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Abstract

In this paper, we treat organization design as a sorting (or clustering) process. We used a card sorting methodology where participants were asked to decide who (in a set of people/roles) should be organized in the same team, given information about each person (or role's) tasks and interdependencies toward other roles. We compared the participants' decisions to an algorithmically derived solution, and also developed an index to measure the distance between the participants' decision and the optimal solution. We found that the results were dependent on the complexity of the task: Performance was lower on the more complex tasks, consisting of 9 and 12 roles, than the simple task with 6 roles. We also found that the tendency to discard interdependencies between roles and use a simple heuristic (i.e., to sort the roles based on their titles) was somewhat stronger with the 9-role task compared to the simplest task; but the results did not support the hypothesis with regards to the 12-role task. Finally, the data suggest that the likelihood of identifying the optimal solution increases with the time spent on each task (this relationship was significant for the 9 and 12-role tasks). We believe that our methodology can be used to identify the "microfoundations" of organization design and we discuss how the methodology can be refined and serve as the basis for future studies.

Organization design decisions: A card sorting approach

There is a large literature about various organizational forms. It is clear that all organizations of a certain size are differentiated, in the sense that they are sub-divided into multiple smaller units, such as teams and departments (Donaldson, 2001). Several criteria have been proposed to guide the choice of organizational forms (Burton, Obel, & Håkonsson, 2015; Worren, 2018). Yet the *process* by which decision makers determine the appropriate grouping of roles or sub-units has received little attention (Puranam, 2018).

In principle, there are two basic approaches that may be taken when determining the organizational structure. The first is to group by skill or professional expertise. This gives rise to the traditional, functional organization. As an example, such an organization may have departments for procurement, engineering, sales and customer service. From a decision making perspective, this is relatively straightforward, as one can rely on pre-existing categories such as the title or educational background of people to form the sub-units ("all engineers will belong to the engineering department"). The other approach is to consider the work processes, and group roles depending on how they interact to develop or deliver a service or product. Many popular management approaches, including Re-engineering (Hammer, 1990), Lean (Jones & Womack, 2010), Agility (Denning, 2018), and the Horizontal organization (Ostroff, 1999) emphasize the need to align the organization with the work processes. However, it is more difficult to identify an appropriate grouping of roles or sub-units when using processes as a criterion. First, it is usually only the formal roles and reporting relationships that are documented (in the form of an organization chart); interdependencies that arise as a result of work processes are rarely documented. Secondly, even when such information is available, it is computationally challenging to group a set of roles based on their interdependencies (C.-H. Lee, Hoehn-Weiss, & Karim, 2016; Puranam, 2018). For this reason, one would expect that decision makers frequently resort to using a heuristic method when defining a new organizational model.

For this study, we developed a new approach to studying organizational design decisions, based on observations and participation in actual organization design processes over many years[1]. These observations suggested that organization design is fundamentally a task of grouping interdependent elements, such as roles or sub-units, into sub-systems. The observations also suggested that decision makers frequently find this task to be challenging and that they are uncertain about whether they have found an appropriate organizational model. To represent the decision making task in a realistic manner, we developed a card sorting approach. Participants are shown a set of role descriptions, like those in Figure 1, that describe the job or title of each person/role, and the main interdependencies toward the other roles in the set[2]. The participants are then informed that there is a rule in this organization that each team can have a maximum of, say, three members, and are asked to find out how to group the roles into two or more teams.

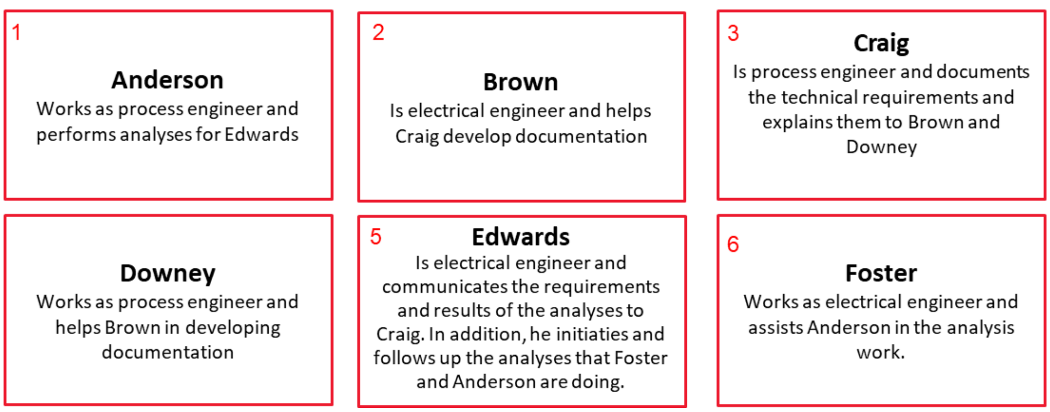

Figure 1. Example of stimuli used in the study (Task 1)

[1] The first author is a former management consultant and has participated in nearly 30 organizational re-design projects for firms of various sizes in multiple industries.
[2] Although our study focused on roles, this type of task is in principle independent of level. For example, the elements in Figure 1 could instead have represented business units in a large firm rather than individual level roles and interdependencies.

