Search and Evaluation of Coevolving Problem and Solution Spaces in a Complex Healthcare Design Science Research Project

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***Abstract*—This article employs design ethnography to study the design process of a design science research (DSR) project conducted over eight years. The DSR project focuses on chronic wounds and how Information Technology (IT) might support the management of those wounds. Since this is a new and complex problem not previously addressed by IT, it requires an exploration and discovery process. As such, we found that traditional DSR methodologies were not well-suited to guiding the design process. Instead we discovered that focusing on search, and in particular, the coevolution of the problem and solution spaces, provides a much better focus for managing the DSR design process. The presentation of our findings from the ethnographic study includes a new representation for capturing the coevolving problem/solution spaces, an illustration of the search process and coevolving problem/solution spaces using the DSR project we studied, the need for changes in the purpose of DSR evaluation activities when using a search-focused design process, and how our proposed process extends and augments current DSR methodologies. Studying the DSR design process generates the knowledge that research project managers need for managing and guiding a DSR project, and contributes to our knowledge of the design process for research-oriented projects.**

***Index Terms*—(5-10) design science, chronic disease, problem representation, problem space, smartphone, solution alternatives, solution space, wound management.**

I. Introduction

OVER the last decade, the authors have been conducting *design science research (DSR)* with the goal of creating a smartphone app to support patients with advanced type 2 diabetes, including support for managing the care of diabetic foot ulcers, i.e., the chronic foot wounds that are common with advanced type 2 diabetes. Type 2 diabetes requires daily care to manage glucose and activity levels and chronic foot wounds. Despite the complexity of this care, patients with type 2 diabetes are expected to manage it themselves between visits to physicians.

A smartphone based app could provide support that significantly improves the quality of life of such patients. Developing such an app, however, is a complex research problem because the smartphone must analyze images of foot wounds taken with the smartphone camera and present patients with information about the healing progress of their wounds.

As we started to use existing DSR methodologies to guide our DSR project, we encountered challenges in applying them, starting with the initial steps of defining the problem. Our problem was not well defined and feasible solutions were unknown, and as a result, our research problem and its feasible solutions evolved as we conducted a series of DSR projects. Each project involved search of a new or revised problem space and search for appropriate solutions for that space. Thus, a methodology based on defining the problem and building an artifact that would solve the problem did not fit well.

As a result, our DSR took on an additional goal of investigating, designing, and developing appropriate revisions to traditional DSR methodologies, e.g., Peffers *et al.*'s [1] DSR methodology and Hevner *et al.*'s [2] DSR guidelines, to accommodate the gaps between what we needed to do and what DSR methodologies recommend. This article reports our rethinking of aspects of DSR methodologies, why changes were necessary, and how the changes we propose can contribute to other complex DSR projects.

We employ *design ethnography* as the method for studying, observing, reflecting on, and documenting our design process revisions as they emerged. As ethnographers, the authors had the advantage of also being the designers and managers of the chronic wound DSR project. Thus, we were always "in the field" throughout the nearly decade-long project and have a deep understanding of the project and the design process. To avoid any bias that our overlapping roles might introduce, we carefully followed appropriate methods. We also examined the roots of design science, especially in Simon's *Sciences of the Artificial* [2]– [4]. For Simon, design focuses more on search and discovery processes [4] than do today's DSR methodologies.

Our ethnographic study revealed two key *design challenges* that are not well addressed by DSR methodologies. First, we

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needed approaches for conceptualizing and managing design as a process of searching problem and solution spaces that are not well-defined, rather than assuming we can define the problem and then build the solution. Second, we needed to rethink the purpose of evaluation, as compared to its purpose in existing DSR methodologies. In particular, evaluation must expand beyond evaluating artifacts to evaluating the search process in order to provide the information that research managers need for guiding that process.

Our design ethnography study makes three key contributions. First, we identified two specific challenges in applying DSR methodologies to complex design problems in which the problem and solutions are not well-defined or known. Second, we created solutions to those challenges. Our solutions augment current DSR methodologies, thus retaining their excellent parts while extending them in two areas. Third, our ethnographic approach ensures that the challenges identified and the solutions proposed were derived from actual DSR project management experiences.

The rest of this article is organized as follows. Section II provides background and motivation for our problems. Section III describes our design ethnography methods. Section IV presents our proposed new design process that captures our discoveries about the process of searching the problem and solution spaces. In particular, the process captures the coevolution of the problem and solution spaces as we searched for and evaluated potential solutions, which then informed revised problem representations. Section V presents the new role of evaluation for assessing search processes and progress. Section VI discusses our findings in light of existing literature, presents their contributions, and concludes the article.

II. Background and Problem Motivation

This section presents background and motivation for the three different groups of problems in this article. The first group is the healthcare problems for which our DSR project sought solutions, specifically type 2 diabetes and chronic wound support. The second group is the research problems investigated in our DSR project, e.g., how to analyze images of chronic wounds using a smartphone. The third group is the design methodology challenges we encountered in our DSR project, for which we used design ethnography to investigate. This article focuses on the third group, which we call design challenges to distinguish them from the other two groups. Because investigating the design challenges requires some understanding and motivation for the other two problem groups, all three are briefly presented in this section.

A. Healthcare Problems: Advanced Type 2 Diabetes and Chronic Wound Care

Our overall healthcare research interest was patients with chronic diseases and conditions and how technology, such as smartphones, could assist them with managing their chronic conditions. Early on, we decided with our clinical partner, a Wound Clinic at a University Medical Center, to focus on patients with type 2 diabetes and diabetic foot ulcers, one of the more common types of chronic wounds. Our partner provided medical expertise in chronic wounds, type 2 diabetes, and behavioral medicine, i.e., how to engage patients in improving their health habits.

Chronic wounds, such as diabetic foot ulcers, are persistent, nonhealing wounds. Such wounds are a significant health issue affecting more than eight million in the U.S. [5]. They are painful, susceptible to infection, and often lead to amputating the affected limb. Diabetes related lower limb amputations numbered approximately 108 000 in the U.S. in 2014 [6]. These amputations are the result of nonhealing ulcers, typically of the foot, and their associated complications. Despite many advances in treatment techniques for foot ulcers, the prevalence of foot ulcers did not change in the past two decades [7]. The cost of managing diabetic foot ulcers are estimated at $9–13 billion in the U.S. [8]; overall diabetes healthcare costs were estimated at $174 billion in 2007, and is expected to double by 2034 with the increasing prevalence of diabetes and its complications [9].

Daily patient self-care, in collaboration with physician advice and regular clinic visits, is the standard treatment for diabetes and diabetic foot ulcers, unless complications arise requiring surgery [10]. Daily care can accelerate wound healing, dramatically reduce the need for amputations, and significantly reduce complications related to diabetes and chronic wounds [9]. Diabetes self-care management is complex even without the presence of foot ulcers. It includes activities such as blood glucose monitoring, managing fats, fiber, and sweets in daily diet, exercise, and feet monitoring [11]. For patients with diabetic foot ulcers, they must also clean and care for their wounds, assess their wound condition, and recognize the presence of any new wounds. These wounds can exist for many months and require diligent care over this time to heal. Once healed, their recurrence is common requiring another round of treatments.

Type 2 diabetes and associated diabetic foot ulcers are important problems for patients, and they also generate major healthcare costs. Methods for improving patients' ability to self-manage their diabetes and chronic wounds are urgently needed. Information technology (IT) is a possible solution, e.g., the Institute of Medicine [12] identified IT that engages patients actively in their own care as key to more effective and cost-efficient chronic disease management.

