26th INTERNATIONAL DEPENDENCY AND STRUCTURE MODELING CONFERENCE, DSM 2024
STUTTGART, GERMANY, 24 – 26 September, 2024

Process Versus Knowledge Interdependencies: Balancing Alternative Grouping Criteria

Runar Solberg[1], Ali Yassine[2], Nicolay Worren[1,3], Tore Christiansen[3]

[1]Norwegian University of Life Sciences, [2]Stevens Institute of Technology, [3]Reconfig AS

Abstract: When creating team-based DSMs, researchers have traditionally focused on capturing interactions due to work process interdependencies. Grouping or clustering of DSM elements (roles or units) has then been performed to minimize coordination costs. However, recent research suggests that work process interdependencies are distinct from knowledge interdependencies, which may suggest an alternative grouping criterion, namely, to maximize functional learning. We explore this possibility by proposing a survey approach to map knowledge interdependencies in addition to work process interdependencies. We use a multicriteria method, known as the analytical hierarchy process (AHP), to weigh the two criteria, and propose a revised clustering method to find groupings that satisfy both criteria.

Keywords: Design Structure Matrix (DSM); organization design; knowledge interdependencies; clustering; criteria

1 Introduction

Organization design scholars have long recognized that there is more than one way to group roles and units within an organization (Galbraith, 1973; Gulick, 1937; March and Simon, 1958). This is also widely recognized in extant research on product development utilizing the DSM as a tool to analyze and group roles and units based on their interactions due to work process interdependencies. Several authors have pointed out that roles may not only be grouped according to function (e.g., skills or specialization), but also according to interaction due to work process interdependencies (McCord and Eppinger, 1993; Sosa et al., 2004; Yassine et al., 2013). Sosa and Mihm (2007) emphasize the importance of organizing roles by function when there is a need for specialization–i.e., functional learning. However, a tradeoff that has received limited attention is whether to group roles based on work processes or the employees' knowledge interdependencies. (Mintzberg, 1979; Solberg et al., 2023; Yassine et al., 2021). Grouping by work process would optimize coordination costs, by aligning the formal organization with the work process interdependencies, while grouping by knowledge would increase functional learning, by grouping those with similar knowledge in the same unit. These two alternative grouping criteria have opposing strengths and weaknesses: While grouping by work process interdependency optimizes coordination costs (Thompson, 1967), it may simultaneously decrease functional learning because it implies that roles that are functionally related (e.g., engineers; accountants; marketing specialists etc.) are potentially spread across multiple teams or units (Hansen and Podolny, 2020). Alternatively, by grouping according to knowledge, one establishes units that facilitate functional learning among functional specialists but may complicate collaboration and communication with roles that are grouped in other units, leading to an increase in coordination costs if the roles are interdependent. This tradeoff is important for modern organizations with unpredictable workstreams, where workers and managers co-design the organization as task structure doesn't always dictate all forms of interdependence (Raveendran et al., 2020).

Relatively sophisticated tools based on the Design Structure Matrix (Eppinger and Browning, 2012) exist to optimize the grouping based on the work process interdependencies (e.g., Worren et al., 2018). However, these tools assume that this is the appropriate design criterion, and do not aid the decision-maker in evaluating the relative feasibility of a work process versus a functional grouping, or identify a grouping that takes into consideration both types of interdependencies. To our knowledge, despite the extensive literature on this topic (e.g., Hansen and Podolny, 2020; Mintzberg, 1989; Raveendran et al., 2020), no author has so far proposed an analytical approach to balance different grouping criteria.

Several coordination mechanisms can be implemented to compensate for sub-optimal groupings (Browning, 2009; Mintzberg, 1979). This study focuses on the effect of grouping roles on coordination costs and functional learning, and more specifically improving the organization by suggesting an approach to balance the two grouping criteria. Our study addresses this challenge by proposing a novel methodology that combines DSM clustering methods with the analytical hierarchy process (AHP).

The rest of the paper is structured as follows: We begin with a theoretical overview of recent definitions of process and knowledge interdependencies, and theory on multi-domain optimization in DSMs and AHP. Next, we present a step-by-step framework to weigh the importance of two grouping criteria using a survey with Likert scale ratings, and compare it with an AHP approach using pairwise comparisons. We then map interdependencies with a survey, and show how to group roles based on individual criteria or both, using criteria weights. We illustrate the framework with a hypothetical example involving 9 roles in a manufacturing plant. Finally, we conclude by discussing limitations and future research directions.

2 Theory

2.1 Process versus knowledge interdependencies

We build on the following definitions which separate work process interdependencies from knowledge interdependencies:

- Two work processes (or tasks within the processes) are interdependent if the value generated from performing each is different when the other process is performed versus when it is not (cf. Puranam et al., 2012, p. 421).
- Two individuals 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).

To facilitate coordination and functional learning due to work process and knowledge interdependencies, roles and business units need to be able to interact or otherwise influence one another. The organization design will affect the interactions by either grouping the individuals in question in the same team or unit or separating them into different teams or units.

The traditional view of interdependencies (see e.g. March and Simon, 1958; Thompson, 1967) is often represented as the reciprocal or mutual need for information by the involved activities or roles. However, the above definitions differ somewhat from the traditional understanding of interdependencies, as their emphasis on value involves not only optimizing the organization design based on current interaction patterns but also *future potential*. As such, the definitions subsume the traditional meanings of interdependencies which optimizes grouping based on current interaction patterns and adds to it consideration of future potential benefits and costs (i.e., value). In essence, the definitions consider interdependencies as a source of current and possible synergy and can be approached as an investment–with potential performance returns. We emphasize that in this particular study, as a simplification, we narrow in on the immediate benefits and costs of regrouping, and do not consider future potential. However, we note that a few recent studies have combined a similar understanding of interdependencies with a DSM approach. In particular, Yassine and Naoum-Sawaya (2017) studied investment decisions in components vs. design rules and their relationship to integral-modular dynamics of a product system evolution of performance. Simply put, the organization design can impact the value of various flows such as information due to task interdependencies or the transfer of knowledge in the form of functional learning, and we seek an organization design that facilitates the flows in a manner that gives the greatest performance return towards the goals of the organization.