Since this is basically a clustering task, the solutions that the participants generate can be compared to an optimal model, or more precisely, to an algorithmically derived solution. We used a generic algorithm developed by Soldal (2012) with the objective function (or fitness function) proposed in Yu et al. (2003) to identify the optimal model.

Prior to conducting the study, we had used examples with 6 roles, such as the one shown in Figure 1, in classes with master level students and in workshops with managers. We observed that the majority of participants identified the appropriate grouping, but that some failed to do so, even when they were explicitly asked to identify a grouping that would facilitate collaboration and information exchange. The key motivation for our study was to test how people would handle tasks with varying degrees of complexity. Hence in addition to the task with 6 roles, we developed one with 9 and one with 12 roles.

EXISTING THEORY AND RESEARCH

Interdependencies as a grouping criterion

The use of interdependency as basis for structuring organization is most often associated with Thompson (1967), who stated that "…"Under norms of rationality, organizations group positions to minimize coordination costs" and "Organizations seek to place reciprocally interdependent positions tangent to one another, in a common group, which is (a) local and (b) conditionally autonomous (p. 57). However, a number of other authors, including Simon (1962), Alexander (1964) and Rechtin (1991) have proposed similar design principles. The main assumption is that one will reduce coordination costs by grouping interdependent roles, as this implies that those that need to interact and reach agreement on various issues are placed in the same sub-unit (and are potentially co-located), report to the same manager, and pursue the same overall goals. In contrast, a situation where there is a large number of interdependencies across sub-units will lead to higher coordination costs, as one will need to interact and reach agreement with people who belong to different sub-units, report to different managers, and potentially pursue other goals (Kilmann, 1983).

Cognitive load theory

Thompson (1967) did not take into consideration the possibility of errors due to cognitive limitations or biases. As mentioned above, grouping or clustering tasks are computationally challenging. Decision makers have to take into account multiple elements and their interdependencies. It is natural to assume that the required memory storage and information processing will lead to a high cognitive load (Sweller, 1988) that may produce errors, given the limited capacity of human working memory (cf. Ayres, 2001). With higher cognitive load, one would generally expect lower cognitive performance, including a greater reliance on heuristics rather than analytical problem solving strategies (Allred, Crawford, Duffy, & Smith, 2016).

There is also a relationship between time usage (or response time), cognitive load, and performance. It has been shown that response time increases with higher task complexity (Huang, Eades, & Hong, 2009). According to the dual systems model of cognition, intuitive thinking ("System 1"), which relies on heuristics, is generally faster than analytical thinking ("System 2") (Kahneman, 2011). Experiments also show that time pressure inhibits analytical reasoning processes (Evans & Curtis-Holmes, 2005). This is consistent with field research in organizations, which suggests that managers often perceive time pressure, even when there is no deadline, and that this leads to short cuts in decision making processes (Nutt, 1999, 2010).

The dual systems model has received criticism from some scholars (e.g., Kruglanski & Gigerenzer, 1999) and adjustments of the theory have been proposed by, among others, Hammond (1996) and Jacoby (1991). However, after reviewing the arguments by the critics, Evans & Stanovich (2013) conclude that the evidence does support the main tenets of the theory. Yet they argue that the defining feature is not speed per se, but the fact that System 1 is autonomous while System 2 requires working memory and explicit processing effort (deliberate reasoning).

Microfoundations

The notion of "microfoundations" has been described as a research program to unpack how individual-level factors impact organizational-level outcomes (Felin & Foss, 2005). During the last couple of decades, a number of studies have been conducted to identify the microfoundations of organizational-level constructs such as firm capabilities (Felin, Foss, & Ployhart, 2015). However, we are only aware of two studies that consider the role of individual level factors in relation to organization design. Following Simon (1962), Lee & Puranam (2015) conceptualized organization design as a problem solving activity. They compared the solutions of 16 experts with 16 novices when finding a solution to a case problem. A verbal protocol method was used where the participants were asked to explain their choices while they were developing a solution. They found that the experts spent more time during the exercise on integration, while the novices spent more time on partitioning tasks. The experts would typically propose organizational designs based on information flows or interdependencies ("These two guys need to interact frequently..") while novices would typically propose sub-division into different groups based on task differences ("I think we have three different markets that [needs a] specialized representative […] each"). The second study we identified was conducted by Raveendran, Puranam & Warglien (2016), who investigated how people make decisions about division of labour when constructing a Meccano model. In their experiment, participants were given the assembly instructions and parts, and worked in groups to assemble the model. They found that the participants had a tendency to select an "object based" as opposed to an "activity based" division of labour. For example, they would typically allocate the responsibility of assembling the wheels to one person, and the motor to another. Fewer would allocate responsibility based on activities (e.g., "find the pieces for each step"). However, they caution that their results are mainly relevant for project based organizations. We assume that their results may also be relevant to design decisions at a lower level in an organization, where one can start from a well-defined sequence of production steps. At a more strategic level, though, we believe that organization design decisions are made in a somewhat different manner. Generally, decision makers do not start from a predefined sequence of tasks (like the assembly instructions for the Meccono model) but with the existing formal structure (i.e., roles and unit groupings) combined with implicit or explicit knowledge about interdependencies. Adjustments to the existing structure are then made based on considerations about: 1) whether certain roles or specialities (e.g., IT people; account managers; service personnel) “belong” together or may benefit from being organized in the same unit, versus 2) what grouping of roles (or sub-units) would facilitate coordination and collaboration (i.e., optimize on coordination costs)[3].

