The Impact of Product Architecture and Organization Structure on Efficiency and Quality of Complex Product Development

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A well-planned and well-executed new product development (NPD) process, which produces a stream of timely and high quality products, can provide significant competitive advantage to a company. Focusing on two key measures of NPD performance, efficiency and quality, and making use of social network tools and statistical analysis, we examine a vehicle design process and identify the technical, individual and organizational factors that affect performance on these dimensions. Specifically, we investigate process efficiency as measured by individual rework rate and task tardiness, and examine the final product quality as measured by warranty claims. Our results suggest that engineers who are highly central in the organization network are less prone to generating problems requiring rework, but are also slower to resolve problems for which they are responsible. We also characterize mismatches between product architecture and organization structure by defining a new metric, called "coordination deficit", and show that it is positively correlated with quality problems. These results deepen our understanding of the impact of organizational structure and product architecture on the NPD process and provide tools with which managers can diagnose and improve their NPD systems.

Key words: new product development; product architecture; organization structure; complex networks
History:

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1. Introduction and Literature Review

Product innovation has always been central to business creation and growth. But in recent years, as globalization has made it more difficult to sustain competitive advantages from market access or operational efficiency, innovation has become even more crucial. Firms that are able to bring a steady stream of timely and well-executed products to market are likely to enjoy long term financial success. For example in a study of the U.S. pharmaceutical industry, Roberts (1999) found that sustained high profitability results when a firm repeatedly introduces innovations that target previously unmet consumer demands.

From an operational perspective, two key measures of innovation performance are *speed* (time from concept to commercialization) and *quality* (conformance to customer preferences, which can be gauged via various proxy metrics). Achieving high levels of performance along these two dimensions requires a new product development (NPD) process that is both *efficient* (capable of translating objectives into products without excessive delay or unnecessary cost) and *accurate* (capable of generating products that meet design specifications). As General Motors Vice Chairman of Product Development Robert Lutz put it:" Our role is to execute high quality gotta-have products quickly and efficiently” (Welch 2001). In this paper, we examine a vehicle design process with a focus on identifying the technical, individual and organizational factors that affect performance in terms of both process speed and product quality.

Our work builds upon and integrates two streams of research: (i) operations of complex product development and (ii) social network analysis of organizational performance. These two streams are closely related and have been studied together under two major research headings. The first is *knowledge networks* (see Nonaka and Takeuchi 1995, Contractor and Monge 2002). Researchers have investigated various aspects of knowledge networks in the context of product development and have provided critical insights into why some business units are able to make effective use of knowledge from other parts of the company, while others find knowledge to be a barrier to innovation (Hansen 2002, Carlile 2002). The second stream of research deals with *modularity*, which refers to methods for reducing the number of interactions and interfaces among parts and components in product design (Ulrich 1995, Baldwin and Clark 2000). Organizational implications of modularity, as well as the organizational factors that support use of modularity, have been studied by several researchers (see Sanchez and Mahoney 1996, Schilling 2002, Ethiraj and Levinthal 2004, Fleming and Sorenson 2004).

Given that complex product development involves development of a “network of components” by a “network of people”, it is not surprising that networks have been used to model and analyze new product development. Product development researchers have studied both organizational and product networks broadly in the context of product architecture (Krishnan and Ulrich 2001, Henderson and Clark 1990, Ulrich 1995) and organization structure (Clark and Fujimoto 1991, Brown and Eisenhardt 1995). These two streams of research have enhanced our understanding of the role of design interfaces (a network of components) and interactions between engineers (a network of people) in complex product development. Sosa et al. (2004) integrated these two approaches and investigated the alignment of design interfaces and communication patterns. This integration provides a new avenue for understanding the product development process and offers critical insights into organizational and architectural interdependencies. In particular, Sosa et al. (2004) identified factors that cause misalignment and suggested that these can have detrimental consequences. But they did not offer clear metrics for the severity of misalignment and did not actually measure the consequences. In this paper, we build on the research of Sosa et al. (2004) by (a) defining a new metric, called “coordination deficit”, which quantifies the mismatches between product architecture and organization structure, and (b) empirically investigating the effect of coordination deficit on end product quality.