B. Research Problems: Diabetes and Wound Care Support via Smartphone

Our DSR project was tackling two key research problems. The first was providing support for engaging patients with type 2 diabetes in healthier living by helping them track and manage their glucose levels, weight, and physical activity. From a technology viewpoint, this is a relatively straightforward design problem that involves implementing the advice of behavioral medicine experts on how to engage patients and encourage healthier behaviors.

The second research problem was determining how to use the smartphone to capture and analyze wound images and report on healing progress. This is a major technical research problem involving designing and developing sufficiently accurate image analysis algorithms that run in less than a minute on a smartphone, representing a problem in the computational genre of DSR [13]. Finding solutions to this technical problem required an iterative search process through a solution space of potential algorithms. This article focuses on this second research problem because its complexity and lack of known solutions generated the design challenges we encountered using DSR methodologies. In attempting to find solutions, the problem space and solution space evolved as we searched each space for solutions.

A further complication in developing solutions to this second research problem was a lack of wound images to study. When the project started, the clinical process did not involve wound image collection, although clinicians started to capture images during our project. Thus, we collected wound images as part of our research project, gradually obtaining enough images to apply machine learning (ML) solutions that produce good results in other image analysis settings. As the project evolved, we collected images of more complex wounds, leading to categorizing wound characteristics by which algorithms worked well on them.

Our diabetes and chronic wound management project is clearly DSR. The objective is to build a useful and usable artifact, specifically a smartphone-based app, that supports and contributes to improved health of those with chronic wounds. The chronic wound problem is important and complex—presenting challenges for clinicians, patients with wounds, and their caregivers. A smartphone-based solution is a research problem, thus a DSR project, because image processing executed on a smartphone is new with unknown feasibility.

C. *Design Methodology Challenges*

In our DSR projects, gaps arose when the problems and possible solutions were not well-defined or well-understood, typically when the problems were complex and potential solutions had unknown feasibility. Knowledge about how best to conduct a design process when problems are complex and feasible solutions are unknown is lacking in the DSR literature. This lack of knowledge about the design process when it involves new and complex problems and solutions is problematic for DSR project managers who are left to treat a project as if it was better defined and known so that they can follow standard design and development methodologies or to attempt to manage it using general R&D management principles, e.g., those described in [14].

One reason for the literature's lack of DSR design process knowledge is its focus on reporting design outcomes, rather than new knowledge about the design process. In contrast, Simon notes that, "both the shape of the *design* and the shape and organization of the *design process* are essential components of a theory of design" [4]. Guidelines for reporting DSR projects recommend reporting about the resulting artifact, its evaluation, and contributions to knowledge [2], [15]–[17], i.e., design outcomes, including contributions to kernel theories and to any emerging theories and design principles.

Reporting of the design process is often viewed as reporting the use of a DSR methodology. DSR projects, especially in universities, often follow a DSR methodology to ensure research rigor, specifically Peffers et al.'s DSR methodology [1] or Hevner et al.'s DSR guidelines [2]. Reports about DSR projects include the methodology used, and how each of the method's recommended activities or guidelines were executed, with little about handling problem and solution complexity and unknowns. Thus, DSR project managers have insufficient knowledge about managing when problems and solutions are complex and not well-defined.

To some extent, the Hevner *et al*. [2] and Peffers *et al*. [1] methodologies acknowledge this difficulty. For example, in Guideline 6, *Design as a Search Process*, Hevner *et al.* [2] acknowledge the roots of DSR in Simon [4] and his focus on design as search. Yet, Gregor and Hevner [16] do not specifically require discussion of this guideline in reporting DSR projects. Peffers *et al*.'s DSR methodology, frequently used in DSR studies, seems to assume that the problem and possible feasible solutions are known. For example, Activity 1, *Problem identification and motivation*, is to define the specific research problem and justify the value of a solution. Activity 2, *Define the objectives for a solution,* is to infer the objectives of a solution from the problem definition and knowledge of what is possible and feasible. Following this methodology, one then designs and develops the artifact, demonstrates that using the artifact solves the problem or parts of the problem, and evaluates the artifact. Both Hevner *et al*. [2] and Peffers *et al.* [1] primarily address any unknowns by stating that the process is necessarily iterative.

For our DSR projects, the existing DSR methodologies did not provide sufficient support for the complexities and unknown aspects in our problem and its potential solutions. For example, we did not know what was feasible, e.g., can image analysis be done on a smartphone?[1] These weaknesses of DSR methodologies for our project generated the two design challenges noted in the introduction. First, lack of knowledge about the problem led to the problem being frequently refined and redefined, which meant that the possible solutions also changed. In contrast, DSR methodologies assume that the problem can be defined and possible solutions specified, and thus, do not explicitly address what to do when that condition does not hold. Second, evolving problem definitions and unknown solutions led to needs for evaluation that differed from DSR methodologies' evaluation that assesses outcomes from using a built artifact. These challenges led us to create augmentations to recommended DSR design processes.

Our primary augmentation draws on Simon's conceptualization of the process of design as a search process. Design is search within the space of alternatives, which is made more difficult when the solution alternatives are not known or well-understood. Furthermore, Simon discusses problem representation and how problem solving may involve changes in that representation. These concepts of the space of alternatives and changes in problem representation are captured in the concepts of the *problem space* and the *solution space* (see Hevner's discussion in [13]), which are the terms we use in this research.

III. METHOD

A. *Ethnography Study of the Design Process*

We take a design ethnography approach [18]. Specifically, we use Baskerville and Myers' [19] second approach for employing

[1]Our claim that we could figure out how to use a smartphone as a wound image analysis device was a core claim in our NSF research proposal.

ethnography in DSR studies, a method they call *Ethnography to Study Design*. This approach seeks to understand designers and the design process through an ethnographic lens on the design process. While most studies using this approach focus on designers [19], our focus is the design process. We study the design process of one large DSR project. Specifically we study the complex series of projects that form our diabetes and chronic wound app development project, undertaken over nearly a decade, and ongoing. Our project and the healthcare and research problems investigated are sufficiently rich to illustrate the design process challenges we encountered and the managerial approaches and recommendations we created for addressing them.

Ethnographic methods produce deep understanding of the problem domain and a rich description of what is being observed [20]. This fits our goal of developing a deep understanding of the design process so that we could better manage and guide that process, and through this article, develop new knowledge for other managers and design researchers. On the downside, ethnographic methods are time consuming due to the time needed in the "field" and they require thorough documentation and analysis of that documentation. These are less of a problem for us because we are in the field anyway and are keeping good records for producing publications and reporting to our sponsors. As part of our DSR work, we are thinking deeply about the design process and regularly reviewing our progress in an attempt to effectively use our limited resources. As Baskerville *et al.* note, an ethnographic lens is implicitly part of most DSR projects, especially for understanding the problem and appropriate solutions [19].

Similarly, DSR projects implicitly have aspects of action research [19] because DSR authors are involved in the design process. Action research, however, typically involves the authors as interveners in the process, purposely introducing changes [21]. Interventions are not our focus. Thus, we characterize our primary method as ethnography. That is, we are acting as ethnographers, rather than action researchers.

B. Ethnographic Analysis Process

As our ethnographic study of this DSR project progressed, we integrated literature, especially Simon's view of design as search, into the analysis of our design process. We observed that we were regularly redefining the problem, exploring potential solutions to that revised problem, and based on evaluations of those solutions, continuing to refine and improve our solutions, and at some point, revising the problem again. Combining our observations with Simon's view of design as search, as well as Hevner *et al.*'s guideline 6 for DSR [2], led us to focus on design as search. This focus, in turn, led us to analyze our process in terms of the problem and solution spaces that we were searching. Searching necessarily involves frequent evaluations to determine which problems and solutions to explore further or to drop. Focusing on the challenges of design as search and how that changed evaluation enabled us to articulate our design process more clearly, in particular to articulate it as a process involving the coevolution of problem and solution spaces, and the management of that coevolution process through frequent small evaluations.