The Design Structure Matrix and clustering algorithms

Task interdependencies in an organization can be represented by means of the Design Structure Matrix (Eppinger & Browning, 2012). DSM is a square matrix where the elements (along the rows and columns) represent the components in the system (in this case, roles or sub-units). Dependencies between elements are marked as “X”s in Figure 2, but may also be quantified based on frequency or criticality. The DSM is “bilateral” in the sense that is shows relationships between two elements in each cell. Starting with an element along the left column, such as element A, one reads across the columns to see which elements that A depends on (e.g., needs information, resources or approval from; in this case it is E and F).

[3] A third consideration (which we do not cover in this study) would be separation or splitting of roles or sub-units that are incompatible (see Worren, 2018).

	A	B	C	D	E	F
A					X	X
B			X	X		
C		X			X	
D			X			
E	X					X
F					X	

Figure 2. Design structure matrix representing the interdependencies depicted in the role set in Figure 1.

Clustering algorithms have been developed that can take DSM-type data as input and produce an optimal grouping, according to an objective function. The usual criteria for a clustering algorithm are to minimize the number of interdependencies between clusters, and maximize the number of interdependencies between clusters. The optimal solution given these criteria for the example shown in Figure 1 is shown in Figure 3.

	F	E	A	C	B	D
F		X				
E	X		X			
A	X	X				
C		X			X	
B				X		X
D				X		

Figure 3. Clustering (of elements shown in Figure 1 and 2).

The logic of the objective function (or fitness function) in the clustering algorithm is straightforward: It will evaluate alternative solutions that are generated by assigning a “penalty” for each discrepancy from optimal clustering. A simple example is shown in Figure 4. If each discrepancy has a weight of 1, the total score will be 2 in this case: First, there is a penalty for not including the D-A interdependency within a cluster (1) (Type 1 error). Secondly, there is a penalty for including C together with D even though they are not interdependent (2) (Type 2 error).

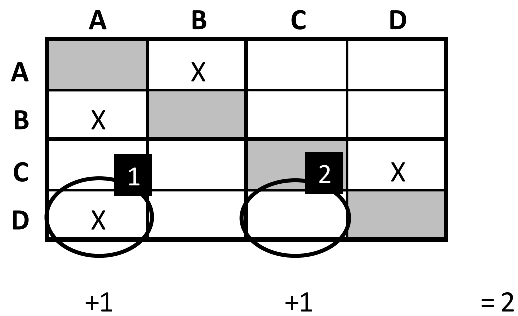

Figure 4. Calculation of “distance score”.

A similar logic may be applied when comparing different matrices, for example, two solutions generated by two different algorithms, or one solution generated by the algorithm, and another generated manually. One can count the number of discrepancies between the two matrices and thus derive a “distance score” which is a measure of the relative similarity between the two matrices (a lower score indicating higher degree of similarity).

HYPOTHESES

Our main interest was in understanding the level of cognitive difficulty involved in making organization design decisions, more specifically, those involving grouping of interdependent elements. We expected that performance, as measured by the distance score (i.e., similarity with the algorithmically derived grouping), would decrease with increasing complexity (i.e., across the three tasks with 6, 9 and 12 roles). We wanted to control for time usage, as participants might simply spend more time on the tasks with more roles (as there was no time limit) to cope with the increasing complexity.

> **Hypothesis 1:** With increasing task complexity, performance will be reduced, taking into consideration the time used.

Given the literature on cognitive load described above, we reasoned that there might be a greater tendency to use a heuristic when task complexity increases. If the decision maker has information about the role titles, which provides an indication of education and/or specialization, one option is to group the roles by function (i.e., based on titles) rather than by interdependency. Grouping by function is a simpler task, as it only involves categorization.

> **Hypothesis 2:** With increasing task complexity, there will be a greater tendency to propose a functional grouping (i.e., one based on titles).

Finally, based on the dual processing theory of cognition, we wanted to investigate the relationship between time use and performance. Since it clearly requires analytical thinking to find the appropriate grouping and since analytical thinking generally requires more time than intuitive thinking, we expected that participants who use less time would have a greater tendency to select the functional grouping (based on titles) rather than the analytical solution based on interdependencies.

> **Hypothesis 3a:** The likelihood of identifying the optimal solution will increase with time usage per task.

> **Hypothesis 3b:** The tendency to select a grouping based on interdependencies will decrease with time usage per task.

METHOD

The stimuli material consisted of three different tasks created by using the card sorting feature in Survey Gizmo, an online survey tool. The participants were first shown a set of roles, which also included information about interdependencies (as in Figure 1), and then asked to sort the roles into groups (see Figure 5).The role descriptions and the card sorting task were presented on the same screen and it was possible to scroll up and down (hence it was not necessary to memorize the information). There was no time limit, but the time used for each task was automatically recorded by the survey tool.