In a larger sense, this paper contributes to the literature on product development and organizations by making use of social network tools (see Wasserman and Faust 1994) to capture interactions among people (as well as interactions among components) in order to evaluate the impact of organizational network structure on the efficiency of product development. Using task tardiness and individual rework rate as proxies for efficiency, we find that coordination among engineers, measured via network summary statistics (i.e., degree centrality), significantly impacts efficiency.

However, unlike most of the previous literature on organizational networks (see, e.g., Brass 1984, Sparrowe et al. 2001) which favors centrality (i.e., the more connections you have, the better you perform), we find that centrality enhances individual performance but at the cost of increased task tardiness. These results suggest that there is "operational overhead" associated with maintaining links in a social network, which is a notion often overlooked in the social networks literature.

From a practical perspective, our work may help managers to systematically identify and quantify potential problem areas that can be addressed to improve the efficiency of the design process and the quality of the resulting products. While our regression models do not provide accurate numerical predictions of future process delays or product quality problems, we show that they do reliably predict which subsystems are likely to present the most extensive problems. Targeted improvements in the development process, including improving coordination among engineers and better aligning the formal task coordination process with product architecture, can improve both the efficiency of the design process and the quality of the end products.

The remainder of the paper is organized as follows: In the next section we give an overview of the vehicle development process, along with a description of the critical data components. In Sections 3 and 4 we investigate product development efficiency as measured by individual rework rate and task tardiness. Section 5 examines the impact of product architecture on quality. Section 6 introduces a new concept we call *coordination deficit* that characterizes mismatches between product architecture and organization structure. In Section 7 we explore the predictive power of our model as a tool for identifying potential future quality problem areas. We present conclusions and future research directions in Section 8.

2. Overview of the System

Our empirical analyses are based on a detailed study of the new vehicle development process of a large US auto manufacturer. Because it involves many interdependent tasks over an extended period, automotive design is a prototypical example of complex product development. To create a useful model, one of the authors spent two summers (about 6 months) on site for data collection and analysis. This allowed us to gain a good understanding of the product development process through observation of common practices and obstacles. Figure 1 gives a schematic representation of the process for designing a vehicle and delivering it to the market. While manufacturing is an important part of this process, which has a strong influence on product quality, we treat it as a “black box” and devote our attention to the design process. To flesh out our description of Figure 1, we detail the design process, the product, and the product development organization below.

