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Design problem decomposition: an empirical study of small teams of facility designers

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Abstract

Decomposing complex design problems is an important component of design processes. When a design problem is too complex to solve all at once, the problem is decomposed into manageable subproblems. Previous work on design processes has identified some general decomposition patterns and has studied how individual designers decompose design problems; this study examines the way variables are grouped into subproblems, the process of decomposition, and whether small teams use similar decomposition patterns. Data were collected from five teams as they solved a facility design problem, and the subproblems that they considered were analyzed and compared. Using a mix of qualitative and quantitative analysis techniques, we examined (1) whether their subproblems group tightly coupled design variables (and separate weakly coupled variables); (2) whether their decompositions (subproblems and the sequence in which they were solved) follow a top–down design process; and (3) whether different teams used the same decompositions. Our results suggest that teams followed a partial top–down design process that moved from breadth- to depth-first search, and that subproblems were often driven by two types of coupling among design variables. However, the inconsistency of observed approaches suggests that there is room for improvement in how human designers decompose problems. By identifying these issues, the results lay a foundation for future research to provide better support for human designers in decomposing problems.

Keywords Design teams · Decomposition · Facility design

1 Introduction

When a design problem is too complex for a design team to solve all at once, it is decomposed into more manageable subproblems that may be solved in different sequences or in parallel. The choice of subproblems and the order in which they are solved may influence the design process and the quality of the solutions that are generated. An important first step towards studying this relationship is to understand the types of subproblems that designers create when solving a design problem.

This paper describes the results of a study to identify the types of subproblems created by small design teams when they are given no guidance on how they should decompose the design problem. Understanding these "intuitive" decompositions and assessing their similarities and variability are important steps towards explaining design cognition and creating design guidelines and methods. Although decomposition has been studied for many years, design researchers have focused more on the process of decomposing than on the subproblem content and have studied individuals rather than small teams (e.g., Liikkanen and Perttula 2009; Ho 2001; Sun et al. 2016; McComb et al. 2017a, b).

To fill these gaps, this study aimed to identify the decompositions created by small design teams, including (1) the types of variables that are typically grouped into subproblems; (2) typical sequences in which subproblems are solved; and (3) commonalities and differences in the subproblems and sequences across different design teams. Specifically, our analysis sought to examine whether human designers follow prescribed design approaches, including (1) whether their subproblems group tightly coupled design variables (and separate weakly coupled variables); (2) whether their decompositions (the sequence of their subproblems) follow a top–down design process that begins with a high-level design problem, then preliminary layout problems,

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and then detailed design problems; and (3) whether different design teams use similar decompositions. Our research goals are exploratory: we seek to identify patterns based on an in-depth analysis of a small number of teams solving one particular design problem [as other researchers have done before us for individuals rather than teams (Ho 2001; Goel and Pirolli 1992; Ball et al. 1997)]; future research can later confirm whether these patterns hold in a wider array of teams and settings.

To accomplish these aims, small design teams made up of public health professionals were observed and recorded as they solved a public health facility design problem (all the professionals had training and experience in solving this type of problem). The observational data were coded to identify the design variables discussed by teams over time. The coded data were analyzed to discover which variables were typically solved together as a subproblem and in what sequence the subproblems were solved. We then compared the subproblems and sequences of each team. The results identify the types of decompositions used by these teams when no guidance on decomposition is provided, on a problem of moderate complexity solved by a small team of experts. They suggest patterns in how designers decompose facility design problems. Our analysis of these patterns suggests needed improvements to the design approaches of small teams and lays a foundation for creating design guidelines to enable such improvements.

The remainder of this paper includes the following: Sect. 2 reviews related research on decomposition in design. Section 3 describes the data collection and analysis methods. Section 4 presents the results of our analysis of the decompositions. Section 5 discusses these results and their implications for practice and research. Section 6 concludes the paper and describes the contributions of this work.

2 Related literature

Design processes Engineering design occurs via a series of decisions (March and Simon 1958; Hazelrigg 1998; Herrmann and Schmidt 2002, 2006). Some decisions may be done sequentially, while others occur concurrently, and different patterns of decision making can occur (Lewis and Mistree 1998). A design process includes the tasks needed to make these decisions. Some models of design processes consider the activities that need to be done, as in Gantt charts, the PERT and critical path methods, IDEF, the design structure matrix, Petri nets, and signposting (Eppinger et al. 1994; McMahon and Xianyi 1996; Clarkson and Hamilton 2000; O'Donovan et al. 2005).

The design literature recognizes that design decisions and the design process affect the quality of the design solutions. Some empirical studies have considered how specific design activities and team characteristics affect design solution quality (Kraemer and Pinsonneault 1990; Bostrom et al. 1992; Meredith 1997; Hammond et al. 2001). A second stream of research has used models of simple design processes to assess the quality of the design processes by evaluating the quality of the product designs that are generated, accounting for certain characteristics of bounded rational designers (Krishnan et al. 1997; Lewis and Mistree 1998; Gurnani and Lewis 2008; Herrmann 2010, 2015; McComb et al. 2017a).

Design organizations commonly use design processes that are a series of distinct, well-defined phases (Cooper 2008, 1994). When human designers work within organizations, they usually follow the organization's design process, but they may use more informal or unstructured processes when solving design problems within those phases or when creating a design rapidly (e.g., Sherwood and McCleese 2013; Sutton and Hargadon 1996). The informal design processes employed by humans are partially dictated by the way they decompose problems (Ball et al. 1994, 1997; Liikkanen and Perttula 2009).

Decomposition of design problems The design and systems engineering literature acknowledges the critical importance of appropriately decomposing design problems to enable a successful solution. Evidence shows that some differences in the system performance depend on how the work is decomposed, such as whether there are too many or too few modules (Ethiraj and Levinthal 2004). Evidence also shows that the structure of the design process, and in particular of the organization that executes the design process, is correlated with the type of design achieved (MacCormack et al. 2012).

The literature suggests that successful decompositions are those in which subproblems group strongly coupled design variables and separate weakly coupled design variables (e.g., Simon 1962; Baldwin and Clark 2000) and enable appropriate iterations (e.g., Wynn and Eckert 2017; Browning 2001). Many tools and methods have been developed for designing such decompositions, such as those based on design structure matrices (Browning 2001; Eppinger and Browning 2012).

The literature also suggests that designers should use a top–down approach. Pahl et al. (2007), for example, suggest a top–down process starting with a high-level conceptual design (or physical principles), then preliminary layout (or working principles), then progressively more detailed designs. This is a prescriptive model in that it suggests how designers ought to design.

Human designers and decomposition Descriptive studies, on the other hand, explore how humans actually do design. Empirical studies of human designers are important because they enable characterization of their design processes to analyze them and suggest improvements

(Dinar et al. 2015). Researchers have investigated the type of activities performed by human designers, such as problem structuring, preliminary design, refinement, and detail design (Goel and Pirolli 1992) and found that problem structuring or framing is a key feature of design expertise (Cross 2004). The problem's framing may involve some decomposition or may influence the decomposition later used.

Researchers have investigated several phenomena related to problem decomposition by human designers. The first is the distinction between "explicit" and "implicit" decomposition (Ho 2001). Explicit decomposition involves decomposing the design problem upfront, while implicit decompositions evolve as the problem is solved. Designers appear to rely more heavily on implicit decomposition, especially novice designers (Liikkanen and Perttula 2009), but explicit decomposition is a more effective approach (Sun et al. 2016). A second phenomenon is the search sequence. Consistent with the prescriptions of top-down design approaches described above, evidence suggests that designers progress from conceptual design to preliminary design to detailed design (Goel and Pirolli 1992; Ball and Ormerod 1995), which corresponds with a breadth-first search strategy, and that experts in particular are likely to use this breadth-first approach (Ho 2001; Sun et al. 2016; Ball et al. 1997); however, some experts occasionally deviate from this approach in an opportunistic manner (Ball et al. 1997; Guindon 1990).

Research gap Empirical investigations of human designers decomposing problems have thus far focused largely on the process by which humans decompose problems: whether explicitly or implicitly designed and the order in which subproblems are solved. Moreover, studies of decomposition by human designers have focused on individual designers using verbal protocols (Goel and Pirolli 1992; Liikkanen and Perttula 2009; Ho 2001; Sun et al. 2016; Ball et al. 1997), and many of these have used students as subjects (Sun et al. 2016; Liikkanen and Perttula 2009; Ho 2001; Goel and Pirolli 1992). Studies of teams have focused more on team composition and team dynamics (Dinar et al. 2015).

Thus, studies are needed to investigate how teams of professionals decompose design problems, including whether they follow the general design processes that have been prescribed by the design literature and whether they are similar to the approaches used by individuals. This includes considering the important question of which design variables are contained in the subproblems that make up the decomposition; this can be used to evaluate how well human designers group tightly coupled variables and separate loosely coupled variables, and whether their subproblems support a top-down and breadth-first design process. Like other researchers in this area (Ho 2001; Goel and Pirolli 1992; Ball et al. 1997), we begin with an exploratory approach, analyzing a small number of design teams in depth to identify patterns that can later be tested in a wider variety of settings.

In other work, we have described previous studies that considered other aspects of our research into how small design teams decompose system design problems. Gralla and Herrmann (2014) and Gralla et al. (2016) discussed the data collection and analysis method. Tobias et al. (2015) considered how often designers explicitly decomposed the design problem. Azhar et al. (2016) discussed the use of one clustering technique to identify subproblems for teams who solved a factory redesign problem. Morency et al. (2017) evaluated different clustering algorithms on four teams (two solved a factory redesign problem; two solved the facility design problem discussed in this paper). The study presented in this paper presents new data and analysis approaches.

3 Methods

To identify the subproblems considered by design teams, we studied the activities of five design teams engaged in a half-day design session. We recorded each team's activities, used inductive qualitative coding to identify the design variables teams considered, and then used clustering algorithms to identify how those design variables were grouped into subproblems.

A design variable identifies a single decision that a team made or a set of very closely related decisions that the team treated as a single decision. (That is, the team did not discuss separately any components or "sub-variables" of the decision.) A subproblem is defined as a collection of design variables that are discussed and determined together by a team. We assumed that a variable belongs to only one subproblem. This assumption simplified the process of identifying subproblems and seemed reasonable based on our observations of team activities. It could be relaxed in future work to show how subproblems are coupled or change. A decomposition is a set of subproblems used by a team (not all design variables may necessarily be grouped with others; some may be considered individually or not considered at all). We are also interested in the sequence in which these subproblems were solved by each team, which may include subproblems arranged in parallel, in series, or considered iteratively.

3.1 Study design

We studied the activities of five design teams made up of public health and emergency response professionals designing a point of distribution (POD), a temporary facility for rapidly dispensing prophylactic antibiotics in response to an anthrax attack (Abbey et al. 2013). Designing such PODs is part of the professional responsibilities of each participant, and it typically must be completed in a very short time, so

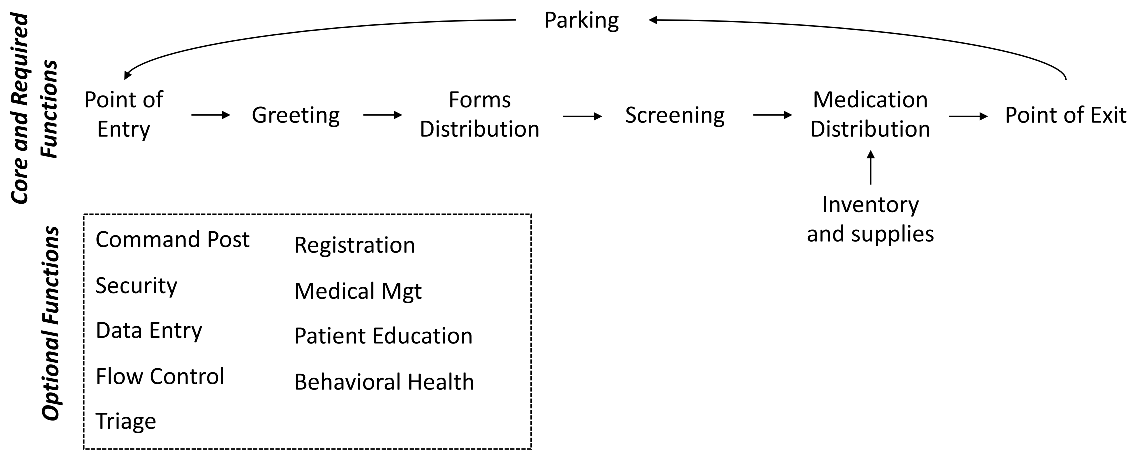

Fig. 1 Core POD process with flow of people and supplies

the setting is realistic. We chose this type of field experiment because it enables observation of all the design activities undertaken by a team, it enables us to see multiple teams solving the same design problem under the same conditions, and yet it provides a nearly realistic design setting since participants are using the same tools and interacting with the same people as they would in solving this problem in reality (Hendrick and Kleiner 2002).