2.1.1 Mapping of interdependencies

Various methods can map process and knowledge interdependencies, each with strengths and weaknesses. These methods can be placed into three main categories (Eklund, 2024): survey-based, proxy-based, and archival-based. Survey-based methods, like those used by Worren et al. (2020), are highly tailored and rely on respondents' perceptions, requiring relatively little data collection effort. For instance, communication frequency can be captured using questionnaires (see e.g. McCord and Eppinger, 1993). Proxy-based methods, like deriving interdependencies from patent databases (Arora et al., 2014), deriving interdependencies by analyzing personality traits based on LinkedIn data (van de Ven et al., 2017), or capturing email or message exchanges can provide objective measures, but these are indirect and context-specific. Archival-based methods, like analyzing public reports or databases such as BoardEx (see e.g. Firk et al., 2022), can derive interfaces but often lack depth. This study focuses on a survey-based approach, adapting prior methods by Worren et al. (2020).

2.2 Multi-domain optimization in DSMs

Handling tradeoffs is nothing new in the DSM literature. For instance, product decomposition involves clustering components based on energy, material, and information flows (Huang and Kusiak, 1998; Pimmler and Eppinger, 1994). Optimization can span multiple domains such as product, process, and people (Yassine et al., 2013). However, clustering based on energy may impede effective information flow, and vice versa.

Research has pointed to a common simplification in decision-making of prioritizing a single main criterion (Simon, 1946). While optimizing the process or knowledge domains independently can be useful to the organization; however, the benefits are limited as such models are confined to a single domain and do not address the challenge of finding a grouping that optimizes for both criteria. Instead, Multi-DSM models simultaneously integrate and optimize two or more domains. For example, when considering the process domain, it cannot be isolated from the rest of the organization, which includes the people and the products. Yassine et al. (2013) showed how a simultaneous global optimization objective function could be used to optimize elements with interactions across three domains (process, people, and product). Heuristic and meta-heuristic techniques were used to solve the optimization problem and obtain the optimal arrangements for the product, people, and process DSMs.

General matrix mapping approaches were formalized by Yassine et al. (2003). Their work introduced the concept of a relationship map, which relates two domains to each other. In addition, the concept of a connectivity map, which combines two relationship maps into a single matrix, was also defined. Similarly, Danilovic and Browning (2007) introduced the domain mapping matrix (DMM), which is an approach to map two different analysis domains. More specifically, DMM is a rectangular (*m x n*) matrix that relates two DSMs of sizes *m* and *n*, respectively (DMM is very similar to the matrix mapping approach suggested by Yassine and Braha (2003). Finally, Maurer & Lindemann (2007) recommended arranging the domains in a square matrix, which they named the multi-domain matrix (MDM). The MDM arranges the domains and illustrates the relationships between them.

2.3 The Analytical Hierarchy Process and the DSM

Building on the concept of multi-domain optimization, process and knowledge interdependencies can be viewed as separate domains. Assuming we can map these interdependencies, decision-makers would typically vary in their preferences when weighing the alternatives of optimizing for functional learning versus reducing coordination cost.

Traditional survey-based methods rely on the use of Likert scales to capture decision-makers preferences. While useful, such methods also present some challenges related to ordinal vs. cardinal scales. In particular, if we seek to use the arithmetic mean to aggregate across goals and sub-goals and capture the preferred balance between optimizing based on functional learning vs. coordination costs. The AHP, a multicriteria decision-making (MCDM) method originally developed by Thomas Saaty (1988), offers several advantages over traditional Likert scale survey-based methods, including improved decision-making precision through detailed comparisons and consistency checks, prioritization and ranking via weighted priorities and a comprehensive view of decision factors, and greater flexibility in handling multi-criteria evaluations and adaptability to various decision-making contexts. While a bit more complex than traditional survey-based methods using Likert scales, these benefits result in more reliable, nuanced, and actionable insights for complex decision-making scenarios. It is by far the most popular and widely used MCDM (Zyoud and Fuchs-Hanusch, 2017), applied in a number of fields, ranging from conflict resolution in the Middle East (Saaty et al., 2015) to forecasting and strategy formulation in banking and finance (Sipahi and Timor, 2010; Tramarico et al., 2015). In AHP, the goals, sub-goals, and alternatives are structured in a problem hierarchy. Figure 9 illustrates a problem hierarchy with the overall goal of optimizing the grouping of roles regarding the two criteria, with possible sub-goals of the organization in question such as "Ensure that less experienced employees receive supervision".