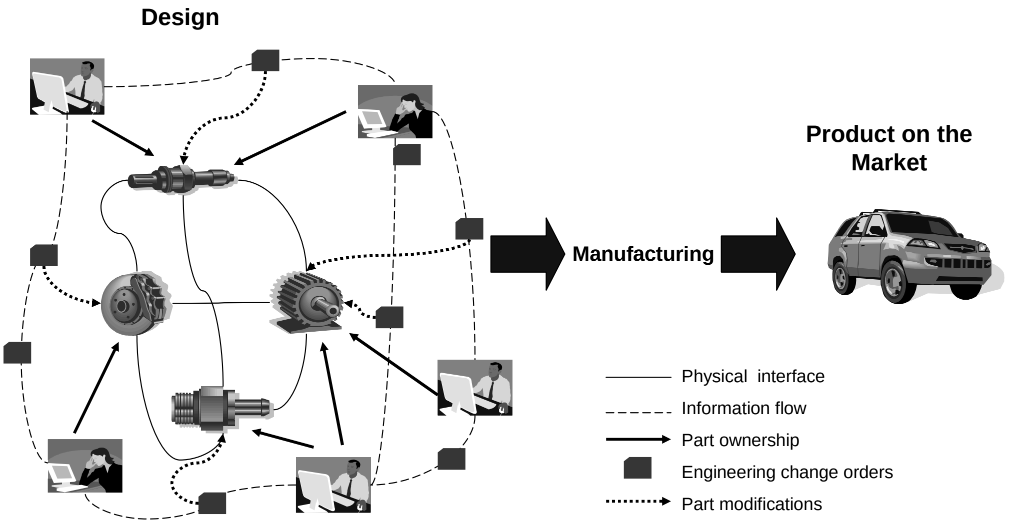

Figure 1 **Schematic of the Vehicle Design Process**

2.1. Design Process

Vehicle design is an iterative process that converges to a solution that meets a host of design specifications within a tightly constrained time frame. This process involves considerable interaction between design engineers and interplay between these engineers and the interconnected set of components on which they are working. *Engineering Change Orders (ECO’s)* play a critical role in the management and documentation of this process. An ECO is filed by a design engineer every time a new part is released (i.e., *new release ECO*) or an old part is changed in any way. In our study, the ECO system contained approximately 100,000 separate ECO’s. A typical ECO contains the identity of the engineer who initiated it, a reason code that explains why the ECO was issued, the identities of other engineers to be notified as part of a distribution list about activity related to the ECO, part numbers associated with it and dates of completions. We have grouped ECO's in three mutually exclusive sets in our analyses: (1) *new release ECO's*, which are filed for all parts of a new model (note that some of these parts are new, while others are old parts from a previous model that have been renumbered for the new model), (2) *problematic ECO's* whose reason codes were identified by several design engineers with whom we consulted as indicating problems in the Design process, and (3) *other ECO's*, which include all ECO's not contained in the above categories (e.g., ECO's due to a cost reduction initiative or a change in government regulations).

There have been several studies (see Clark and Fujimoto 1991, Huang and Mak 1999, Terwiesch and Loch 1999, Loch and Terwiesch 1999) of ECOs in the design process. These studies examined the broad significance of ECO generation without specifically capturing product architecture information or organization structure. Since ECO's are filed when an individual part fails to meet specifications, two or more parts have interface problems, or product changes are made that affect part designs, the ECO database contains a great deal of information about the efficiency and quality of the product development process. To our knowledge, this study is the first attempt to use the ECO system to capture product and organization interactions.

Two types of information from ECO's are particularly relevant to the efficiency of the design process. The first is the rate at which problematic ECO's are generated, which we use as our first efficiency metric. Since problematic ECO's are filed by the engineer who is responsible for the design problem, we are also able to divide this rate according to the responsible engineer. A second measure of efficiency is the time it takes to resolve an ECO. Each time an ECO is generated, a required completion date is set. If this due date is not met, the design process may be delayed. Therefore, we use tardiness of ECO's as our second efficiency metric.

2.2. Product

Most previous researchers have studied product architecture at the product and system level (see Ulrich 1995). However, more recently scholars have examined product architecture at the component level using a network approach (Sosa et al. 2006). In our study, we followed our client in dividing an automobile into 243 architectural subsystems, which contain roughly 150,000 parts that interact with each other. Conducting our study at the intermediate level of subsystems gives us more detail than conducting it at higher levels (e.g., product level studies), while allowing us to get more data (e.g., on warranty repairs) than we could at the detailed component level. To make maximum use of the available information, we defined the *Product Architecture Network* at the subsystem level. This network reveals that the various subsystems differ substantially in terms of their connections to other subsystems. For example in a car, the wire harness subsystem has physical connections to almost every subsystem, while the air cleaner subsystem has only a limited number of physical connections with the rest of the system.

We construct the Product Architecture Network by defining subsystems as nodes. We define links between these nodes by looking at only new release ECO's. These ECO's are not a result of a problem or later changes, and hence establish unbiased connections. If an ECO includes parts both from subsystems i and j, we count it as one connection between these two subsystems. By summing the number of connections between subsystems i and j contained in the full set of new release ECO's, we calculate a weight for the link between nodes i and j. Figure 2 shows a portion of the resulting Product Architecture Network. Note that we characterize the level of connectivity of a subsystem by computing its degree centrality score (sum of link weights emanating from a node).