The 20 participants that participated in the study were all public health emergency preparedness professionals from jurisdictions across the state of Maryland; they had an average of 10.8 years of experience, with a minimum of 6 months and a maximum of 42 years. They were stratified by experience level and then randomly assigned to one of five teams, ensuring an even distribution of experience levels on each team. This team formation process was meant to minimize social and personal effects by forming teams with persons who do not normally work together. All of the participants had formal training and prior experience in POD design, but no specific problem decomposition approach was dictated in their training.

3.2 Design problem

In this exercise, the participants created the layout and staffing plan for a POD in a new high school in Maryland. The exercise took approximately 3 h. The design prompt did not provide an explicit decomposition of the design problem but rather gave a problem statement similar to those provided in POD training materials (CDC SNS 2012).

Participants were provided with the blueprints of the school, basic data about the population the POD must serve, and the average time required for each step in the POD. They were asked to draw a POD layout that described the flow of clients into and through the POD, the location and number of POD stations, and the staff at each station. The participants were asked to satisfy a capacity requirement, with constraints on the available staff and the space and layout. Budget and other resource constraints were not specified explicitly, but our professional subjects knew the implicit budget constraints; this is consistent with the real-life version of this design problem. Teams were not asked to optimize any specific performance measures, except that they sought to make it as convenient and safe for clients as possible. (All the teams created designs with adequate capacity.)

There were eight required functions: greeting, forms distribution, screening, medication distribution (sometimes abbreviated as med dsn), points of entry and exit, parking, and inventory and supplies; and there were nine optional functions that could be included if the teams considered them relevant. Figure 1 depicts the flow of people and supplies through the required functions and shows the complete set of optional functions mentioned in the design problem (some teams also added a staff break room, which was not mentioned in the design problem). Although the teams assigned each function to a different “station”, this was not required by the design prompt (although some of the functions, such as the “command post”, implied it). For clarity, we use the term “station” throughout the paper.

The designers carefully considered how residents would drive into the facility, park, enter the facility, wait in lines, and exit; they considered how supplies would be brought in, stored, and transported, and how all the required stations would be staffed. They also had to determine a detailed internal layout for each station in the POD. The layout and staffing had to be determined to serve a particular number of people in a 24-h period using the facilities, furniture, and staff available to them.

This design problem is a useful setting in which to study how problems are decomposed. It includes many design variables that interact with one another and constraints that are challenging to satisfy. Because it is not overly complex, it can be solved in a short time, enabling detailed observation and analysis of teams as they solved it. On the other hand, the problem is realistic and complex enough to require designers to wrestle with multiple relationships among different aspects of the problem and consider various possible solutions. In particular, the problem facilitates evaluation of whether the teams followed the literature's prescriptions on how to decompose problems, based on important coupling among design variables and a clear distinction among high-level, preliminary, and detailed design, as described in the next paragraphs. (The following description of the design problem's coupling and structure was not provided to the teams but supports our analysis of their approaches.)

There are many relationships among the design variables in the problem. The attributes of each station (such as its location, staffing, and internal layout) are tightly coupled to each other because each attribute limits the feasible values for the other attributes: for example, the choice of location limits the choices of internal layout because it may constrain possible entry and exit locations, boundaries, and other features. Similarly, the attributes of contiguous stations (such as greeting and forms distribution) are also tightly coupled because they constrain or influence each other. For example, because POD visitors must go directly from the greeting to the forms distribution station, placing these two stations near one another reduces the distance that visitors must travel, which is desirable, so fixing the location of one constrains feasible locations for the other; on the same principle, the internal layout of greeting determines how people exit the station, constraining the internal layout—in particular, the entry point—for the forms distribution station. Finally, there is strong coupling among some particular attributes across all stations. For example, since the total number of staff is limited, assigning more staff to one station limits the availability of staff for the remaining stations.

In the terms of a function structure (Pahl et al. 2007), the overall function of a POD is to give visitors appropriate medication. The main POD functions were shown in Fig. 1. This involves two key material flows: the flow of visitors and the flow of medication; both flows enter and exit the POD, move between stations in the POD, and move within each station. There is a flow of medical information from POD visitors to POD staff, which is a type of signal flow. Finally, there is a flow of signals among the POD staff as the POD leadership monitors activities and directs staff to respond appropriately.

Finally, the design problem's structure enables a distinction between high-level, preliminary layout, and detailed design decisions [corresponding to the standard stages of conceptual design, embodiment design, and detailed design (Pahl et al. 2007; Dym et al. 2009)]. In conceptual design, a designer considers different schemes that give the relationships of the principal components of a system that will satisfy the requirements; in POD design, the corresponding high-level design problem sets the overall layout and flow of the POD; this determines just a few key locations for the material flows of visitors and medication. In embodiment design (also called preliminary design), a designer specifies the most important attributes of a system's components; in POD design, the corresponding preliminary layout problem sets the specific locations of the stations and the flow among them; this determines more locations for the material flows of visitors and medication. In detailed design, a designer determines specific values for the details of the system's components; in POD design, the corresponding detailed design problem sets the internal layout and staffing at each station; this determines specific locations for the material flows of visitors and medication. We used these three stages to describe design variables and subproblems in our analysis.

3.3 Data collection

Data were collected on the participants' design activities by video and audio recording. A camera was positioned to see the layout as participants drew on it, moved stations around, or pointed out their ideas for the layout. Because it was a team activity, participants naturally verbalized their thoughts as they designed by sharing their ideas with others on the team, so the data are somewhat similar to a verbal protocol without requiring designers to verbalize artificially (see, e.g., Dinar et al. 2015).

3.4 Data analysis

The data were analyzed in a multi-step process. As the following paragraphs explain, we first coded the data to identify the variables that the teams were discussing as they solved the design problem, and when they were determining each variable. Second, we identified the clusters of variables that were determined concurrently, which likely represent the subproblems into which teams decomposed the design problem.

Identifying and coding variables We developed codes to describe the design variables that the teams were discussing and used the codes to describe when teams considered each variable over time. Our method followed standard qualitative data analysis approaches for the inductive development of key themes or codes (e.g., Corbin and Strauss 2008) and the identification of processes from qualitative data (e.g., Langley 1999).

First, we developed an initial set of design variables based on the standard engineering models of facility design. For example, facilities are commonly designed using block layouts, so one set of codes described the location of each major station. Other codes described the staff assigned to each station.

Second, we inductively refined these codes to ensure that they represented the design variables actually considered by the teams. To do so, we "coded" the videos of teams' design activities by dividing the video into 2-min segments and noting the variables discussed by teams within each segment. We refined the codes by closely examining similarly coded data segments, removing or adding codes, editing code definitions to better represent the observed behavior of the teams, and re-coding the data to repeat the process. As we iterated, we updated a codebook that clearly defines each variable to indicate what types of discussion are considered evidence that the team is discussing that variable. We stopped refining the codebook when new iterations yielded no new insights, which suggested that the codes fully described the data [that is, the coding reached theoretical saturation (Corbin and Strauss 2008)]. For this problem, the final set of codes included the initial set of codes and some additional high-level codes that we added to capture discussions at a higher level of abstraction. For example, "Calculating Staff Needs" was added to capture teams considering their need for staff in the entire facility; the initial set of codes only captured decisions about the need for staff at each individual station. This iterative process maximized the chances that the final set of codes actually reflects those perceived by the designers, rather than a construct imposed by the researchers, because they were refined and re-evaluated until they matched the discussions in the video.

Third, the videos were coded using the final set of codes: each 2-min time segment was labeled with one or more codes that describe the variables considered during that time segment. A subset of the data were coded by two researchers to ensure that there were high rates of agreement. The inter-coder agreement, measured by Cohen's kappa, was 0.73, where 0 indicates agreement only by chance and 1 indicates perfect agreement. This relatively high value of agreement suggests that the codes were well-defined and the coders were able to reliably and consistently describe the variables discussed by the teams. The output of this data analysis process was a set of timelines for each team, coded to describe which variables were being discussed at each time. Figures 4, 5, 6, 7 and 8, at the end of the paper, show the final timelines for all teams.

Clustering variables into subproblems The second step in the data analysis process was to identify subproblems based on the coded timelines. We assumed that if a team considers two variables concurrently (in the same 2-min segment), then they are more likely to be part of a subproblem, and if they consider one without the other, then they are less likely to be part of a subproblem. The 2-min segment duration was chosen after a pilot study showed that this duration was long enough to determine the variables that a team was considering as coupled but short enough to determine when a team switched from one topic to another. Based on a close analysis of the pilot video, including several video segments in which the teams had clear transitions between discussing different sets of variables (see Morency 2017 for details), the use of shorter (e.g., 1 min) time intervals tended to separate variables that appeared to be considered as coupled by the designers, which could cause them to be clustered in separate subproblems. On the other hand, the use of longer (e.g., 5 min) time intervals would cause variables to be clustered together which clearly seemed to belong to two separate subproblems.

We used a clustering algorithm to identify the most likely groupings of variables into subproblems, based on their occurrence in the same or different time segments. We tested four different clustering algorithms (Markov clustering, Ward's hierarchical clustering, spectral clustering, and association rules), and we found that the Ward's and spectral methods both have high accuracy in identifying clusters for timelines of this size. In a test dataset designed to resemble our data, Ward's method correctly identified the subproblem to which a variable belonged 93% of the time for noise levels up to 10% (described in Herrmann et al. 2017). We assume that the clusters identified by the Ward's method represent the subproblems used by each team.

There are, of course, limitations to any clustering method. One particular weakness of this approach is that the algorithm tended to exclude infrequently discussed variables from any cluster. Because they represent a group of variables treated in the same way by teams, we treated these variables as one subproblem, to include them in our analysis. Therefore, some of the teams have a large subproblem made up of infrequently discussed variables. A second weakness of this approach is that if two subproblems are discussed within one 2-min segment and never discussed separately in any other segments during the design session, they might be mistakenly grouped together as one cluster. We consider this limitation minor because it occurs relatively rarely and because grouping together any two subproblems considered so briefly and so close together might not be very disruptive to our conclusions. Finally, a relevant question is whether this approach imposes subproblems on a process that actually did not involve decomposition at all. Teams did not often explicitly discuss decomposition in the recordings, but this type of "implicit" decomposition is commonly observed in other studies (Ho 2001; Liikkanen and Perttula 2009). It seems likely that the teams did actually decompose the problem, based on the patterns seen in our results and on much previous research which documents problem decomposition as a commonly observed phenomenon in human designers (e.g., Ho 2001; Liikkanen and Perttula 2009; Sun et al. 2016).

4 Analysis and results

We analyzed the teams' data from several perspectives to examine three research questions: (1) whether their subproblems group tightly coupled design variables (and separate weakly coupled variables); (2) whether their decompositions (the sequence of their subproblems) follow a top–down design process that begins with a high-level design problem, then preliminary layout problems, and then detailed design problems; and (3) whether the different teams used similar decompositions.

The following sections describe a series of analyses that investigate these three questions. We (1) analyzed the design variables discussed by the teams, (2) examined the characteristics of the subproblems into which the variables were grouped, (3) identified typical sequences in which the teams solved subproblems, (4) determined similarities and variability across the teams, (5) developed a representative set of subproblems based on the similarities, (6) analyzed the types of variables in these representative subproblems, and (7) compared the teams' subproblems to these representative subproblems.

