An Exploration of Course Design Heuristics Identified from Design Meetings, Design Artifacts, and Educator Interviews

Dr. Nicholas D. Fila, Iowa State University

Nicholas D. Fila is a postdoctoral research associate in Electrical and Computer Engineering and Industrial Design at Iowa State University. He earned a B.S. in Electrical Engineering and a M.S. in Electrical and Computer Engineering from the University of Illinois at Urbana-Champaign and a Ph.D. in Engineering Education from Purdue University. His current research interests include innovation, empathy, engineering design, instructional design heuristics.

Prof. Seda McKIlligan, Iowa State University

Dr. Seda McKilligan is an Associate Professor in the Department of Industrial Design at Iowa State University, in the United States. She has a B.I.D. in Industrial Design from METU in Turkey and an M.F.A. in Design and a Ph.D. in Design Science from the University of Michigan, in the US. Her current research on approaches in the design innovation process, ideation flexibility, investigations of problem-solution spaces, and concept generation and development practices of novices through practitioners is supported by multiple grants from the National Science Foundation. She produces theory, design principles and systems to support design, engineering and educational innovation processes, through studying experiences of individuals and teams that lead to innovative thinking and through integrating that knowledge into organizational change.

An Exploration of Course Design Heuristics Identified from Design Meetings, Design Artifacts, and Educator Interviews

Introduction

This research paper investigates differences between course design heuristics used in engineering that have been identified from three distinct data sources: course design meetings, course design papers, and educator interviews. Heuristics are used in the daily practice of many diverse disciplines, including industrial design [1], orienteering [2], songwriting [3], and medicine [4]. These represent "specific experience-based guidelines" [5] to support positive decision-making, problem exploration, and solution development specific to those disciplines. More recently, the study of heuristics has expanded to instructional design [6] and engineering course design [7], where course design is framed as a problem-solving activity and heuristics represent approaches used implicitly to guide the design process and transform the course design object.

Identifying heuristics used by experts in a discipline can have many practical benefits. Heuristics can be used as tools to scaffold expert behavior among novices [8]; make challenging tasks more efficient [9]; reduce cognitive load [10]; and explore the nature of a domain, task, or discipline [3]. For example, a previous study of course design heuristics not only identified what educators did to modify a course but demonstrated features of the course design problem space [7].

Heuristics across domains have been identified by utilizing different data types. In product design, for example, heuristics have been found through analysis of artifacts and products, think aloud protocols, and design process case studies [11]. Others have utilized Delphi studies [6], task protocols [12], and interviews [3]. As course design heuristics in engineering education is a nascent research area, the purpose of this study is to unpack differences in heuristics used when designing (e.g., identifying, selecting, transforming, and/or implementing) course elements (e.g., including content, pedagogy, assessment, and logistics), that have been independently identified from different data types. Through this analysis, we hope to better understand the role these types of data can play in identifying course design heuristics and support more informed methods decisions in future studies.

Literature Review

Heuristics in Design Domains

Heuristics originated in psychology to describe cognitive rules of thumb or biases problem solvers used to quickly make judgments or decisions, often related to complex problems [13]. Cognitive heuristics do not always offer the best solution, but they can be used as search algorithms or shortcuts that either direct individuals toward optimal solutions [14] or produce decisions that are often "good enough" or "reliable enough" [15]. In many disciplines—such as industrial and engineering design [1,11], artificial intelligence [16], user interface design [17], and medicine [4]—heuristics have been identified through analysis of experts' processes and outcomes or based on idealized processes, and have been employed to scaffold decision-making and/or improve problem-solving related to complex tasks [8,18].

Heuristics have been particularly emphasized in design domains, where problem spaces are complex, potential solutions are many, and processes can be intuitive [19]. For example, a recent multi-phase study translated the cognitive heuristics theoretical framework to identify "Design Heuristics" related to idea generation within engineering and product design [1,11,20]. Researchers identified expert designers' heuristics based on analysis of award-winning products, protocol studies, and a journal chronicling a long-term design process. Researchers found 77 Design Heuristics that informed unique patterns of concept variation. For example, the heuristic *allow user to reorient* featured the designer transforming an existing product by allowing users to rotate or flip the product to create different functionality [11]. These heuristics, represented as ways to transform design concepts to create new concepts, were later used to improve ideation outcomes among engineering students [8].