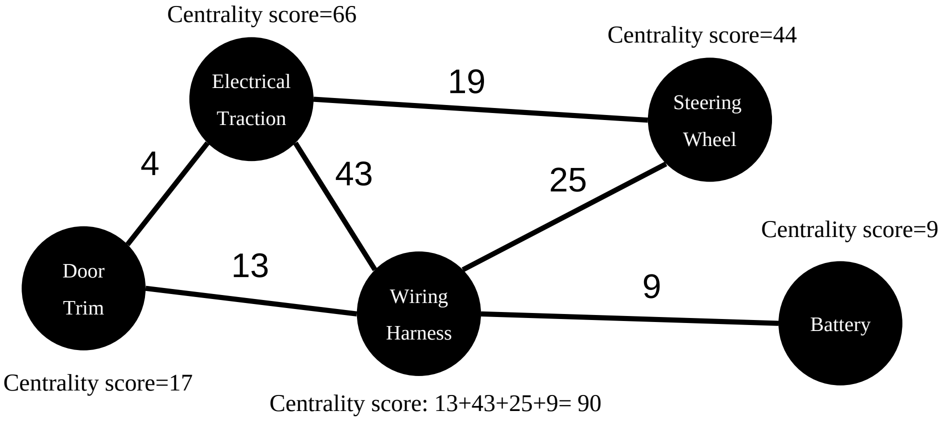

Figure 2 **Calculating degree centrality scores in Product Architecture Network**

2.3. Product Development Organization

The primary actors in a vehicle development organization are design engineers. In the system we studied, there were about 10,000 engineers involved in product design across all programs. These engineers are responsible for creating the parts, making sure that they meet design specifications and coordinating interfaces with other parts. Within the ECO system, design engineers coordinate with each other through *distribution lists*. Whenever there is an activity related to an ECO, designated engineers who are directly involved (e.g., an engineer whose parts share a direct physical interface with a modified part) or indirectly involved (e.g., an engineer whose part shares an indirect functional interface) are notified via the distribution list for the ECO. Some of these engineers are placed on this distribution list by management, while others are added by the engineer responsible for the ECO.

We capture this coordination interaction among engineers via the *Coordination Network*. In this network, nodes represent design engineers involved in the ECO system (which includes all three types of ECO's). We define a link between two engineers if they are listed together in the same distribution list of an ECO. We define the weight of the link between two engineers as the number of ECO's for which they appear together in the distribution list.

Many organizational studies (see Ibarra 1993, Krackhardt and Hanson 1993, Burt 2004) have studied communication and advice networks of individuals by using empirical data sets that are usually collected through surveys or questionnaires. This study differs from these by making use of formal institutional connections, rather than informal social ones. One benefit of this approach is that it permits organizational analysis with data already being recorded, and so does not subject the organization to the burden of a detailed survey. A second benefit is that it focuses on links over which management has a great deal of influence (i.e., who is listed on which distribution list networks). Hence, any levers indicated by these research results can be directly translated into concrete management policies.

3. Efficiency

We now turn to our analysis of the factors that affect efficiency of the vehicle design process. We first use task rework as as our performance measure (in Section 3.1) and then turn to ECO tardiness (in Section 3.2). We examine product quality in Section 4.

3.1. Task Rework

Within a product development organization, any time an individual design task must be corrected or repeated, there is the potential for disrupting or delaying the overall design process. Thus, one reasonable performance metric is design task rework. We use the number of problematic ECO's filed by an individual engineer as a proxy for the engineer's performance (i.e., rework rate). In addition to the obvious factors (e.g., experience, task complexity, skill as evidenced by past performance), one possible determinant of the rework rate of an individual engineer is his/her interaction with other engineers and managers in the system.

To characterize these interactions among engineers, we use the Coordination Network defined in Section 2.3.

