers, we are compelled to better understand how learners can effectively bring this complex knowledge to bear in the process of innovation.

We are applying the learning framework of adaptive expertise to focus our work and guide the research [1]. Adaptive expertise is an emerging area of research on learning that has shown promise in providing enhanced understanding of knowledge transfer. Such critical research directly relates to U.S. global competitiveness by providing an improved understanding of what is required to train innovative and effective problem solvers who can transcend narrow disciplinary fields. The framework of adaptive expertise has been presented as a way of thinking about how to prepare learners to flexibly respond to new learning situations, which is precisely what students are expected to do in the context of engineering design innovation. We focus on 'computational adaptive expertise,' which we abbreviate CADEX, since a major portion of an engineering curriculum focuses on developing flu-

ency in knowledge associated with analytical, computational, and modeling abilities [2]. Yet, students often struggle with applying or transferring this knowledge in the context of design and innovation.

We focus on modeling since this is a core skill for engineering students and a pervasive feature of the engineering curriculum. Modeling is one activity that students are expected to perform throughout any engineering curriculum including fundamental engineering and foundational math and sciences courses. The nuanced and complex activity of modeling presents a challenge in engineering education that our research has indicated even senior year students often do not have fully developed conceptions of modeling capabilities and uses [5].

We have collected data from several studies, over several years from introductory, intermediate, and capstone design courses. Throughout our data collection we have focused on various aspects of CADEX including decision making in design [3], mathematical modeling competency [4], and conceptions of modeling for design and innovation [5]. The current paper reports results from our study on student and faculty conceptions of the role of modeling in engineering design. The study sheds light on potential changes that might occur in the engineering curriculum to help explicitly teach the concept of modeling to support the process of innovation.

2. Review of literature

Schwartz, Bransford, and Sears [1] proposed that adaptive expertise emerges from a balance between efficient use of knowledge and the innovation skills

associated with accessing prior knowledge, and generating new ideas and knowledge. Using a two-dimensional graph they propose an efficiency scale (x-axis) indicating an individual's competence to fluently apply knowledge and skills to complete activities they have significant experience performing, and an innovation scale (y-axis) indicating a process of generating new knowledge and ideas that are useful for achieving a novel goal (Fig. 1).

As individuals advance their ability to replicate performance on familiar tasks, they advance along the efficiency axis to develop 'routine' expertise. As Hatano and Inagaki [6] noted 'routine experts are outstanding in speed, accuracy, and automaticity of performance, but lack flexibility and adaptability to new problems' (p. 266). In contrast, the innovation scale introduces the notion of adaptive expertise making the target a combination of developing fluency along the efficiency scale combined with recognizing how knowledge applies in novel ways. Adaptive experts can go beyond procedural efficiency and 'can be characterized by their flexibility, innovative, and creative competencies within the domain' [7] (p.28).

Some of our previous work has explored the type of knowledge that might characterize efficiency in the context of design. Specifically we have examined students' development of design process knowledge, and how this gets applied when developing design solutions [8, 9]. This work has shown that students develop appropriate fluency in design process knowledge including the use of brainstorming as an idea generation technique, constructing mock-ups for user testing, defining the problem in consultation with users and clients, and using project management tools such as Gantt charts and decision matrixes. While we found significant gains in aspects of several areas of a human-centered design process, one area that was missing is students' recognition of the role of analysis in developing design solutions.

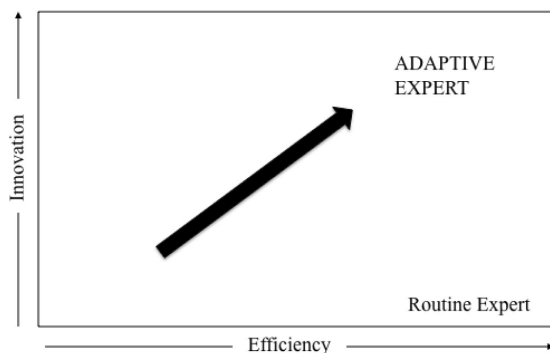


Fig. 1. Adaptive expertise as a balance between two dimensions: efficiency and innovation [diagram adapted from reference 1].

