Using net benefit analysis to value costs and benefits of re-grouping in organization design

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Abstract:

DSM clustering methods and software tools for organization design utilize data about task interdependencies to optimize a solution based on a single grouping criterion: Minimization of coordination costs. At the same time, there may be unwanted side-effects of optimizing based on this criterion alone, such as an increased difficulty of functional learning (e.g., supervision and knowledge exchange among functional specialists). The challenge is that it has so far been difficult to quantify and analyze such additional criteria, which may be qualitative. In this paper, we consider whether the "net benefit" method from medicine can be utilized to bring together qualitative and quantitative criteria on the same scale and compare both the costs and benefits of alternative organizational structures.

Keywords: DSM; organization design; interdependencies; clustering; criteria

1 Introduction

A key principle in organization design is to group organizational entities, such as roles, into semi-autonomous units (teams or departments) based on the task interdependencies between the roles. This design principle often leads to the establishment of cross-functional teams and is intended to minimize coordination costs (Thompson, 1967), enhance speed and flexibility (Baldwin & Clark, 2000; Sanchez, 1995), and promote unit accountability (Kilmann, 1983).

At the same time, there are potential downsides to this grouping principle, most notably, a decrease in *functionally-related* learning and knowledge sharing. The reason is that workers with the same functional specialization (e.g., IT; operations; finance; etc.) will be spread across the different cross-functional teams. Unfortunately, current DSM clustering methods (Yu et al., 2003)—which are also implemented in software tools (e.g, Worren et al., 2018)—only consider task interdependencies and do not allow the simultaneous evaluation of multiple criteria (such as task versus knowledge interdependencies).

One of the challenges is that alternative grouping criteria (or more generally, "harms" from grouping by task interdependencies) may be difficult to quantify. Nonetheless, they may be identified and assessed, but one will then need to convert the assessments to a common scale to allow a systematic analysis of the costs and benefits of a given clustering solution. Similar challenges have been addressed in other fields, including medicine, by employing a decision-making methodology known as 'net benefit'. This methodology is also applicable in our context, as it can be used to quantify and compare two or more decision criteria specifically associated with clustering or grouping. The purpose of this paper is to demonstrate how this methodology can be integrated with the DSM when considering alternative organization design solutions.

2 Theory

2.1 Task versus knowledge interdependencies

Within the field of organization design, it is widely accepted that there are typically trade-offs between different criteria and that alternative solutions are associated with both costs and benefits (e.g., Galbraith, 1974). But scholars have also observed that there is a tendency to simplify decision-making by focusing on one dominant criterion (e.g., Simon, 1946). One reason may be that some criteria are easier to quantify than others. Thanks to software tools (e.g. Worren et al., 2018) it is now straightforward to collect data about task interdependencies by utilizing survey questionnaires that are distributed to employees in an organization. But so far, there is no systematic method for assessing and comparing alternative grouping criteria.

Although task interdependency is a well-established criterion for grouping roles (Thompson, 1967), it is not the only possible criterion. It can be contrasted with the traditional way of organizing employees, namely, the functional organization, which groups functional specialists together in the same units (e.g., sales; marketing; operations; development). In principle, such an organization groups employees based on (the assumed) knowledge interdependencies (Raveendran et al., 2020) rather than task interdependencies. Although the benefit of grouping roles by task interdependency (in terms of reduced coordination costs) is clear, provided that one has collected and analyzed the appropriate data, the potential cost or harm from a functional perspective is not quantified or analyzed. Grouping by task interdependency often leads to the establishment of cross-functional teams. As pointed out by (Larson et al., 2022, p. 10) cross-functional collaboration "imposes a burden on team members to maintain communication exchange between functional subgroups." Moreover, regarding the embeddedness of product architecture knowledge in communication patterns, Sosa et al. (2004) highlight the consequences of misalignment between product architecture and organizational structure during complex product development. Their research shows how factors such as organizational and system boundaries, the robustness of design interfaces, the presence of indirect interactions, and the degree of system modularity can influence the alignment of design interfaces and team collaborations.