The study of design-style heuristics has extended to the instructional design domain. Expert instructional designers have been found to use heuristics when designing new or revising instructional systems across a variety of studies [6,21-25]. For example, York and Ertmer [6] conducted a Delphi study and examined previous think-aloud findings [21] to identify 61 instructional design heuristics. Example heuristics in this study included *know your learners/target audience* and *be honest with the client*, emphasizing strategies to guide the designer through the design process, compared to strategies to transform design concepts in product design heuristic studies [1,11,20]. Other instructional design studies have also shown approaches that resemble heuristics, using a variety of methods and participant populations. Visscher-Voerman [23] conducted retrospective interviews to identify 16 "principles" used by instructional designers. Kirschner and colleagues [24] explored how instructional designers (in both academic and business contexts) used Visscher-Voerman's 16 principles through a Delphi-type study and a team design task. Perez and colleagues [25] used a laboratory think-aloud protocol to investigate instructional design practices among both novices and experts.

Despite differences in sample populations and data collection methods among the studies by Perez and colleagues [25], Visscher-Voerman [23], and York and Ertmer [6], these studies reported some similarly themed heuristics/approaches. Each of the studies featured at least one (and usually more) heuristic/approach that emphasized each of four key activities within the design process: working with stakeholders, learner (user) and context analysis, problem framing, and prototyping and testing designs. However, specific wording/framing of heuristics in these areas, number of heuristics in each area, and additional areas covered varied between the studies. For example, York and Ertmer's [6] study featured at least 20 unique heuristics that involved working with stakeholders while Perez and colleague's [25] featured one such approach. Conversely, Perez and colleagues [25] identified more nuanced approaches within learning task analysis and developing features of instruction. These differences may have stemmed from differences in task focus (broad consideration of the instructional design process vs. a short-term laboratory design task), number of participants (31 vs. 9), and other factors. Thus, while heuristics within a domain may be robust, means of data collection can influence the details and nuances identified. Selection of such methods and participants should be well-informed and suited to the purpose of the study.

Exploring Heuristics and Related Approaches in Engineering Course Design

Course design in higher education can be a complex task for which engineering faculty are often ill-prepared [26,27]. Ambrose and Norman, for example, note that many early-career faculty design courses based on ways they were taught, colleague's courses, or from lists of important topics, rather than through systematic approaches highlighted in the literature. Ziegenfuss [28] explored variation in the ways faculty across disciplines experienced course design. This study identified five distinct categories: course design as (1) part of a bigger picture, (2) process or sequence-driven, (3) outcomes based, (4) needs focused, and (5) within a structure or framework, each identifiable through differences in content selection, course format, and strategies for student engagement. While many of these categories suggested connections to systematic approaches, individual approaches to course design among each participant represented unique combinations of these categories and were often "nebulous and implicit" (pg. 78). Thus, a heuristic approach may be well-suited for understanding the daily practice of course design. Further, the focus on aspects such as content selection, course format, and strategies for student engagement suggests that heuristics in this field may align with the Design Heuristics approach of exploring transformations of the design object [11] rather than the instructional design heuristics approach of considering guidelines for the overarching design process [6].

Methods

In this study, we explored the patterns of differences among course design heuristics, identified in engineering education settings, from three distinct datasets: (1) course design team meeting recordings, (2) educator retrospective interviews, and (3) course design papers (i.e., design artifacts). First, content analysis revealed a unique set of course design heuristics from each of the three data types. Using these heuristics as data, we employed an inductive, six-stage thematic analysis [29] process to identify patterns in the types, content, and manifestation of heuristics across the three datasets.

Data Sources

A variety of data sources have been used to identify heuristics within and across domains. These tend to focus on either (1) analyzing outcomes for evidence of heuristic applications or (2) documenting heuristics as they occur in situ. These types of approaches are preferred because heuristics are often used implicitly and can be challenging to verbalize [13]. In design domains, for example, common methods involve analyzing products, concepts recorded by expert designers, and outcomes of laboratory protocols of design tasks [11]. Studies in other domains have used interviews and surveys as primary means of data collection. Beech [3], for example, used semi-structured interviews detailing personal experiences, approaches, and perspectives to identify songwriting heuristics. York and Ertmer [6] employed a Delphi structure in which participants themselves identified and collectively selected key instructional design heuristics. These methods have successfully identified heuristics in their domains but, as York and Ertmer [6] note, may lack a basis in authentic practice. Still, the opportunity for experts to comment on their practices may add clarity and insight otherwise unavailable with the distanced methods of product, protocol, and document analysis.