Building on this notable absence of an important skill in students' design process we conducted follow-up studies to explore the role of analysis in design. We targeted modeling as a specific type of analysis since engineering students perform modeling, whether it is acknowledged explicitly or not, throughout their entire engineering curriculum. For example, all of the engineering fundamental courses regardless of discipline engage in modeling anytime they use an equation, flow chart, force diagram, or any other representation of some physical phenomena. In this way modeling relates to both design process and analysis even though students do not always recognize the full and nuanced ways these two interact. As Dym [10] also noted there are 'several languages or representations used in design, including . . . graphical representations . . . mathematical or analytical models' (p. 147). In particular, design process knowledge can be described as a multidimensional and interdependent set of representational languages, or models, that are enacted at different stages [11]. Moreover, studies have suggested that representational skills may be a hallmark of expertise [12, 13] and an important skill for how engineers and designers communicate with each other [14].

Given the pervasiveness of modeling in engineering, and the absence of this in our earlier studies of students' design process, our current paper explores students' and faculty conceptions of modeling. Starfield, Smith, and Bleloch [15] claim there are two categories of models: descriptive and predictive. Descriptive models represent what is expected, while predictive models represent theoretical behaviors. Our study revealed an overwhelmingly descriptive-centric conception of modeling. We believe that this conception is based on more than just semantic issues that arise with the term modeling [16]. Students appear to be developing specific notions of engineering modeling in large part based on their course experiences. This suggestion reflects not just what is present in the curriculum but rather, what is absent or tacit.

The teaching of modeling is easily complicated by semantics in that the term 'model' can be a noun, verb, or adjective. Maki & Thompson [16] note that the term modeling has different meanings depending on the context. In everyday use, modeling references a display version or miniaturization of something. This use of the term corresponds in engineering to physical models intended for experimentation, display, and emulation purposes. Engineers also use the term model in a much more precise way, e.g. predictive models—theoretical, logical, and mathematical—which represent behaviors [15]. It is important to recognize that meaning derived from everyday use of the term is not

always consistent with the nuanced technical meaning.

A goal for teaching modeling is therefore to guide students in the discovery of the intended uses, appropriate applications, and embedded assumptions of models. Modeling is a process not just a product. As Lesh & Doerr [17] describe, modeling is a cyclic activity consisting of real world descriptions, prediction manipulation, and verification. Modeling as a process provides students with an understanding of how to create purposeful and meaningful representations.

Perkins [18] cautions that the term model does not include everything. For example, he explains that Newton's equations of motion may *describe* the way things move but not necessarily *model* the way things move. Furthermore, he explains that models are intrinsically ambiguous, and that often, additional information is necessary to make sense of any model. To determine which properties of a model are important, we highlight features with words or labels. This can lead to a compound effect of using one type of model (e.g. words, symbols, etc.) to explicate or highlight aspects of another model (e.g. sketch, diagram, etc.). As Perkins states 'models fill our everyday life and thought . . . their commonality becomes invisibility' (p.131). This statement captures an important point for the teaching of modeling. As educators we take for granted that students understand that we are teaching different types of modeling that are appropriate for different types of analysis and decision-making. The explicit reasons for modeling fade in the background such that they become invisible causing students to often lose sight of or not even notice that they are engaging in the process of modeling, and for what purpose.

3. Research methods

3.1 Participants

Two pools of participants were solicited at a large southwest university to obtain both faculty and student conceptions. Faculty responses were represented by 24 of 38 engineering faculty (68% response rate) at the rank of professor, associate, assistant, and lecturer. Faculty were recruited at the monthly faculty meeting for the department of engineering. Teaching experience for the given sample ranged from one to forty years ($M \sim 16$ years) in a variety of engineering-related courses. Students were recruited from a sophomore-level required project-based design course. Of the 63 students enrolled in the course, 60 students (95% response rate) completed the survey.