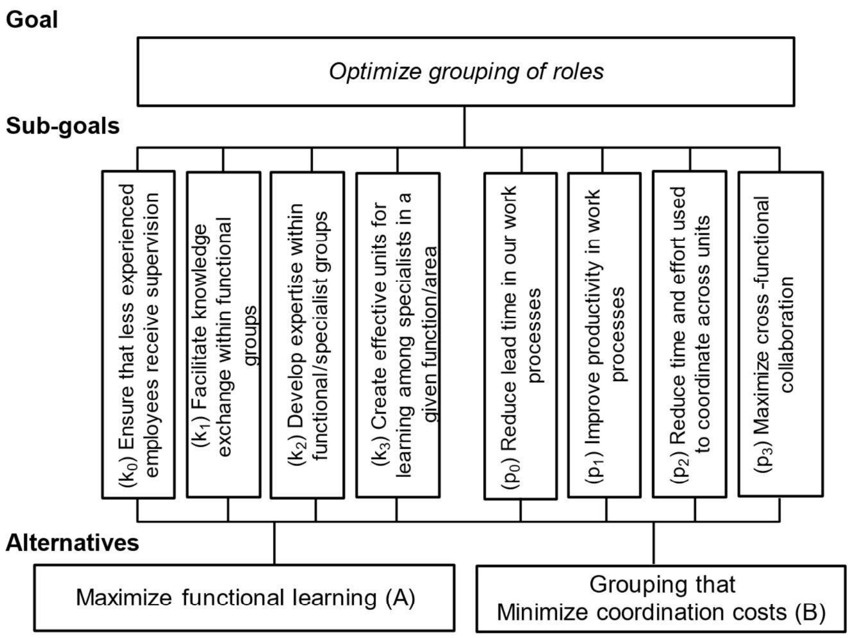


Figure 9. Example of an AHP problem hierarchy to prioritize sub-goals and alternatives

An important benefit of the AHP is its ability to aggregate preferences across multiple decision-makers and stakeholder groups with different concerns. An additional advantage of using AHP and pairwise comparison over traditional survey approaches is that the latter can incentivize the respondent to rate all sub-goals favorably. Pairwise comparison, on the other hand, forces the respondent to directly compare the sub-goals with each other towards a higher-level goal. In AHP, decisions are broken down into a series of pairwise comparisons which are compared and arranged in a $n\ x\ n$ square matrix **A**. Each element of this matrix represents the relative importance or preference of one element over another in achieving the goal or sub-goals, which is given using a fundamental exponential scale. AHP uses the principal eigenvector of this matrix to derive weights in the form of a priority vector from the pairwise comparison matrix A. Using diagonalization, a diagonal matrix can be found that is similar to the original matrix representing the pairwise comparisons. The diagonal matrix contains the eigenvalues, while the matrix used to diagonalize the original matrix contains the eigenvectors. AHP's emphasis on consistency leads to the eigenvalue formulation (Saaty and Vargas, 2012):

$$\boldsymbol{Aw} = n\boldsymbol{w} \tag{2.1}$$

Let $\boldsymbol{A}$ be an $n \times n$ pairwise comparison matrix where a_{ij} represents the importance of element i relative to element j. The goal is to find the vector w such that: $\boldsymbol{Aw}=\lambda_{\max}$ where $\lambda_{\max}$ is the principal (largest) eigenvalue of $\boldsymbol{A}$, and $\boldsymbol{w}$ is the principal eigenvector, normalized so that its components sum to 1. $\boldsymbol{w}$ represents the priority vector. If $\boldsymbol{A}$ can be diagonalized, it can be expressed as $\boldsymbol{A}=\boldsymbol{PDP}^{-1}$ where $\boldsymbol{P}$ is the matrix of eigenvectors, $\boldsymbol{D}$ is the diagonal matrix of eigenvalues, and $\boldsymbol{P}^{-1}$ is the inverse of P. Matrix $\boldsymbol{P}$ contains the eigenvectors as its columns. To find the priority vector $\boldsymbol{w}$, we calculate the normalized principal eigenvector associated with $\lambda_{\max}$.

3 Proposed Approach

We propose the following step-by-step approach, as shown in Figure 10:

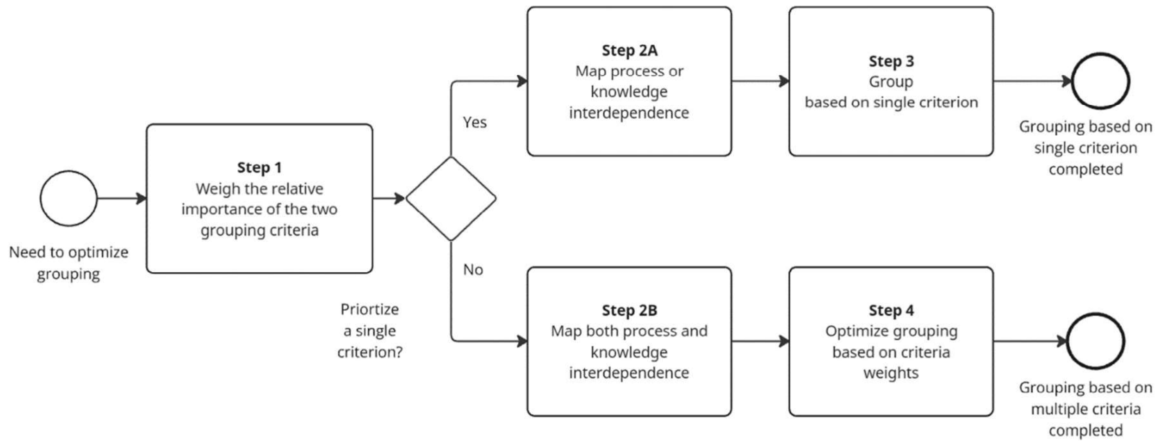


Figure 10. Proposed step-by-step approach

Assuming an identified need to consider grouping or regrouping, Step 1 involves weighing the relative importance of the two grouping criteria—minimization of coordination costs versus maximizing functional learning. The individuals performing Step 1 should represent key stakeholders, such as managers or employees, with relevant knowledge about the importance of the criteria. The output from this initial exercise informs Step 2A or 2B, where process and/or knowledge interdependencies within the organization will be mapped using a survey instrument. If the resulting weights from Step 1 show that one criterion is particularly dominant, the decision-makers can decide to map only one domain of interdependencies. However, there are situations where both interdependency type needs to be mapped. This decision is represented by the decision gateway in Figure 10 (the diamond). If the results from Step 1 indicate a strong preference for reducing coordination costs, it is sufficient to map work process interdependencies and vice versa. The same is true for Step 3, which involves the grouping of elements based on a single criterion. In most cases, however, we expect decision-makers to prefer improving their organization according to both criteria (Step 4), necessitating a solution that accounts for both process and knowledge interdependencies. This makes the clustering problem more challenging. We use a DSM with a weighted objective function to arrive at a "hybrid" role grouping that considers both criteria, tilting it in one or the other direction, depending on their relative importance as judged by the decision-makers in Step 1.