In this study, we compiled data collected from three current studies [7,30] that explore course design heuristics utilized by electrical, computer, and software engineering educators, three related but distinct fields that are often housed within the same academic department. The first dataset comprised audio recordings and transcripts from the biweekly design meetings of a team of ten educators revising an embedded systems course for electrical, computer, and software engineering students, over four months. The second dataset comprised a corpus of 1000 peer-reviewed conference and journal papers that detail development or revisions to electrical, computer, and software engineering courses between 2005–2017, 183 of which were analyzed in this study (due to heuristic saturation). The third dataset comprised audio recordings and transcripts from semi-structured interviews with five electrical and computer engineering educators that detailed their approaches to course design and experiences designing courses.

These three types of data were selected to allow comparison across the span of relevant heuristic data collection methods. Because heuristics are implicitly used and often difficult to verbalize [13], each data source focused on either observations/accounts of heuristic application or the products of such applications. Further, each of the datasets focused on heuristics used in authentic settings, rather than laboratory protocols or hypothetical approaches. The team meetings dataset focused on behavioral, verbal, and contextual evidence of heuristics in use. The instructor interviews dataset focused on retrospective accounts that detailed heuristic use and their outcomes. Heuristics were not identified directly by the participants but allowed to be uncovered through analysis of the course design experiences and design outcomes they discussed. Further, these interviews were semi-structured, which allowed follow-up questioning to provide additional detail, context, and examples. The course design papers dataset focused on the outcomes of heuristic application (i.e., revised courses) and featured substantive background and rationale for course changes, which added context to heuristic identification. Further, to support effective comparison, we ensured that these datasets captured participants similar in role and discipline (primarily electrical, computer, and software engineering faculty) engaged in similar processes (the design or redesign of an electrical, computer, or software engineering course over one or more semesters). Features of the datasets are reported in Table 1.

Table 1. Comparison of Data Sets

Aspect	Team Meetings	Instructor Interviews	Course Design Papers
Participants	Team of 10 educators (3 ECE faculty, 3 ECE TAs/postdocs, 1 design faculty, 1 design student, 1 education postdoc, 1 aero engr. faculty)	Individual ECE faculty (5 total)	1-7 educators, mostly ECE/SE faculty
Duration	Single four-month course design process, 17 hours of meeting recordings	Five 60–90 minute interviews discussing 2–4 course design experiences each	One-hundred eighty-three 2-30 page papers each detailing 1–2 courses
Focus	Observing evidence of heuristics in action	Discerning heuristics from retrospective accounts of experience and outcomes	Discerning heuristics from course descriptions and supporting rationale

Data Analysis – Identifying Heuristics

In each sub-study, heuristics were identified through summative, latent content analysis [31]. This approach was inductive to avoid bias from extant heuristics and, thus, to allow for more

nuanced comparisons between the heuristics derived from the different datasets. However, the framing of heuristics was still informed by previous studies in related domains (e.g., engineering and product design [11]).

We began with an operational framing of course design heuristics that was iteratively developed when analyzing the first dataset [7]. In alignment with previous studies focused on Design Heuristics [8,11,20], this framing suggested the heuristics be identified through generation and/or transformation of courses and their comprising elements. This framing allowed consistency among analyses in determining what might constitute a heuristic, without prescribing the specific content or structure of heuristics. For each dataset, researchers independently coded sections of the data to identify potential heuristics. Consistent with previous heuristics studies [11,20], the researchers convened regularly to discuss the potential heuristics, review the data, refine heuristics, create larger categories of heuristics, and, eventually, agree upon a final set of heuristics, with detailed definitions and case examples.

We employed three checks to limit potential influences between sub-studies. First, heuristics were identified independently for each dataset. Two researchers, experienced in engineering education and qualitative analysis, oversaw development of heuristics in each sub-study but individual coders differed for each. Data coding, team meetings, and final decisions featured no discussion or overt consideration of heuristics from other sub-studies. Second, if the researchers noticed findings from a previous study coming to mind as they moved through analysis, they attempted to mitigate those considerations and let heuristics and categories remain based solely within the current dataset. Finally, the sub-studies were conducted sequentially (first, team meetings, then course design papers, and, finally, instructor interviews), with breaks in between, to limit the potential for overlapping analysis.

To provide context, the Tables 2 and 3 present examples of distinct and like heuristics, including the types of information about each heuristic that was available during analysis. The original data (i.e., transcripts, audio, and papers) and coded excerpts were also available throughout analysis.