Network researchers have long been interested in the relationships between network structure and organizational performance. Centrality is by far the most popular metric used in these studies. For example, performance in knowledge-intensive work has been positively associated with centrality of the agents in an information network (Cross and Cummings 2004). In an information network, actors are the knowledge workers who collaborate and cooperate to achieve a common goal. Because it facilitates the transfer of knowledge from one user to another, network structure is an integral part of this transfer process (Reagans and McEvily 2003). In our system, design engineers are the knowledge workers who are responsible for different parts and they interact with other engineers on a daily basis. When an engineer makes a modification on a part, he/she should coordinate with other engineers who will be affected by this change. For example, an engineer working on a part in Front Steering has to coordinate with other engineers in her immediate physical vicinity (e.g., Steering Column and Steering Wheel), as well as functional vicinity (e.g., Suspension). Regardless of how well individual engineers perform their tasks, unless they coordinate with the appropriate parties, there is a high potential for generating problems. Because of this, we expect an engineer who is centrally positioned in the Coordination Network to perform better due to his/her relative advantage in accessing relevant information and obtaining knowledge from peers. Hence, we expect to observe a lower rework rate for highly central engineers, as we propose in the following hypothesis:

> **Hypothesis 1**. *Engineers with higher centrality in the coordination network generate fewer problems that result in ECOs.*

3.1.1. Analysis To test the above hypothesis, we formulated a regression model that characterizes the relationship between coordination network structure and design task rework rate. Since individual characteristics such as tenure, education, etc., may influence performance, we obtained a sample of 1048 regular design engineers for whom demographic information (salary level, education, experience) was available and we performed our analysis on this group.

For the dependent variable in our model, we used the fraction of problematic ECO's written by each engineer out of the total number of ECO's written by them. This fraction is a good proxy for individual rework rate because problematic ECO's are associated with events in the design process that require correction. Note that we used the fraction instead of using the absolute number of problematic ECO's as our dependent variable, because an engineer who writes more total ECO's has more opportunities to generate problematic ones (we noted that the correlation between the number of problematic ECO's and non-problematic ECO's is $\rho = 0.73$, which is consistent with our interpretation of the fraction of problematic ECO's as a "rework rate"). We only considered 2005 model year for which a complete set of 102,032 ECO's was available.

A host of factors could affect an individual engineer's rework rate. These can be aggregated into three categories: organization-, task- and individual-related variables. To test the impact of organizational structure on rework rate of an engineer, we used, as our primary independent variable, the degree centrality of that engineer in the coordination network of the 1048 engineers of interest. (See Ahuja et al. (2003) and Freeman (1979) for examples of studies that used degree centrality in a similar context). An engineer with a high degree centrality has many connections to other engineers in the design organization and is therefore strongly connected to the rest of the organization. Individual degree centralities for 1048 engineers were calculated using UCINET 6 (Borgatti et al. 2002). In addition to this organizational independent variable, we considered several control variables in the task-related and individual categories (see Table 1 for a summary).

We considered four task-related control variables: (i) the number of parts assigned to the engineer, (ii) the total number of subsystems on which the engineer works, (iii) the fraction of new parts the engineer works on, and (iv) the average degree centrality of the subsystems worked on by the engineer. The logic of including the number of parts and subsystems is obvious—the more separate components and/or disparate subsystems assigned to an engineer, the more complex his/her task will be, and hence the chance of errors will be higher. Similarly, we would expect to see higher error rates with the new parts than old ones. The degree centrality of the subsystems worked on by an engineer may be relevant because high centrality parts have more interfaces and hence may be more complex. However, high centrality parts are also more visible and thereby may elicit more organizational attention. So it remains to be seen whether and how this variable affects rework rate.

Finally, we have also controlled for individual characteristics of engineers which might influence their performance. These four control variables are highest education level, salary level, seniority and time spent in current salary level.