The ethnographic study of our design process produced a rich description of our search process. From that description, we were able to articulate and abstract the search process that we needed to use as a process that others can follow, thus going beyond merely describing our process. We also recognized that our proposed new process was an extension of current DSR methodologies, which have many valuable components that can continue to be used as is, especially for the more routine parts of a design problem.

We present the results of our ethnographic analysis in Sections IV and V below. Each section focuses on one of the two design challenges, Section IV on the need for an elaborate search process and Section V on the need to rethink the purpose of evaluation. Each provides solutions and recommendations discovered during our study. These two challenges were frequently evident as we designed, developed, and evaluated smartphone apps over the last decade to support chronic disease management, specifically type 2 diabetes and chronic wounds.

IV. Managing Design as Search of Problem and Solution Spaces

A. Challenge—Changing and Coevolving Problem and Solution Spaces

In a DSR project like ours where the problem and solution spaces are complex with many unknowns, discovery through exploration is critical. Thus, design is largely a search process of problem and solution spaces. Because these spaces are not well-defined, the problem and solution spaces change and coevolve. Managing such a DSR project then becomes managing the coevolution and search of problem and solution spaces. Such exploration for discovery and the associated coevolution of problem and solution spaces to be searched does not fit well in current DSR methodologies, despite their emphasis on iteration. As noted earlier, current DSR methodologies assume a relatively routine design and development process, and use iteration to handle problem and solution unknowns.

In the remaining parts of Section IV, we present the search process in our DSR project as a means of illustrating what it means for the problem and solution spaces to change and evolve as the project progressed, how these spaces coevolved through the search and discovery process, and how we managed our DSR project as a search and discovery process. We start with a representation we developed of problem and solution space coevolution.

B. Representing and Conceptualizing Problem and Solution Space Coevolution

Fig. 1 shows the generic search process that captures the methodology we developed. First, we start with a problem description that captures at a high level what our problem space is. As we *explore* that problem space, by working with potential users and our medical experts and by working on preliminary designs/solutions, the problem space tends to *expand* to include

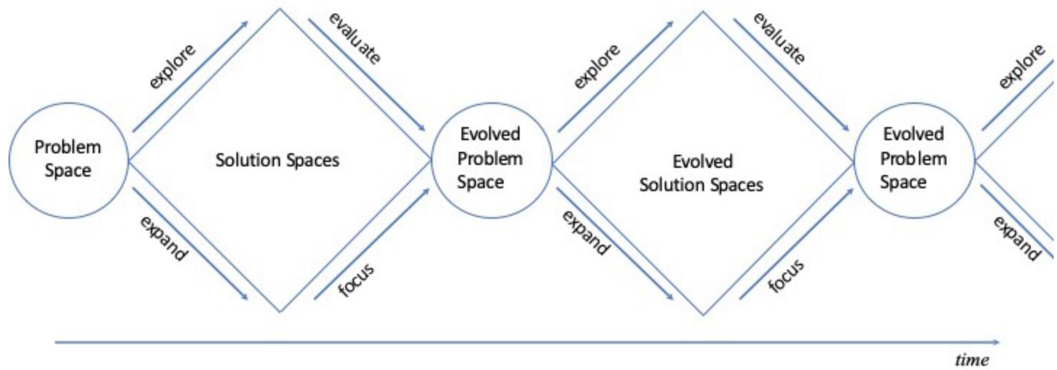

Fig. 1. Design search process.

more detailed aspects of the problem space and aspects of the problem we had not considered, but might be important. Simultaneously, this exploration and expansion of the problem space is developing into an associated solution space.

The managerial challenge is both 1) to allow and support exploration and expansion of the problem space and associated solution spaces because these processes are necessary when problem and solution spaces are not well-defined or known, but also 2) to ensure the initiation of efforts to *evaluate* potential solutions and bring *focus* about what the problem and potential solutions are. The result is an *evolved problem space* capturing a clearer problem understanding, which in turn leads to *evolved solution spaces* that are explored and expanded as needed.

Of course, the process is not as well delineated as Fig. 1 indicates, e.g., the transition from *explore and expand* to *evaluate and focus* is not a well-defined point in time. The problem space may also be continually evolving, rather than changing at discrete points when an evolved problem space emerges. Yet there were times in our process when there was a clear recognition that the problem space had changed.

Fig. 1 captures our DSR search process. While the traditional build and evaluate paradigm of DSR is implicit in this process, we found that build-evaluate was not a useful way to think about our DSR project, and in particular, not an effective way to manage its progress. Sections IV-C–IV-F (below) provide a detailed description and discussion of the coevolution of our problem spaces and the associated development and evaluation of solution spaces. Our objective is to illustrate the value of our DSR search process as a methodological enhancement of current DSR methodologies. Our enhancement adds the flexibility of discovery by being less rigid than current DSR methodologies. Our search process is designed to facilitate discovery and innovation, while simultaneously keeping the rigor of a DSR methodology as its focal point.

C. *Problem Space 1: Chronic Wound Management (2011)*

Our DSR project started in 2011 with the awarding of an NSF grant, although we had conducted preliminary investigations. Our initial problem space was thus defined by the scope of our grant proposal. We proposed to develop a smartphone app to support patients with advanced type 2 diabetes characterized by the presence of a diabetic foot ulcer (chronic wound on the bottom of the foot). The app would support home self-care by patients for their advanced diabetes, including tracking and advice on glucose levels, weight, exercise, their wound, and decision support for setting and achieving behavioral goals related to glucose levels, weight, and amount of physical activity. See Fig. 2 for evolution of our problem and solution spaces.

Because clinicians must monitor patient subjects using the app, we also developed a clinical support system for them. It displays patient data, both medical values, e.g., glucose, weight, and activity levels, and frequency of use of all the app functions, all of which are uploaded from the app on a regular basis to a server. Clinicians used these data to inform their bi-weekly phone calls to patients.

Most of the solutions to address this problem space are routine design and development with iterations that delivered enhanced functionality based on small evaluations. For example, we followed the recommendations of our behavioral medicine expert on goal setting and behavioral support [22]. We presented our app design at various medical conferences to get feedback from clinicians. Based on feedback from one conference, we redesigned the app's color scheme, both to include more medically soothing colors and to ensure the colors were consistent in indicating app functionality. On the technical side, we implemented code to automatically record glucose and weight from Bluetooth enabled meters and scales. We tested the app in our user experience lab [23], and finally tested it with a 6-week at home study. Much of this was relatively routine, and consistent with DSR methods.

