Creating Strategies for Enhancing Complex New Product Development: Cluster Analysis of DEA Results

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Firms need to constantly innovate to survive and remain competitive in the marketplace. Despite this, little research has examined the dynamics that affect innovation in large-scale, complex organizations that leverage multiple teams. This study utilizes data envelopment analysis output from a sample of new product development teams to create clusters based on how teams need to change communication-related inputs to increase creative efficiency. The study results exemplify how this approach can provide recommendations that sets of teams can implement, optimizing the use of resources compared to making individual adjustments. Implications are provided for new product development and large multinational enterprises.

Keywords: new product development, cluster analysis, Data Envelopment Analysis

INTRODUCTION

Firms must constantly innovate to survive in the market (Dul & Ceylan, 2014). Despite the critical importance of innovation for firm survival and performance, there is a lack of research addressing the dynamics that affect innovation in large-scale, complex, team-based organizations (Glynn, Kazanjian, & Drazin, 2010). As projects involving multiple teams become increasingly common, such as those involved in developing new aircraft, automobiles, space projects, and defense contracting, research is needed to suggest strategies that may generalize to large, complex organizations that leverage multiple interdependent teams. Such projects include developing the Boeing 777 and the Airbus A380, which involved around 10,000 engineers and 250 teams and 5,000 engineers and 110 teams, respectively. In addition, as innovation is increasingly taking place virtually and at a record pace (Berruti et al., 2022), factors that affect collaboration, such as team communication, become relevant.

Previous research has examined the application of Data Envelopment Analysis (DEA) to assess the efficiency of new product development teams' creative output, using communication factors as inputs (Flores, Kiss, & Moreno, 2022). This study extends this line of research, exemplifying cluster analysis while leveraging DEA outputs to provide recommendations applicable to a group of decision-making units

(DMUs). While DEA is useful for identifying target values for individual non-efficient DMUs based on examining the most efficient units, Cluster Analysis allows further exploration of the characteristics of teams showing superior efficiencies and identifying routes to efficiency that can apply across a set of units.

DATA ENVELOPMENT – AND CLUSTER ANALYSIS

Data Envelopment Analysis was initially developed to estimate production frontiers by applying linear programming (Charnes, Cooper, & Rhodes, 1978). This non-parametric method compares possible inputs and outputs of available data and has been widely used to examine the decision-making units (DMUs) that operate most efficiently. Additionally, DEA creates strategies for those less efficient units to improve based on the top-performing peers.

Cluster analysis is a numerical method of identifying similarities among a set of data points and grouping them accordingly (i.e., data points in one cluster are more similar to each other than to those in other clusters). Cluster analysis was first developed by Driver and Kroeber (1932) to research cultural relationships and has since developed into one of the most extensively used scientific methods. Due to the wide variety of application areas, several types of clustering algorithms were developed. However, the basic principles are very similar: Based on quantitative or qualitative attributes, find several close subsets and thus form groups with distinguishable attributes from other groups. Business research and practice build on clustering extensively, such as:

- Identifying customers who are alike so that they can carry out targeted marketing campaigns
- Grouping together consumers of similar digital content to maximize media consumption
- Identifying similar patients in health care to better optimize insurance coverage
- Etc.

In this study, clustering is used to identify similar teams (Decision Making Units from DEA) regarding how they should change their input to be more efficient in their processes. From the wide range of different clustering methods, hierarchical clustering will be used, which iteratively groups together the most similar observations (DMUs in our case) until all observations are in one giant cluster. When the process is mapped out, the researcher can identify the point where there was the correct number of distinguishable clusters with sufficiently differing characteristics for the goal of the given analysis. There is no optimum objective for this point, as it is highly dependent on the specifics of the research.

In literature connected to New Product Development (NPD), clustering has been used by Valle and Avella (2003) to show that using cross-functional teams leads to a more effective development process. In addition, Yang et al. (2018) used a two-staged clustering criterion to optimize new product development organization. Their results indicate that their method can reduce an organization's complexity and thus lead to better results. Yang et al. (2019) also approached product development through clustering based on social cohesion among teams based on Social Network Analysis.

A NEW AREA OF APPLICATION

New Product Development considers two main phases: initiation and implementation. The initial phase involves idea generation, screening, and concept testing, while the second involves product development, market testing, and product launch (Johne, 1984). This study focuses on the application of Cluster Analysis on relevant inputs for the creative phase of NPD, precisely the dimensions of a team's communication (the safety of the team's communication environment, the levels of richness of the channels used for communication, and the amount of internal and external communication at different levels). These are relevant inputs as innovation and digitalization are occurring at a record pace with primarily remote communication (Berruti et al., 2022). Research suggests that a psychologically safe communication climate may offset the negative impact that dispersion may have on innovation (Gibson & Gibbs, 2006). In addition, a team's performance may depend on the match between a task's characteristics and the communication channels used (Oke & Idiagbon-Oke, 2010), as well as a team's communication frequency (Leenders, Engelen, & Kratzer, 2003).