4.1 The variables discussed by the teams

To understand whether teams considered the same or different sets of variables when they solved the design problem, we analyzed how many teams discussed each variable (without yet considering how they were grouped together into subproblems). This analysis provides a basis for identifying commonalities and differences across the teams (Research Question 3).

Teams discussed different total numbers of variables. One team discussed 25 variables, three teams discussed between 36 and 40 total variables, and one team discussed 50 variables. Across all five teams, 73 distinct variables were discussed.

Many of the variables were discussed by multiple teams, and others were unique to one team. Of the 73 variables, 26 variables were discussed by at least four teams. On average, teams discussed 24 of these 26 common design variables. These common design variables include the locations of and staffing at the required stations, the internal layout and flow within the screening and medication distribution stations, staff needs and layout for the entire POD, and the parking-related variables.

The common design variables make up two-thirds of the variables considered by a team, on average, so numerous design variables also differ across teams. The teams discussed different sets of these singular (less common) design variables. First, they considered different optional stations; when a team included an optional station, they typically considered both its location and staffing. Second, some teams discussed whether to include each optional station, but other teams included optional stations without discussing their inclusion. Third, some teams considered the internal layout of stations that others did not.

It appears that the teams discussed the same set of common design variables. The variations in the design variables discussed by teams were driven by which optional stations they decided to include and the amount of detail they discussed on the internal layout and flow of each station. This evidence suggests that although the teams solved the same design problem, they included different features in their solutions.

4.2 The subproblems and their characteristics

The second analysis aimed to understand which variables were typically grouped together into subproblems (Research Question 1).

The clustering algorithm produced a set of subproblems based on the data for each of the five teams. The subproblems for each team are described in Table 8, at the end of the paper, which shows which variables are included in each subproblem and gives each subproblem a label and a description. Table 1 summarizes the characteristics of the subproblems for all five teams. The number of subproblems solved by each team varies from 5 to 11 (but the total number of variables also varies). The teams' average subproblem size varies from four to five variables.

To determine which variables are typically grouped together, the characteristics of the variables in the subproblems were analyzed. To support this analysis, the variables were categorized as described in Table 2. Three of the variables in this design problem were classified as high-level variables, such as the overall POD layout or overall staffing needs. The remaining variables are labeled "station attribute variables": they all focused on one particular station in the POD, such as the greeting or forms distribution station; and on one attribute of that station, such as its location, its staffing levels, or its internal layout. Table 2 provides the complete list of attributes and stations. Most "station attribute" variables are a combination of one attribute with one station, such as "Location of Greeting" or "Flow within Screening"; some combine the "Flow between" attribute with two stations, such as "Flow between Greeting and Forms Distribution". The stations were further divided into two categories: the core stations (representing required functions in the core flow of people and supplies) and the non-core functions (recall Fig. 1). The attributes were further divided into two categories: those dealing with the preliminary layout of the POD (location of, inclusion of, and flow between stations)

Table 1 Characteristics of teams' subproblems

	Team 1	Team 2	Team 3	Team 4	Team 5
Numbers and size					
Number of variables	38	25	40	50	36
Total number of subproblems	8	5	10	11	8
Average size of subproblems	4.8	5.0	4.0	4.5	4.5
Comparing subproblems to archetypes	Number of subproblems in each category				
Attribute	2	0	1	0	0
Same and/or contiguous stations	1	2	0	0	1
Attribute and either same or contiguous stations	1	2	4	8	4
None of the above	4	1	5	3	3
High level	2	1	1	1	1
Preliminary layout	1	1	1	2	3
Mix of preliminary layout and detailed design	3	1	4	5	1
Detailed design	2	2	4	3	3
Core	3	2	5	5	5
Non-core	1	0	1	1	1
Mix of core and high level	1	0	0	0	1
None of the above	3	3	4	5	1

Table 2 Variable types

Station attribute variables				High-level variables
Attributes		Stations		
Preliminary layout	Detailed design	Core stations	Non-core stations	
Location Include Flow between	Internal layout Flow within Staffing at Visual aids	Point of Entry Greeting Forms distribution Screening Medication distribution Point of exit Inventory and supplies Parking	Command post Staff break room Security Data entry Flow control Triage Registration Medical mgt Patient education Behavioral health	POD layout Calculating staff needs Design drive through

and those dealing with the detailed design of each station (all remaining attributes).

Based on the design problem structure (described in Sect. 3.2), we also identified four "archetypes" that reflect the types of subproblems we would expect to see if designers followed prescribed design approaches (discussed in Sect. 2). More specifically, if designers followed the prescription to group tightly coupled variables and separate loosely coupled variables, then we would expect to see groupings driven by each of the types of coupling present in the design problem. Two important types of coupling were explained in Sect. 3.2, and these were the basis for archetypes 1 and 2 below. One additional type of coupling is the basis for archetype 4. Finally, if designers followed the prescribed top–down design approach, we would expect to see subproblems grouping variables that make up each level of that approach; this is the basis for archetype 3.

1. "Stations" archetype: due to the coupling among the variables for each station (such as location, internal layout, and flow into one station) and the coupling among the variables for contiguous stations, each subproblem is a group of variables for the same station or for contiguous stations.
2. "Attributes" archetype: due to the coupling among the variables with the same attribute (across multiple stations), each subproblem is a group of variables of the same attribute (such as staffing).
3. "Top–down" archetype: in a top–down decomposition, three types of subproblems should be seen. High-level subproblems determine the overall POD layout by

grouping high-level variables with some preliminary layout variables such as the locations of entry, exit, and other key stations; preliminary layout subproblems group preliminary layout variables with one another, such as the locations of a smaller number of largely contiguous or non-core stations; and detailed design subproblems group detailed design variables with one another, such as the internal layout and flow within one or two stations. These definitions were determined following the descriptions of conceptual design, embodiment design, and detail design decisions set out by Pahl et al. (2007); see Sect. 3.2 for details.

4. "Core and non-core" archetype: because core stations are more tightly coupled to one another, non-core stations are not tightly coupled to core stations or each other, and high-level variables may be coupled to all the others, some subproblems will group variables for core stations, some subproblems will group variables for non-core stations, and high-level variables may be mixed with variables for core stations.

First, we compared the results to the "Stations" and "Attributes" archetypes. To do so, we classified the subproblems into the following categories: (1) "attribute": at least 70% of its variables are about the same attribute and less than 30% are about the same or contiguous stations; (2) "same and/or contiguous stations": at least 70% of its variables are about the same station or multiple contiguous stations and less than 30% are about the same attribute; (3) "attribute and either same or contiguous stations": at least 30% of variables are about the same attribute and at least 30% are about the same station or multiple contiguous stations; and (4) "none of the above": does not fit into any of the above categories. (Each subproblem may fit into only one of these categories, but category 3 suggests that a subproblem fits both the "Stations" and "Attributes" archetypes.)

As shown in Table 1, for all teams, at least half of their subproblems were in categories (1)–(3), meaning that subproblems contained variables with the same attributes, same or contiguous stations, or both. However, for two teams, half of their subproblems were in the "none of the above" category, meaning that the subproblems were not driven by either of these types of coupling. These results suggest that coupling among stations and/or attributes is one important driver of the grouping of variables into subproblems, but does not fully explain the subproblems observed in these teams.

Second, we investigated whether the subproblems aligned with the "Top–down" archetype. The subproblems observed in each team were classified according to: (1) "high-level" contained at least one high-level variable and at least 50% preliminary layout variables; (2) "preliminary layout" contained no high-level variables and at least 70% preliminary layout variables; (3) "mix of preliminary layout and detailed design" contained at least 30% preliminary layout and 30% detailed design variables; and (4) "detailed design" contained less than 30% preliminary layout variables.

Table 1 shows that all teams solved at least one high-level subproblem, but they rarely solved more than one. Many teams also solved at least one preliminary layout subproblem and several detailed design subproblems, which aligns with expectations for the top–down design process. However, many teams also solved a substantial number of subproblems that consisted of a mix of preliminary layout and detailed design variables, suggesting that they did not follow a purely top–down design process.

Third, we analyzed whether subproblems aligned with the "Core and non-core" archetype. To do so, we classified the subproblems into different categories: (1) "core" and (2) "non-core", which means that at least 70% of variables fall into that category and no other category has more than 30%; (3) "core and high-level", for which at least 30% of its variables are about core stations and at least 30% of its variables are high-level variables; and (4) "none of the above": not one of the previous three categories.

As shown in Table 1, there were more subproblems about core stations than about non-core stations, as expected since they are the main focus of the problem. Non-core stations were often grouped into a separate subproblem (Teams 1, 3, 4, and 5 each discussed one majority non-core subproblem). There are also a substantial number of subproblems that fit in none of these categories, suggesting that coupling among variables for core and non-core stations is one important driver of the grouping of variables into subproblems, but it does not fully explain the subproblems observed in these teams.

Table 8 shows which variables are in each subproblem and describes the focus of each subproblem. A detailed examination of each of the subproblems confirms that each team's subproblems are driven by different types of coupling or by none of the analyzed types of coupling.

Taken together, these findings suggest that teams often but not always grouped variables into subproblems based on the degree of coupling between the variables, but that no single type of coupling drove the design of every subproblem. Subproblems include variables that are more coupled because they deal with the same or contiguous stations, with several core stations, with the same attributes, and with preliminary layout or detailed design attributes. However, there are a substantial number of subproblems that do not appear to be driven by each of these types of coupling. As we discuss later, these results suggest that there is room for improvement in how teams of human designers decompose problems.

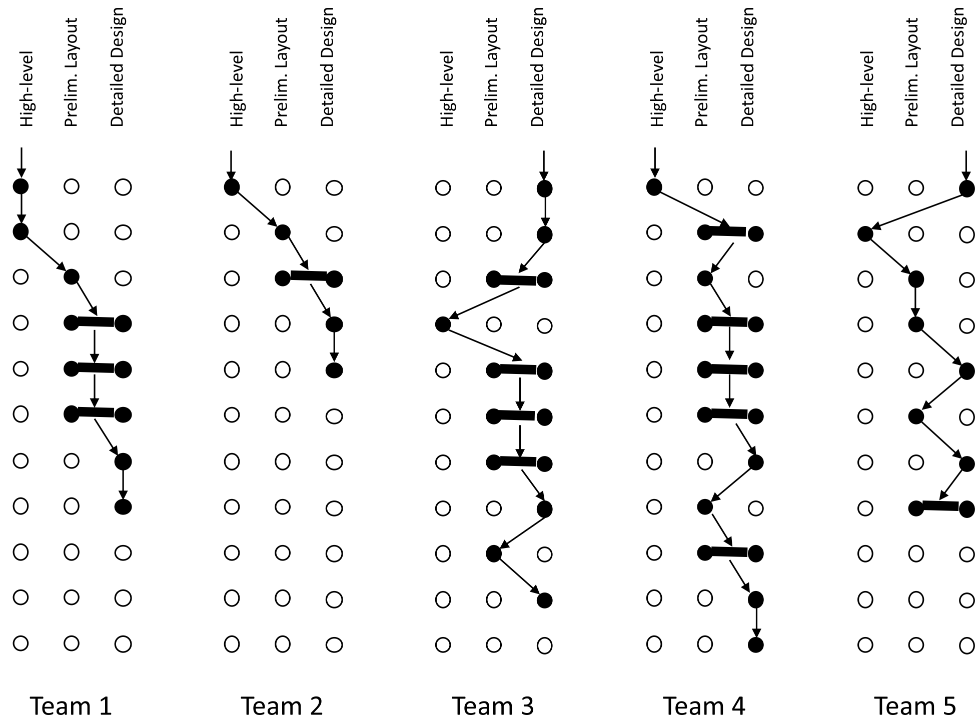

Fig. 2 Search sequences for each team, showing how they moved between high-level (left), preliminary layout (middle), and detailed design (right) subproblems. Many subproblems combined preliminary layout and detailed design, indicated by the heavy horizontal lines

4.3 Analysis of sequences of subproblems for each team

The third analysis aimed to understand the typical sequences in which subproblems were solved (Research Question 2).

For each team, we created a timeline that shows when the variables in each subproblem were discussed. Figures 4, 5, 6, 7 and 8, at the end of the paper, show the timelines for each team. The subproblems are ordered roughly in chronological order based on when the bulk of work on each subproblem was begun. The following paragraphs summarize the sequences for each team and then collect insights across all teams.