Table 2. Comparison of Three Distinct Heuristics, One from Each Dataset

	Team Meetings	Instructor Interviews	Course Papers
Title	Promote professional formation	Use own experiences to guide instruction	Get out of the classroom
Description	Imbue course activities with aspects of professional formation (such as teamwork and design thinking)	When developing activities and format, align with what best supported your learning as a student	Connect students to learning experiences that occur outside lecture and lab
Purpose	Increase relevance of class material and experience, support engineering identity development, and better prepare students for their careers	Optimize learning experiences for students	Leverage external opportunities, situate learning in different and authentic contexts, and connect students to different industry, academic, and community populations
Example(s)	Integrate design thinking activities into technical labs	Increase the difficulty of and time spent on lab projects because the challenge was how you developed as an engineer	Introduce a design project in which students design for and with an elementary school class

Table 3. Comparison of Similar Heuristic Observed in All Three Datasets

	Team Meetings	**Instructor Interviews**	**Course Papers**
Title	Increase activity within lecture	Get students active in lecture	Increase activity in lecture
Description	Add hands-on, collaborative, and reflective activities to lectures	Employ various group activities throughout lectures	Utilize learning exercises, small projects, and group discussions in lecture
Purpose	Engage students Support active and social learning	Engage students Support active learning Encourage attendance	Engage students Support active and social learning
Example(s)	Create a jigsaw activity for a challenging class topic	Split class into sections, each working on a different problem. Share findings after small group discussion.	Flip classroom Integrated lab format

Data Analysis – Comparing Heuristics

We employed an inductive, six-stage thematic analysis process to identify patterns in the types, content, and manifestation of heuristics across the three datasets [29]. First, each set of heuristics was reviewed. This included reading each category and its constituent heuristics as well as descriptions and examples thereof. Second, codes were generated to highlight key features of each dataset, especially as related to differences or potential differences between the datasets. Third, the initial codes were reviewed, refined, and grouped to identify initial themes. These themes were focused on aspects that differed between the datasets. Fourth, themes were reviewed with respect to internal coherence, alignment with the supporting codes, alignment with the datasets collectively. Fifth, themes were named and defined to provide additional clarity and nuance. Finally, the results narratives were developed to feature clear and concise reporting of the themes and relevant examples that supported these narratives.

Results

Exploration of the sets of heuristics from each of the three studies revealed four themes that represented key differences. In the following sections, we describe these themes and discuss potential reasons they may have been observed.

Quantity

The first theme focused on the number of heuristics identified per unit of analysis. Table 4 demonstrates that, on average, team meeting recordings produced the most heuristics per unit of analysis (22) and course design papers produced the fewest (5.56). Although, one interview demonstrated more heuristics (25) than the collection of team meetings (22) and several course design papers also produced substantive numbers of heuristics (max = 19). The purpose here is not to suggest meaningful statistical differences but to recognize that the type of data analyzed may affect the volume of heuristics and may have implications for saturation, scale, and scope.

Table 4. Number of heuristics per unit of analysis

Unit of analysis	Mean	Max	Min	Total
Team meetings	22	22	22	22
Instructor interviews	20.4	25	18	64
Course design papers	5.56	19	2	190

There were also differences in how frequently each heuristic appeared in each dataset. In many instances within instructor interviews and course design papers, individual heuristics occurred only once or twice, while heuristics often surfaced several times during the team meetings. In some cases, this occurred when one team member utilized the same heuristic multiple times in reference to similar course aspects. However, there were also many instances of different team members applying the same heuristic to diverse course aspects. For example, the heuristics *add collaboration*, *connect to the real world*, and *promote professional formation* were evident in almost every meeting analyzed and were each used by at least four team members. In situ and longer-term observations, thus, may provide better opportunities for analysis of multiple examples and frequency counts.

Organizing Heuristics

The second theme focused on differences in how heuristics were organized (based on categories of heuristics identified) and was comprised of three subthemes. In each dataset, individual heuristics were organized into categories based on the purpose for which they were utilized. Differences in categories represented unique orientations of the course design process, at least as suggested by heuristics analysis. While many similarly titled and oriented categories existed between the datasets, differences in breadth, specificity, and conceptualization were evident.

Breadth of heuristics

This subtheme refers to the differences in the overall breadth of heuristics as presented by categories in each dataset. There were many similarities between the datasets. Each had categories that focused on, or at least evidenced, activities such as selecting content, determining instructional strategies, communicating with students, being student-centered, and building the course iteratively. In addition to categories in these areas, both the instructor interviews and course design papers datasets demonstrated categories related to student assessment and identifying/creating resources for students. The team meetings dataset did not contain categories in these areas. Coverage could be a concern when comprehensive mapping is needed.