2.2 Net benefit analysis in clinical research

Net benefit analysis is frequently used in the medical sciences. In medicine, diagnostic tools are typically evaluated by their sensitivity and specificity. Sensitivity is a measure of how well a diagnostic test can correctly identify individuals who have a particular condition or disease. It tells us the percentage of true positive results the test can detect. Specificity is a measure of how well a diagnostic test can correctly identify individuals who do not have a particular condition or disease. It tells us the percentage of true negative results the test can provide. However, sensitivity and specificity alone do not provide information on the overall clinical impact for the patient (Vickers et al., 2016). According to Kazdin (1999), clinical impact or significance refers to *"the practical or applied value or importance of the effect of an intervention–that is, whether the intervention makes a real (e.g., genuine, palpable, practical, noticeable) difference in everyday life to the clients or to others with whom the clients interact".*

For instance, when diagnosing a patient for possible prostate cancer, various tests, models or markers can be used to inform decisions on how to proceed. However, while the tests may vary in sensitivity or specificity, they may also vary in terms of harm to the patient. If the test is not 100 % specific, a decision to treat a diagnosed cancer patient based purely on statistical measures could entail unnecessary harmful interventions for instance for individuals who do not have the underlying condition (false positives), or when the quality of life for patients with the condition (true positives) is reduced by curative treatment to such an extent that they might be better of not having the treatment. Therefore, to assess the value of a test or intervention in clinical practice, decision analysis considers the clinical consequences, such as the benefits of early disease detection or the harms of unnecessary testing or curative treatment. As such it takes into account the outcomes or results of the decisions made based on the utilization of models or tests.

In essence, one should quantify the clinical net benefit of utilizing a diagnostic test compared to default strategies of treating all or no patients. The net benefit is determined over a range of threshold probabilities, which are defined as the lowest probability of disease at which additional intervention would be considered justifiable. The net benefit can be calculated according to the following formula (Vickers et al., 2019):

$$\textit{net benefit} = \textit{sensitivity} \times \textit{prevalence} - (1 - \textit{specificity}) \times (1 - \textit{prevalence}) \times w \tag{1}$$

where sensitivity represents the true positive rate or the ability of the prediction model or diagnostic test to correctly identify individuals with the disease, prevalence refers to the proportion of the population that has the disease, specificity represents the true negative rate or the ability of the prediction model or diagnostic test to correctly identify individuals without the disease, w denotes the odds at the threshold probability, which indicates the estimated benefit or weight assigned to the decision of intervening or treating patients at that specific threshold probability.

Equation (1) can be reformulated as follows (Vickers et al., 2016):

$$Net\ benefit = \frac{True\ positives}{N} - \frac{False\ positives}{N} \times \frac{p_t}{1 - p_t} \tag{2}$$

Where the ratio of $\frac{p_t}{1-p_t}$ is utilized as an exchange rate to indicate the relative benefits and harms of various clinical outcomes resulting from a decision.

2.3 Existing methods using DSM to inform organization design decisions

In the field of organizational design, several methods address task interdependencies. These include methods based on graph theory, network science, mathematical optimization, and simulation techniques, which primarily focus on minimizing coordination costs based on analysis of task interdependence (Galbraith, 1974).

The Design Structure Matrix (DSM) is a tool for visualizing and analyzing dependencies/interactions between components in complex systems, projects, and organizations (Eppinger & Browning, 2012). In organizational (also called team-based) DSMs, these interactions are usually based on the frequency of communication or the number of deliverables exchanged between them. Then, a clustering technique is used to place the various organizational elements into different groups (or clusters). Initially, each element is randomly assigned to a group, and then a coordination cost metric is calculated based on the location of each element in a specific group. The objective is to keep altering the elements' group membership until the coordination cost is minimized. This is the essence of the DSM clustering problem and algorithm.

The assumption is that the proper placement of elements into groups will increase communication inside teams, and minimize inter-cluster communications, which in turn reduces the chance of communication errors (or cost).

Clustering algorithms (used to cluster DSMs) can be classified into two main categories: hierarchical and partitional (Khoriaty et al., 2018). Hierarchical techniques generate a set of nested clusters, which can be either agglomerative or divisive (Jain & Dubes, 1988). Agglomerative methods begin with singleton clusters. There are as many clusters as there are nodes or elements in the network and each cluster is made up of one element only. Then, step-by-step, two clusters are joined together to form one cluster as the clusters' sizes begin to grow. The clusters are joined based on a distance, similarity, or proximity measure. Eventually, one cluster containing all the elements remains. Alternatively, divisive techniques use the opposite approach. One cluster made up of all the elements is sequentially divided into smaller-sized clusters until singleton clusters remain. A drawback of hierarchical methods is that once an element joins a cluster (agglomerative) or leaves a cluster (divisive) it cannot be undone.