Summaries of timelines Team 1 solved two clear high-level problems at the start, set the locations for some stations, and continued to revisit staffing and location decisions throughout their timeline. Two subproblems in the middle of their timeline focused on preliminary and detailed design for the core screening and medication distribution stations.

Team 2 first considered the overall POD layout and the location of the medication distribution station and then considered the locations of other core stations. Two subproblems in the middle of their timeline focused on the details of the screening and medication distribution stations. The team then reconsidered an earlier subproblem on staffing and non-core stations.

Team 3 first considered subproblems related to staffing, which they reconsidered throughout their timeline. They then considered subproblems about location of core stations and subproblems about the internal layout and flow through these stations. Finally, they considered many aspects of non-core stations.

Team 4 first considered a subproblem related to the overall POD layout and a subproblem related to entry and parking. Next, they dealt with a series of subproblems that together consider many aspects of both core and non-core stations. Toward the end, they considered subproblems related to the flow through the entire POD, staffing, and the internal layout of many core stations.

Team 5 first considered a staffing subproblem and revisited this throughout. Next, they considered subproblems related to the layout of and flow among core stations and then subproblems about the flow and internal layout of core stations. Next, they revisited the first staffing subproblem, considered another staffing subproblem, and worked on a subproblem related to some non-core stations.

Insights across all five teams Across all five teams, there were several typical features of the sequences in which subproblems were considered.

First, most teams solved a high-level subproblem up front (these did not consist only of high-level variables, as discussed in Sect. 4.2, but rather combined high-level variables with preliminary layout variables). Specifically, most teams considered a subproblem related to the overall POD layout, such as setting the locations of or flow among the core stations in the POD. This was the first one or two subproblems for Teams 1, 2, and 4, but Teams 3 and 5 first considered staffing.

Second, teams appeared to search the design space in a partially but not entirely breadth-first sequence. In a breadth-first sequence, we would expect to see an early overall layout problem, then one or more preliminary layout subproblems, followed by detailed design subproblems. Figure 2 illustrates the search sequence of each team by showing the order in which different types of subproblems were (first) considered by each team. As discussed above, all teams solved an overall layout problem early, but two of them started with a staffing subproblem first (classified as detailed design in Fig. 2). Only Team 2 progressed through the subproblems in a clearly breadth-first order. Teams 1, 3, and 4 solved a series of subproblems that combined preliminary layout with detailed design, and Team 5 jumped back and forth between preliminary layout and detailed design; neither sequence is consistent with the breadth-first sequence of solving a preliminary layout before the detailed design. Overall, then, teams started with a high-level problem but then used different search strategies, four of which were more aligned with depth-first approaches.

Third, some teams considered the stations in the order in which a client would visit them: after the initial high-level subproblems (such as POD layout and staffing), the details for greeting and forms distribution were often settled before those for screening and medication distribution. For example, the timeline for POD Team 3 shows this clearly (subproblems 4, 5, 6, and 7).

Fourth, while many subproblems were considered only once, others were considered multiple times, suggesting that teams iterated on their design choices. All five teams iterated on subproblems related to screening and medication distribution, perhaps because it was the most complex and critical portion of the POD. Subproblems that focused on staffing or locations of multiple stations were also commonly revisited, perhaps because these decisions were coupled to one another and therefore required revisiting when something changed.

4.4 Analysis of differences in decomposition across teams

The third analysis examined how similar the decompositions of each team were to one another (independent of the time at which subproblems were considered). This section analyzes the extent of similarity quantitatively, and the next section examines the nature of the identified similarities and differences (Research Question 3).

We compared the subproblems for each pair of teams by considering the variables that were discussed by both teams and evaluated the similarity of the teams' subproblems by determining how often the variables that were together in one team's subproblem were also together in another team's subproblem. We took one team as the "baseline" team and the other as the "target" team. Then, for each variable v, let $S_B(v)$ be the baseline team's subproblem that includes v, and let $S_T(v)$ be the target team's subproblem that includes v. Let

Table 3 Similarity (average true positive rate) of the subproblems (clusters) for pairs of teams

Baseline Team	Team 1	Team 2	Team 3	Team 4	Team 5
Team 1	–	0.4393	0.2094	0.1111	0.2000
Team 2	0.2601	–	0.2424	0.1043	0.3333
Team 3	0.3141	0.4848	–	0.3125	0.2172
Team 4	0.1615	0.2301	0.4062	–	0.1481
Team 5	0.2693	0.4666	0.2380	0.1322	–

$n^+(v)$ be the number of variables that are in both $S_B(v)$ and $S_T(v)$ (the intersection of these two sets). Let $n^*(v)$ be the number of variables in $S_B(v)$. We determined the true positive rate for variable v as $tpr(v) = (n^+(v) - 1)/(n^*(v) - 1)$ and calculated the average true positive rate across all variables that were discussed by both teams. (If $n^*(v) = 1$, then we set $tpr(v) = 0$). A larger true positive rate indicates that more of the variables in $S_B(v)$ were also in $S_T(v)$ and that these two subproblems are more similar.

As shown in Table 3, the average true positive rates are low to moderate (less than 0.5). Thus, by this measure, these subproblems are only somewhat similar to each other. For this analysis, we considered only the true positive rate rather than the true negative rate. Considering both (as described in the calculation of accuracy in Sect. 4.5.2) results in scores near 0.8 because the small size of the subproblems led to large true negative rates. Thus, although the five decompositions share many general characteristics, their subproblems contain different variables. This is not particularly surprising since, as discussed in Sect. 4.1, about one third of the variables discussed by each team differed from those discussed by other teams.

4.5 Toward representative subproblems: analysis of common pairs across all teams

This section continues to explore how similar the decompositions of each team were to one another, complementing the quantitative analysis above with a detailed qualitative analysis of the nature of the similarities and differences across teams (Research Question 3). We used a different type of analysis to build "representative" subproblems based on pairs of variables discussed concurrently by multiple teams. Focusing on a subset of variables—those pairs most commonly discussed concurrently—reduced the variability across the teams because it focused on those variables discussed by most of the teams. We compared each team's subproblems to these representative subproblems (RSs) to examine their correspondence, then analyzed the characteristics of the most common pairs and the RSs that were formed based on these pairs.

Table 4 Number of most-common pairs of variables discussed by each team

Team	Both variables discussed	Pairs discussed concurrently	Pairs in same subproblem
Team 1	32	23	14
Team 2	33	28	17
Team 3	39	26	22
Team 4	37	32	14
Team 5	39	29	12

4.5.1 Creating representative subproblems based on common pairs

The first step in creating representative subproblems was to identify pairs of variables that were discussed concurrently (in the same time segment) by multiple teams. A total of 41 pairs were discussed concurrently by a majority of the teams (3, 4, or 5 teams). These 41 most-common pairs involved 28 variables (25 of which are in the set of 26 common design variables discussed in Sect. 4.1). (We refer to these 28 variables as "representative variables".) Table 4 shows, for each team, the number of these 41 most-common pairs for which both variables were discussed by the team, for which both variables were discussed concurrently, and for which both variables were in the same cluster (subproblem). These data show that each team discussed most of the variables in these common pairs (78–95%), that each team discussed a large portion of the common pairs concurrently (67% of them on average), but that teams did not always group the pairs in the same subproblem (38% of them were in the same subproblem, on average).

These pairs of variables suggest common groupings of sets of variables. We defined a network in which each variable is represented by a node and the arcs connect pairs. After quantitatively analyzing the adjacency matrix for this network and considering the connections between these variables, we divided the network into five groups of variables, as shown in Fig. 3. There are only two pairs that span groups, and each group is much more connected within the group than without. (The screening and medication distribution group is larger than the other groups because of the many connections between these variables.) Each group is considered a representative subproblem. In the next sections, we first compare them to the subproblems previously identified for each team and then analyze their characteristics.

4.5.2 Comparison of team subproblems to pair-based representative subproblems

We next considered how closely each team's subproblems (the clusters described in Sect. 4.2 and Table 8) corresponded to the five RSs constructed based on the concurrent pairs. We first examined the similarity mathematically and found limited similarity between the teams' subproblems and the RSs. Then, we performed a qualitative comparison and discovered that each team considered different subsets of the variables in each RS. The following paragraphs explain each analysis in detail.

Mathematical analysis of similarity Because only 28 representative variables are in the RSs, not all of the variables that a team discussed are in the RSs, and no team discussed all 28 representative variables. Thus, to measure the correspondence between a team's subproblems and the RSs, we calculated the following measure of accuracy by first

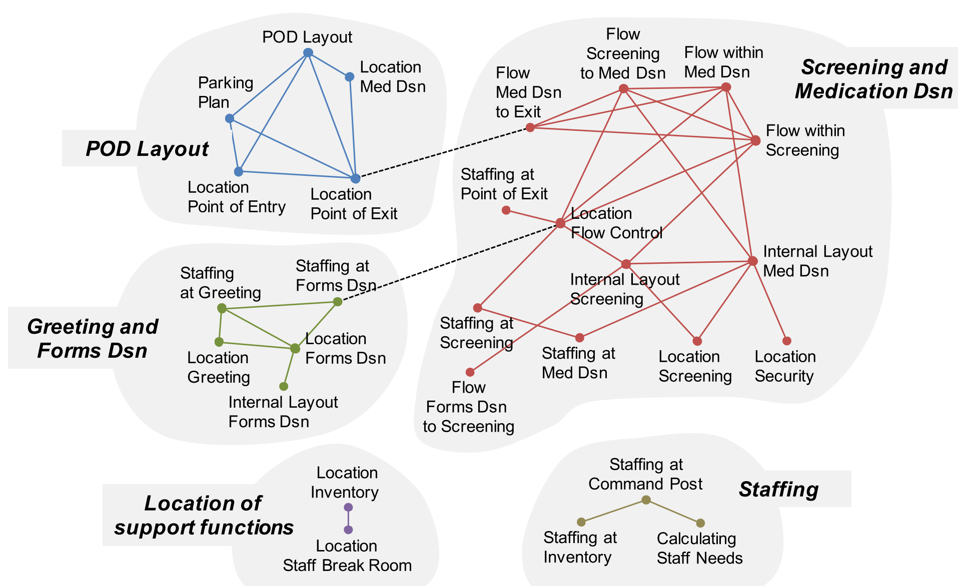

Fig. 3 The five representative subproblems (RSs) of the 28 variables in the 41 most-common concurrent pairs. Each line segment indicates one pair. Pairs of variables in the same RS are connected by a line segment of the same color. The two black dashed line segments indicate the two most-common pairs that span two RSs. (Color figure online)

Table 5 Correspondence (accuracy) of each team's subproblems (clusters) and the representative subproblems

Team	Accuracy $\bar{A}$
POD Team 1	0.5132
POD Team 2	0.5442
POD Team 3	0.5020
POD Team 4	0.3888
POD Team 5	0.5156

determining the accuracy from each representative variable's perspective and then averaging those values.

Let N_v be the total number of representative variables that the team discussed. For the representative variable i that the team discussed, let $n^*(i)$ be the number of representative variables in the RS that contains variable i, let $n_c(i)$ be the number of representative variables in the team subproblem (TS) that contains variable i, and let $n^+(i)$ be the the number of representative variables from the RS that contains variable i that are also in the TS that contains variable i. Note that $n^+(i)$ counts variable i. Then, $N_v - n^*(i)$ is the number of representative variables that the team discussed and are not in the RS that contains variable i, and $n_c(i) - n^+(i)$ is the number of representative variables in that cluster that are not in the RS that contains variable i.

From this data, we determined $tp(i)$, the number of true positives, $tn(i)$, the number of true negatives, and the clustering accuracy $ac(i)$ associated with variable i and calculated the average accuracy $\bar{A}$ as follows:

$$tp(i) = n^+(i), \tag{1}$$

$$tn(i) = (N_v - n^*(i)) - (n_c(i) - n^+(i)), \tag{2}$$

$$ac(i) = (tp(i) - 1 + tn(i))/(N_v - 1), \tag{3}$$

$$\bar{A} = \frac{1}{N_v}\sum_{i=1}^{N_v} ac(i). \tag{4}$$

Thus, the accuracy for each variable i reflects the number of variables "correctly" grouped in its RS or left outside its RS, divided by the total number of variables. The average of these values across all the variables is an overall measure of how nearly the team subproblems correspond to the RSs developed based on the most-common pairs.