Level of specificity

This subtheme refers to differences in specificity of related heuristics categories. In some areas, datasets featured one encompassing category while other datasets distributed the area across several categories. In general, the course design papers provided the most specificity and team meetings provided the least. The instruction/pedagogy-related categories provide a key example of this subtheme. The instructor interviews dataset covered this area with two distinct categories (determine instructional approaches and determine instructional techniques). The course design papers dataset utilized six categories, each focused on a different type of change (challenging students, contextualizing, diversifying teaching modalities, establishing foundations, facilitating collaboration, and utilizing learning environments). The team meetings dataset had one category in this area (communicating course content), but evidence of related heuristics in several other categories.

Alternative conceptualizations

This final subtheme refers to differences in the focus of similar categories within each dataset. In several cases, each dataset contained a related heuristics category but framed it differently than the other datasets. For example, both the course design papers and instructor interviews datasets contained "restructuring" categories that focused on how content, activities, and assessments were placed and organized within a semester or course period. Despite similar focuses, the individual heuristics within each category represented differing priorities as to what aspects were restructured. In the instructor interviews dataset, heuristics in the restructuring category tended to focus on setting due dates and activities to maintain a smooth and logical course flow (e.g., *place homework and exams around the project*, *keep labs topically aligned with lecture*). In the course design papers dataset, heuristics in the restructuring category tended to focus on reformatting the course environment and/or timeline to maximize learning (e.g., *repeat/extend experiences with key activities and processes*, *format course as a story*). In general, these differences seemed to align with unique features of the datasets (e.g., instructors discussing their individual processes and experiences, paper authors reporting major course changes).

In another example, all three datasets had categories related to student-centeredness, but all three demonstrated a different focus. The team meetings dataset focused on heuristics that promoted student engagement in class. The instructor interviews dataset focused on learning about students throughout the course. The course design papers dataset contained a category more generally focused on increasing student-centeredness that featured individual heuristics covering each of the aspects covered in the similar team meetings and instructor interviews categories. This example also demonstrates the two prior subthemes. The course design papers dataset's category featured less specificity than the other two datasets but greater overall breadth.

Individual Heuristic Specificity

The third theme focused on differences between individual heuristics. The types of heuristics identified within each dataset differed in ways consistent with the previous theme (i.e., based on overarching categories). They also differed within like categories, often, based on level of specificity. For example, the team meetings dataset contained the heuristic *connect to the real world*. The course design papers dataset contained several more specific heuristics that connected to this more general heuristic. These heuristics included: *illustrate practical use of technologies*, *add/emphasize hands-on activities*, *provide realistic project experience*, *provide realistic design problems/prompts/scenarios*, *facilitate environment analogous to professional working conditions*, *introduce customer interaction/consideration*, *present learning within real-world context and/or system*, *use case studies as a pedagogical tool*, and *add industry interaction*. This more nuanced field of heuristics likely reflects opportunities for increased levels of specificity that the course design papers dataset demonstrated in its categories.

In general, the course design papers dataset presented some of the most specific heuristics while the team meetings dataset presented the least specific heuristics. However, the latter also demonstrated some of the most unique heuristics (e.g., *facilitate solution space exploration*, *identify big rocks*), most likely due to the unique priorities of the single course design team. These heuristics would likely merge with more general heuristics within a larger dataset and

perhaps lose some of their nuance. For example, *facilitate solution space exploration* would likely be an example of the *encourage students to be creative* heuristic in the course design papers dataset. Similarly, the instructor interviews dataset contained several specific heuristics, seemingly based on unique instructor personality priorities (e.g., *make lab documents fun*, *start class with a joke*).

Locus of Clarity in Individual Examples

The final theme focused on the clarity of coded examples. Each dataset presented heuristics in a unique format. In the team meetings dataset, examples were conversation excerpts representing heuristics' applications in real-time. In the instructor interviews, examples were first-person accounts of past heuristic applications, often containing examples of the specific changes they led to in courses. In the course design papers, examples were crafted descriptions of course changes, often with rationale and details suggesting how the heuristics were applied.

The different formats did not necessarily affect clarity overall but affected which aspects of each example tended to be clearer. Team meetings examples tended to feature the richest and most contextualized application details. These examples provided greater insights into the origin and precise mechanics of each heuristic compared to the retrospective accounts of instructor interviews, and course design papers which often omitted such information entirely. Course design papers often featured limited details on heuristic application but tended to feature the clearest detail on the outcomes produced by heuristics (i.e., course changes). These details where well processed, justified, and articulated for a scholarly audience. Instructor interviews often provided clarity in similar areas but traded articulation for additional details.

Discussion

Summary of Results

This study explored differences in course design heuristics identified from three distinct data sources: team meeting transcripts, instructor interview audio, and course design papers. Thematic analysis revealed four key differences: quantity, heuristic organization, individual heuristic specificity, and locus of clarity in heuristic examples.