3.1.2. Results and Insights We computed bivariate correlations among the independent and control variables, and found these to be acceptable (i.e., the highest correlation was 0.37). We then used ordinary least squares (OLS) regression to test our first hypothesis (see Table 1). Model 1 examines the effects of the control variables, while Model 2 introduces organizational network centrality in order to evaluate its incremental impact. In both models, the total number of subsystems an engineer works on and time spent in current salary level (i.e., a proxy for poor performance) is significant and positively correlated with the fraction of problematic change orders. Salary level has a negative coefficient and is significant, suggesting that more highly paid (and presumably more skilled) engineers generate fewer problems.

Table 1. OLS Regression Model of Design Rework Rate

	Variable	Model 1	Model 2
Organizational factors			
	degree centrality of an engineer		-0.0386***
Task factors			
	average degree centrality of subsystems	0.0612	0.0325
	total number of parts assigned to an engineer	0.0083	0.0317
	total number of subsystems an engineer works on	0.0029**	0.0084**
	fraction of new parts	0.0923*	0.0748*
Individual factors			
	highest education level	-0.6586	0.5129
	salary level	-1.9841**	-2.5792**
	seniority	-0.0013	-0.0011
	time spent in current salary level	0.0042**	0.0019**
	R^2	7.9%	14.4%
	adj R^2	7.4%	13.8%
	F	11.41***	13.72***
	n	1048	1048

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Most importantly, Model 2 provides support for Hypothesis 1. Degree centrality of an engineer in the coordination network is significant with a negative coefficient. Moreover, while Model 1 explains only 7.9 percent of variation, adding degree centrality as an independent variable increases the fraction of variation explained to 14.4 percent (almost twice as large). The implication is that engineers with more central positions in the coordination network are less likely to generate problematic change orders.

The low R^2 value in Model 2 implies that most of the variation in problematic ECO's is due to factors other than the variables in this model. Considering the complex nature of the design process and many extrinsic factors (e.g., differing skill levels among engineers, varying complexity of individual parts, management policies, etc.) that influence the likelihood that an engineer creates a problematic ECO, this is not surprising. Since, our main goal is not to predict the rate of design task reworks precisely, but rather to understand the relationship between an engineer's interaction with other engineers and his/her performance, the low R^2 value is not a serious problem.

Note that the number of parts assigned to an engineer does not have a significant impact on his/her rework rate. We conjecture that this is due to the fact that some engineers are assigned to many small and comparatively simple parts, while others are responsible for one or two very complex parts. Unfortunately, our client did not have measures of part complexity, nor do we know of any generic complexity metrics. So, to provide some measure of task difficulty, we considered the average degree centrality of the subsystems worked on by an engineer in the product architecture network. Our reasoning is that subsystems with higher degree centrality have more interfaces with other subsystems and therefore offer more opportunities for design problems. Indeed, Table 1 shows that average degree centrality is positively correlated with design rework rate. Fraction of new parts is also positively correlated with the design rework rate, as expected.

Finally, we note that, highest education level (i.e., highest degree) and seniority do not have any predictive power in models, but salary level and time spent in current salary level are both significantly negatively correlated with the rate of problematic ECO's, as we would expect.

These results suggest two major insights for design organizations. The first is that design engineers tend to perform better when they work on fewer architectural subsystems. Presumably, working on too many things at once diminishes their focus on details and accuracy of task performance. Second, as engineers have more coordination links to their peers, they perform better. By establishing links between engineers through formal distribution lists, management can reduce the number of design errors and the time to correct them.

3.2. ECO Tardiness

The above observation that more coordination links among engineers reduces errors is consistent with earlier results in the social networks research literature for networks of employees (see Brass 1984) and advice networks of individuals (see Sparrowe et al. 2001). But maintaining these links comes with a price. Monitoring and/or discussing messages related to ECO's takes time that could be devoted to other tasks. This leads us to conjecture the following:

Hypothesis 2. *ECO's that involve engineers with higher centrality in coordination network have longer delays (i.e., higher tardiness).*

3.2.1. Analysis To test this hypothesis, we constructed a statistical model in which the dependent variable is ECO tardiness for all three types of ECO's, calculated by subtracting the actual completion date from the required completion date. If an ECO is closed before the required completion date, ECO tardiness is zero. As in the previous model, this model only considers ECO's for the 2005 model year which results in a total number of observations $n =$102,032.