This particular engineering curriculum is unique in that students enroll in project-based/design

courses every semester. In addition to emphasizing a very hands-on, applied approach, the program is multidisciplinary. The department is not structured according to traditional engineering disciplines, but rather applies a multidisciplinary approach to engineering that is supported by the structure of the curriculum, the types of projects, and perhaps most importantly, the beliefs and culture of the department. For example, students do not choose a major but have the option of choosing primary and secondary concentration areas in topics such as mechanical engineering systems, robotics, electrical engineering systems, and social entrepreneurship.

The nature of the department attracts a unique student body representing a range of traditional and non-traditional student populations. Some students have enrolled directly from high school, but many others are transfer students and/or older students returning to college after working full-time or serving in the military. Many of the students have families and work either part- or full-time. Therefore, while data collection occurred in a sophomore-level project course, we want to acknowledge that the individuals in the class may not be representative of 'typical' sophomores.

3.2 Data collection

Data was collected during the Spring 2011 semester. Faculty responses were recorded in January prior to the start of the semester. Student responses were collected twelve weeks into the semester. Both pools of respondents were asked to answer a series of open-ended questions regarding their conceptions of modeling in design. In this paper we focus on the first two items:

1. Describe different ways to model a design idea or solution.
2. In what ways can models be useful/helpful in the design process?

3.3 Data analysis

An open-coding approach was taken to identify emergent categories in the data [19, 20]. A single rater first read each student's response to determine a set of categories compiled into a rubric. The rubric was then used to code each student's response. A second rater then used the rubric to test its reliability across raters. The second rater repeated a two-step process consisting of 1) coding 10% of the responses using the rubric, and 2) consulting the first rater's codes, until agreement was reached. Changes to the rubric were made to establish 100 percent inter-rater reliability between the two raters.

Seven codes of interest emerged from the data for question one: physical, computer, mathematical, theoretical/conceptual, written, verbal, and the

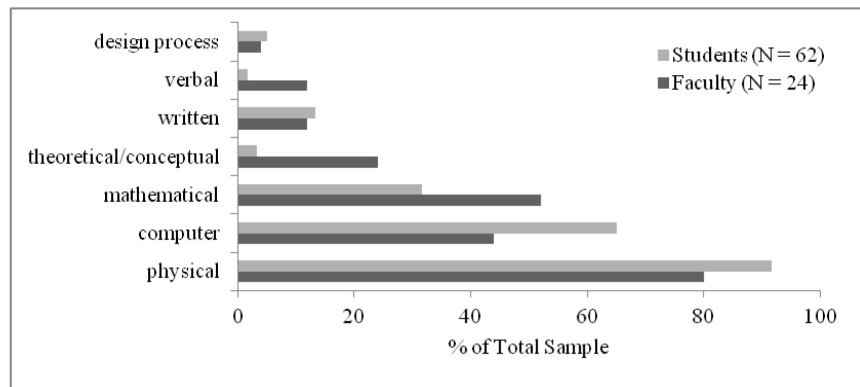


Fig. 2. Percent of faculty and students identifying each category as a component of modeling.

design process. Physical models included statements regarding a tangible artifact including prototypes, mockups, artwork (e.g. drawings, sketches), systematic diagrams, and charts or graphs. Computer models refer to either artwork that has been transformed into a computer representation or computer simulations that conceptualize theoretical ideas. Mathematical models are ideas represented by mathematical equations and calculations. Theoretical/conceptual models represent untested ideas based on what is known about the real world. Written descriptions are models in the form of written words, while verbal models are models represented by spoken word. The final code, design process, represents when a respondent assumes that the entirety of the design process is equivalent to modeling.

Twenty-four codes were identified for question two: aesthetics, alternatives, communicate, cost consideration, decision making, documentation, estimate of performance, feasibility, feedback, implementation, improvement, interaction, iteration, make the design concrete/physical, optimize, predict, simplify, simulate, test performance, confirm requirements, time management, understand the problem, understand the solution, and visualize. While some of our current codes may combine in the future to be consistent with an overarching theme, at this stage of the analysis we are keeping the codes separate and distinct. Our intent is to avoid premature grouping that may miss a nuance in the data. Moreover, the process of grouping requires inference and interpretation of meaning, which we plan to include as part of the next stage of our research and analysis.