3.1 Example: Multi-criteria clustering of individuals in a manufacturing plant

To demonstrate our proposed approach, we consider a simple hypothetical scenario of nine individuals working in a manufacturing plant, shown in Figure 11, with their respective work process and knowledge-related interdependencies. Note that the information given in Figure 11 represents the actual implicit interdependencies, but for our purposes, they have not yet been explicitly mapped.

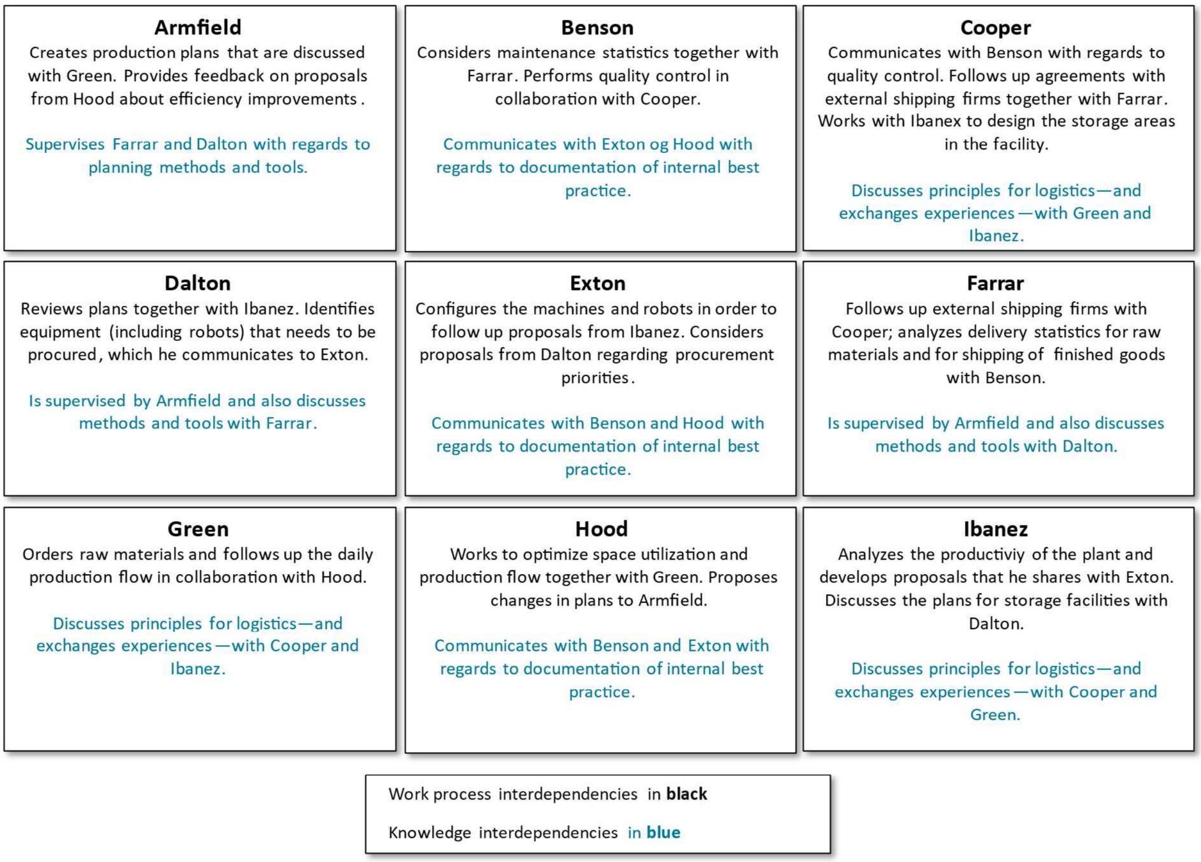


Figure 11. Work process (black) and knowledge interdependencies (blue). Knowledge interdependencies represent an extension of a similar figure in Cammelli and Worren (2024), in review

Step 1: Weigh the relative importance of the two grouping criteria

One alternative for weighing the relative importance of each criterion is to ask stakeholders, such as managers or employees to rate the criteria using a survey questionnaire using a Likert scale, as shown in Figure 12.

Items	Response scale	Work process	Learning/ Knowledge
Reduce lead time in our work processes	1 Unimportant ○ ○ ○ ○ ○ 5 Very important	X	
Ensure that less experienced employees receive supervision from specialists within their functional area (e.g., accounting/finance; marketing; manufacturing)	1 Unimportant ○ ○ ○ ○ ○ 5 Very important		X
Improve productivity in work processes	1 Unimportant ○ ○ ○ ○ ○ 5 Very important	X	
Facilitate knowledge exchange within functional groups (e.g., for accounting/finance; marketing; manufacturing)	1 Unimportant ○ ○ ○ ○ ○ 5 Very important		X
Reduce time and effort used to coordinate across units	1 Unimportant ○ ○ ○ ○ ○ 5 Very important	X	
Develop expertise within functional/specialist groups (e.g., within accounting/finance; marketing; manufacturing	1 Unimportant ○ ○ ○ ○ ○ 5 Very important		X
Maximize cross-functional collaboration	1 Unimportant ○ ○ ○ ○ ○ 5 Very important	X	
Create effective units for learning among specialists in a given function/area	1 Unimportant ○ ○ ○ ○ ○ 5 Very important		X

Figure 12. A potential initial survey among stakeholders about design criteria in Step 1