Because an ECO may have several engineers associated with it, associating engineer centrality with ECO tardiness requires two steps: (1) calculating individual degree centralities of engineers in the coordination network, as we did in the previous section, and (2) averaging of the centralities of the engineers for each ECO. We use the resulting *average degree centrality of engineers* as our primary independent variable.

Similar to the previous section, we included several control variables in our model. We use *average degree centrality of subsystems* in product architecture network associated with ECO's to characterize the complexity of subsystems in terms of the number of interfaces with other subsystems. We also include as control variables the *number of people associated with an ECO* (because more reviews and/or more sign offs may lead to more delay), the *number of parts associated with an ECO* (because more parts may mean more issues to resolve and hence more delay), *and the fraction of new parts associated with an ECO* (because higher fraction of new parts may mean longer delay).

3.2.2. Results and Insights Because the dependent variable in our model will have a value of 0 if an ECO is completed on time, and a value greater than 0 if it is delayed, we made used of the Tobit model (Tobin 1958) for our analysis. After calculating the correlations among independent and control variables, and observing acceptable levels of correlation (i.e., maximum correlation less than 0.47), we fitted the Tobit regression model. The results are summarized in Table 2.

Table 2. Tobit Regression Model of Tardiness of ECO's

	Variable	Model
Organizational factors		
	average degree centrality of engineers	0.037**
Task factors		
	average centrality of subsystems	-0.093
	number of people	0.197**
	number of parts	0.053
	fraction of new parts	0.079**
	R^2	13.8%
	adj R^2	13.4%
	F	9.975**
	n	102,032

*p <0.1, **p <0.05, ***p <0.01

Note that average degree centrality of engineers is significant and has a positive coefficient. This supports Hypothesis 2, suggesting that ECO's involving engineers with a high average centrality tend to experience greater tardiness than ECO's involving engineers with low average centrality. Not surprisingly, the number of engineers associated with an ECO and fraction of new parts are also significant and positively correlated with ECO tardiness. However, number of parts and average centrality of subsystems are not significant.

The results of this section temper the observation of the previous section that increasing connectedness in the coordination network improves performance. While increasing degree centrality of an engineer does reduce the number of problematic ECO's he/she generates (good for performance), it also increases the time required to resolve them (bad for performance). The managerial implication is that simply adding engineers to distribution lists is unlikely to improve overall efficiency of the vehicle development process. However, as we will see in the next section, targeted changes in the distribution lists may improve end product quality without sacrificing efficiency.

4. Product Quality

We now turn to the other major performance metric for the product development process—quality of the end product. As a proxy for quality we use warranty incidents. We first examine the effect on this metric of the position of the subsystems in the product architecture network. Then we look for mismatches between the coordination network and the product architecture network, and evaluate these as predictors of quality problems.

4.1. Impact of Product Architecture on Product Quality

In the previous section, we observed that highly central subsystems tend to generate more ECO's than peripheral subsystems. So one might expect these central subsystems to also result in more warranty claims. But this neglects the effect of engineering and management attention. Highly central subsystems are so heavily connected to other subsystems that we can expect them to receive intense attention from the organization. While these subsystems may require many ECO's as part of their design process, we would not expect them to be allowed to reach the field with problems that could/should have been corrected. In contrast, peripheral parts are intrinsically less complex to develop and hence should not experience quality problems in the field, despite not receiving the attention of the central subsystems.