As shown in Table 5, the values of $\bar{A}$ are moderate (near 0.5). Thus, these groups do not correspond well to any one team's subproblems, even though they describe the most common concurrent variables. This result is not surprising, since we found that the team subproblems were not very similar to one another (cf. Table 3). Despite this result, however, the next section examines specific similarities and differences, and finds that each team discussed several subproblems that were similar to the RSs and other subproblems that were not.

Qualitative analysis of similarity To complement the mathematical analysis above, we also qualitatively compared each of the team subproblems (TS) with the five RSs listed in Fig. 3. We said that a TS corresponds with a RS if its variables include most of the variables in that RS and that a TS is a subset of a RS if it has some of the variables from that RS.[1] The results are shown in Table 6.

Many of the RSs correspond with subproblems or sets of subproblems in multiple teams (see the columns in Table 6). Four of the five teams (all except Team 4) discussed a subproblem that corresponds with the POD Layout RS. All five teams discussed multiple subproblems with subsets of the screening and medication distribution RS. Two teams (Teams 1 and 3) discussed a subproblem that corresponds with the greeting and forms distribution RS, and two teams (Teams 4 and 5) discussed subproblems with subsets of this RS. Two teams (Teams 1 and 3) discussed a subproblem that corresponds with the staffing RS. Two teams (Teams 1 and 2) discussed a subproblem that corresponds with the location RS.

Although POD Team 4 discussed 26 of the 28 variables in the five RSs, the team's subproblems do not correspond well with the RSs (see row 4 of Table 6). The team's lower average accuracy $\bar{A}$ reflects this. Only three of the team's subproblems have subsets of these RSs, and eight other subproblems correspond with none of the five RSs (they include variables not in any RS or include variables in multiple RSs).

For all the other teams, the majority of each team's subproblems correspond to RSs or subsets of RSs (see the rows of Table 6). The POD layout RS is usually present, and the screening and medication distribution RS and the forms distribution and greeting RS are usually divided into multiple subproblems by each team. These RSs have variables that are tightly coupled to each other, so it is reasonable to see teams considering these RSs (or subsets of them) as subproblems. Staffing and location are less commonly seen as subproblems in the team results; the variables in these two RSs are not as tightly coupled to each other.

We conclude that the RSs based on common pairs are a useful summary of the types of subproblems created by most teams, but they represent groupings that are often further subdivided in different ways by different teams.

4.5.3 Characteristics of representative subproblems

As we did for the teams' subproblems (see Sect. 4.2), we examined these RSs to determine whether they align with the archetypes mentioned in Sect. 4.2. This analysis elaborates

[1] Specifically, for a TS to correspond to a RS, a TS had to have two to four of the variables in three to five variable RSs, depending on the size of the RS. For a TS to be a subset of a RS, it had to have two to six of the variables in the RS. A TS is related to no RS if it had at most one variable from any RS or if it corresponded to multiple RSs.

Table 6 Team subproblems that correspond to representative subproblems (RSs)

Team	POD layout	Greeting and Forms Dsn	Screening and Med Dsn	Staffing	Location of Supp. Stns	None
POD Team 1	X	X	S, S, S	X	X	1
POD Team 2	X		S, S		X	1
POD Team 3	X	X	S, S, S	X		4
POD Team 4		S	S, S			8
POD Team 5	X	S, S	S, S, S			2

The value under "None" is the number of subproblems that correspond with none of the RSs

X one subproblem corresponds to this RS, *S* a subproblem corresponds to a subset of this RS

Table 7 Correspondence of representative subproblems with the archetypes described in Sect. 4.2

Representative subproblem:	POD layout	Greeting and Forms Dsn	Screening and Med Dsn	Staffing	Location of Supp. Stns
Correspondence to "stations" and "attributes" archetypes, based on % variables for same stations (SS), contiguous stations (CS), and/or same attribute (A)	*Primarily A:* 60% A	*CS with A:* 100% CS; 40% A	*CS with A:* 77% CS; 23% A	*Primarily A:* 67% A	*A:* 100% A
Correspondence to "top–down" archetype: each subproblem is classified as high-level (H), preliminary layout (PL), and/or detailed design (DD) based on the % variables in each category	*H:* 60% PL, 20% H	*PL and DD:* 40% PL; 60% DD	*PL and DD:* 46% PL; 54% DD	*DD:* 67% DD	*PL:* 100% PL
Correspondence to "core and non-core" archetype, based on % variables that are core (C), non-core (NC), and/or high-level (H)	*Primarily C:* 80% C	*C:* 100% C	*Primarily C:* 85% C	*Neither:* 33% C, NC, H	*Neither:* 50% C, NC

Subproblems are classified as focusing on attributes of multiple stations or attributes of contiguous stations; focusing on high-level design, preliminary layout, and/or detailed design; and on high-level, core, and/or non-core variables. Below each classification, the percentage of variables conforming to that classification is provided. Percentages may not sum to 100% because variables may fall into more than one category or into none of the reported categories

on which variables were typically grouped together into subproblems (Research Question 1). The results are summarized in Table 7.

Regarding the "Stations" and "Attributes" archetypes, the RSs group by either attributes and/or stations. Table 7 shows the actual percentages of variables that carried common attributes and contiguous stations (since several values were close to the thresholds provided earlier). The "POD Layout", "Staffing", and "Location of support stations" RSs are oriented primarily by attributes; in particular, the variables in these RSs represent attributes that are coupled across stations: location and staffing (since decisions about the location (or staffing) at one station constrain the locations (or staffing) at others). Each of the other two RSs includes several variables for two contiguous stations.

The RSs do not follow the "Top–down" archetype. Although the "POD Layout" RS is a high-level subproblem (which fits this archetype), the "Greeting and Forms Dsn" and "Screening and Med Dsn" RSs combine preliminary layout with detailed design of these sets of contiguous stations, when these stages would be separate according to the "top–down" archetype.

The RSs only follow the "Core and non-core" archetype to some extent. Three of the RSs, "Greeting and Forms Dsn", "Screening and Med Dsn", and "POD Layout", each group variables for core stations. The "Staffing", and "Location of support stations" RSs, on the other hand, group core with non-core and high-level variables.

5 Discussion

This section summarizes the results, presents the insights that these results suggest, and discusses implications for practice and research.

5.1 Key insights

In summary, the analysis of how teams decomposed a design problem has led to several insights that shed light on (1) the types of variables that are typically grouped into subproblems; (2) typical sequences in which subproblems are solved; and (3) commonalities and differences in the subproblems and sequences across teams.

5.1.1 Groupings of variables

Variables are typically grouped into subproblems in multiple ways: no single driver for grouping of variables emerged from our results. However, two types of coupling among variables appeared to drive the groupings in the representative subproblems. The first type of coupling is among different attributes of contiguous stations. As evidence, two of the five RSs grouped variables for contiguous stations (see Table 7); in addition, it was rare for any team's subproblem to focus only on one station (see Table 1). The second type of coupling is among the same attribute across different stations. As evidence, three of the five RSs included primarily (but not exclusively) the same attribute across many stations, such as location of or staffing at several stations (see Table 7); in addition, four of the five teams solved a subproblem involving the location of several stations (but the evidence is less clear for the other attributes) (see Table 6). These patterns suggest that designers wanted to consider a small number of contiguous stations whose attributes were coupled (i.e., constrain one another) or a single attribute across multiple stations. However, a number of teams used subproblems that do not fall into either of these categories (see Table 1), and/or do not appear driven by any of the types of coupling we identified.

The two common types of coupling we identified partially align with some of the prescribed approaches for facility design in the literature. Most prescribed approaches suggest using either block layouts or assembly lines/cells (Black and Hunter 2003; Drira et al. 2007; Tompkins et al. 2003). The block layout approach implicitly involves a first subproblem that lays out the location of each station, then subproblems that design the other attributes (such as staffing and internal layout) of each station. The assembly lines/cells approach implicitly involves subproblems that first group the internal sub-functions of several stations into assembly lines/cells, then settle the attributes of each line/cell (which involves several stations at once). The two types of coupling we observed align better with the assembly lines/cells approach, since designers did not consider one station at a time, but rather the coupled attributes of contiguous and/or multiple stations (analogous to a line/cell). In particular, the greeting and forms distribution stations were considered as one cell, and the screening and medication distribution stations were a second cell. Before moving to the screening station, the POD visitors would spend time completing the forms that they received at the forms distribution station, which would act as a buffer decoupling these two stations. This conclusion must be considered very preliminary, however, because it is based on the subproblems identified from a small number of teams.

The results also suggest that small teams of human designers only partially follow the literature's prescriptions to group tightly coupled variables and separate loosely coupled variables (Baldwin and Clark 2000; Simon 1962). The literature clearly shows that such subproblems or modules enable more efficient design processes (Browning 2001; Baldwin and Clark 2000). However, our results show that multiple types of coupling drive different subproblems, and not all subproblems appear driven by coupling. Therefore, our findings suggest that the design approaches of human designers could be improved by supporting better choices of subproblems.

5.1.2 Sequences of subproblems

The sequences in which subproblems are solved have one key typical feature: a partial top–down design progression beginning with a high-level layout subproblem. As evidence, one of the representative subproblems is a high-level "POD Layout" subproblem; in addition, all five teams solved a high-level layout subproblem early in the design process (four of them were similar to the "POD Layout" RS). After this high-level layout subproblem, most teams deviated from the top–down design progression: four teams combined or alternated preliminary layout with detailed design subroblems in a more depth-first approach (recall Fig. 2); and two of the four remaining RSs combine preliminary layout with detailed design (see Table 7).

The results suggest that small design teams only partially follow the top–down design approach recommended in the literature. The prescribed approach of progressive refinement of designs (e.g., Pahl et al. 2007) is not followed strictly, since the preliminary layout and detailed design phases were often accomplished together in the same subproblem (see Fig. 2). Additionally, our results are only partially aligned with the finding that expert designers use breadth-first search sequences (Sun et al. 2016; Goel and Pirolli 1992). In contrast, our experienced designers appeared to use some depth-first exploration by combining preliminary and detailed design. It is possible that this approach is an artifact of the coupling in this specific design problem, since tight coupling among contiguous stations may have made a depth-first approach more attractive; more likely, this is an instance of the opportunistic depth-first exploration of ideas observed by other researchers (Ball et al. 1997; Guindon 1990).

5.1.3 Commonalities across teams

The results showed that teams decomposed the problem into different sets of subproblems, but that there were nevertheless many commonalities across these subproblems.

As evidence, most of the subproblems for four of the five teams corresponded with all or part of the "representative" subproblems that we identified. Therefore, although the specific subproblems of each team were quite different from one another, the underlying factors that drove the grouping of variables into subproblems appeared to be similar (these factors were described in Sect. 5.1.1).

As far as we are aware, the literature does not specifically suggest whether teams are expected to use similar or different subproblems. Approaches using design structure matrices to group tasks or variables into modules (subproblems) typically find that many different such groupings perform similarly (e.g., Browning 2001), so it is reasonable to find some differences among the teams.

5.2 Implications for design research and practice

Our results provide several implications for design research and practice.

First, comparing our general findings with those in the literature, many of the patterns we identified are aligned with previous research on the decomposition approaches of individual human designers (such as initial breadth-first search, and occasional depth-first exploration) (Liikkanen and Perttula 2009; Goel and Pirolli 1992; Ball and Ormerod 1995; Ho 2001; Sun et al. 2016; Ball et al. 1997; Guindon 1990), suggesting that teams use similar strategies to those found in extant research on individuals. Future research can test this claim in different design settings and with different teams.

Second, our results suggest that there is room for improvement in the way small design teams decompose problems. The lack of consistency in the types of coupling that drove subproblems suggests that humans may be unable to identify the best ways to decompose problems, even when they have deep expertise in the problem area, as our professional subjects did. The literature clearly demonstrates that better designs can be obtained when subproblems group tightly coupled variables (e.g., Simon 1962; Baldwin and Clark 2000). Therefore, our findings suggest a need for better support and/or training to enable design teams to create better subproblems.