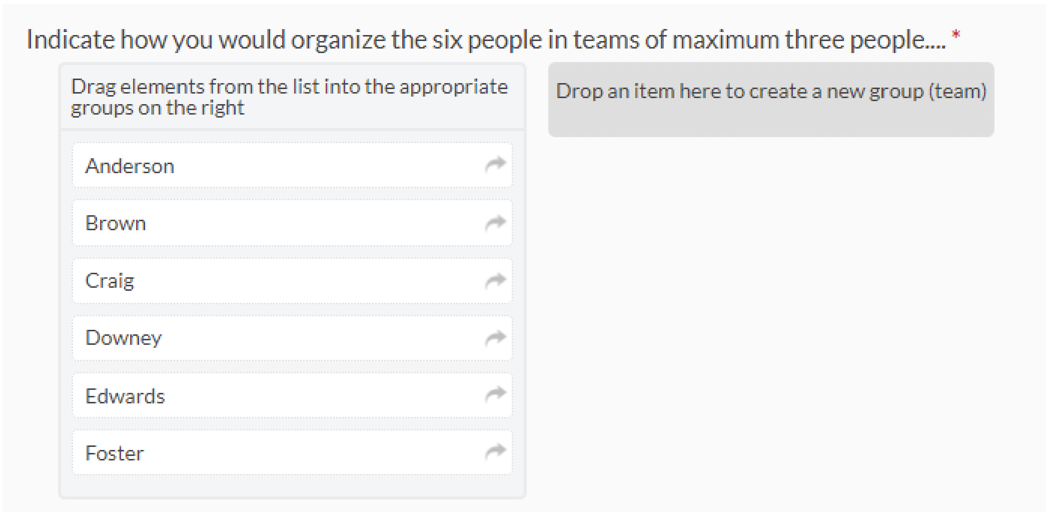

Figure 5. Example of one of the tasks in the study.

We developed three different tasks. The main intention was to vary the level of complexity. There was no pre-existing theory that we could rely on to guide this effort, but we reasoned that task complexity would be a function of mainly three factors. First, that complexity would increase with an increase in the number of roles. Hence the tasks contained 6, 9, and 12 roles, respectively. In order to avoid (unwanted) transfer between the tasks (i.e., a learning effect or analogical reasoning), we chose different types of scenarios. The first task is the set of roles shown in Figure 1. This role set is intended to reflect typical roles in an engineering project. The second task with 9 roles contained information about an IT firm, while the task with 12 roles described a pharmaceutical firm. Furthermore, we reasoned that task complexity would be related to the total number of interdependencies between roles. The three tasks contained 10, 14 and 33 interdependencies, respectively (see Table 1). Third, we believed that task complexity would be related to the number of interdependencies that remain between groups (or teams) after clustering; following Simon (1962), this reflects the degree of "decomposability" of the system (Puranam, 2018)[4]. Finally, we also made an attempt at creating tasks with face validity: The role descriptions were written in such a way that

[4] However, it is not only the number of interdependencies that matter, but their perceived strength. For this reason, Table 1 represents a simplified comparison between the tasks.

they would produce plausible teams both when one grouping them by function (i.e., by role title in this case) and when grouping them by interdependencies.

Table 1. Comparison between the three tasks in the study

	Task 1	Task 2	Task 3
Number of roles	6	9	12
Total number of interdependencies between role	10	14	33
Number of interdependencies remaining between clusters after grouping ("decomposability")	1	2	8
Similarity ratio ("non-orthogonality") between heuristic and analytical solution	0.47	0.5	0.55

The optimal solution in terms of grouping by interdependencies was identified by using Reconfig, an organization design software tool. This tool uses a genetic algorithm (Soldal, 2012) combined with the fitness function proposed by Yu et al. (2003, p. 109):

$$fDSM(M) = (1 - \alpha - \beta)\,(Nc\,log(Nn) + (\log(Nn) \sum_{1}^{Nc} CLi + (\alpha\,[|S1|\,(2log(Nn + 1))] + \beta[|S2|(2log(Nn + 1))])$$

Where:
Nc = Number of clusters in the DSM
Nn = Number of rows/columns in the DSM (i.e., elements such as number of roles)
CLi = number of nodes in cluster i
S1 = Sum(Type 1 error) - Type 1 error = "Errors of omission" (failing to include an interdependent element in a cluster)
S2 = Sum(Type 2 error) - Type 2 error = "Errors of commission" (including a non-interdependent element in a cluster)
Alpa and beta = weights between 0 and 1.

The objective is to find a solution that minimizes fDSM (i.e., coordination cost).

A number of different clustering algorithms have been proposed (see Schaeffer, 2007). For larger and more complex data sets, these may produce somewhat different solutions. However, with small data sets like the one we use here, the solution is straightforward and most clustering algorithms will converge on the same solution and are not highly sensitive to the weights (Indeed, one can verify the optimal solution manually for the problem sets in our study.) In addition, we identified the functional grouping that would result from clustering the roles by title. We compared each participant's actual grouping with both the optimal solution and the functional grouping, using distance scores. The distance score was calculated by adding 1 for each discrepancy from the solution matrix.