D. *Problem Space 2: Wound Progress Assessment (2013)*

As we designed and developed solutions for the routine portions of the app described above, it became clear that the wound analysis portion of the project required its own problem space and associated solution spaces. See second problem space in Fig. 2 (Wound Progress Assessment for Diabetic Wounds) and associated solution spaces. Specifically, automated wound analysis is a new problem. While existing image analysis methods could be applicable, we needed to define the problem in terms of image analysis, and to adapt and test various image analysis algorithms for their applicability. We did not know whether

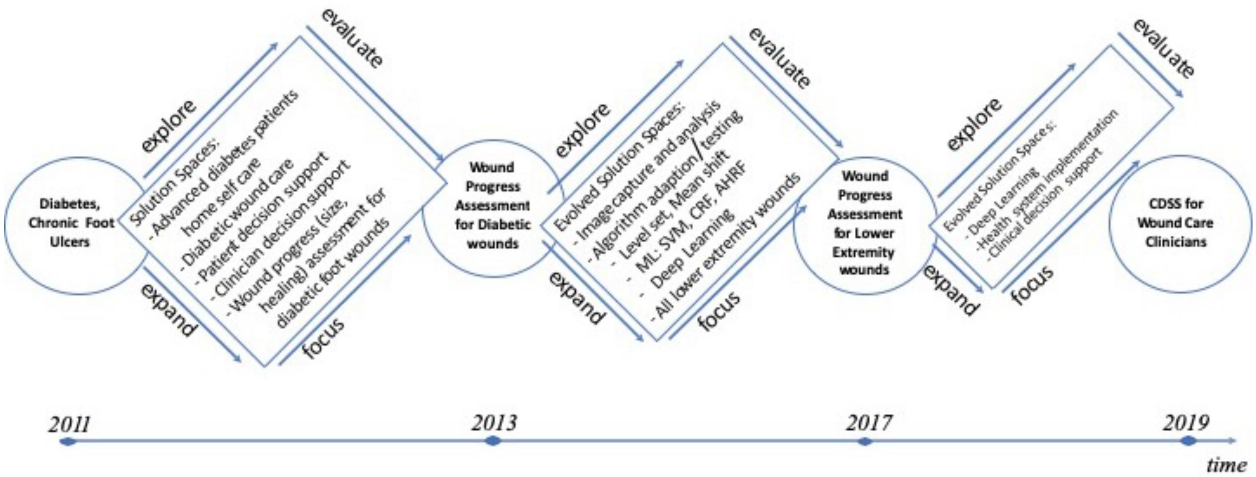

Fig. 2. Our DSR project design process.

Fig. 3. Footbox.

these algorithms would work or whether they would execute sufficiently fast on the smartphones available at the time.

With advice from our wound clinicians, we defined a healing wound as one that is getting smaller (reduced surface area) and has a higher portion of red (healing) tissue, as compared to yellow and black tissue. Thus, the output of the app's wound image analytics engine should be the wound size (area) and percentage of red tissue—metrics that would be used to assess wound image changes over time to determine healing progress.

1) Two Subproblems and Their Solution Spaces: We then decomposed the wound progress assessment into two subproblems, one to capture a wound image with the smartphone camera and one to analyze that image. These two subproblems, however, are dependent because characteristics of the captured image can affect the computational efficiency of analysis algorithms, which must be efficient to execute on a smartphone. Thus, we defined the image capture subproblem as capturing images under controlled lighting, distance, and camera angle conditions to avoid additional computation.

The solution space for image capture then became designing and building an image capture box, which we call a footbox. The footbox (see Fig. 3) enables patients easily to take a picture of the bottom of their foot (where their diabetic foot ulcer is), which is important given the limited mobility of many patients with advanced type 2 diabetes. It uses dual front-surface mirrors, a LED light source, and a fixed position for the smartphone to ensure that all images taken by a patient (e.g., at different times) have very similar lighting, distance, and camera angle, and ensuring that images are analyzable, ideally in reasonable computational time on a smartphone, and are comparable over time. The footbox design evolved over four design and evaluation iterations, as we experimented with box materials (must be lightweight) and box size, types of mirrors and lighting, how best to hold the smartphone in place while also ensuring ease of insertion and removal, and how to appropriately use voice activation to tell the smartphone to take a picture.

Given an image of the sole of a foot, captured using the footbox to ensure controlled lighting, the second subproblem involves first finding the wound within that image, which essentially means finding the wound boundary by finding the curve that separates normal foot skin from the wound. Because computing wound size given a wound boundary is easy and because computationally efficient methods for distinguishing color are available, the key computational problem is detecting the wound boundary. To enable patients to self-manage their wounds, we must automatically detect a wound boundary—in a way that runs on a smartphone. For clinician use, applications have avoided automatic boundary detection by requiring clinicians to draw the wound boundary on the image. We evaluated various boundary detection solutions on our set of 100 wound images collected from 15 patients over two years at the wound clinic.

2) Solution Space for Wound Boundary Detection as Level Set Based Algorithms: For finding the wound boundary, we first defined the solution space as level set algorithms. These algorithms were developed [24] and then adopted to image processing research [25], [26]. The model underlying level set-based methods assumes that we can generate (randomly) an initial closed contour in which the wound (object to be found) is located. Level set algorithms then work by iteratively moving (shrinking) the contour until it represents the boundary between the wound and the normal foot tissue. We evaluated level set algorithms until we found good initial contours and stopping rules.

Our algorithm provided sufficient accuracy for what we call best possible wound images, i.e., the wound is within the sole

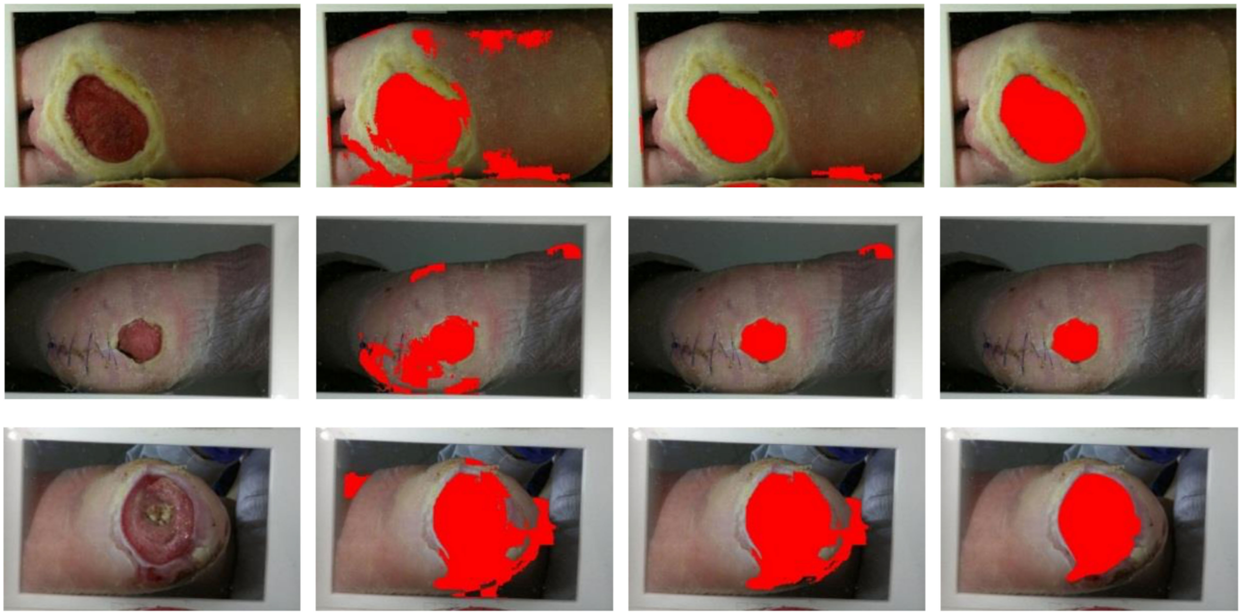

Fig. 4. Examples of wound boundary determination results (the determined wound areas are covered with red color). Column 1: the original image. Column 2: the boundary determination results by applying our two stage classifier. Column 3: the results after applying the CRF refinement technique. Column 4: the results after the outlier removal or hole filling up.

of the foot (not near an edge or toe) and the nonwound sole is of uniform healthy skin color that generates the contrast needed to recognize the wound boundary [27]. Nonideal wounds, however, were common, in which case, the algorithm does not converge to the wound boundary. In addition, its computational time was high. Although level set-based algorithms are used in image analysis [28], we concluded that they are not satisfactory for wound image analysis.