Third, our work lays a foundation for developing this needed support and/or training by identifying different types of decompositions used by design teams—such as those driven by different types of coupling among variables and those that solved subproblems in different sequences. Some decompositions were probably "better" than others either because they enabled teams to explore better regions in the design space (which led to higher quality designs) or because they efficiently led teams to generate good solutions more quickly. This work is an important first step toward understanding the impact of decomposition on solution quality. By characterizing the decompositions used by design teams, we can next analyze, model, and evaluate how well the different approaches work and suggest improvements. Future work should investigate whether the types of decompositions identified in this study enable high-performing designs (e.g., high throughput, low cost, safe and convenient), and which types of coupling are most important in decomposing design problems, in order to provide guidelines and support to design teams.

Fourth, our work is one of the first to consider not only the process of decomposition but also the content of the subproblems. Our results also suggest that studying the content of subproblems adds important nuances to previous studies of decomposition by human designers. For example, while designers touched on all the top–down design phases, from high-level through preliminary layout to detailed design, the subproblem contents show that they often considered the latter two layers together, not separately as suggested in many previous studies. Future work could clarify whether differences are due to the type of design problem, the professional experience of subjects, differences between individuals and teams, the methods of investigation, or other factors.

Many products and systems are designed by small, unstructured teams of designers like those we studied in this research. For example, specialized design firms often rely on small teams (Sutton and Hargadon 1996), and PODs like those studied in this paper are also designed rapidly by small teams. This paper has begun to characterize how such teams decompose problems, which is an important step toward the development of guidelines or design tools that can support the efforts and improve the results of small design teams.

5.3 Implications for public health research and practice

Public health practitioners can directly benefit from these insights in two ways: (1) they can use the set of representative subproblems as a model of how to design PODs for their communities; although previous descriptions of POD design have described important aspects of locating and planning PODs (Abbey et al. 2013) and determining how many staff are needed at each station (Aaby et al. 2006), they have not provided a process for designing the details of a POD layout. Our findings thus provide specifics to existing general guidance and complement staffing models. (2) Public health practitioners can also identify the important factors that these five teams overlooked in their design processes and determine how to avoid such oversights when designing PODs. For instance, including areas for serving persons with special needs is an important design element (Abbey et al. 2013), but none of the teams considered that in their design process. These oversights would become a limitation of using these representative subproblems directly as a design process. Additional work is needed to identify such oversights and include them to form a more comprehensive POD design process.

Public health practitioners also stand to benefit from the development of support and/or training for small design teams, as outlined in Sect. 5.2. For POD design specifically, future research could evaluate the effectiveness of the specific decomposition embodied by the representative subproblems identified in this research, in comparison to the decompositions suggested by a purely top–down approach or extant facility design approaches such as block layouts or cellular designs. If its performance is superior or even comparable, this type of decomposition could be provided as a guideline for future POD designers, since our findings suggest it is intuitive to public health practitioners. If, on the other hand, its performance is worse, alternative guidelines could be developed to support improvements in POD design.

Even simple guidelines for sequencing the POD design process could provide useful support to POD designers. The Centers for Disease Control (CDC) of the United States conducts training courses for POD designers using an exercise similar to the one described in this paper. Their guidelines and training materials (CDC SNS 2012) focus largely on the standards the POD must meet, including complex medical considerations, rather than on the process of designing the POD. Simply providing a sequence of subproblems to provide guidance on which decisions to make and in what order could contribute to more efficient and effective design processes.

5.4 Limitations and generalizability

The limitations of this research must be considered in interpreting our findings. The analysis was limited to five teams, so the research must be considered exploratory: we seek to identify patterns that could be confirmed in future research with a larger number of subjects. Nevertheless, the scale of the work is aligned with previous studies of decomposition by individual human designers, which typically included either a moderate number of students (16 for Liikkanen and Perttula 2009 and 23 for Sun et al. 2016) or a small number of professionals or advanced graduate students (2 in Ho 2001, 6 in Goel and Pirolli 1992, and 6 in Ball et al. 1997). The alignment with previous findings on individual designers, moreover, suggests theoretical explanations for our results and lends credence to the findings. Future research, nevertheless, should seek to understand their generalizability beyond the results of this study and the design problem considered here.

A second limitation is the possible influence of leadership, communication, and other social dynamics on the results. Although we attempted to minimize these factors by grouping people who do not normally work together, and we found no evidence of poor team dynamics, such as serious conflict or lack of participation by team members, in reviewing the videos, the teams likely varied in capability, ease of working together, and other important factors. Any real teams would also exhibit this natural variability. Future research could investigate a larger number of teams to further explore the issue.

These issues raise two key questions: (1) Are these insights specific to this design problem? (2) Are there other types of design problems to which these insights might apply? The POD design problem was neither very simple nor very complex. There were many possible variables (72 unique variables were discussed by at least one team), and few constraints were imposed on the designers. On the other hand, we performed a similar exercise with a much more complex facility design problem (more variables, more constraints), and we saw much more variation in decompositions across teams and more iteration to reconsider earlier subproblems. Therefore, we believe that these insights are specific to problems of low to moderate complexity. Beyond facility design, future research can determine the extent to which these insights are applicable. We think it likely that most of the insights apply, since many problems of moderate complexity have a similar structure, with several functions (analogous to our stations) to be arranged and designed in detail and important relationships that couple design variables for different functions.

We believe, however, that these insights are specific to designers who have experience with the problem. Inexperienced designers might not be able to understand the inherent coupling among the decisions and decompose it accordingly, as these designers did, and previous research has found significant differences in the decompositions of expert and novice designers (see Sect. 2). Finally, the insights are specific to small teams who are not given a decomposition to follow. In summary, we believe these insights are likely to apply to other design problems of low to moderate complexity when solved by small teams of experienced designers.

6 Summary and conclusions

This paper described the results of an empirical study of small design teams in which experienced professionals solved a facility design problem in a half-day exercise. We collected and analyzed data about the design teams' activities. In particular, we (1) identified the design variables that they discussed and how they were grouped into subproblems; (2) analyzed the sequences in which subproblems were solved; and (3) identified similarities in the teams' decomposition strategies.

Our findings suggest, first, that the coupling between the design variables influences but does not completely determine the teams' decompositions. No single type of coupling drives all of a team's subproblems. Second, the decompositions do not correspond perfectly to a top–down design sequence; rather, they embody a partial breadth-first approach, beginning with a high-level problem, but many end with a more depth-first sequence. Third, although each team created fairly different decompositions, their subproblems represented different combinations and subsets of five "representative" subproblems. Many differences were driven by features considered by one team and not another, but there were fewer differences in how the most common and critical design variables were grouped. The most general pattern seen in these decompositions has two components: (1) solving a high-level subproblem to determine the outline of the design, and (2) completing specific subproblems focused on either setting multiple attributes for a small set of contiguous stations or setting a single attribute at various stations. However, there were many deviations from this general pattern, especially the latter part.

These results show that neither top–down design approaches nor single types of coupling determined team decompositions, contrasting with the approaches suggested by the design literature (e.g., Pahl et al. 2007; Baldwin and Clark 2000). Therefore, our results suggest there is room for improvement in how human designers decompose the problem; the findings also identify productive directions for improvement. Specifically, future research can build on our results by considering how the different decompositions we identified affect the quality of the design solutions that are generated and determining which decomposition strategies lead to better solutions. Developing guidelines and support for improved decompositions could support POD designers in particular and, if extended to other design problems, small design teams more generally.

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Data availability The observations of human designers cannot be shared to protect the confidentiality of the research subjects. However, the coded data generated and analyzed in this study are fully described in Figs. 4, 5, 6, 7 and 8 and Table 8. The data are available in MS Excel or comma-separated value formats from the first author upon request.

Compliance with ethical standards

Ethical approval The research on human subjects described in this paper was conducted in compliance with ethical standards, with the approval of the Institutional Review Boards of the University of Maryland and the George Washington University.

Appendix

Figures 4, 5, 6, 7, and 8 show the timelines for all teams, including which variables were worked on at which times, and their clustering into subproblems. Table 8 describes all the subproblems found for each team, including which variables are included in each subproblem, a label and a description for each.