4. Findings

4.1 Ways to model a design

The percent of faculty and students referring to each category from question one are displayed in Fig. 2. Responses were coded by assigning a value of one

Table 1. Chi-square values between students and faculty for question one: Describe different ways to model a design idea or solution

	X^2
physical	1.99
computer	2.61
mathematical	3.68*
theoretical/conceptual	9.34***
written	0.01
verbal	4.44*
design process	0.03

*** $p = 0.001$; ** $p = 0.01$; * $p = 0.05$.

when a code was present and zero if a code was not. The most prevalent code for both groups were physical models with a major emphasis on prototypes, mockups, and artwork. Computer and mathematical models were also highly cited by both groups. Significant differences between groups were seen for mathematical [$X^2(1, N=84) = 3.68, p = 0.05$], theoretical/conceptual [$X^2(1, N=84) = 9.34, p = 0.001$], and verbal models [$X^2(1, N=84) = 4.44, p = 0.05$] (Table 1). Faculty significantly cited these three categories more often than students. Responses referring to physical, computer, and written models, as well as the overall design process, were not significantly different between the two groups.

4.2 Models useful/helpful in design

The percent of faculty and students referring to each category from question two are displayed in Fig. 3. Responses varied between the two groups with significant differences seen for models being useful/helpful in visualizing [$X^2(1, N=84) = 6.66, p = 0.01$], determining feasibility of the design [$X^2(1, N=84) = 1.97, p = 0.05$], making the design idea concrete [$X^2(1, N=84) = 6.74, p = 0.01$], providing feedback [$X^2(1, N=84) = 9.11, p = 0.01$], understanding the problem [$X^2(1, N=84) = 19.09, p = 0.001$], identifying alternatives [$X^2(1, N=84) = 4.18, p = 0.05$], confirming requirements [$X^2(1, N=84) =$

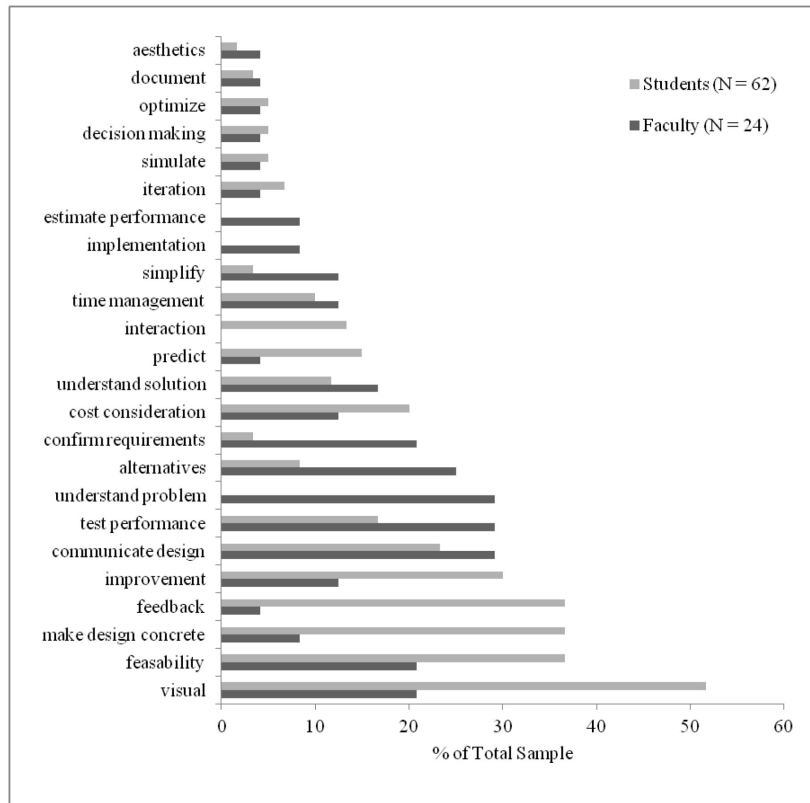


Fig. 3. Percent of faculty and students identifying each category as useful/helpful in the design process.