3) Solution Space for Wound Boundary Detection as Mean Shift Based Algorithms: We next investigated mean-shift algorithms [29], [30]. They segment images into similar clusters by assuming a feature vector associated with each pixel (e.g., its color and position in the image) is a random sample from an unknown probability distribution and then finds clusters within this distribution. Our images have three clusters, background around the foot, the normal foot skin, and the wound.

Mean-shift algorithms have several advantages for our problem, including that they consider spatial continuity within the image and they have parameters enabling adjustment to skin color and color consistency, both of which contribute to more accurately assigning a pixel to the appropriate cluster. Since these algorithms operate at a pixel level, we could parallelize for a smartphone's GPU. From our explorations of level-set algorithms, we learned that parallelizing parts of any algorithm and using the GPU would be necessary for executing on a smartphone. Mean-shift algorithms have a downside in that they oversegment, requiring an additional step to merge similar regions [29]. Fortunately, the merge algorithms are efficient.

For our adaptation of mean-shift algorithms to our problem, we tested various parameters and developed parallelized algorithms for the smartphone GPU, in a process of iterative development and evaluation. Our mean-shift algorithms were accurate with a few minor problems along the boundary, which we solved with a smoothing algorithm as long as wounds were not on the edge of the foot [31]. The algorithms had difficulty recognizing wound boundaries when the wound was on the edge of the foot.

We augmented our algorithm to handle two regularly occurring special cases, i.e., wounds on the edge of the foot and a foot with an amputated toe, that made it difficult for the mean-shift algorithm to detect a wound boundary (see Fig. 4). For wounds on the edge of the foot, a preprocessing algorithm determined whether the edge of the wound is within the foot image. If not, then the foot edge is used as the wound boundary for that part of wound. For a foot with an amputated toe, this condition is added as a setting to the wound engine. A preprocessing algorithm then adjusts the foot boundary so that the amputated toe area is not part of the image and thus does not confuse the algorithm by looking like a wound.

With these augmentations, the mean-shift algorithm worked well for our wound boundary detection problem, finding most wound boundaries in acceptable time [32]. In addition, because the two special conditions are known before the algorithm runs, the augmentations are only run when those conditions are present. Thus, we found an acceptable solution to our problem of finding algorithms sufficiently fast to run on a smartphone with excellent accuracy for wounds located on the sole of a foot.

4) Solution Space for Wound Boundary Detection as Machine Learning Algorithms: Wounds with special characteristics, especially wounds on the edge of the foot, were not consistently detected by mean shift algorithms, even with the augmented version designed to handle more of such cases. Thus, we searched for more advanced algorithms that could learn from images illustrating those special cases, i.e., ML algorithms, even though those algorithms might not run on the smartphones available at the time of our research.

We started with support vector machine (SVM)-based classifier algorithms. For our problem, the algorithm is a binary classifier that decides whether each superpixel is wound area (true value) or nonwound (false value). The process first segmented the image into homogenous regions, called superpixels, using the simple linear iterative clustering method [33]. Feature descriptors were generated for each super pixel and fed into the binary classifier. All superpixels designated as wound (true) were combined as the wound area. The search process was to select feature descriptors, apply the classifier algorithm, and evaluate the results. We created and evaluated four different feature descriptors, all developed based on the literature [34]–[41]. We evaluated these descriptors on accuracy and speed using a single-stage binary SVM classifier applied to our 100 wound images. One descriptor produced good results using the entire image, another produced good results with a restricted image of mostly the wound, while the other two were not as good.

As a result, we designed a new algorithm—a two-stage process, i.e., two ML training stages, with one descriptor used on the entire image and another on the restricted image from the first stage. The first stage ruled out irrelevant regions of the image. The second learned to distinguish healthy tissue from wound regions for superpixels misclassified in the first stage. Finally, we smoothed the wound boundary by applying a Conditional Random Field (CRF) image processing technique [42]. The resulting two-stage algorithm required more computational time than the single-stage SVM algorithms, but still ran in 20 s on the our smartphones (Nexus 4 phones with Android version 4.4) and provided greater accuracy [31], [32].

5) Removing the Problem/Solution Space Restrictions: Our final exploration changed both the problem and solution spaces by investigating advanced ML algorithms that require more computational power than our smartphones (Nexus 4) could provide. Relaxing the problem requirement of doing all computation on the smartphone allowed us to assess how much our smartphone constraint restricted our ability to improve the results. Because smartphone computing power is increasing, these algorithms may eventually be smartphone implementable. Additionally, the wound clinic physicians, after observing our smartphone wound processing, wanted to test it in their office. For that environment, we could use a powerful PC to process images taken with a smartphone, whereas for patients we could not assume connectivity to a more powerful server. Finally, these advanced algorithms could analyze images taken with less control over lighting, distance, and camera angle, allowing clinicians the flexibility to capture images without using the footbox and also to capture larger wounds or wounds in other locations.

We designed and evaluated two algorithms based on CRF models because the CRF-based boundary refinement for our two-stage algorithm worked well and CRF model-based algorithms are increasingly used for image processing [43], [44]. CRF is an ML approach that directly models the conditional probability of different class labels (e.g., wound and nonwound in our case) given a set of images [45]. Both CRF-based algorithms, however, produced less accurate results than our two-stage algorithm, and required significantly more computational power.

We then designed and evaluated an algorithm based on Associative Hierarchical Random Field (AHRF) models. AHRF models integrate top-down and bottom-up approaches by working at two levels, a pixel level where potential terms are based on pixels or pairwise pixels and a superpixel level where potential terms are based on superpixels and pairwise superpixels, plus connective potential terms across the two levels. We used the mean shift algorithm, discussed earlier, to generate the superpixels. Our AHRF-based algorithm is somewhat more accurate than our two-stage algorithm with its CRF refinement [46]. The downside, however, is a requirement for the computational power of a powerful PC. A significant advantage is that it handles images taken without the footbox, i.e., images taken in uncontrolled environments with varying lighting, distance, and camera angles.

6) Discussion of the Search Process: Our search and discovery process started with simple problems, e.g., for wounds, starting with moulage wounds [47], [48], artificial wounds used for training purposes that we attached to an artificial foot, and for health behavioral change, starting with simple tracking of glucose and weight. Then, as we found solutions for the simple problems, we enlarged the problem space, e.g., with more realistic, complex wounds. We learned the types of problems each solution could or could not handle, thus facilitating our learning of our problem space. Thus, the problem and solution spaces coevolved. They also coevolved for external reasons, e.g., smartphones had more computing power, ML algorithms became more computationally efficient, and our wound experts started capturing wound images, which affected our problem and solution spaces.

During these first five years (2011–2016), we would explore, expand, focus, and evaluate, as shown in Fig. 2. When we *explore*, we consider different solution spaces that could address the problem space (e.g., we considered an app to support self-management of wounds and algorithms for wound assessment). When we *expand*, we exhaust different solutions within a solution space (e.g., within wound assessment, we examined Level set, SVM, foot box) given the definition of the problem space (e.g., home-based wound assessment by patients). When we *focus*, we pick the most promising solutions and discard others, and then we *evaluate* by doing more rigorous evaluations to identify new discoveries (e.g., our fuller evaluation of ML algorithms, which eventually led to exploring the possibility of using deep learning). Through this article, we achieved our research goals of doing diabetic foot ulcer image processing on the phone and producing an app that supported those with advanced type 2 diabetes.

In continuing this research, we decided to focus on chronic wound management, which broadened our problem space to chronic wounds beyond diabetic foot ulcers. It also narrowed our problem space by dropping our focus on supporting patients with advanced type 2 diabetes. Diabetes support is important, but relatively routine and other apps were appearing that tracked glucose, weight, and physical activity. In contrast, wound analysis, assessment, and management is important and hard, with a shortage of medical experts. We had developed significant expertise and excellent medical partners in an area with few other researchers. We also changed our user focus from patients with chronic wounds to clinicians who analyze and treat such wounds, including those without advanced wound training.