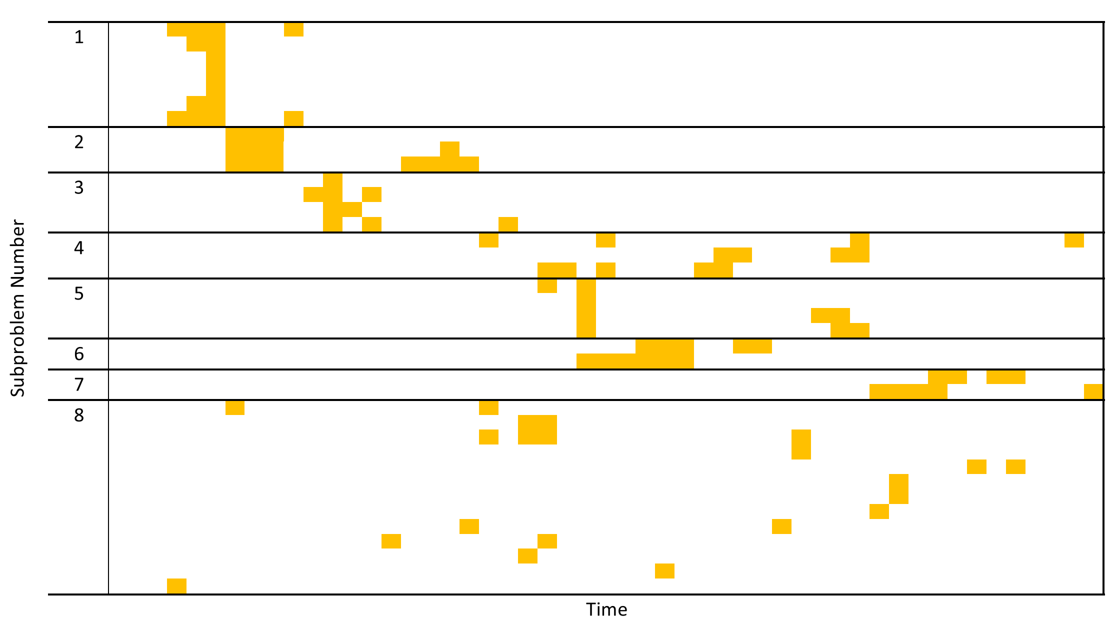

Fig. 4 Timeline for Team 1

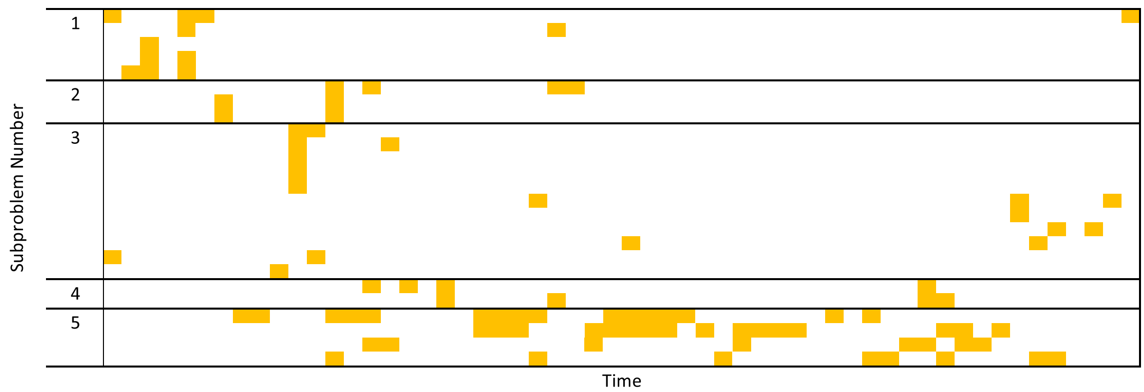

Fig. 5 Timeline for Team 2

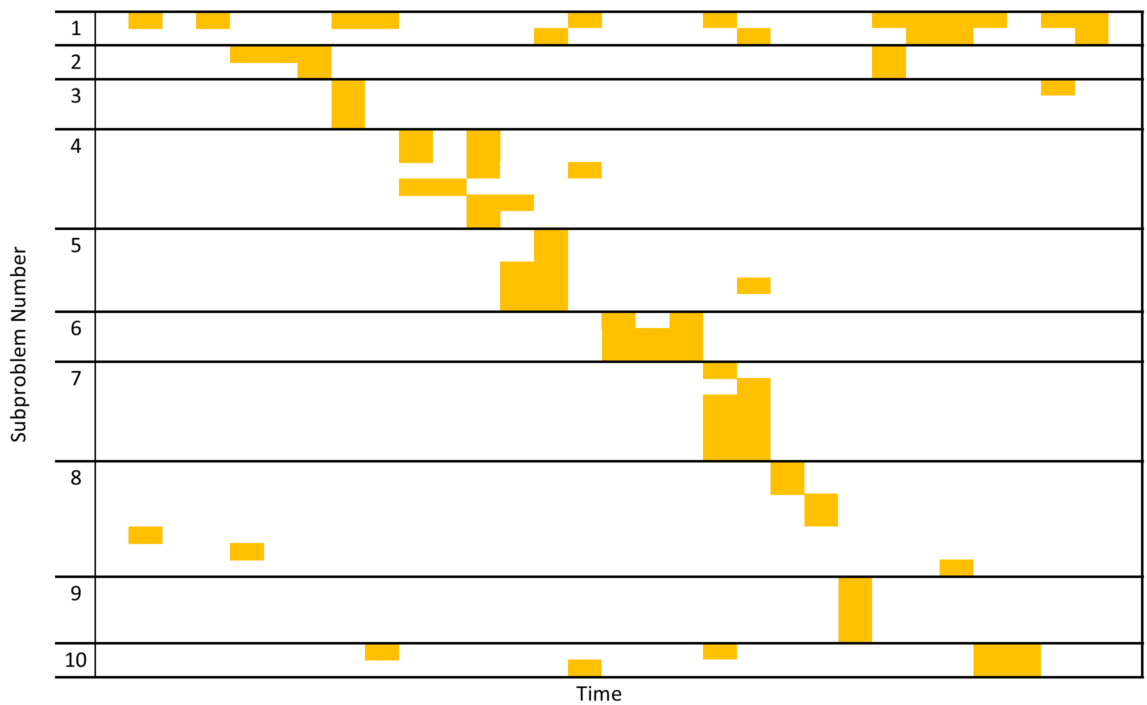

Fig. 6 Timeline for Team 3

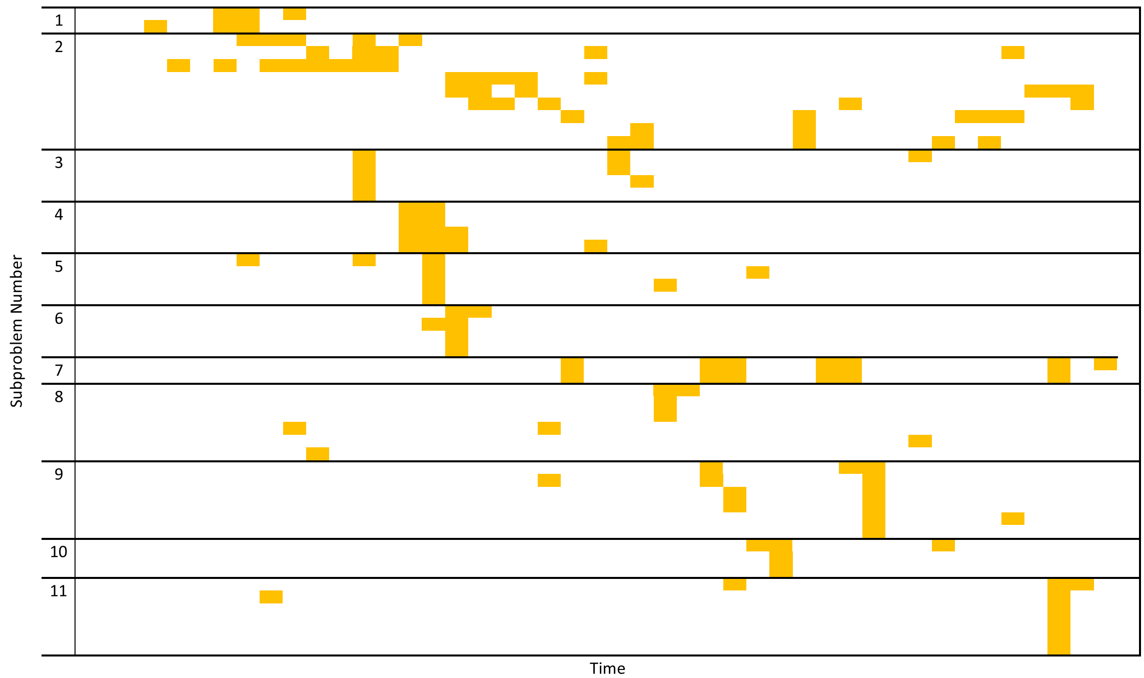

Fig. 7 Timeline for Team 4

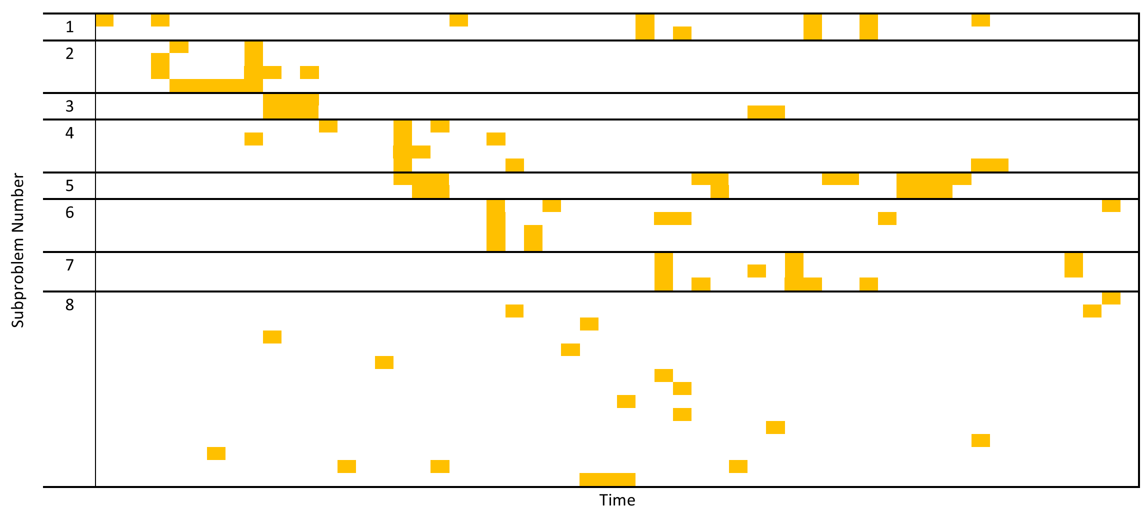

Fig. 8 Timeline for Team 5

Table 8 Subproblems for each of the five teams

No.	Subproblem name	Variables included	No. vars	Description
Team 1				
1	Overall flow	Design Drive Through Drive Through Flow Entry to Greeting Drive Through Flow Greeting to Forms Dsn Drive Through Flow Forms Dsn to Screening Drive Through Flow Screening to Med Dsn Drive Through Flow Med Dsn to Exit Parking Plan and Vehicle Traffic Flow	7	Flow through all core stations for a drive-through POD (H)
2	Overall layout	Location Point of Entry Location Point of Exit POD Layout	3	Overall POD layout with points of entry and exit (H)
3	Preliminary layout of core/non-core stations	Location Staff Break Room Location Inventory and Supplies Location Triage Location Behavioral Health	4	Location of several non-core stations (PL)
4	Prelim. and detailed design of core/non-core stations	Location Security Location Flow Control Internal Layout Screening	3	Location and internal layout of more non-core stations (PL and DD)
5	Prelim. and detailed design of Screening and Med Dsn	Location Screening Location Med Dsn Staffing at Screening Staffing at Med Dsn	4	Location and staffing for screening and medication distribution (PL and DD)
6	Prelim. and detailed design of Med Dsn	Flow Screening to Med Dsn Internal Layout Med Dsn	2	Flow to and internal layout of medication distribution (PL and DD)
7	Staffing	Staffing at Command Post Calculating Staff Needs	2	Staffing overall and for command post (DD)
8	Staffing and mix *(groups many infrequently coded variables)	Location Greeting Location Forms Dsn Staffing at Greeting Staffing at Forms Dsn Staffing at Inventory and Supplies Staffing at Triage Staffing at Behavioral Health Staffing at Flow Control Additional Staffing Flow Forms Dsn to Screening Internal Layout Forms Dsn Flow within Med Dsn Include Drive Through	13	Staffing, location, flow and internal layout for many core and non-core stations (DD)
Team 2				
1	Overall layout	Parking Plan and Vehicle Traffic Flow Location Point of Exit Include Drive Through Location Med Dsn POD Layout	5	Overall layout with exit, parking, and one key station (H)
2	Preliminary layout of core/non-core stations	Flow Med Dsn to Exit Location Staff Break Room Location Inventory and Supplies	3	Location of inventory and staff break room, with flow from medication distribution to exit (PL)

Table 8 (continued)

No.	Subproblem name	Variables included	No. vars	Description
3	Prelim. and detailed design at core/non-core stations	Staffing at Forms Dsn Location Flow Control Internal Layout Forms Dsn Location Forms Dsn Location Screening Staffing at Screening Staffing at Inventory and Supplies Additional Staffing Location Security Location Point of Entry Visual Aids Residents	11	Location and staffing at core and non-core stations (PL and DD)
4	Detailed design of Screening	Internal Layout Screening Flow within Screening	2	Internal layout and flow within screening (DD)
5	Detailed design of Medication distribution	Internal Layout Med Dsn Flow within Med Dsn Flow Screening to Med Dsn Staffing at Med Dsn	4	Internal layout, flow to and within, and staffing at medication distribution (DD)
Team 3				
1	Staffing	Calculating Staff Needs Staffing at Flow Control	2	Overall staffing and at flow control (DD)
2	More staffing	Staffing at Command Post Staffing at Inventory and Supplies	2	Staffing at command post and inventory (DD)
3	Parking and flow control	Staffing at Parking Control/Mgt Include Flow Control Include Parking Control/Mgt	3	Staffing and inclusion of parking and flow control (PL and DD)
4	POD layout	Location Point of Entry Location Med Dsn Location Inventory and Supplies POD Layout Flow within Inventory and Supplies Location Point of Exit	6	Overall layout with location of entry/exit, medication distribution, inventory (H)
5	Prelim. and detailed design for Forms Dsn and Greeting	Location Forms Dsn Staffing at Forms Dsn Staffing at Greeting Location Flow Control Location Greeting	5	Location and staffing for greeting, forms distribution, and flow control (PL and DD)
6	Prelim. and detailed design of Med Dsn and Screening	Location Screening Internal Layout Med Dsn Internal Layout Screening	3	Internal layout and location of screening and medication distribution (PL and DD)
7	Prelim. and detailed design in core stations	Flow Med Dsn to Exit Staffing at Point of Exit Flow Forms Dsn to Screening Flow Screening to Med Dsn Flow within Screening Flow within Med Dsn	6	Flow through and within forms distribution, screening, medication distribution, and exit (PL and DD)
8	Detailed design of non-core stations	Flow within Parking Control/Mgt Visual Aids Residents Parking Plan and Vehicle Traffic Flow Location Security Include Drive Through Staffing at Medical Mgt Staffing at Behavioral Health	7	Mix including parking and drive through, staffing for non-core stations (DD)
9	Prelim. design of two non-core stations	Location Command Post Location Medical Mgt Include Command Post Include Medical Mgt	4	Include and locate command post and medical management (PL)
10	Detailed design of Med Dsn and Screening	Staffing at Med Dsn Staffing at Screening	2	Staffing at medication distribution and screening (DD)

Table 8 (continued)