One challenge when comparing heuristic and analytical groupings is that they will not be completely orthogonal. As we have described, the roles can be divided into groups in two ways: One based on interdependencies and one based on titles. Unfortunately, there will be some overlap in the two solutions (see Table 2). It is logically impossible to avoid this situation. However, what is more important than the lack of orthogonality is the consistency across the three tasks: If the degree of orthogonality differed, it would make it difficult to interpret the results comparing the three tasks. To verify that the consistency was acceptable, we first calculated the distance scores between the heuristic and analytical solutions of each of the three tasks. We then calculated the "difference ratio" (the sum of distances between the two matrices, divided by the number of non-diagonal elements) and then the "similarity ratio (1 – the difference ratio). This exercise confirmed that the degree of similarity, or non-orthogonality, was quite similar across the three tasks (see Table 1).

Table 2. Comparison between analytical and heuristic solution (overlap marked in bold, numbers refer to group membership).

Task 1 (6 roles)	Analytical grouping based on interdependencies	Heuristic grouping based on titles
Anderson	**1**	**1**
Brown	**2**	**2**
Craig	2	1
Downey	2	1
Edwards	1	2
Foster	1	2

In addition to these considerations, there are two ways of calculating the distance scores in this type of study. The simplest one is to simply count whether or not a role has been placed in the cluster (or group) as defined in the optimal solution (or in the alternative, heuristic solution). This essentially involves using a symmetrical matrix when calculating the distance scores. With the functional grouping based on titles, only a symmetrical matrix is possible (you either group related roles together or not). However, for the analytical solution, an alternative is to distinguish between roles that are dependent (i.e., have a one-way relationship) from those that are interdependent (i.e., have a two-way, reciprocal relationship). This implies using a non-symmetrical matrix (Figure 4 shows an example of a non-symmetrical matrix). One will give a larger penalty to an incorrect placement of a role (e.g., outside of a cluster where it should have been included) if there are two-way interdependencies compared to only one-way dependencies; whereas the first approach does not distinguish between the two. We chose the latter approach as it is more consistent with the theory (Thompson, 1967), which does distinguish between one-way (or sequential) and two-way (reciprocal) interdependencies[5].

One hundred and seventy-two undergraduate students at the Norwegian University of Life Sciences participated in the study to receive course credit. The participants completed the survey on-line working individually (we added an item at the end to verify that the tasks had been solved individually). To eliminate learning effects, we created six variations of the survey, one for each of the six possible sequence of tasks (1-2-3, 1-3-2, and so on). The participants were randomly assigned to one of the six versions. Before conducting the data analysis, we had to develop a new data transformation procedure. The raw data from the card sorting tasks could not be analyzed directly. We wrote an Excel function to reformat the data and exported the data to Stata to perform the statistical analysis.

[5] However, we also run the analysis with distance scores calculated based on a symmetrical matrix. The main results were similar to those reported here. The main difference was for the third hypothesis (Model (6)), where only one of the tasks (12 roles) achieved significance.

ANALYSIS AND RESULTS

The main variable of interest in our analysis is the proportion of minimal distance scores[6] with respect to the optimal and the heuristic solutions. Albeit these binary measures imply a loss of information when compared to a continuous distance score, they provide us with performance measures that are comparable across tasks[7] (In the following, when we refer to "optimal solution" we refer to a solution with a minimal distance score. We use the term "heuristic solution" to refer to a solution with zero distance score to the functionally based grouping based on titles.)

In Table 3 we report descriptive statistics for performance measures and time usage across the three tasks. As expected, the proportion of optimal solutions decrease from 76% for the 6-role task to 66% for the 9-role task and 60% for the 12-role task (Figure 6). However, the proportion of heuristic solutions does not increase linearly: It first increases from 6% for the 6-role task to 17% for the 9-role task, but then decreases again to 7% for the 12-role task. The time needed to accomplish the task increases with the number of roles. The increase is linear from the 6-role tasks to the 9-role task (a 50% increase), however, time use is twice as high for the 12-role task as for the 9-role task. These results will be discussed in more detail below. In table 3 we report the findings from random effects logistic regression analyses for our key variables.

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[6] The minimal distance score is zero with respect to the heuristic solution, but it is larger than zero for the analytical grouping. The reason is the use of the non-symmetrical matrix explained in the text; this means that even with a perfect solution, there will be some "penalty" due to interdependencies across clusters (e.g., between the elements C and E in the first task, cf. Figure 3).

[7] In principle, one should correct for the different random chance of identifying the correct solution across tasks. However, given the high number of possible combinations of elements, this probability is very close to zero in these cases. Comparing distance scores to the optimal analytic or intuitive solution across tasks is even more problematical, because distance scores increase with the number of possible interdependencies (i.e. the possible number of mistakes), which in turn increases exponentially with the number of roles. Distance scores need to be standardized, yet it is not clear whether weights should grow linearly or exponentially. For instance, standardizing by the number of roles (6, 9 and 12) does not account for the exponential increase in interdependencies as roles increase, while standardizing for the number of maximum interdependencies (30, 82 and 132) compress the distance scores distribution towards zero, reducing the leverage of optimal answers with minimal distance score. Weighting for the actual number of interdependencies in each task (10, 14, 33) might over penalize distance scores from the 12 compared to the 9 roles task, as the first displays more than double the number of interdependencies than the second.