Data was captured using a Qualtrics panel of survey data from 128 U.S.-located new product development teams. Communication richness was operationalized by creating an index based on items from previous research (Oke & Idiagbon-Oke, 2010). Communication channels were weighted based on the amount of information they could convey, and their usage frequency was considered (Johnson & Lederer, 2005). Face-to-face communication, for example, was considered the richest channel, while paper-based memos and bulletins were considered the leanest. Communication frequency was measured in a manner consistent with previous literature (Keller, 2001). The first item assessed the amount of internal communication within the project group. Three items measured the amount of external communication. They considered the amount of communication outside the project group but within the business unit, the amount of communication outside the business unit but within the company, and the amount of communication outside the company. Communication safety was measured using four items on a seven-point scale based on previous literature (Gibson & Gibbs, 2006) which assess the level of psychological safety of the communication environment. A sample item read: "When there is a problem, members talk about it.". Lastly, creativity was assessed using six items following previous literature (Moreau & Dahl, 2005), three assessing the novelty dimension, and the other three assessing usefulness. Consistent with previous literature, a single index was created to assess overall creativity (Burroughs, Dahl, Moreau, Chattopadhyay, & Gorn, 2011).

DEA analysis using VRS and an input-oriented approach was conducted from the data to identify the relatively most efficient DMUs (see Flores et al., 2022). The results revealed that forty-seven of the one hundred and twenty-eight teams achieved the highest levels of efficiency.

While the Data Envelopment Analysis provided specific suggestions on how each team could adjust their inputs to be as efficient as their most efficient peers, Cluster Analysis was used to identify groups of teams (DMUs) that shared similarities in the changes required on their inputs to reach efficiency.

To make the study's output easily interpretable and actionable, the six inputs were compressed into three by taking their average and creating a "Communication" variable from the current four distinct communication frequency variables (Int Com, ExtCom2, ExtCom3, ExtCom1). The analysis then used the relative (%) needed to decrease in values to eliminate the potential problems posed by the differing scales. The resulting dataset is shown in Table A.

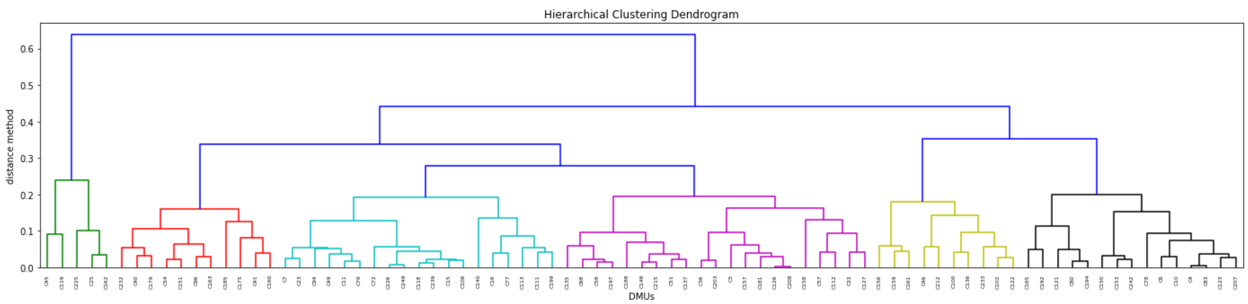
TABLE A
RELATIVE DECREASE NEEDED TO ACHIEVE EFFICIENCY

DMU	Communication Safety	Channel Richness	Communication Average
C3	30.00%	31.00%	33.00%
C4	14.00%	14.00%	19.75%
C6	12.00%	19.00%	18.00%
C7	16.00%	16.00%	22.75%
C10	9.00%	19.00%	18.25%
...	...	...	...
C242	8.00%	23.00%	11.75%
C249	19.00%	19.00%	28.50%

CLUSTER ANALYSIS OF DEA RESULTS

In the next step of the analysis, clusters were created from the teams based on the data in Table A. A hierarchical clustering calculation was used where the DMUs were iteratively grouped based on their relative similarities. Figure A plots the visual representation of the process. Six clusters were created based on the output (shown in different colors on the plot). It is important to note that the number of clusters is subjective, and a different number of clusters could have been created. In this case, the number of clusters was determined by observing that after six clusters, the distance between them would grow significantly, and using fewer clusters would entail grouping together data points relatively far from each other.