The partitional technique divides the elements into clusters or “partitions” where the configuration of elements is optimal as per an evaluating/clustering criterion, like coordination cost or Minimum Description Length (ibid.). All combinations of possible clusters may be evaluated, based on the clustering criterion, to select the optimal arrangement; however, this is impractical. Normally, elements are moved across clusters only if the value of the criterion shows an improvement (this is referred to as hill climbing). Thus, a smaller number of partitions is examined. One drawback is that the optimal solution could turn out to be at a local minimum.

All these techniques provide a unidirectional assessment of the impact of placing an element in a cluster or moving an element between different clusters. This means an improvement in the clustering criterion must occur. This constitutes a benefit factor for moving elements around the different organizational clusters. However, none of these techniques strike a balance between the benefits and costs of moving elements around the different organizational clusters. While these methods are effective, they often overlook other critical factors like learning and knowledge interdependencies. The net benefit method, on the other hand, goes beyond cost minimization to address inherent potential of regrouping. By capturing subjective preferences of involved parties, it provides a more holistic approach that simultaneously considers multiple criteria, including learning harm and coordination benefits. This approach is particularly beneficial in complex organizational settings where learning and knowledge transfer are just as important as cost efficiency. Thus, in this paper, we will introduce a cost-benefit analysis approach to address the organizational DSM clustering problem.

Few authors in the DSM literature have noted principles and methods for making exceptions to the main clustering principle (A. A. Yassine & Khoury, 2021). The concept of a ‘bus’ module is one such example. A bus is an element that interacts with most other elements and serves as a system-level integrating component. For example, in an engineering project, the integration team (Browning, 2009; Cusumano & Nobeoka, 1998) communicates with almost all other teams. Decisions about consolidation are not necessarily based on existing task interdependencies but on the potential value from consolidation. For example, even if there are no existing task interdependencies, teams that provide IT support may still benefit from being grouped together for increased utilization, standardization, or learning (A. Yassine et al., 2021).

Another related concept is ‘field separation’, which defines boundaries or constraints that have consequences for how elements are grouped in a physical product to avoid interferences between components or external forces (Otto et al., 2020). Field separation has only been applied to physical products so far, but a similar concept, functional conflict (Worren & Pope, 2022), has been proposed for making organization design decisions. Functional conflict exists when the function or goal of a role conflicts with that of another role in the same unit. While both field separation and functional conflict imply that some elements should be separated from each other, consolidation is mainly driven by the perceived positive benefits of grouping.

2.4 Net benefit analysis applied to re-grouping in organization design

Applying the net benefit approach to re-grouping in organization design involves quantifying and comparing the benefits and harms associated with different design alternatives for an organization, and using an exchange rate to put them on the same scale.

As in clinical research, organization design decision-making involves the assessment of trade-offs, i.e. the trade-off between the benefit of doing something (in this case re-grouping, which supposedly reduces coordination cost) and harm from re-grouping (resulting from any side effect to doing this re-grouping such as reduced learning potential within subject matter experts groups). For example; implementing agile methodologies which advocate the use of cross-functional "product" teams could sometimes lead to increased efficiency and autonomy within the team, but at the expense of efficient resource utilization or conflicts due to overlapping authority/mandate with other units (Worren & Pope, 2022). Or, when establishing a shared service unit to better meet variability in the demand for services can result in unwanted side effects of reduced service quality (Elston & MacCarthaigh, 2016).

In the context of organization design and applying a net benefit approach, "true positive" and "false positive" are not typically used in the same way as in medical or statistical contexts. However, we can draw some parallels to these terms: a "true positive" could refer to taking some action by implementing a design alternative that is identified as beneficial (positive), and indeed results in positive outcomes or benefits when implemented in the organization. In other words, it would represent a design alternative that is accurately identified as beneficial through the net benefits analysis and proves to be effective in achieving the desired outcomes. A "false positive" could refer to implementing a design alternative that is identified as beneficial (positive) based on the net benefits, but does not result in positive outcomes or benefits when implemented in the organization.