Thus, our chronic wound work is continuing with two revised problem spaces, one focusing on lower extremity chronic wound analysis (problem space 3) and one on clinical decision support for wound care clinicians (problem space 4). These are only briefly described below because these explorations are still in progress and because the key points about managing the coevolution of problem and search spaces should be clear to readers without much detail.

E. Problem Space 3: Lower Extremity Chronic Wound Analysis (2017)

In 2017, we expanded our focus to all lower extremity wounds (except for surgical wounds), which includes diabetic foot ulcers (on the bottom of the foot), but also includes venous, arterial, and pressure ulcers. This expanded problem space requires analysis of images taken with the smartphone in a variety of lighting conditions, angles, and distances, that is, removing the requirement of using the footbox (see problem space 1). Not being restricted to the footbox allows images to be taken in clinics during exams or in any place a visiting nurse might encounter a patient with lower extremity wounds.

Thus, we initiated a controlled experiment to capture wound images under a variety of lighting conditions, camera angles, and distances. To do this, we used moulage (artificial) wounds, which were placed on an artificial leg. A camera was mounted on a computer-controlled arm that took pictures at pre-set arm positions. The goal was to determine the correction needed to an image to standardize its lighting, angle, and distance, so that images of the same wound at different times are comparable (after standardization) even when the image is not taken under the same conditions. We also tested several different cameras because each produces slightly different colors. We also determined limits on conditions, i.e., when the conditions distort the image sufficiently that correction does not work well. This knowledge will be used in training clinicians to capture images.

Changing the problem space to lower extremity wounds also required a change in our methods for assessing healing progress. Wound size and color, which we used for diabetic foot ulcers, is not sufficient for all lower extremity wounds. Thus, we are exploring the possibility of using the Photograhic Wound Assessment Tool (PWAT) [49], [50], a scale that clinicians can use to assess wounds along several dimensions from a photograph. We are also exploring various deep learning methods for automatically computing PWAT from a wound image.

F. Problem Space 4: CDSS for Wound Care Clinicians (2019)

For lower extremity wounds, we decided to focus on wound care clinicians, rather than the patients with wounds, as our app users for several reasons. First, our wound experts had moved from their traditional practice of recording textual notes about wound size and healing to taking pictures with their smartphones, and as a result, wanted to use our app as well as have their EHR system store the images. Second, analyzing a wound is difficult, and since most clinicians are not wound experts, patients often do not receive the most appropriate treatment, resulting in slow or nonhealing wounds. An image processing app could provide decision support to clinicians who are not wound experts. For example, many wounds occur among the elderly who may have their wounds assessed by a visiting nurse with limited wound expertise.

Thus, we initiated a focus on clinical decision support for lower extremity wounds. With advice from our wound experts, we choose three wound assessment decisions as follows:

1) continue current treatment (typically clean the wound and apply a new dressing);
2) refer to a wound expert (nonurgent);
3) immediate referral to a wound surgeon for assessment.

We have developed an initial set of decision rules based on the deep learning assessment of the characteristics of a wound, using the PWAT scale. The results from these rules are being compared to results from two different wound experts, a nurse practitioner specializing in wound assessment and a wound surgeon, using the several hundred wound images we have captured during our DSR project. As with the previous problem spaces, the problem and solution spaces coevolved, and we developed more detailed understanding and knowledge of the problem.

V. Evaluation to Provide Search Feedback

We now discuss how evaluation can and should provide feedback to the search process and the management of the coevolution of problem and solution spaces. As described in the prior section, our design process involved exploring, developing, and evaluating various pieces, e.g., an algorithm, for including potential artifacts, e.g., a smartphone app or smartphone plus PC. Throughout the process, we conducted small evaluation activities that provided feedback about our search progress, which in turn developed new understanding as we defined, redefined, and refined our problem spaces.

A. Challenge—Changes in the Purpose of Evaluation

In DSR methodologies, the purpose of evaluation is to assess the extent to which designed artifacts address the problem—implicitly assuming a well-defined problem. For example, the *Evaluation Activity* in the DSR Methodology [1] is to "observe and measure how well the artifact supports a solution to the problem." Hevner *et al.*'s *Design Evaluation guideline* [2] states that "the utility, quality, and efficacy of a design artifact must be rigorously demonstrated via well-executed evaluation methods." The guideline recognizes that iteration is likely, stating that "the evaluation phase provides essential feedback to the construction phase …," consistent with DSR's implicit build-evaluate paradigm.

The needs for and purpose of evaluation in our DSR projects differed substantially from DSR's evaluation phase. We needed evaluation to assess the search process in a way that provides feedback to guide and select the next steps in the search process.

As a result, we needed to embed evaluation within the design as search process, in addition to evaluation as a later phase for assessing a built artifact. In summary, the primary purpose of our evaluations are to assess the search process and provide feedback for guiding it, while the primary purpose of evaluation in DSR methodologies is to assess the designed and built artifact, and if iteration is needed, to provide feedback for constructing the next version of the artifact.

To guide search, we need to conduct evaluation differently. The usual evaluation methods do not assess our understanding of the problem or solution spaces and whether that understanding is increasing. Nor are they designed to assess the search process and whether the problem or solution spaces should be expanded, become more focused, or otherwise changed. Given the exploration and discovery processes that our DSR project required, the standard DSR evaluation processes, including their purpose, methods, criteria, and frequency do not provide the information that a research project manager would need to assess progress. Thus, we propose two modifications to DSR evaluation recommendations.

B. Guide the Search Process With Small, Frequent Evaluations

We recommend using many small, frequent evaluations to assess the intermediate steps in a search process. The feedback from these evaluations supports decision making about where best to focus research attention during the search. In our projects, the questions we needed to answer as we searched included the following:

1) Should a problem space be changed, refined, or redefined?
2) Which solution spaces had the most potential to address a problem?
3) Should a solution space be expanded or focused on specific solutions within that space?
4) Which solution alternatives have the most potential and which should be eliminated from further consideration?

Overall, we needed to evaluate and understand our progress as the problem and solution spaces coevolved. These small evaluations were needed to support decisions for effectively managing the search process and the coevolution of the problem and solution spaces.

We compare our recommendations for small, frequent search-based evaluations that arose from our study to the recently published Framework for Evaluation in DSR (FEDS) [51]. The objective of FEDS is better tailoring of evaluation efforts to the needs of particular research projects. It is a two-dimensional framework, where the x-axis is anchored in formative versus summative evaluation and the y-axis is anchored in artificial evaluation, e.g., in a lab, versus naturalistic evaluation, e.g., field studies or experiments. FEDS proposes a path of evaluation starting from the zero point (formative and artificial), usually culminating in a summative, naturalistic evaluation. The path differs by how many smaller evaluations are conducted along the path and how quickly those evaluations move to summative and naturalistic. Thus, FEDS extends standard DSR methods by adding early, small evaluations. The purpose of evaluation, however, remains focused on the artifact rather than the design (search) process and leads to the same final evaluation phase as in DSR methodologies.