While relatively little effort is required from the respondent, such a Likert scale survey approach can lead to skewness of the data; all the items in Figure 4 can be deemed important, making it difficult to derive a clear priority. As an alternative, we now demonstrate how AHP can be used to weigh the criteria. Unlike Likert scale survey approaches, which can provide imprecise ordinal data, AHP offers a consistent framework to quantify and prioritize elements based on relative importance using pairwise comparison of items on a common attribute. We assume, as illustrated in the problem hierarchy in Figure 9, that decision-makers agree on the following overall goal:

Goal (G1): Optimize grouping of roles

The first step in our proposed framework involves comparative judgment using the fundamental scale described in AHP. By arranging the sub-goals (the second level in the hierarchy in Figure 1) into a matrix, the decision-makers or relevant stakeholders evaluate the relative importance of each element in relation to the goal (G1). The typical format of the question is: "Of the two sub-goals being compared, which do you consider to be more important, and how much more important is it with respect to the overall goal?" In our particular case, one may ask the following question:

Q1: *"To optimize the grouping for the nine individuals, how important is it to ensure that less experienced employees receive supervision compared to reducing lead time in the work processes*?"

This is repeated for all pairs of sub-goals, establishing a priority vector $\mathbf{v_1}$ using equation **Fehler! Verweisquelle konnte nicht gefunden werden.**) representing the relative weights of the sub-goals ($k_{0\text{-}3}$ and $p_{0\text{-}3}$) on the second level as shown in Figure 13:

Sub-goal		k_0	k_1	k_2	k_3	p_0	p_1	p_2	p_3	Priority vector
(k_0) Ensure that less experienced employees receive supervision	k_0	1	6	4	3	3	3	3	3	0.278
(k_1) Facilitate knowledge exchange within functional groups	k_1	1/6	1	3	3	3	3	3	3	0.164
(k_2) Develop expertise within functional/specialist groups	k_2	1/4	1/3	1	3	3	3	1/3	3	0.122
(k_3) Create effective units for learning among specialists in a given function/area	k_3	1/3	1/3	1/3	1	3	3	3	3	0.113
(p_0) Reduce lead time in our work processes	p_0	1/3	1/3	1/3	1/3	1	3	7	3	0.112
(p_1) Improve productivity in work processes	p_1	1/3	1/3	1/3	1/3	1/3	1	3	1/8	0.052
(p_2) Reduce time and effort used to coordinate across units	p_2	1/3	1/3	3.0	1/3	1/7	1/3	1	3	0.081
(p_3) Maximize cross-functional collaboration	p_3	1/3	1/3	1/3	1/3	1/3	8	1/3	1	0.078

Figure 13. Pairwise comparison matrix for sub-goals

We now need to compare the two alternatives at the bottom level of the AHP problem hierarchy shown in Figure 9; (A)– maximize functional learning and minimize coordination costs (B). This is done by pairwise comparison with respect to how much better one is than the other in satisfying each criterion on the second level. This gives eight 2x2 matrices to consider, as we have eight elements on level two, and two alternatives that need to be pairwise compared for each element.

Figure 14 shows the eight 2x2 matrices for the two criteria and their local priorities for each of the level 2 sub-goals.

Level 2 Sub-goals	(k_0) Ensure that less experienced employees receive supervision		(k1) Facilitate knowledge exchange within functional groups		(k2) Develop expertise within functional/specia list groups		(k3) Create effective units for learning among specialists in a given		(p0) Reduce lead time in our work processes		(p1) Improve productivity in work processes		(p2) Reduce time and effort used to coordinate across units		(p3) Maximize cross-functional collaboration	
Alternatives	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B
A - Max. learning	1	1/3	1	1/2	1	5	1	1/4	1	1/3	1	3	1	5	1	1/3
B - Min. coordination cost	3	1	2	1	1/5	1	4	1	3	1	1/3	1	1/5	1	3	1
Normalized priorities	0.750	0.250	0.667	0.333	0.167	0.833	0.800	0.200	0.750	0.250	0.250	0.750	0.167	0.833	0.750	0.250

Figure 14. Pairwise comparison matrices for level 2

We then synthesize the priorities using the distributive mode–we establish the final priority of the alternatives (A) and (B) by multiplying each column of vectors by the priority of the corresponding criterion and adding across each row, as shown in Figure 15.

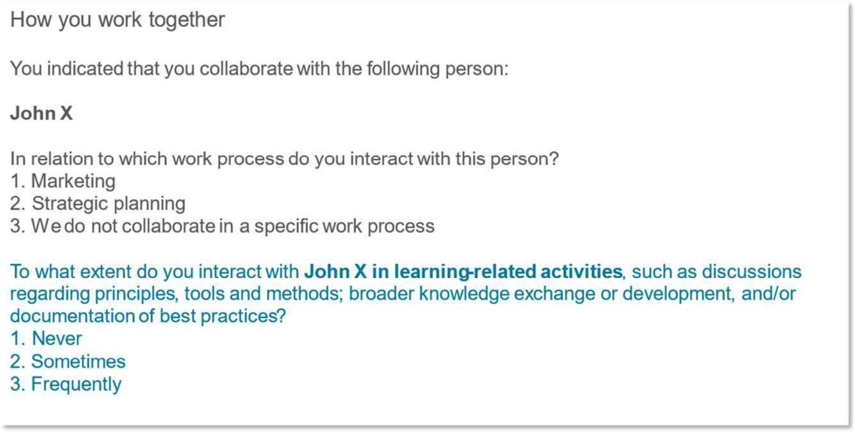
	k_0 0.2778	k_1 0.1645	k_2 0.1222	k_3 0.1129	p_0 0.1116	p_1 0.0523	p_2 0.0809	p_3 0.0779	Final weight
Distributive mode									
A	0.750	0.667	0.167	0.800	0.750	0.250	0.167	0.750 =	0.597
B	0.250	0.333	0.833	0.200	0.250	0.750	0.833	0.250	0.403

Figure 15. Synthesis

As shown to the right, we see that (A) maximize functional learning is preferred and has a relative weight of 0.597 compared to (B) minimize coordination costs. These weights are later used in our weighted objective function, which measures the deviation (D) of any suggested clustering arrangement compared to ideal clustering arrangements.