6.87, $p = 0.01$], implementing the design [$X^2(1, N=84) = 5.12, p = 0.05$], and estimating performance [$X^2(1, N=84) = 5.12, p = 0.05$] (Table 2).

Table 2. Chi-square values between students and faculty for question two: In what ways can models be useful/helpful in the design process?

	X^2
visual	6.66**
feasability	1.97*
make design concrete	6.74**
feedback	9.11**
improvement	2.80
communicate design	0.31
test performance	1.66
understand problem	19.09***
alternatives	4.18*
confirm requirements	6.87**
cost consideration	0.66
understand solution	0.38
predict	1.92
interaction	3.54
time management	0.11
simplify	2.57
implementation	5.12*
estimate performance	5.12*
iteration	0.19
simulate	0.03
decision making	0.03
optimize	0.03
document	0.04
aesthetics	0.46

*** $p = 0.001$; ** $p = 0.01$; * $p = 0.05$.

Faculty significantly cited understanding the problem, alternatives, implementation, and estimation more often than students, while students cited visualizing, feasibility, making the design idea concrete, providing feedback more often than faculty. All other codes were not significantly different between the two groups.

5. Summary, implications, and future work

The current study sheds light on how faculty and students conceive of ways to model a design idea and the role of modeling in the process of design. We found that the primary conception for a method of modeling, from both the student and faculty perspective, is to build some type of physical representation. Students even use particular design language such as mock-up and prototype when describing these types of models. This indicates that students are appropriating the language of the design community, which is a positive finding. We also found that more abstract types of models such as mathematical or theoretical/conceptual, are mentioned less often. A significant difference was found between students and faculty responses in providing mathematics or theory as an approach to modeling a design solution. This finding illustrates that there are strongly held notions that the types of models

useful in design are primarily tangible/physical artifacts.

These findings relate to our primary motivation for engaging in this research. Abstract modeling is as pervasive and important an activity in the engineering curriculum as building physical mock-ups or prototypes. Students manipulate mathematical equations, sketch diagrams that demonstrate interactions, and implicitly make assumptions about behaviors of systems regardless of engineering discipline. Our studies indicate that students do not recognize this type of abstract modeling as a useful and powerful method in the process of design.

We find these results both interesting and problematic. It is interesting to note that even though students receive extensive instruction in developing analytical skills that represent core fundamental engineering principles, students do not perceive of these skills as ‘modeling’ such that they would be useful in the process of design. For the very same reason we view our results as problematic. Specifically, it reveals a critical disconnect between learning techniques, tools, and methods for modeling in one setting, and the lack of recognition for how they might be usefully applied in a novel setting. This relates directly to the adaptive expertise framework; that is, how to engage students on the path to adaptive expertise so they develop a fluent ability to recognize when prior knowledge applies and an ability to use it effectively in the process of innovation.

There is a well-known body of literature, often referred to as ‘transfer’ literature, that describes the phenomena of individuals’ inability to apply knowledge learned in one setting to a different and novel situation. While one might argue that our findings illustrate a transfer of knowledge issue, we claim there may be a more nuanced story. In particular, we suggest that students do not necessarily recognize that the abstractions used in analysis-focused engineering fundamentals courses are models. In this case, students are not in a position to transfer what they haven’t developed or learned in the first place.

We suggest that one approach would be to make the process of modeling more explicit such that students are trained in the full range of modeling approaches, inclusive of abstract representations through concrete physical artifacts, and their roles and purposes in the process of design and innovation. We envision that this type of explicit instruction would take place in both the analysis and design focused courses as a way to make clear connections. At a minimum this should raise students’ awareness of the different methods for modeling and help them to recognize when they might apply in a novel situation.

Future work includes continued analysis of our current data to explore potential categorization of results. Students and faculty will be interviewed to help us gain further insight into our findings. In addition, we will analyze students’ design deliverables (project reports and presentations) to examine how they use modeling, and the types of modeling that are using. Finally, we will compare our current data to our existing data from a senior, discipline-specific design course. This comparison hopes to reveal potential differences between sophomores and seniors, in a multidisciplinary vs. disciplinary design setting.