Assuming we have a DSM measuring instrument that gives us an estimated benefit of reduction in coordination cost in % compared to the current clustering as a baseline. Based on the decision-maker's preferences the harm from clustering might be valued differently than the benefits. Therefore, we need to develop an exchange rate between these two different measurement units to be able to weigh this trade-off properly. However, one important challenge of applying a net benefit approach to organization design is that we do not know the sensitivity ("rate of false positives") of the screening instrument used. This means that we cannot use equation (2) to calculate the net benefit. In the lack of this information, we propose two alternative approaches which address this challenge.

3 Proposed Approach

In this section, we present an approach to determine an exchange rate between two criteria to put them on the same scale to calculate net benefits. As a simplification, we demonstrate an approach involving only a single decision-maker and one additional criterion. However, the approach can easily be extended to incorporate multiple decision-makers and multiple criteria. Furthermore, while several preference elicitation techniques exist, we focus on demonstrating a binary choice similar to conjoint analysis (Rao, 2014). The approach is then demonstrated using an illustrative example.

3.1 A post-clustering analysis approach using conjoint analysis

Assuming we have an organization with a current organizational structure represented as A_0. A DSM clustering analysis tool (M), using a single criterion C_1 of reduction in coordination cost, has identified an alternative structure A_1 with an estimated reduction in coordination cost, dC_2 measured in percent reduction compared to A_0. Now consider that the decision-maker (DM) wants to take into consideration another criterion (C_2) when deciding whether or not to implement A_1. C_2 could, for instance, be harms or benefits related to functional learning measured in some understandable scale such as a percent reduction in time spent mentoring junior resources within a functional area or task. Assume the DM estimates the harm to functional learning (dC_2) as a consequence of implementing A_0 to be reduced by some percent per year. To compare the benefits of reduction in coordination cost with the harm of reduction in learning we need to determine an exchange rate to put the two criteria C_1 and C_2 on a common scale. A key point here is that this exchange rate represents the DMs' preferences regarding the trade-off between the benefits and harms, i.e. 5 % of coordination benefit is not necessarily valued equally as 5 % of learning benefit by the DM in the particular situation.

Determining the exchange rate

In this context learning time refers to the period it takes for an employee or groups of employees to acquire new skills, knowledge, or behaviors necessary for their roles or for the overall performance of the organization. This could include learning new software, understanding company protocols, mastering a new production process, or adapting to a change in the organizational structure or culture. The learning time can depend on the specialization regime (Raveendran et al., 2022, p. 7). In regimes with high specialization, employees excel in a smaller range of tasks. On the other hand, in low specialization regimes, employees have more evenly distributed skills across all tasks, but at a lower proficiency level, reflecting the trade-off between specialists and generalists. For instance, broader roles could require learning a wide range of skills, potentially increasing learning time. On the other hand, highly specialized, hierarchical organizations may have narrower roles, potentially reducing the breadth of skills an individual needs to learn, but may increase the learning time if interdepartmental collaboration and knowledge transfer is needed.

The reduction in learning time, as used in this paper, refers to the decrease in the time it takes for an employee to become proficient in a task as a result of changes in the organization design. It hinges on the principle that close interaction and collaboration among team members can foster knowledge transfer and, consequently, expedite the learning process. It is an important consideration in our net benefit analysis as faster learning times can lead to increased productivity and efficiency in the organization, while a reduction in learning time can have similar but detrimental effects.

To determine the exchange rate one could ask direct questions such as "How many units of harm (i.e. here "reduction in learning time") are you willing to accept for N units of benefits (i.e. here "reduced coordination cost")? By directly asking the DM this question for varying N, one gets pairwise combinations of dC_1 and dC_2 and one can easily calculate a regression equation like Y = a + bX, where Y =dC_1 and X =dC_2. The exchange rate between the two criteria is then b. However, answering such direct questions poses several challenges well established in the choice literature (Thurstone, 1927). Therefore we recommend applying an indirect technique to map DM's preferences founded in random utility theory, i.e. a preference elicitation technique referred to as conjoint analysis (Rao, 2014). In conjoint analysis, respondents are typically presented with a set of attributes and asked to choose from the set of attribute levels based on a particular criterion, such as preference or importance. In this scenario, a choice option pertains to one of the attribute levels for the criteria C_1 and C_2 that are presented as shown in Table 1.