Table 3. Descriptive statistics

	Task 1 (6 roles)				Task 2 (9 roles)				Task 3 (12 roles)			
	mean	SD	min	max	mean	SD	min	max	mean	SD	min	max
Proportion analytic	0.756	0.431	0	1	0.657	0.476	0	1	0.599	0.492	0	1
Proportion heuristic	0.064	0.245	0	1	0.174	0.381	0	1	0.070	0.255	0	1
Distance scores analytic	6.186	4.196	4	20	13.767	8.600	8	32	27.988	16.275	16	98
Distances scores heuristic	15.105	4.060	0	18	28.081	14.063	0	42	52.314	18.692	0	108
Time (seconds)	265	278	34	2452	395	485	27	4494	797	1503	46	16818
Log of time	5.273	0.746	3.526	7.805	5.666	0.744	3.296	8.410	6.181	0.913	3.829	9.730
Observations	172				172				172			

Table 4. Random effect logistic and OLS estimates of proportions and distance scores

VARIABLES	Model (1) Prop_analytic	Model (2) Prop_analytic	Model (3) Prop_analytic	Model (4) Prop_heuristic	Model (5) Prop_heuristic	Model (6) Prop_heuristic
Group 2	-0.640**	-0.788**	-2.833	1.681***	1.932***	2.418
	(0.294)	(0.309)	(2.117)	(0.542)	(0.613)	(3.660)
Group 3	-0.978***	-1.337***	-3.226	0.131	0.722	5.835
	(0.299)	(0.346)	(2.082)	(0.514)	(0.627)	(4.584)
Log of time		0.414**			-0.747*	
		(0.188)			(0.404)	
Group 1 * Log of time			0.148			-0.394
			(0.359)			(0.678)
Group 2 * Log of time			0.532*			-0.506
			(0.272)			(0.398)
Group 3 * Log of time			0.495**			-1.318*
			(0.233)			(0.742)
Constant	1.525***	-0.694	0.695	-4.287***	-0.323	-2.147
	(0.258)	(1.020)	(1.896)	(0.734)	(1.864)	(3.299)
Individual RE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	516	516	516	516	516	516
Number of no	172	172	172	172	172	172
Log pseudo-likelihood	-308	-305	-304	-150	-147	-146
Chi2 p-value	0.0047	0.0017	0.0010	0.0002	0.0016	0.0127
Wald test 6 vs 9 roles task (p-values)	0.0296	0.0107	0.1807	0.002	0.02	0.509
Wald test 6 vs 12 roles task (p-values)	0.0011	0.0001	0.1213	0.8	0.25	0.203
Wald test 9 vs 12 roles task (p-values)	0.1579	0.0246	0.8385	0.000	0.003	0.392

Standard errors clustered at the individual level. Standard errors in parentheses

Significant at: *** p<0.01, ** p<0.05, * p<0.

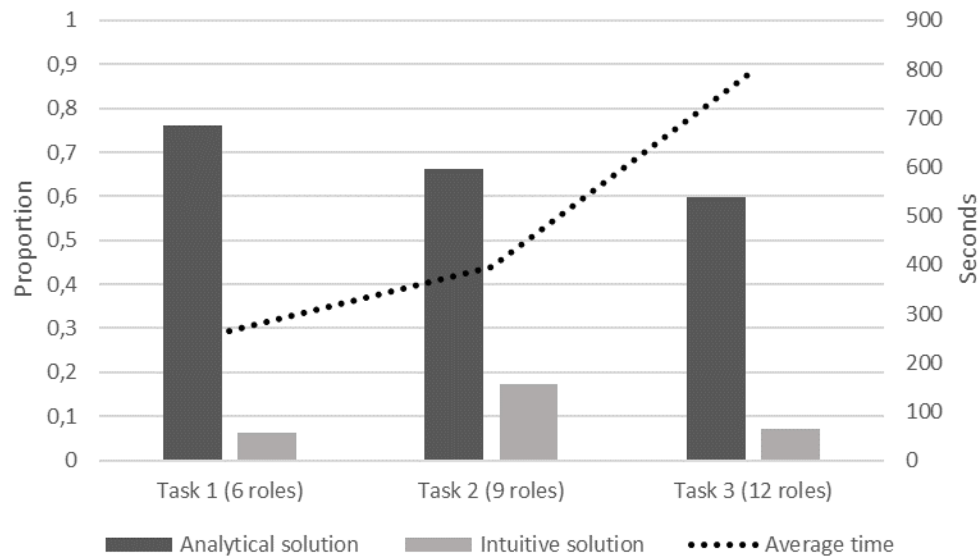

Figure 6. Proportion of analytical versus intuitive solutions and time usage across the tasks.

Hypothesis 1. The first hypothesis stated that performance would be reduced with increasing task complexity, taking into consideration time usage. We tested the difference in mean proportions of optimal solutions (Models (1) and (2)). We controlled for time spent on the task by using the log of time (Model (2)), based on the assumption that there is a diminishing return of one unit of time (e.g., one second) as time elapses. Wald tests of intercepts reveal that performance decreases significantly as task difficulty increases, confirming hypothesis one. However, the difference between 9 and 12 roles task is slightly insignificant if we do not control for time, because participants invest more time in more difficult tasks. (Note that we in the Wald test of the intercepts assume equal slopes in the regression for the data from the three tasks; in our test for Hypothesis 4 below we allow for differing slopes among the three tasks.)