Team meeting transcripts produced, on average, the most heuristics and the most detailed examples of in-the-moment heuristic application. This likely corresponds to the immersive and unfiltered nature of the data. The interviews and papers featured retrospective accounts of course design experiences, but team meetings featured all heuristics uses, regardless of whether they were eventually applied to course changes or viewed as relevant by the participants. The team meetings also demonstrated gaps in heuristics coverage and inconsistent heuristic specificity. These two limitations may be the result of focusing on a single course design team in the act of designing a single course, and might be mitigated with additional data collection.

The course design papers produced, on average, the fewest heuristics but greatest overall breadth of heuristics and most consistent specificity of individual heuristics and heuristics categories. Further, while their examples were often less detailed, they provided the clearest evidence of

how and why heuristics informed implemented course changes. The former can likely be attributed to the volume of examples compiled, which was aided by their accessibility and, often, concise and eloquent nature. The latter can likely be attributed to the processing of design experiences and decisions for a target audience, with value placed on concrete results and clarity of description and purpose. While these papers were initially intended as analogs to design artifacts in the course design space—rather than products or concept sketches—the aspects of thick description and rationale provided additional insights in the heuristic identification process.

The instructor interviews generally placed between the team meetings and course design papers in reference to each of the themes and sub-themes. In other words, they provided median specificity, coverage, volume, and clarity of utilization and application. They did offer two key benefits over the other two datasets. The most obvious benefit was the opportunity to probe meaning and details of instructor experiences. Interviews are still limited by what instructors are able and willing to share and, in the case of this study, time restrictions, but follow-up questioning can be used to clarify uncertain aspects and provide additional detail in relevant areas. The other, less obvious, benefit was the presence of several unique heuristics that seemed to be imbued with the personality and/or priorities of individual instructors (e.g., *start class with a joke*). These heuristics tended to be smaller in scope and more personal, which may explain their absence from the team meetings and course design papers datasets (i.e., instructors/faculty might not have deemed them relevant to the course design team or reading audience).

Overall, it appears that each dataset contains unique strengths and weaknesses. This study does not purport that all such datasets will contain the same strengths and weaknesses, particularly due to the other aspects that may have influenced these differences (e.g., unique participants and settings, volume of data). However, this study does demonstrate that data selection can substantively influence the eventual set of heuristics identified and suggests several ways the set of heuristics may be influenced.

Considerations for Investigating Engineering Educators' Heuristics

In this section, we present four considerations for researchers exploring heuristics in engineering course design or similar constructs in similar domains. Due to limitations in the comparison herein (e.g., differences in number and variety of participants, variety in course design projects) we present these as considerations rather than outright recommendations. Further, we align these discussions with a well-established framework for quality in interpretive research, Walther, Sochacka, and Kellam's [32] *Qualifying Qualitative Research Quality (Q³)*, to connect to broader discussions of quality within the engineering education research community (see Table 5). Walther and colleagues emphasize considerations along five themes (theoretical validation, procedural validation, communicative validation, pragmatic validation, and process reliability) in both "making data" and "handling data." Due to the focus on data collection in this study, we focus on aspects of "making data," e.g., selecting participants and collecting data.

#1: Consider utilizing multiple data sources

In this study, different data sources produced differences in quantity, heuristics framing, individual heuristics, and types of examples. These differences demonstrate that, if combined,

Table 5. Alignment with Five Aspects of Q^3 Framework [32]

Quality Aspect	Description	Considerations	Alignment
Theoretical validation	Data captures "full extent of the social reality" (pg., 640)	Utilize multiple data sources Appropriate volume of data	Data sources highlight different features of social reality, provide a broader scope Ensuring appropriate volume of data ensures limited cases do not highlight limited facets of social reality.
Procedural validation	Strategies in data collection "improve the fit between reality and theory generated" (pg., 640)	Utilize multiple data sources How data sources affect results	Multiple data sources allows triangulation Considering each data source helps researchers consider how each source improves fit
Communicative validation	Data collection captures participants' "inter-subjective reality" (pg., 640)	Variety of participants and settings How data sources affect results	Variety supports broader picture of participant groups' reality, allows comparison and contrast Different data sources may be more aligned with reality participants can communicate
Pragmatic validation	Data collection compatible with "reality in the field" (pg., 640)	Variety of participants and settings	Variety provides a broader scope of course design activity within the field
Process reliability	Data "collected and recorded in a dependable way" (pg., 640)	All	Considerations assume reliable data collection methods

the datasets investigated likely would have produced a more comprehensive and consistent set of heuristics than any of the three individually. Factors other than the type of data source may have influenced these results—e.g., volume of data, unique participants—but there were also clear distinctions that could be linked to each data type. One key difference was the locus of clarity theme, which demonstrated how the focus of the data (course design papers: presenting and rationalizing course design decisions, instructor interviews: describing prior course design approaches, and team meetings: in-the-moment course design) supported unique insights into the presence and character of heuristics. Similar strategies have been employed in other domains, such as industrial and engineering design [11].