FIGURE A
HIERARCHICAL CLUSTERING OF DMUS



After clustering was completed, an analysis was run to determine the characteristics of each of the six clusters. As the analysis was done with the help of Table A, clusters differed in terms of which of the three variables they had to decrease to reach efficiency. A 3D visual plot of the 6 clusters provided more insight into these characteristics. Figure B contains two different angles of the three-dimensional plot.

FIGURE B
THREE-DIMENSIONAL PLOT

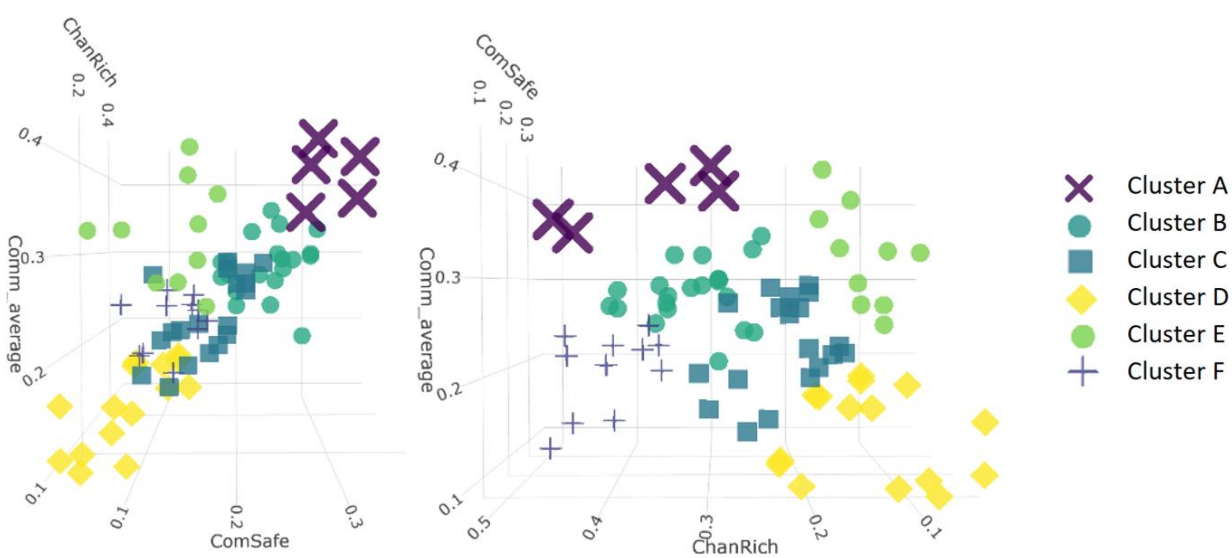


Figure B supported the identification of six distinctive cluster characteristics:

- Cluster A: This cluster appeared to be the least efficient as it needed a high decrease in all three dimensions.

- Cluster B: This cluster sat in the middle of the pack. These teams need relatively major adjustments in all three dimensions but on a smaller scale than Cluster A.
- Cluster C: This cluster was an improved version of Cluster B: The adjustment needed in all three dimensions was less pronounced, all sitting under 30%.
- Cluster D: This cluster appeared to be the most efficient since it needed only minor adjustments (all under cca. 20%) in all three dimensions.
- Cluster E: This cluster was unique compared to the previous ones since the chancel richness and communication seem adequate (a minor adjustment is needed), but these teams need to adjust their communication level significantly to be efficient.
- Cluster F: This cluster was similar to Cluster E because it performed well on two dimensions (Communication Safety and Communication Average), yet these teams need a significant adjustment on Channel Richness on the road towards efficiency.

As illustrated, clusters A through D sit on the same axis, representing teams that need to adjust all their inputs simultaneously, but on a different scale. On the other hand, clusters E and F are doing relatively well on two dimensions and only need to adjust the third one.

MANAGERIAL IMPLICATIONS AND CONCLUSIONS

DEA results can indicate how to improve operations related to product development on an individual level. However, Cluster Analysis can support the identification of team patterns, enabling researchers to identify improvement methods that can be applied to a whole set of teams belonging to a cluster, radically reducing the time needed for improvement compared to making individual team recommendations. In addition, once a team is identified to be in a cluster, it can apply a "blueprint" of solutions developed for that cluster and would need fewer resources to develop an individualized plan.

As illustrated, this approach may be relevant for firms conducting complex product development involving multiple teams and requiring the implementation of strategies for a group of teams instead of individually adjusting decision-making units. In addition, this approach may be helpful for multinational enterprises (MNEs) leveraging multiple teams and facings rising demands for flexibility and global integration, such as those utilizing more fluid meta-teams that quickly form and disperse to address a firm's needs (Santistevan & Josserand, 2019).

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