Hypothesis 2. The second hypothesis stated that there would be a greater tendency to propose a heuristic grouping (i.e., one based on titles) with increasing task complexity. We tested this hypothesis in the same manner as for Hypothesis 1 (models (4) and (5) in Table 3). As indicated in Table 2 and Figure

6, the proportion of heuristic solutions increases between the tasks with 6 and 9 roles, but then decreases from the task with 9 roles to the task with 12 roles. Hypothesis 2 is partially supported.

Hypothesis 3. The third hypothesis stated that (a) the likelihood of identifying the optimal solution will increase with time usage per task, whereas (b) the tendency to use heuristics and select a grouping based on titles will decrease with time usage. We tested this hypothesis in a similar manner as Hypothesis 1, that is, by considering the proportion of optimal solutions (as well for the proportion of heuristic solutions), but we also consider time usage (In terms of the regression equations we here allow for different slopes for each of the three tasks.) (Table 3, Model (3)). We find that the likelihood of identifying the optimal solution increases significantly with the log of time with regards to the second (6 roles) ($p < 0.1$) and third task (12 roles) ($p < 0.05$). When looking at the heuristic solutions instead, we find the same relationship, in reverse: The likelihood of proposing a heuristic solution decreases as a function of time, but is only significant for the 12 role task (Model (6)). Thus hypothesis 4 receives partial support.

The overall pattern with regards to these results appears more clearly in a chart. In Figure 7, we see that the probability of a participant identifying the optimal solution generally increase as a function of time, and that the relationship is strongest for the 6 and 12 role tasks (as we would expect from the analysis reported is Table 3). This can be compared with the results with regards to the heuristic solution. We see that the probability of a participant proposing the heuristic solution generally decreases as a function of time. Here, too, we see that the tendency is strongest for the 6 and 12 role tasks.

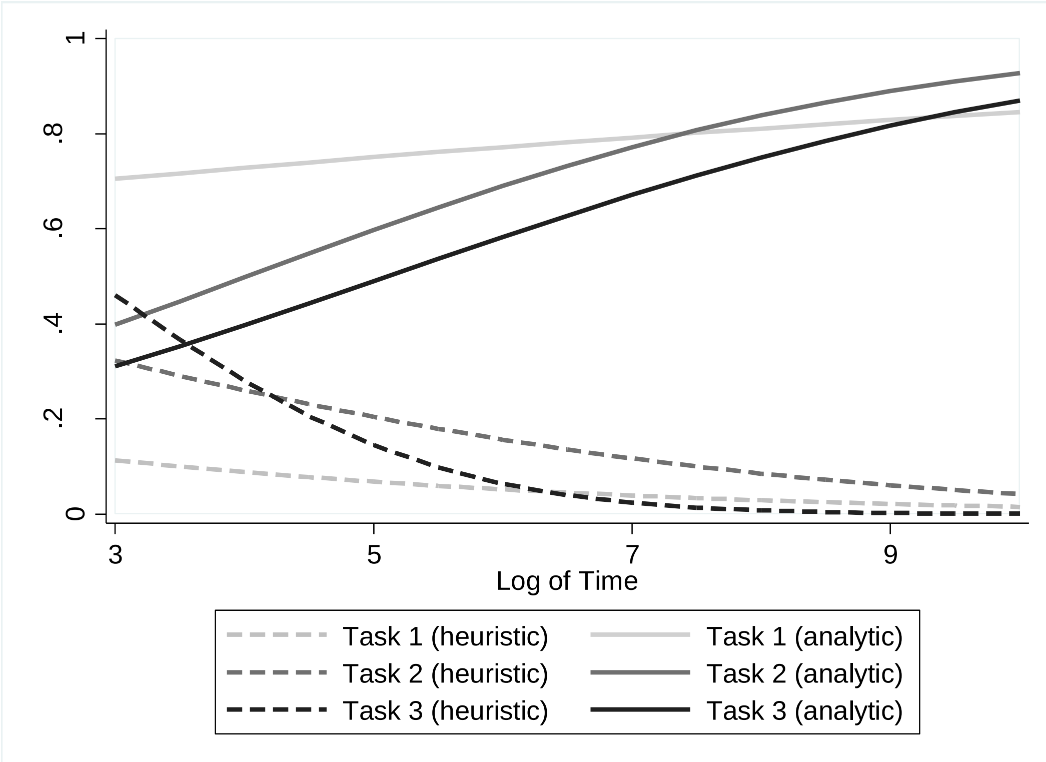

Figure 7. Log of time impact on the probability of identifying the analytic (i.e., optimal) versus heuristic solution across tasks (probabilities are calculated from models 3 and 6 in Table 4)

DISCUSSION

In this study, we explored how people make organization design decisions. The study consisted of three tasks. Each task consisted of a number of interdependent roles that participants were asked to sort into groups (teams). We examined two main variables: Task complexity (6, 9 and 12 roles) and time utilization per task. We considered the effects of these variables on task performance. As for task performance, we studied the ability to identify the optimal solution (i.e., roles are grouped according to interdependencies) versus the tendency to propose a heuristic solution (i.e., roles are grouped according to titles).