#2: Consider exploring a variety of participants and settings

The course design papers dataset produced the broadest and most consistently nuanced coverage of the overall heuristics space. It also bought together the broadest and most varied set of "participants," which spanned over 300 authors and six continents and likely influenced the breadth of the dataset. The unique categories and heuristics present in the more individualized datasets (instructor interviews and team meetings) demonstrate the distinct contributions various individuals can make. A more varied dataset, as evidenced by the course design papers, may have the potential to capture and incorporate these distinct heuristics and categories. Paradoxically, dealing with a such a volume of data might also limit the extent to which unique features manifest in the final dataset (i.e., uniquely personal heuristics may be combined with similar heuristics into composites). Researchers may wish to consider a potential tradeoff between specificity/uniqueness of participants and comprehensiveness of total heuristics space coverage.

#3: Consider appropriate volume of data

It was clear that by limiting the team meetings dataset to a single team focusing on a single course, the resulting dataset presented gaps in heuristics space coverage. Collecting more data (e.g., additional teams and courses or extended coverage of the extant team's process) may have filled some of these gaps. However, such data collection was more invasive than collecting course design papers and the 15 meetings produced as many pages of data as approximately half of the course papers dataset. The data also took longer to process and analyze due to the conversational, unedited nature. Researchers should consider whether benefits would warrant more extensive data collection.

#4: Consider how data sources may affect aspects of the results

The previous three items are framed as possible considerations because this study can only suggest, not confirm, potential effects of data type, variety, and volume. However, three datasets within the same domain (electrical, computer, and software engineering course design) differed across four themes: quantity, heuristic framing, individual heuristic specificity, and locus of specificity of examples. Different heuristics studies have been used for different purposes. For example, many seek to support more informed problem-solving and design behaviors [6, 11-18], while others seek to better understand human behavior [3,7]. As researchers plan heuristics studies in various domains, especially engineering course design, the considerations and themes presented in this study can provide a starting point for framing the focus and extent of data collection. More specifically, researchers should consider how differences in quantity; heuristic space coverage, specificity, and conceptualization; specificity of individual heuristics; and locus of specificity in heuristics examples may be relevant to their study and its overarching goals.

Conclusion

This study compared the course design heuristics identified using three distinct data collection methods. While analysis focused on comparison, it was evident that the three methods produced similarities in heuristics and their overarching categories. However, key differences were also evident in quantity of heuristics identified per unit of analysis; coverage, specificity, and orientation of the heuristics spaces; specificity of individual heuristics; and locus of clarity of heuristics examples. These demonstrate that careful consideration of the scale, format, and setting in data collection should be made. Further, utilizing a variety of data collection may support both comprehensiveness and nuanced framing of heuristics. Factors beyond data collection may have influenced the results of this study. Interestingly, these emergent factors may be considerations in future studies. As researchers and practitioners draw upon identified heuristics, it is important to continue considering how those heuristics were identified and how choices in research methods might have affected those heuristics.

Acknowledgments

References

[1]   Yilmaz, S., & Seifert, C. M. (2011). Creativity through design heuristics: A case study of expert product design. *Design Studies*, *32*(4), 384–415.

[2]   Eccles, D. W., Walsh, S. E., & Ingledew, D. K. (2002). The use of heuristics during route planning by expert and novice orienteers. *Journal of Sports Sciences*, *20*(4), 327–337.

[3]   Beech, H. F. (2015). Songwriting and transformation: The subjective experience of sharing self through song. *International Journal of Transpersonal Studies*, *34*(1), 187–201.

[4]   Blumenthal-Barby, J. S., & Krieger, H. (2015). Cognitive biases and heuristics in medical decision making: a critical review using a systematic search strategy. *Medical Decision Making*, *35*(4), 539-557.

[5]   Riel, A. J. (1996). *Object-oriented design heuristics*. Addison-Wesley Publishing Company.

[6]   York, C. S., & Ertmer, P. A. (2011). Towards an understanding of instructional design heuristics: An exploratory Delphi study. *Educational Technology Research and Development*, *59*(6), 841-863.