Attribute	Attribute levels
Coordination benefit	5%, 10%, 15%, 20%
Learning harm	5%, 10%, 15%, 20%

Table 1. Example attributes with levels and units

This would result in a total of $2^4 = 16$ possible combinations of the two attributes. The DM is asked to pairwise compare several such combinations of attributes and levels, as illustrated in Figure 1.

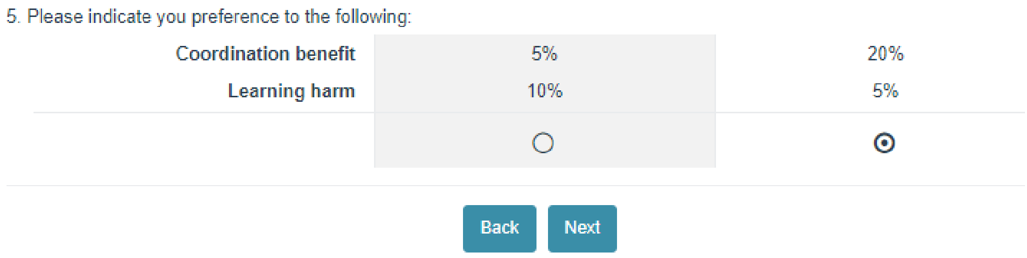

Figure 1. Hypothetical choice set for a binary choice of a combination of attributes and levels

By giving the DM various (realistic) combinations of dC_1 and dC_2 it is possible to capture the DMs preferences by counting the number of times an attribute level is preferred. Based on these counts, one can calculate the part-worth utility for each attribute level.

To calculate the exchange rate using the part-worth utility for a single respondent (here the DM), we can calculate the part-worth utilities for each level of each attribute using a statistical method such as Maximum Likelihood Estimation. Using the differences in part-worth utilities between the levels, we can then calculate the exchange rate between the two attributes for the DM based on their preference for one attribute over the other. The exchange rate provides a measure of the trade-off we are looking for between the two criteria in terms of their relative importance to the DM.

3.1.1 Example – functional learning vs. optimizing for process flow

We now apply the proposed approach to an illustrative example. In a (medium-sized) organization a CIO has identified a coordination problem between existing functionally structured departments. The CIO is considering adopting agile methodologies to increase productivity. Currently, the organization has a traditional functional hierarchical structure. The CIO has access to a new tool/prediction model that uses DSMs to identify viable clustering alternatives based on collected data about task interdependence using a single clustering criterion of reduction in coordination cost. The output of the tool indicates a percent reduction in coordination cost of 10 %. The proposed design solution(A_1) is illustrated in Figure 2. The CIO is however worried about how this will affect learning between the currently co-located functional specialists. Therefore we use "learning harm" as the additional criterion C_2 in this case. The colors represent different functional specializations such as "tester", "full-stack software developer" or "User experience designer".