Step 2: Mapping of process and knowledge interdependencies

To map process and knowledge interdependencies, we suggest using a survey questionnaire, as shown in Figure 16. The questionnaire can be sent to each individual in the organization, who indicates who he/she works with, both in terms of more concrete deliverables in the work processes (i.e., work process interdependencies) and functional learning-related activities (i.e., knowledge interdependencies).


How you work together

You indicated that you collaborate with the following person:

John X

In relation to which work process do you interact with this person?
1. Marketing
2. Strategic planning
3. We do not collaborate in a specific work process

To what extent do you interact with **John X in learning-related activities**, such as discussions regarding principles, tools and methods; broader knowledge exchange or development, and/or documentation of best practices?
1. Never
2. Sometimes
3. Frequently

Figure 16. Example survey to capture knowledge interdependencies

The collected data can be used to map process and knowledge interdependencies into a binary DSM, which can be used for further grouping analysis.

Step 3: Grouping based on process or knowledge interdependencies

Figure 17 shows two DSMs representing a hypothetical set of 9 interdependent individuals. The blue and black "X" matches the interdependencies information provided in Figure 11. For instance, it is stated that *"Armfield creates production plans that are discussed with Green and provides feedback on proposals from Hood about efficiency improvements"*–this is represented as an "X" in position (1,2) and (1,3) in the DSM-matrix to the right in Figure 17 representing the ideal grouping to minimize coordination cost. Further, for knowledge interdependencies, it is stated that *"Armfield supervises Farrar and Dalton with regards to planning methods and tools,"* which is represented as a blue "O" in positions (7, 8) and (7,9) in the DSM-matrix to the left in Figure 17. In this extreme example, there is no overlap between the two dimensions, meaning that the individuals do not have work process-related and knowledge interdependencies toward the same person. The figure shows the appropriate grouping into teams if one were to group solely based on one criterion, respectively. For example, on the left in Figure 17, this would correspond to a situation where the weights would be 1.00 for maximizing functional learning and 0 for minimizing coordination costs.

Ideal grouping to maximize functional learning

Name		B	E	H	C	G	I	A	D	F
Benson	B		O	O						
Exton	E	O		O						
Hood	H	O	O							
Cooper	C					O	O			
Green	G				O		O			
Ibanez	I				O	O				
Armfield	A								O	O
Dalton	D							O		O
Farrar	F							O	O	

Ideal grouping to minimize coordination costs

Name		A	G	H	B	C	F	D	E	I
Armfield	A		X	X						
Green	G	X		X						
Hood	H	X	X							
Benson	B					X	X			
Cooper	C				X		X			
Farrar	F				X	X				
Dalton	D								X	X
Exton	E							X		X
Ibanez	I							X	X	

Figure 17. Ideal grouping based on a single criterion to solely maximize functional learning (left) or minimize coordination costs (right)

If the goal is to optimize only on a single criterion, Figure 17 represents the respective *ideal* groupings. However, in situations where one needs to balance the two criteria–i.e., the weights of the criteria do not indicate a strong preference for either–the problem of grouping the individuals becomes more challenging, as one should seek a solution that strikes a balance between the two ideals forms of grouping. In our example, the criteria weights from step 1 of maximizing functional learning are 0.597 vs. 0.403 for minimizing coordination costs, representing such a situation.

Step 4: Optimize grouping based on criteria weights

To address this challenge, our proposed approach uses the AHP method as demonstrated in step 1 in our framework to generate the weights for the different criteria (i.e., maximize functional learning vs. minimize coordination costs) and then utilizes these weights to build a weighted objective function that measures the deviation (D) of any suggested clustering arrangement as compared to the ideal groupings shown in Figure 17.

The weighted objective function is as follows:

$$D = w_k E_k + w_p E_p \tag{3.1}$$

where w_k and w_p are the corresponding weights for the knowledge and process criterion, respectively, and E_k and E_p are the deviations from the ideal clustering arrangement based solely on either the knowledge criterion or the process criterion, respectively.

The objective is to select the clustering arrangement that minimizes Equation (3.1). The ideal groupings serve as a reference point to which we can compare any other possible alternative grouping. For instance, in our example, one alternative could be that management has identified a set of possible grouping alternatives, and we want to compare them to find the best one according to the criteria. To illustrate, let's assume that we have an initial grouping as shown in Figure 10(a), and we want to compare it to an alternative grouping as shown in Figure 10(b). We note that in both alternatives the number of interactions and groups are kept constant, while the configuration of grouping membership differs.

(a) Initial grouping

Name		A	B	C	D	E	F	G	H	I
Armfield	A				O		O	X	X	
Benson	B			X		O	X		O	
Cooper	C		X				X	O		O
Dalton	D	O				X	O			X
Exton	E		O		X				X	X
Farrar	F	O	X	X	O					
Green	G	X		O					X	O
Hood	H	X	O			O		X		
Ibanez	I			O	X	X		O		

(b) Alternative grouping

Name		A	D	F	B	E	G	C	H	I
Armfield	A		O	O			X		X	
Dalton	D	O		O		X				X
Farrar	F	O	O		X			X		
Benson	B			X		O		X	O	
Exton	E		X		O				O	X
Green	G	X						O	X	O
Cooper	C			X	X		O			O
Hood	H	X			O	O	X			
Ibanez	I		X			X	O	O		

Figure 18. Clustering example (a) initial grouping, (b) alternative grouping

The deviations (E_k and Ep) are calculated as follows: Since the ideal knowledge clustering DSM has B, E, and H in the same cluster, we note their cluster membership in the suggested clustering arrangement. Since B is in a cluster that does not contain either E or H, then it is assigned an error term of 2. Furthermore, when inspecting the ideal process clustering DSM, B is in the same cluster with C and F. In the suggested arrangement, B is in a cluster that includes C (but not F), then it gets an error term of 1. This error assignment process results in $E_k = 14$, $E_p = 12$, and D = 13.19 (using $w_k = 0.597$ and $w_p = 0.403$).