[7]   Fila, N. D., McKilligan, S., & Abramsky, S. (2018). How Engineering Educators Use Heuristics When Redesigning an Undergraduate Embedded Systems Course. 2018 ASEE Annual Conference & Exposition, Salt Lake City, UT.

[8]   Daly, S. R., Yilmaz, S., Christian, J. L., Seifert, C. M., & Gonzalez, R. (2012). Design heuristics in engineering concept generation. *Journal of Engineering Education*, *101*(4), 601-629.

[9]   Gigerenzer, G., Todd, P. M., & ABC Research Group, T. (1999). *Simple heuristics that make us smart*. Oxford University Press.

[10]   Lewis, T. (2006). Design and inquiry: Bases for an accommodation between science and technology education in the curriculum?. *Journal of Research in Science Teaching*, 43(3), 255–281.

[11]   Yilmaz, S., Seifert, C.M., Daly, S.R., & Gonzalez, R. (2016). Evidence-based Design Heuristics for idea generation. *Design Studies, 46*, 95-124.

[12]   Kaplan, C. A., & Simon, H. A. (1990). In search of insight. *Cognitive Psychology*, *22*, 374–419.

[13]   Nisbett, R. E., & Ross, L. (1980). Human inference: Strategies and shortcomings of social judgment.

[14]   Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science*, *211*(4481), 453-458.

[15]   Gilli, M., Maringer, D., & Winker, P. (2008). Applications of heuristics in finance. In *Handbook on information technology in finance* (pp. 635-653). Springer, Berlin, Heidelberg.

[16]   Newell, A. (1983). The heuristic of George Polya and its relation to artificial intelligence. *Methods of heuristics*, 195-243.

[17]   Nielsen, J. (1995). 10 usability heuristics for user interface design. *Nielsen Norman Group*, *1*(1).

[18]   Wegwarth, O., Gaissmaier, W., & Gigerenzer, G. (2009). Smart strategies for doctors and doctors-in-training: Heuristics in medicine, *Medical Education*, *43*, 721–728.

[19]   Studer, J.A., Murray, J., Daly, S.R., McKilligan, S. & Seifert, C.M. (2017). Case studies of problem exploration processes in engineering design. Paper presented at the 2017 ASEE Annual Conference and Exposition, Columbus, OH.

[20]   Yilmaz, S., Seifert, C.M., Daly, S.R., & Gonzalez, R. (2016). Design Heuristics in innovative products. ASME. *Journal of Mechanical Design, 138*(7): 071102-071102-12

[21]   Ertmer, P. A., Stepich, D. A., York, C. S., Stickman, A., Wu, X. L., Zurek, S., & Goktas, Y. (2008). How instructional design experts use knowledge and experience to solve ill-structured problems. *Performance Improvement Quarterly*, *21*(1), 17-42.

[22]   York, C. S. (2013). Design Heuristics in Academic, Corporate, and Military. *Educational Technology*.

[23]   Visscher-Voerman, J. I. A. (1999). Design Approaches in Training and Education: A reconstructive study. Doctoral dissertation. University of Twente, Enschede, the Netherlands.

[24]   Kirschner, P., Carr, C., Merriënboer, J., & Sloep, P. (2002). How expert designers design. *Performance Improvement Quarterly*, *15*(4), 86-104.

[25]   Perez, R. S., Johnson, J. F., & Emery, C. D. (1995). Instructional design expertise: A cognitive model of design. *Instructional Science*, *23*(5-6), 321-349.

[26]   Ambrose, S., & Norman, M. (2006). Preparing engineering faculty as educators. The Bridge, 36(2), 25–32.

[27]   Lattuca, L. R., Bergom, I., & Knight, D. B. (2014). Professional development, departmental contexts, and use of instructional strategies. *Journal of Engineering Education*, *103*(4), 549–572.

[28]   Ziegenfuss, D. H. (2007). A phenomenographic analysis of course design in the academy. *Journal of Ethnographic & Qualitative Research*, *2*, 70–79.

[29]   Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative research in psychology*, *3*(2), 77-101.

[30]   Fila, N. D., & McKilligan, S. (2019). Course design heuristics: Strategies electrical, computer, and software engineering educators use to revise their courses. Unpublished manuscript.

[31]   Hsieh, H.-F., & Shannon, S. E. (2005). Three approaches to qualitative content analysis. *Qualitative Health Research*, *15*, 1277–1288.

[32]   Walther, J., Sochacka, N. W., & Kellam, N. N. (2013). Quality in interpretive engineering education research: Reflections on an example study, *Journal of Engineering Education, 102*(4), 626–659.