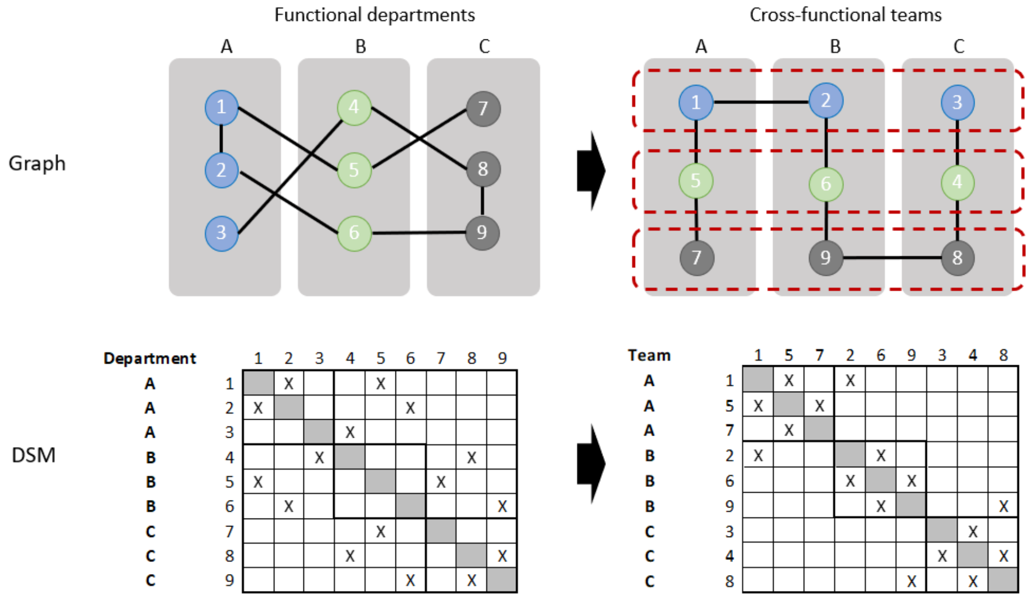

Figure 2 Example of nine roles organized in three departments, represented both as graphs (top) or DSMs (bottom), before (A_0) and after clustering (A_1) based on task interdependencies. For simplicity, there are only reciprocal (two-way) interdependencies in this example

For ease of understanding, we use the attributes and levels presented earlier in Table 1. The DM is asked to answer sets of questions in the format shown in Figure 1 resulting in the following count of the number of times each attribute was selected as shown in Table 2:

Table 2. Conjoint analysis with coordination benefit counts and learning harm counts

Attribute Level	Coordination Benefit Count	Learning Harm Count	Net Score
5%	1	3	-2
10%	2	1	1
15%	4	3	1
20%	3	3	0

The net preference scores indicate the relative preference of each attribute level. Positive scores indicate a preference for Coordination Benefit, negative scores indicate a preference for Learning Harm, and a score of 0 indicates no preference.

To calculate the part-worth utilities, we can assign a reference level for each attribute and calculate the differences in the net scores between each attribute level and its reference level. Here's an example assuming the reference level for both attributes is the 5% level:

Table 3. Calculated part-worth utilities

Attribute Level	Coordination Benefit Net Score	Learning Harm Net Score	Part-worth Utility (CB)	Part-worth Utility (LH)
5% (Reference)	0	0	0	0
10%	1	-2	1	-2
15%	1	0	1	0
20%	0	0	0	0

To establish the exchange rate, we can compare the differences in part-worth utilities. In this case, we observe the following:

- The difference between the part-worth utility of "Coordination Benefit" (CB) between the 10% level and the 15% level is 0.
- The difference between the part-worth utility of "Coordination Benefit" (CB) between the 10% level and the 20% level is 1.
- The difference between the part-worth utility of "Learning Harm" (LH) between the 10% level and the 15% level is 2.

Based on these comparisons, we can establish a preliminary exchange rate between "Coordination Benefit" and "Learning Harm" for the DM: 1 unit of "Coordination Benefit" (CB) is approximately equivalent to 2 units of "Learning Harm" (LH). This exchange rate suggests that the DM is willing to trade off 2 units of "Learning Harm" for 1 unit of "Coordination Benefit" based on their indicated preferences. Concretely, a trade-off of 2 units of "Learning Harm" for 1 unit of "Coordination Benefit" means that the DM is willing to accept a scenario where learning is twice as negatively impacted, provided it results in a corresponding increase in coordination benefits. This might translate into real-world decisions such as placing employees in roles or projects where they have less familiarity (increased learning harm) in favor of improving overall team coordination.

3.2 Integrate additional criteria into the DSM-clustering analysis

An alternative approach is to add additional criteria to the DSM mapping and analysis algorithm. Assuming that we already have in place a questionnaire to capture task interdependence (I_t) to calculate the reduction in coordination cost, we simply propose to extend the questionnaire with additional questions to capture change in learning time due to knowledge interdependence. Whereas the template for questions related to I_t is of the format "I receive input from X in relation to task Y", the format of questions to capture knowledge interdependence (I_k) could be, for example, "I receive tips and hints from X related to our common area of specialization". We could then calculate a weighted average of the factors and apply this score as a clustering criterion.