Using FEDS to characterize evaluations during our project shows similarities and differences. Like FEDS' promotion of multiple evaluations, we did many small evaluations. The need for such evaluations was particularly acute in the parts of our project involved in selecting algorithms for potential use in analyzing wound images. FEDS' path labels, however, are not representative of our project. For example, FEDS' "Purely Technical" label indicates an evaluation that is always in the artificial domain [51]. For our purely technical algorithm analysis, labeling all those evaluations as being conducted in an artificial setting is misleading. On the artificial versus naturalistic scale for algorithm assessment, our use of moulage wounds for initial testing was purely artificial. When we used real wound images, we were in a naturalistic setting but how naturalistic depended on whether we assessed a full range of wound images (fully naturalistic) or whether we assessed a set of wounds selected for focused analysis. Similarly, testing our algorithms on real smartphones (naturalistic) differed from testing them on a powerful laptop (artificial), although our decision to use a powerful laptop for in clinic assessments turned such evaluations into naturalistic. In summary, FEDS is similar to our recommendations in advocating early, small evaluations and an evaluation path. The actual paths, however, are not consistent with our project evaluation needs.

C. Evaluations Should Assess the Search Process and the Coevolution of Search Spaces

To address the needs of projects that are designing novel artifacts where the problem and solution spaces must be explored and new discovery is important, we need evaluation processes to assess and enhance the research discovery process and its outcomes. Thus, we propose shifting our attention to evaluation approaches and metrics that help research project managers and design researchers assess the following:

1) breadth and depth of problem and solution space searching;
2) whether the problem and solution spaces are expanding and focusing as needed;
3) improvement in the relevance and feasibility of the solution space.

We should also provide guidelines for research managers on when and how to do all these.

Our proposed evaluation approach is to focus on, and report about, the coevaluation of the problem and solution spaces and the new understanding resulting from that process, much like we did in our process described in Section IV. This places more focus on the process of discovery and learning. It does not remove the need for some traditional evaluation and to report contributions to kernel theories, but these evaluations are ideally smaller efforts done as part of assessing the problem and solution spaces. In our chronic wound management project, we were regularly evaluating our algorithms as we developed them, which provided feedback for evolving our problem and solution spaces.

We were also regularly doing small evaluations of our app with potential users. For example, we conducted usability studies using an eye tracker and before and after questionnaires with five people in the lab study [23]. We conducted a six-week at home study with seven patients from the wound clinic. That is, we used fewer subjects in each evaluation, but did more evaluations. In doing so, we obtained sufficient information to move on to our next step. Furthermore, our design process of continually adding more complex cases to the problem space worked well with small evaluations of solutions for that problem space. Our search with embedded evaluations increased the knowledge of the problem as the problem space expanded and our knowledge of which IT artifacts (e.g., image analysis algorithms) could address problems in that problem space. Such knowledge is critical for developing an understanding of how IT can provide solutions in the healthcare context for individual patients and clinicians.

VI. Discussion and Conclusion

There are excellent research guidelines about how to conduct and report DSR projects, e.g., [1], [2], [15], [16], [51]. They present logical and well-reasoned advice about the DSR design process. For our DSR project, that advice was not as useful as expected. Thus, we initiated an ethnographic study focused on understanding and documenting the design processes developed during our project. That is, we used design ethnography methodology to study our own project to discover which design processes worked, which did not, why, and what we needed to do.

A. Discussion of the Results From Our Design Ethnography Study

The research findings of our ethnographic case study highlight the coevolution of problem and solutions spaces. A DSR project like ours is not simply one problem space with an associated solution space. Both evolve as we learn more about the problem, its subproblems, and their important aspects, and similarly learn more about the associated solution spaces. The design process we discovered and developed, as shown in Figs. 1 and 2, focuses on these evolving problem and solution spaces, specifically searching these spaces, and managing their coevolution. This process resonated with us as designers, and equally important, as managers of a DSR project. It highlights the criticality of Hevner *et al.*'s DSR guideline about design as a search process [2] and his continued discussion of the search process [13]. It also returns to, and builds on, DSR's foundations in Simon's *Sciences of the Artificial* [4].

Focusing on the design as a search process enables those conducting DSR research to accumulate design knowledge and build design science because it adds attention to and learning about the design process, not only design outcomes. Learning about the design process means studying it to understand the search process and how the problem and solution spaces evolve as the search proceeds. For chronic disease support applications, learning from the search process is critical because many aspects of these problems are not sufficiently well understood to be able to use standard design and development processes.

Coevolution of problem and solution spaces occurred as we developed and focused on subproblems, which developed into solution spaces. That is, there was not a clear distinction between the problem space and the solution space because the problem spaces evolve into a solution spaces, which can lead to different or refined problem spaces. Over time, there was a lot of back and forth and coevolution as designers choose where to focus, and when and how to expand and contract that focus. The coevolution of problem and solution spaces that we observed has also been observed by those who study designers in other fields. For example, Dorst and Cross [52] in their experiments with industrial design professionals observed a coevolution of the design problem and potential solutions as designers searched for good design alternatives and changed their concept of the problem to fit solutions and vice versa.

Our findings also highlight evaluation as a critical component of the search process. Small, frequent evaluations provide feedback for guiding the search process. They provide information about when to expand and explore, and when to focus only on the most promising solutions. Evaluation as search feedback differs from the traditional purpose of evaluation in DSR methodologies as a final summative evaluation of an artifact. In our ongoing DSR project, smaller, more frequent evaluations provided the feedback needed for the next steps in the design search process.

As designers and research project managers, we played an active role in guiding the coevolution of the problem and solution spaces, but these spaces also evolved due to changing solution feasibilities as technology advanced (e.g., more powerful smartphones, more advanced machine learning algorithms) and target users' expectations changed [53]. For example, ML algorithms became so powerful that we started considering deep learning approaches even though there were no available trained algorithms for wounds. These new developments not only altered the set of solutions we could consider, but also changed the definition and representation of problems as well.

Our findings highlight how the problem definition and representation changed as the project progressed. In the *Sciences of the Artificial*, Simon notes the importance of a problem's representation in finding a solution, e.g., changing the representation can make solutions easier to find [4]. For our research, the solution space became clearer as we defined the problem in more detail or changed the definition of the problem. One example is changing the targeted user. Switching from patients with chronic diseases as our app users to clinicians, especially those without wound expertise, significantly changed aspects of our problem, e.g., to the need for clinical decision support rather than patient health behavior change support. Other aspects, such as how to analyze a wound from its captured image, changed less, but still it changed the following:

1) from an image box to no image box;
2) from non-ML algorithms to ML algorithms to deep learning algorithms;
3) from smartphone only computations to some use of powerful laptops.

In our DSR project, this continual changing of the problem and associated solutions was fundamental to our search and discovery process and a necessary part of DSR applied to novel problems.

The chronic wound problem for our DSR project represent a complex, real healthcare problem of societal importance. By addressing a real healthcare problem, we are also tackling a problem whose solution requires multidisciplinary expertise (e.g., researchers with IS, medical, image analysis expertise). Such a complex, ill-structured problem with unknown solutions highlighted the weaknesses of current DSR methodologies and the need to augment them with a design process that addresses coevolving problem and solution spaces. Because the problem and solution spaces are complex and evolving, part of solving the problem is developing a better understanding of it and which solutions might work. While our solutions must be medically sound, they are not purely medical solutions that wound clinicians apply, but are solutions in a complex medical/technical/behavioral solutions space that is not well understood.

Our problem fit well with a DSR approach. It is a complex, not well-defined problem with unknown solutions, as Hevner discusses in [13]. It involves known genres of DSR [13], but highlights the challenges of finding solutions across several DSR genres. Solutions to our problem have aspects of the computational genre of DSR, as outlined by Chen in [13], e.g. our image analysis algorithms. They also include aspects of the representation genre of DSR as outlined by Burton-Jones and Parsons in [13], e.g., our new representation to capture the coevolution of problem and search spaces, as shown in Figs. 1 and 2.