Repeating the calculations for the alternative DSM arrangements shown in Figure 10(b) results in a D = 12.03, which is worse than the previous result. This means that the clustering arrangement in Figure 10(a) is better than that of Figure10 (b) for these weights. By doing a sensitivity analysis of the two grouping alternatives we can compare the two for different weights. By altering the value of $w_k \in [0,1]$ we get the following sensitivity plot as shown in Figure 19 showing a rank reversal for $w(k) > 0.5$–beyond this point the alternative grouping(b) is superior to the initial grouping(a), as D is lower.

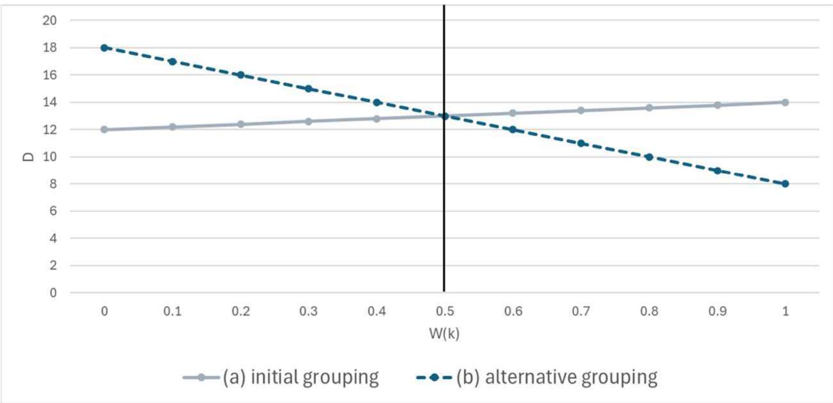


Figure 19. Sensitivity plot of (a) initial grouping and (b) alternative grouping

Assuming a constraint that an individual can only reside in a single cluster, pseudo code for an algorithm used for establishing E_k and E_p is as shown in Figure 21 (pseudocode):

```
For each candidate grouping arrangement G_{i,j} (e.g. as shown in Figure 20)
  For each cluster C_{i,j} within each grouping arrangement G_{i,j}
     For each individual I_{i,j} in C_{i,j}
              Identify the set of individuals N_k for which I_{i,j} is knowledge interdependent (red)
                      Identify the set of individuals N_p for which I_{i,j} is work process interdependent
(black)
  For each cluster IC_{i,j} within each ideal grouping arrangement IG_{i,j}
     For each individual I_{i,j} in IC_{i,j}
        Identify the set of individuals N_ik for which I_{i,j} is knowledge interdependent (red) in the ideal
        grouping cluster and the set of individuals N_ip for which I_{i,j} is work process interdependent (black)
        in the ideal grouping cluster (e.g. as shown in Figure 9)
  Calculate the deviation KD_{i,j} for knowledge interdependencies for individual I_{i,j}  as KD_{i,j} = |N_ik| − |N_k ∩ N_ik|
  Calculate the deviation PD_{i,j} for process interdependencies for individual I_{i,j}  as KD_{i,j} = |N_ip| − |N_p ∩ N_ip|
Calculate the deviation from the ideal clustering E_k by summing all KD_{i,j}
Calculate the deviation from the ideal clustering E_p by summing all PD_{i,j}
```

Figure 21. Pseudo code for calculating the deviation from the ideal

This approach can then be used as a basis for formulating and maximizing an objective function for the set of viable grouping permutations.

4 Summary and Conclusion

Traditionally authors who use team-based DSMs have mainly focused on capturing work process interdependencies between individuals to cluster or group elements to minimize coordination costs. Recent research suggests, however, that work process interdependencies are distinct from knowledge interdependencies (Raveendran et al., 2020; Solberg et al., 2023; Yassine et al., 2021), which may suggest an alternative grouping criterion. This study shows how a second criterion of maximizing functional learning can be incorporated into DSM clustering analysis. We have proposed a step-by-step analytical approach involving (1) weighing the relative importance of the two criteria using the analytical hierarchy process, (2) the mapping of process and knowledge interdependencies using a survey instrument, (3) grouping of roles based on each single criterion, representing an ideal reference point, and (4) an approach to optimize the grouping by minimizing an objective function which uses criteria weights to balance between the two.

The proposed approach rests on a key assumption: that respondents can distinguish between the two dimensions of interdependencies. It is possible that one dimension may "contaminate" or partly result from the other. For example, "John and Stewart work together in the work process because they share substantial knowledge," and conversely, "Jane and Liz meet to share experiences because they collaborate in the same work process." If this cross-contamination occurs, the underlying rationale of our approach might collapse. For future research, we suggest testing this assumption by collecting empirical evidence and incorporating the balancing of the two criteria based on our proposed pseudo code into a genetic algorithm that can perform a quick search for the clustering arrangement that minimizes D. For future research, we suggest to move beyond immediate benefits and costs of regrouping, to also incorporate the value potential inherent in the presented definition of interdependencies. This involves taking the dimension of time into consideration and evaluating grouping alternatives in terms of net benefits.

References

Arora, A., Belenzon, S., Rios, L.A., 2014. Make, buy, organize: The interplay between research, external knowledge, and firm structure. Strateg. Manag. J. 35, 317–337.