To accomplish this we draw on the rating scale introduced by Pimmler and Eppinger (1994), given its advantages with regards to clear linking between the value in the rating scale and corresponding statements, support for positive (benefits) as well as negative (costs) interdependence and incorporation of general types of interdependencies. We further adapt the rating scale proposed by Helmer et al. (2010). In our case, instead of using the spatial, energy, signal, and material types of dependencies, we adopt the following definitions of interdependence:

- Task interdependence: Two tasks are interdependent if the value generated from performing each is different when the other task is performed versus when it is not. (cf. Puranam et al., 2012, p. 421)
- Knowledge interdependence: Two agents are knowledge interdependent if the value they could generate from combining their knowledge differs from the value they could obtain from applying their knowledge separately (Raveendran et al., 2020, p. 45).

Both definitions reflect the generative potential of these two forms of interdependence. When deciding on whether or not to re-group an element, the trade-off between the benefit from a reduction in coordination cost versus the harm from an increase in learning time must be considered. This gives a rating scheme as shown in Figure 3.

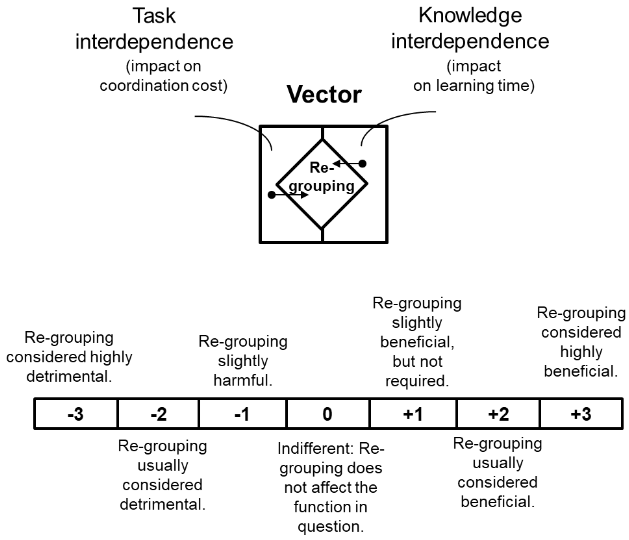

Figure 3. Rating scheme adapted from (Helmer et al., 2010; Pimmler & Eppinger, 1994) using task and knowledge interdependence

For each cell in the DSM, a 1 x 2 vector is populated with a score from the questionnaires for task and knowledge interdependence. Figure 5 shows an example of such questions to capture knowledge interdependence.

As proposed by Helmer et al. (2010), we apply a simple rule for perspective reduction that any higher-level absolute value within one cell will always supersede any quantity of lower-level values, as illustrated in Figure 4. Generally, all marks with higher absolute value prevail against other marks of the same algebraic sign as these act supportive. In the presence of only one type, no trade-off is required and this value is taken, as shown in the top. However, for situations illustrated at the bottom of Figure 4, trade-offs are required. For instance, as shown at the bottom left, the "learning time" is assigned a -3 indicating a highly detrimental effect on learning time if re-grouped.

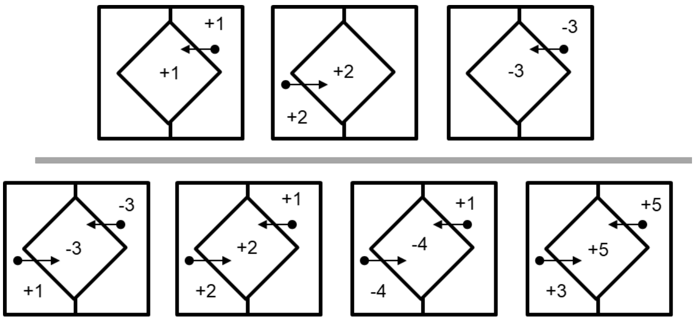

Figure 4. Perspective reduction function 1 (top) and 2 (bottom)

In addition, for conflicting non-trivial cases with adjacent scores manual adjustment can be done to assess the trade-offs, as these will benefit from additional contextual information. For instance, in an "increase productivity scenario" one might accept some degree of learning harm (usually). However, in an innovation scenario, where learning harm is detrimental to the aim, these trade-offs should generally be avoided.