B. Contributions

Our primary contributions are to improve DSR methodologies. First, we identified two specific challenges in applying DSR methodologies to complex, unstructured, and ill-defined design problems. One challenge related to the need for a focus on search and the coevolution of problem and solution spaces. The other challenge related to the need for frequent evaluations that can provide feedback to guide the search and management of the coevolving problem and solution spaces. While others have noted general challenges in applying DSR to complex problems, e.g., Hevner's discussion in [13], we are specific about what those challenges are and why they occur, and thus were able to make progress toward addressing those challenges.

Second, we created solutions to those challenges. Our solutions augment current DSR methodologies, thus retaining their useful aspects while extending them to handle the two identified challenges. Our solution involved developing a new representation for evolving problem and solution spaces (see Figs. 1 and 2), which captured our new way of thinking about design for complex problems in terms of coevolving problem and solution spaces. To support the process of design in terms of coevolving problem and solutions spaces, we also proposed changes to how evaluation should be used during the design process so that feedback from the evaluation process can guide the search process.

Third, by using an ethnographic approach, the challenges identified and solutions proposed are grounded in, and derived from, actual DSR project management experiences. This approach ensures that our solutions are realistic. Our approach plus our findings that illustrate how to conduct and manage a search-driven design process provide credibility that our recommendations can aid design researchers and DSR project managers.

More generally, our contributions represent a shift in the research paradigm for DSR, especially when DSR is applied to complex problems. We are essentially proposing a shift from the current paradigm of build-evaluate, and iterate as needed, to a paradigm focused on searching problem and solution spaces, with evaluation used to assess and guide the search, as well as to provide feedback on artifacts being built. The build-evaluate paradigm focuses more on the outcomes of design than on the design process, which obscures the design focus that is core to DSR. Focusing on coevolution of problem and search spaces puts the emphasis back on design and design theory, rather than outcomes and their evaluation. While Hevner [13] discusses the search process and evolving problem and solution spaces, his solution is more rapid build-evaluate cycles. From our study, we conclude that more rapid cycles are not enough; we must focus explicitly on the coevolution of the problem and solution spaces.

Majchrzak *et al.* [54] advocate expanding the definition of theory to include theories of the problem and theories of the solution. In advocating a paradigm shift in DSR, we are proposing a different way of thinking about DSR problems and their solutions. That is, rather than the current build-evaluate theory of DSR problems and solutions, we are proposing a DSR theory around coevolution of problem and solution spaces. While Majchrzak *et al.* [54] recommend not tackling a theory of the problem and a theory of the solution in one paper, our observations about how problem and solution spaces coevolve make the separation of problems and solutions difficult.

By focusing on search, we are implicitly focusing on a process that promotes learning about the problem. Better understanding and knowledge of the problem is as important as the artifact itself as IS researchers tackle societal problems, such as healthcare, with IT artifacts. In addition, by reporting on search processes and evolving problem and solution spaces, we can articulate better how to conduct DSR and how to address the really difficult societal problems that are confronting us.

C. Implications for Design Science Project Managers

Our revised way of thinking about DSR benefits those managing DSR projects. For them, it highlights the details of the DSR design process, so that they can more easily understand and manage it. It can help them find the leverage points in the process (e.g., when to expand and explore, and when to conduct evaluations of alternatives so as to focus on the most promising paths going forward). Lack of proper exploration can be detrimental by missing opportunities that could lead to viable solutions. At the same time, spending too much time doing a thorough exploration can also be detrimental because without focusing as early as possible on potentially viable solutions, valuable solutions may be significantly delayed.

D. Implications for Design Science Researchers

Our revised way of thinking about DSR also benefits DSR researchers. For them, it broadens the set of problems that can be addressed by broadening the research results that are acceptable. Our approach frees researchers to take on bigger, societal problems that are not well-defined and for which solutions include aspects beyond the artifact. For such problems and solutions, our approach acknowledges that contributions focusing on understanding the problem and solution spaces are important and that realistic summative evaluations may not be feasible or may not provide clear conclusions.

E. Limitations and Generalizability

Our problem—a research problem in the healthcare space—is complex and will not be solved by simply building an artifact. It is a new problem requiring new solutions [55], i.e., it is in Gregor and Hevner's invention quadrant, not their routine design quadrant [16]. Thus, the nature of our problem contributed to the difficulty of applying DSR methods.

Our solutions are likely to be generalizable to other invention quadrant problems because our problem is typical in several ways of the types of problems currently being tackled by IS researchers. First, it has similarities to the problems in the papers in Majchrzak *et al.*'s special issue [54]. The solutions proposed in those papers typically required societal changes, not only an IT artifact, to produce the desired impacts. Furthermore, they are often outside the typical business organizational environment that has characterized DSR and IS research in the past. Second, as discussed previously, our problem involves several of the common DSR genres discussed in [13], and thus is typical of DSR projects, although more complex because of its several genres. Third, our problem is similar to other problems associated with embedding IT into the healthcare space. For example, many apps and devices have been developed to help individuals improve their health, but there is little evidence that this proliferation of solutions has improved health [56]. Thus, a DSR project that develops a solution for the healthcare space is unlikely to show significant effects on health outcomes (even with a well-defined evaluation study). Such a DSR project may, however, have important outcomes in terms of understanding the problem, leading to future solutions.

F. Future Research

As our findings indicate, DSR solutions to complex, unstructured problems with unknown solutions require guiding and managing the coevolution of problem and solution spaces. We developed a method for representing the coevolution (see Figs. 1 and 2) and suggestions for thinking about and guiding that coevolution. Additional research is needed to develop more advanced representations and measures of the coevolution of these spaces.

When tackling societal problems, the primary contribution of DSR projects may be new understanding and knowledge of the problem (e.g., toward a theory of the problem [54]). Similarly, the contribution could focus on the nature of, and theory about, appropriate solutions. Either of these represents an additional form of research contribution that should be valued equally to the contributions from the traditional build-evaluate paradigm that develops a well-defined artifact and demonstrates with a thorough evaluation how it solves the problem. Future research is needed on how best to present a contribution that improves problem and solution understanding, including but not limited to developing a theory of each.

Another area for future research is a different coevolution challenge we encountered during our DSR project. Similar to technology evolving (as expected) during our project, medical practice also evolves. Specifically, medical and technical solutions were coevolving. As we designed technologies to support clinical practice, we were also searching for objective practice rules. By assisting with that search, our medical experts were exploring more objective approaches. A simple example is that clinicians started taking pictures of patients' wounds, which they had not done before. The smartphone and our interest in understanding wounds from images facilitated this evolution in practice. While we had not planned to affect medical practice, our exploration with our medical partners of the problem and solution spaces for technology-based solutions led them to explore augmentations to their medical practices.

In summary, we urge DSR researchers to continue to conduct research on complex problems of societal importance, e.g., in healthcare, and to report their search processes, including how their problem and solution spaces coevolved during their project.

G. Conclusion

In this article, we conducted a design ethnography study of our decade long, on-going DSR project to discover more appropriate approaches to conducting DSR projects when the problem and solutions are not well-defined. We concluded that focusing on problem and solution spaces and their coevolution was critical for addressing the lack of definition and knowledge about the problem and feasible solutions. Thus, we proposed returning to a paradigm of design as a search process, rather than the implicit build-evaluate paradigm of current DSR methodologies. This article indicated that search was a more appropriate paradigm for complex problems with unknown solutions that require a DSR approach, whereas build-evaluate fits better with well-defined problems. In our proposed approach, evaluation was conducted frequently and used to guide the search of problem and solution spaces, as well as to provide feedback about evolving solutions, i.e., evolving artifacts. Our findings and recommended focus on search serve to augment rather than replace current DSR methodologies.

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