Browning, T.R., 2009. Using the Design Structure Matrix to Design Program Organizations. Handb. Syst. Eng. Manag. 1401–1424.

Cammelli, F., Worren, N., 2024. Role grouping experiments: A new methodology for studying organization design decisions. Submitt. Rev.

Eklund, J., 2024. A New Organizational Structure Database: Examining Structure through Top Management Team Composition, in: Decentralization in Organizations (DiO) Conference.

Eppinger, S.D., Browning, T.R., 2012. Design Structure Matrix Methods and Applications, Design Structure Matrix Methods and Applications. MIT press.

Firk, S., Gehrke, Y., Hanelt, A., Wolff, M., 2022. Top management team characteristics and digital innovation: Exploring digital knowledge and TMT interfaces. Long Range Plann. 55, 102166.

Galbraith, J., 1973. Designing complex organizations, Addison-Wesley series on organization development. Addison-Wesley, Reading, Mass.

Gulick, L., 1937. Notes on the theory of organization, in: Gulick, L., Urwick, L. (Eds.), Papers on the Science of Administration. Institute of Public Administration, Columbia University, New York.

Hansen, T.M., Podolny, J.M., 2020. How Apple Is Organized for Innovation. Harv. Bus. Rev. 98, 86–95.

Huang, C.C., Kusiak, A., 1998. Modularity in design of products and systems. IEEE Trans. Syst. Man, Cybern. Part ASystems Humans. 28, 66–77.

March, J.G., Simon, H.A., 1958. Organizations. John wiley & sons.

Maurer, M., Lindemann, U., 2007. Structural awareness in complex product design - The multiple-domain matrix, in: Proceedings of the 9th International DSM Conference. pp. 87–97.

McCord, K.R., Eppinger, S.D., 1993. Managing the Integration Problem in Concurrent Engineering. Concurr. Eng.

Mintzberg, H., 1979. The Structuring of Organizations: a synthesis of the research. Prentice-Hall, Englewood Cliffs, N.J.

Pimmler, T.U., Eppinger, S.D., 1994. Integration analysis of product decompositions, in: Proceedings of the ASME Design Engineering Technical Conference. American Society of Mechanical Engineers, pp. 343–351.

Puranam, P., Raveendran, M., Knudsen, T., 2012. Organization design: The epistemic interdependence perspective. Acad. Manag. Rev. 37, 419–440.

Raveendran, M., Silvestri, L., Gulati, R., 2020. The role of interdependence in the micro-foundations of organization design: Task, goal, and knowledge interdependence. Acad. Manag. Ann. 14, 828–868.

Saaty, T.L., 1988. What is the Analytic Hierarchy Process?, in: Mathematical Models for Decision Support. Springer, pp. 109–121.

Saaty, T.L., Vargas, L.G., 2012. Models, methods, concepts & applications of the analytic hierarchy process. Springer Science & Business Media.

Saaty, T.L., Vargas, L.G., Zoffer, H.J., 2015. A structured scientific solution to the Israeli–Palestinian conflict: the analytic hierarchy process approach. Decis. Anal. 2.

Simon, H.A., 1946. The proverbs of administration. Public Adm. Rev. 6, 53–67.

Sipahi, S., Timor, M., 2010. The analytic hierarchy process and analytic network process: An overview of applications. Manag. Decis. 48, 775–808.

Solberg, R., Yassine, A., Worren, N., 2023. Using net benefit analysis to value costs and benefits of re-grouping in organization design, in: Proceedings of the 25th International DSM Conference (DSM 2023). pp. 39–47.

Sosa, M.E., Eppinger, S.D., Rowles, C.M., 2004. The misalignment of product architecture and organizational structure in complex product development. Manage. Sci. 50, 1674–1689.

Sosa, M.E., Mihm, J., 2007. Organization design for new product development, in: Handbook of New Product Development Management. Routledge, pp. 165–198.

Thompson, J.D., 1967. Organizations in action: social science bases of administrative theory. McGraw-Hill, New York.

Tramarico, C.L., Mizuno, D., Salomon, V.A.P., Marins, F.A.S., 2015. Analytic hierarchy process and supply chain management: A bibliometric study. Procedia Comput. Sci. 55, 441–450.

van de Ven, N., Bogaert, A., Serlie, A., Brandt, M.J., Denissen, J.J.A., 2017. Personality perception based on LinkedIn profiles. J. Manag. Psychol. 32, 418–429.

Worren, N., Christiansen, T., Soldal, K.V., 2020. Using an algorithmic approach for grouping roles and sub-units. J. Organ. Des. 1–19.

Yassine, A., Braha, D., 2003. Complex Concurrent Engineering and the Design Structure Matrix Method. Concurr. Eng. Res. Appl. 11, 165–176.

Yassine, A., Worren, N., Christiansen, T., 2021. Dedicated vs. Shared Resources in Organizations: Modifying the Design Structure Matrix (DSM) to Support Consolidation Decisions, in: DS 112: Proceedings of the 23rd International DSM Conference (DSM 2021), Montréal, Canada, October, 12 - 14, 2021. The Design Society, pp. 10–20.

Yassine, A.A., Chidiac, R.H., Osman, I.H., 2013. Simultaneous optimisation of products, processes, and people in development projects. J. Eng. Des. 24, 272–292.

Yassine, A.A., Naoum-Sawaya, J., 2017. Architecture, Performance, and Investment in Product Development Networks. J. Mech. Des. 139, 1–11.

Zyoud, S.H., Fuchs-Hanusch, D., 2017. A bibliometric-based survey on AHP and TOPSIS techniques. Expert Syst. Appl. 78, 158–181.

Contact: Runar Solberg, Norwegian University of Life Sciences, School of Economics and Business, Department of Strategy, Organization and Leadership, Postboks 5003 NMBU 1432, Ås, Norway, ruso@nmbu.no