No.	Subproblem name	Variables included	No. vars	Description
Team 4				
1	POD Layout	POD Layout Include Drive Through	2	Overall POD layout with whether to do a drive-through POD (H)
2	Prelim. and detailed design of (mainly) core stations	Location Point of Entry Staffing at Parking Control/Mgt Parking Plan and Vehicle Traffic Flow Staffing at Forms Dsn Internal Layout Forms Dsn Flow Forms Dsn to Screening Calculating Staff Needs Location Security Staffing at Command Post	9	Combination of parking/entry and staffing/flow at core stations (PL and DD)
3	Preliminary layout of non-core stations	Location Command Post Include Command Post Location Staff Break Room Include Staff Break Room	4	Location and inclusion of command post and staff break room (PL)
4	Prelim. and detailed design of (first) core stations	Staffing at Point of Entry Flow Entry to Greeting Location Greeting Staffing at Greeting	4	Many aspects of entry and greeting (PL and DD)
5	Prelim. and detailed design of core and non-core stations	Location Inventory and Supplies Flow within Inventory and Supplies Include Triage Flow within Point of Entry	4	Location and flow within inventory and supplies, plus others (PL and DD)
6	Prelim. and detailed design of Greeting and Forms Dsn	Flow within Forms Dsn Flow within Greeting Location Forms Dsn Flow Greeting to Forms Dsn	4	Location and flow within greeting and forms distribution (PL and DD)
7	Detailed design of Med Dsn and Screening	Internal Layout Med Dsn Internal Layout Screening	2	Internal layout of screening and medication distribution (DD)
8	Preliminary layout for (mainly) non-core stations	Staffing at Behavioral Health Location Behavioral Health Include Behavioral Health Location Point of Exit Location Medical Mgt Include Parking Control/Mgt	6	Location, inclusion, staffing at non-core and core stations (PL)
9	Prelim. and detailed design for core stations	Location Flow Control Flow Med Dsn to Exit Flow within Screening Flow within Med Dsn Staffing at Point of Exit Flow Screening to Med Dsn	6	Flow within and through screening, medication distribution, and exit (PL and DD)
10	Staffing at core stations	Staffing at Inventory and Supplies Staffing at Screening Staffing at Med Dsn	3	Staffing at inventory, screening, and medication distribution (DD)
11	Detailed design of core stations	Visual Aids Station Internal Layout Point of Entry Visual Aids Hallway Internal Layout Flow Control Internal Layout Greeting Internal Layout Point of Exit	6	Internal layout of core stations with visual aids (DD)
Team 5				
1	Staffing	Staffing at Med Dsn Calculating Staff Needs	2	Staffing overall and at medication distribution (DD)
2	POD Layout	Location Point of Entry Location Med Dsn POD Layout Parking Plan and Vehicle Traffic Flow	4	Location and layout overall and key stations (H)

Table 8 (continued)

No.	Subproblem name	Variables included	No. vars	Description
3	Preliminary Layout of Greeting and Forms Dsn	Location Greeting Location Forms Dsn	2	Location of greeting and forms distribution (PL)
4	Preliminary layout of core stations	Location Screening Location Point of Exit Flow Screening to Med Dsn Internal Layout Med Dsn	4	Location, flow, and internal layout of screening, medication distribution, and exit (PL)
5	Detailed design of screening	Internal Layout Screening Flow within Screening	2	Internal layout and flow within screening (DD)
6	Preliminary layout of core stations	Location Inventory and Supplies Location Flow Control Flow Med Dsn to Exit Flow within Med Dsn	4	Location and flow in inventory, medication distribution, and exit (PL)
7	Staffing at core stations	Staffing at Greeting Staffing at Forms Dsn Staffing at Screening	3	Staffing at greeting, forms distribution, and screening (DD)
8	Preliminary layout and detailed design of many stations	Location Command Post Location Security Location Data Entry Location Patient Education Include Data Entry Include Triage Staffing at Point of Exit Staffing at Command Post Staffing at Data Entry Staffing at Inventory and Supplies Staffing at Triage Staffing at Flow Control Staffing at Parking Control/Mgt Flow Forms Dsn to Screening Internal Layout Data Entry	15	Location, staffing, and other for many non-core stations (PL and DD)

H high-level, *PL* preliminary layout, *DD* detailed design

References

Aaby K, Herrmann JW, Jordan C, Treadwell M, Wood K (2006) Montgomery County's Public Health Service uses operations research to plan emergency mass-dispensing and vaccination clinics. Interfaces 36(6):569–579

Abbey RL, Aaby KA, Herrmann JW (2013) Planning and managing mass prophylaxis clinic operations. In: Denton BT (ed) Handbook of healthcare operations management. Springer, New York

Azhar A, Gralla EL, Tobias C, Herrmann JW (2016) Identification of subproblems in complex design problems: a study of facility design. In: Proceedings of the ASME 2016 international design engineering technical conferences and computers and information in engineering conference

Baldwin C, Clark K (2000) Design rules. The power of modularity. MIT Press, Cambridge

Ball L, Evans J, Dennis I (1994) Cognitive processes in engineering design: a longitudinal study. Ergonomics 37(11):1753–1786

Ball L, St BT, Evans J, Dennis I, Ormerod TC (1997) Problem-solving strategies and expertise in engineering design. Think Reason 3(4):247–270

Ball LJ, Ormerod TC (1995) Structured and opportunistic processing in design: a critical discussion. Int J Hum Comput Stud 43(1):131–151

Black J, Hunter SL (2003) Lean manufacturing systems and cell design. Society of Manufacturing Engineers, Dearborn

Bostrom RP, Watson RT, Van Over D (1992) The computer-augmented teamwork project. In: Computer augmented teamwork: a guided tour. Van Nostrand Reinhold, New York, pp 251–267

Browning TR (2001) Applying the design structure matrix to system decomposition and integration problems: a review and new directions. IEEE Trans Eng Manag 48(3):292–306

CDC SNS (2012) SNS preparedness course participant workbook. Technical report

Clarkson PJ, Hamilton JR (2000) Signposting, a parameter-driven task-based model of the design process. Res Eng Des 12(1):18–38

Cooper RG (1994) Third-generation new product processes. J Prod Innov Manag 11(1):3–14

Cooper RG (2008) The stage-gate idea-to-launch processupdate, what's new, and nexgen systems. J Product Innov Manag 25(3):213–232

Corbin J, Strauss A (2008) Basics of qualitative research: techniques and procedures for developing grounded theory, 3rd edn. Sage, Thousand Oaks

Cross N (2004) Expertise in design: an overview. Des Stud 25(5):427–441

Dinar M, Shah J, Cagan J, Leifer L, Linsey J, Smith SM, Hernandez NV (2015) Empirical studies of design thinking: past, present, future. J Mech Des 137:1–13

Drira A, Pierreval H, Hajri-Gabouj S (2007) Facility layout problems: a survey. Ann Rev Control 31:255–267

Dym CL, Little P, Orwin EJ, Spjut E (2009) Engineering design: a project-based introduction. Wiley, Hoboken

Eppinger S, Browning TR (2012) Design structure matrix methods and applications. MIT Press, Cambridge

Eppinger S, Whitney D, Smith R, Gebala D (1994) A model-based method for organizing tasks in product development. Res Eng Des 6:1–13

Ethiraj SSK, Levinthal D (2004) Modularity and innovation in complex systems. Manag Sci 50(2):159–173

Goel V, Pirolli P (1992) The structure of design problem spaces. Cogn Sci 16(3):395–429

Gralla EL, Herrmann JW (2014) Design team decision processes in facility design. In: Proceedings of the 2014 industrial and systems engineering research conference

Gralla EL, Herrmann JW, Morency M (2016) Design team decision processes in point of dispensing design. In: Proceedings of the 2016 industrial and systems engineering research conference

Guindon R (1990) Designing the design process: exploiting opportunistic thoughts. Hum Comput Interact 5(2–3):305–344

Gurnani A, Lewis K (2008) Collaborative, decentralized engineering design at the edge of rationality. J Mech Des 130(12):121101 (9 pages)

Hammond J, Koubek RJ, Harvey CM (2001) Distributed collaboration for engineering design : a review and reappraisal. Hum Factors Ergon Manuf 11(1):35–52

Hazelrigg GA (1998) A framework for decision-based engineering design. J Mech Des 120(4):653–658

Hendrick H, Kleiner B (2002) Macroergonomics: theory, methods, and applications. Lawrence Erlbaum Associates, Mahwah

Herrmann JW (2010) Progressive design processes and bounded rational designers. J Mech Des 132:1–8

Herrmann JW (2015) Predicting the performance of a design team using a markov chain model. IEEE Trans Eng Manag 62:507–516

Herrmann JW, Schmidt LC (2002) Viewing product development as a decision production system. ASME paper no. DETC2002/DTM-34030

Herrmann JW, Schmidt LC (2006) Product development and decision production systems. Decis Mak Eng Des. https://doi.org/10.1115/1.802469.ch20

Herrmann JW, Morency M, Anparasan A, Gralla EL (2017) Evaluating clustering algorithms for identifying design subproblems. J Mech Des. https://doi.org/10.1115/1.4040176

Ho C-H (2001) Some phenomena of problem decomposition strategy for design thinking: differences between novices and experts. Des Stud 22(1):27–45

Kraemer KL, Pinsonneault A (1990) Technology and groups: assessment of the empirical research. In: Galegher J, Kraut RE, Egido C (eds) Intellectual teamwork: social and technological foundations of cooperative work. Lawrence Erlbaum Associates, Hillsdale NJ, pp 375–405

Krishnan V, Eppinger SD, Whitney DE (1997) Simplifying iterations in cross-functional design decision making. J Mech Des 119(4):485–493

Langley A (1999) Strategies for theorizing from process data. Acad Manag Rev 24(4):691–710

Lewis K, Mistree F (1998) Collaborative, sequential, and isolated decisions in design. J Mech Des 120(4):643–652

Liikkanen LA, Perttula M (2009) Exploring problem decomposition in conceptual design among novice designers. Des Stud 30(1):38–59

MacCormack A, Baldwin C, Rusnak J (2012) Exploring the duality between product and organizational architectures: a test of the mirroring hypothesis. Res Policy 41(8):1309–1324

March JG, Simon HA (1958) Organizations. Wiley, Hoboken, New Jersey

McComb C, Cagan J, Kotovsky J (2017a) Capturing human sequence-learning abilities in configuration design tasks through Markov chains. J Mech Des 139:1–12

McComb C, Cagan J, Kotovsky J (2017b) Mining process heuristics from designer action data via hidden Markov models. J Mech Des 139:1–12

McMahon C, Xianyi M (1996) A network approach to parametric design integration. Res Eng Des 8:14–32

Meredith JW (1997) Empirical investigation of sociotechnical issues in engineering design. PhD thesis, Virginia Polytechnic Institute and State University

Morency M (2017) Evaluating clustering algorithms to identify subproblems in design processes. Master's thesis, University of Maryland

Morency M, Anparasan A, Herrmann JW, Gralla EL (2017) Using clustering algorithms to identify subproblems in design processes. In: International conference on engineering design

O'Donovan B, Eckert C, Clarkson J, Browning TR (2005) Design planning and modelling. In: Clarkson J, Eckert C (eds) Design process improvement. Springer, London, pp 60–87

Pahl G, Beitz W, Feldhusen J, Grote K-H (2007) Engineering design: a systematic approach. Springer, London

Sherwood B, McCleese D (2013) JPL innovation foundry. Acta Astronaut 89:236–247

Simon HA (1962) The architecture of complexity. Proc Am Philos Soc 106(6):467–482

Sun G, Yao S, Carretero JA (2016) An experimental approach to understanding design problem structuring strategies. J Des Res 14(1):94–117

Sutton R, Hargadon AB (1996) Brainstorming groups in context: effectiveness in a product design firm. Adm Sci Q 41(4):685–718

Tobias C, Herrmann JW, Gralla EL (2015) Exploring problem decomposition in design team discussions. In: International conference on engineering design

Tompkins JA, White JA, Bozer YA, Tanchoco J (2003) Facilities planning. Wiley, Hoboken

Wynn DC, Eckert CM (2017) Perspectives on iteration in design and development. Res Eng Des 28(2):153–184