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References

1. D. L. Schwartz, J. D. Bransford and D. Sears, Efficiency and innovation in transfer, in J. Mestre (Ed.), *Transfer of learning: Research and perspectives* (pp. 1–51), Greenwich, CT: Information Age Publishing, Inc., 2005.
2. A. McKenna, R. Linsenmeier and M. Glucksberg, *Characterizing computational adaptive expertise*. Proceedings of the American Society for Engineering Education Annual Conference & Exposition, Pittsburgh, PA., 2008.
3. J. Cole and A. F. McKenna, *Analyzing student generated evidence for supporting design decisions*, Proceedings of the American Society for Engineering Education Annual Conference, Louisville, KY., 2010.
4. J. Y. Cole, R. A. Linsenmeier, E. Molina, M. R. Glucksberg, and A. F. McKenna, *Assessing engineering students’ mathematical modeling abilities in capstone design*, Proceedings of the American Society for Engineering Education (ASEE) Annual Conference, Vancouver, BC Canada, 2011.
5. A. R. Carberry, A. F. McKenna, J. Cole and R. A. Linsenmeier, *Exploring senior engineering students’ conceptions of modeling*, Proceedings of the American Society for Engineering Education Annual Conference, Vancouver, B.C., Canada, 2011.
6. G. Hatano and K. Inagaki, Two Courses of Expertise, in H. Stevenson, H. Azuma, & K. Hakuta (Eds.), *Child development and education in Japan*, (pp. 262–272), New York, NY: Freeman, 1986.
7. G. Hatano and Y. Oura, Commentary: Reconceptualizing school learning using insight from expertise research, *Educational Researcher*, **32**(8), 2003, pp. 26–29.
8. A. F. McKenna, An investigation of adaptive expertise and transfer of design process knowledge, *ASME Journal of Mechanical Design*, **129**(7), 2007, pp. 730–734.
9. C. J. Atman, D. Kilgore and A. F. McKenna, Characterizing design learning: A mixed-methods study of engineering designers’ use of language, *Journal of Engineering Education*, **97**(3), 2008, pp. 309–326.
10. C. L. Dym. 1999. ‘Learning engineering: Design, languages and experiences,’ *Journal of Engineering Education*, **88**(2), pp. 145–148.
11. C. L. Dym, A. M. Agogino, O. Eris, D. D. Frey and L. J. Leifer, Engineering design thinking, teaching, and learning. *Journal of Engineering Education*, **94**(1), 2005, pp. 103–121.
12. R. B. Kozma and J. Russell, Multimedia and understanding: Expert and novice responses to different representations of chemical phenomena, *Journal of Research in Science Teaching*, **34**(9), 1999, pp. 949–968.
13. Y. Anzai, Learning and use of representations for physics expertise, in K. Anders Ericsson and J. Smith (Eds.), *Toward*

- a General Theory of Expertise: Prospects and Limitations*, (pp. 64–92). New York, NY: Cambridge University Press, 1991.
14. L. L. Bucciarelli, *Designing engineers*. Cambridge: MIT Press, 1996.
 15. A. M. Starfield, K. A. Smith and A. L. Bleloch, *How to model it: Problem solving for the computer age*. Burgess Publishing: Edina, MN., 1994.
 16. D. Maki and M. Thompson, *Mathematical modeling and computer simulation*. Belmont, CA: Thomson Brooks/Cole., 2006.
 17. R. Lesh and H. M. Doerr, Foundations of a models and modeling perspective on mathematics teaching, learning, and problem solving, in R. Lesh and H. M. Doerr (Eds.), *Beyond constructivism: Models and modeling perspectives on mathematics problem solving, learning, and teaching* (pp. 3–33). Mahwah, NJ: Lawrence Erlbaum Associates, Inc., 2003.
 18. D. N. Perkins, *Knowledge as design*, Hillsdale, NJ: Lawrence Erlbaum Associates, 1986.
 19. B. Glaser and A. Strauss, *The discovery of grounded theory: Strategies for qualitative research*. Chicago, IL: Aldine, 1967.
 20. M. Miles and M. Huberman, *Qualitative data analysis: A source book for new methods*. Thousand Oaks, CA: Sage Publications, 1984.

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