Simply averaging the decision maker's (DM's) preferences between learning harm and coordination benefit can oversimplify their intricate relationship. The connection may not be linear, and averaging might assume equal importance for both factors, potentially misrepresenting the DM's priorities. Learning harm and coordination benefit may operate on different scales, and an average might not respect this distinction. Also, the DM may hold different risk preferences for each factor, which an average wouldn't capture. A trade-off analysis using perspective reduction offers a more precise reflection of the DM's preferences. We also assume 100% allocation to one unit, ignoring hybrid solutions.

The trade-offs illustrated in Figure 4 reflect the DM's preferences and can guide organizational design decisions. For instance, if the DM values "Coordination Benefit" over "Learning Harm", tasks could be allocated in a way that maximizes coordination, even at the expense of some learning opportunities. In a concrete organizational context, this could mean grouping together team members who work well together, thus improving coordination, even if it means that some team members may have a steeper learning curve for their assigned tasks. Understanding these trade-offs can help strike an better balance between learning and coordination, tailored to the specific preferences and circumstances of the organization.

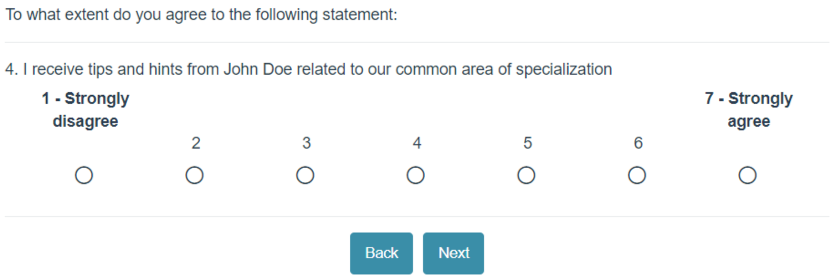

Figure 5. Example of a question to capture knowledge interdependence

To capture the relative importance of the types of interdependencies within the specific context of the DM, we need to establish an exchange rate between the different types of interdependence. Let the weighted average be expressed in equation (3) where w_t and w_k are the weights of task and knowledge interdependence:

$$\text{Weighted Average} = (w_t * I_t) + (w_k * I_k) = \sum_{i=t,k}(w_i + I_i) \qquad (3)$$

To estimate these weights (i.e. the exchange rate), we can use a similar approach as presented earlier, based on part-worth utility before running the clustering algorithm with preceding post-processing adjustments.

4 Summary and Conclusion

Team-based Design Structure Matrices (DSMs) are used as a tool for capturing the interdependencies within an organization and identifying highly interdependent elements such as roles, which can then be grouped into clusters such as teams or departments to reduce coordination costs. However, the value of improved grouping or clustering is subject to assumptions made by organizational studies theories and the clustering algorithms used for this task. Therefore, it is uncertain how much benefit can be derived from grouping, such as increased productivity. So, there is a need to investigate the actual benefit of organization restructuring using DSM clustering approaches. In this paper, we have introduced the “net benefit” method from medicine to bring qualitative and quantitative criteria on the same scale and compare both the costs and benefits of alternative organizational structures.

The proposal has several limitations. One significant limitation is our dependence on respondents possessing an adequate understanding of design criteria and the existing organization. Furthermore, it requires them to quantify the relative importance of coordination costs versus learning, expressed in percentage terms. While difficult, with adequate guidance and adequate preparation in advance it might be possible. Further, the pairwise comparison of attribute combinations adds complexity to the data gathering process. At the same time it allows for a more nuanced understanding of the trade-offs between different criteria. In practice, it requires the decision-maker (DM) to compare different combinations of attributes, but it does not necessarily imply that this must be done for all tasks related to the project. Instead, representative tasks or typical scenarios can be selected for this purpose, minimizing the data gathering burden while still capturing the essence of the decision-making context. The approach of estimating part-worth utilities from binary choice data using has limitations related to subjectivity, including limited sample size, lack of heterogeneity, limited generalizability, potential biases, and the influence of contextual factors. Finally, the approach can be challenging to validate, however, one way can be to test the model by presenting a group of experts with realistic vignettes/scenarios in an experimental setting, manipulating attribute levels in a controlled manner.

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