We first considered performance in relation to task complexity while controlling for time. We found that the proportion of participants who identified the optimal solution decreased from 6 to 9 roles and from 9 to 12 roles. The implication is that the higher the complexity, the more organization design decisions involving grouping of roles (or sub-units) will depart from an algorithmically correct solution.

Secondly, we predicted that while participants will have increasing difficulty in identifying the optimal solution as task complexity increases, they will have a gradually increasing tendency to propose a heuristic grouping instead. This hypothesis was partially confirmed. We found the expected trend from the 6 role task to the 9 role task, but not between the 9 role task and the 12 role task. In other words, for the 12-role task, the decrease in performance may at least partly be due to an increase in more “random” responses, rather than solutions based on using heuristics as defined here. However, because the three tasks vary on more than one parameter, it is difficult to identify the precise cause of this result (see further discussion below).

Finally, we predicted that the likelihood of identifying the optimal solution would increase with the use of time, and vice versa, that the tendency to propose a heuristic solution would decrease with the use of time. From the charts we can see that this is indeed the overall tendency, however, the relationship is not significant for all tasks.

Contribution. This study makes several contributions to the literature. Most importantly, we introduce a new approach to study how people make organization design decisions. The key feature is to conceptualize organization design decisions as involving the *grouping of interdependent roles*. Our fieldwork suggests that this captures the essence of how such decisions are actually made in organizations. We also believe that it is in accordance with how the classic texts presents the problem (March & Simon, 1958; Thompson, 1967). To study grouping decisions, we introduce a card sorting approach where each card represents a role (but each card may also represent a sub-unit in an organization). Secondly, we show how participant solutions may be compared with an algorithmically derived, optimal solution. Third, we introduce the concept of “distance scores” to compare participants’ solutions and measure the difference from the optimal solution. In sum, these features make it possible to study – and quantify – how people make organization design decisions and identify factors that influence effective decisions.

Limitations. As the first study of its kind, our study is subject to several limitations. We believe the most important limitation is that we effectively varied task complexity along three dimensions simultaneously (cf. Table 1): The number of roles, the number of interdependencies, and the decomposability (i.e., the number of interdependencies remaining after grouping/clustering). Our motivation was partly to identify where the "point of difficulty" emerges in these types of decision processes. Our fieldwork led us to believe that it happens somewhere between 6 and 12 roles with approximately 10-30 interdependencies. We might have underestimated somewhat the capacity that people have to solve these kinds of problems, at least when working individually as in this case. Our prior fieldwork was based on observations of teams given similar tasks, and there is some evidence that individuals may use a more analytical approach than groups (Raveendran et al., 2016). The trends in the data are as predicted but are not always significant. Particularly surprising are the results for the 12 role task. The data show that the proportion of analytical solutions decrease (as predicted) but not that the proportion of heuristic solutions increases; instead the solutions include a larger proportion of seemingly random configuration of elements. We re-examined the task but were unable to find any characteristics that would make the heuristic solution (i.e., a grouping based on titles) less plausible in this case than for the other tasks. It may be that fatigue plays a role (but also note that we varied the sequence and that the 12 role task was presented first for one third of the participants.)

Suggestions for further research. Given these considerations, we would suggest that future research employs tasks with a higher number of roles, more interdependencies, or with lower decomposability. Another implication is that one should try to vary one parameter at a time to identify the underlying mechanism. For example, one could repeat our study but keep the number of roles constant, while varying the interdependencies or the decomposability (e.g., 0, 3, and 6 remaining interdependencies). To disentangle the effects of the context and instructions, one could compare one group where participants are given the same information as in our study, with another group where participants are only provided with information about the role interdependencies and asked to organize the roles to minimize coordination costs. One could also study ways of improving participants' performance by means of decision aids. Cognitive load theory also suggests that working memory can be extended when one faces a complex task. One way to "offload" working memory is to use diagrams (Jaeger, Shipley, & Reynolds, 2017; Pastore, 2010). Consistent with the research in other areas (e.g., Pantziara, Gagatsis, & Elia, 2009), we would expect that the use of diagrams would improve performance[8].

Conclusion

Many organization design decisions require the grouping of elements, such as roles or sub-units. For example, roles are grouped into teams or departments, and departments are grouped into business units or divisions. To minimize coordination costs, one needs to group these elements in a manner that reflects the work process interdependencies. Although it is a ubiquitous task, it is poorly explored in the literature. Our findings show that grouping decisions become less analytical with increasing complexity. There was partial support for the hypotheses relating to the increase of heuristic solutions as a function of complexity and for decreasing performance as a result of time use. Our study represents a new approach for studying organization design decisions. We have shown that one can use a card sorting approach to study these kinds of decisions processes. With some refinements, we believe that it will enable further studies of the microfoundations of organizations design.

[8] As an exploratory part of the study, we did include on item at the end where the participants were asked whether they had drawn a diagram or not. However, only about 15% reported that the drew a diagram. The results were inconsistent and thus not included in this article. Having only one such item after the last of the three task also made it difficult to untangle the effect on each individual task.

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