This leaves subsystems of intermediate centrality. With neither the intense scrutiny of the highly central subsystems, nor the relative simplicity of peripheral parts, these intermediate subsystems could present potential troublespots. This reasoning leads us to the following:

Hypothesis 3. *End quality of a product subsystem has an inverted U relationship with the degree centrality of that subsystem*

4.1.1. Analysis To construct a model with which to test this hypothesis, we use warranty claims data aggregated from roughly 17,000 unique problem codes up to the subsystem level. We examined 13 vehicle programs, with 243 subsystems in each, giving us a total of $n = 243 \times 13 = 3,159$ observations. Each of the 13 programs corresponded to a 2005 model designed in the US and sold solely to US customers. For each of these we had 12 months of warranty claims. Our client uses *IPTV* (incidents per thousand vehicle) as their metric for assessing warranty issues. Therefore, we made use of IPTV corresponding to each subsystem as our dependent variable.

To test Hypothesis 3, we used *subsystem degree centrality* from the product architecture network as our primary independent variable. However, to look for a (non-linear) U-shaped relationship, we also included the square of this variable. A positive coefficient for the linear variable and a negative coefficient for the squared variable imply an inverted U-shaped relationship between degree centrality and IPTV.

As control variables, we included the number of problematic ECO's and the fraction of new parts (relative to the previous model year) in a subsystem. The rationale for the former is that internal quality problems could lead to external warranty issues. The latter is included because we would expect to experience more quality problems with new parts than old ones.

4.1.2. Results and Insights After checking the bivariate correlations between the independent and control variables and observing correlations at tolerable levels (less than 0.41), we used ordinary least squares (OLS) regression to test Hypothesis 3. We note that subsystem degree centrality is significant for both the linear and quadratic terms. Since the coefficient is positive for the linear term and negative[1] for the quadratic term, these results support the inverted U-relationship of Hypothesis 3. We also note that, both the number of problematic change orders and the fraction of new parts are significant and positively correlated with the number of warranty claims, as expected.

[1] Note that coefficient -0.00000249 is multiplied by the squared degree centrality, which is as large as 8×10^6. Thus although the coefficient is small, it has a significant impact on the U-shape of the model.

Table 3. OLS Regression Analysis of Warranty Incidents For Product Subsystems

Variable	Model
subsystem degree centrality	0.0215***
subsystem degree centrality squared	-0.00000249***
number of problematic ECOs	0.03342***
fraction of new parts	0.06173**
R^2	17.2%
adj R^2	16.9%
F	68.24***
n	3,159

*p <0.1, **p <0.05, ***p <0.01

The positive correlation between problematic change orders and number of warranty claims establishes a clear association between design quality and final product quality. Subsystems for which we observe a high number of problems during design are the very subsystems that result in a higher number of warranty incidents. The implication is that rework via ECO's fixes some problems, but not all of them. Since some design problems reach the marketplace and lead to warranty claims, management efforts to reduce design rework will both speed the vehicle development process and improve vehicle quality.

4.2. Impact of Coordination Deficit on Product Quality

The above results showing that intermediate centrality subsystems exhibit higher defect rates, support our conjecture that central subsystems get sufficient attention, while peripheral subsystems do not need it. In this section, we examine more directly the relationship between the amount of attention given to individual subsystems and the resulting product quality. This line of research is in the spirit of the work of Henderson and Clark (1990), who established a relationship between product architecture and design organization, and pointed out the importance of matching team interfaces to technical interfaces. Our objective is to identify subsystems where the amount of coordination between design engineers is insufficient to support the extent of interconnectedness in the product structure.

4.2.1. Analysis To perform the analysis, we define a metric called *coordination deficit*, which measures the extent to which organizational coordination falls short of product connectivity. To compute this metric, we used the product architecture network from the previous section, where links represent the relative weight of connections between subsystems. To construct a corresponding organizational coordination network, we identified the subsystems associated with each engineer as indicated in the ECO data set which includes all three types of ECO's. Note that an engineer may be associated with more than one subsystem, while a subsystem always involves more than one engineer. We then used the distribution list data to count the total number of links from all engineers associated with subsystem i to all engineers associated with subsystem j.

More formally, we let W^A and W^C represent the product architecture and coordination networks, respectively, where $W^k = [W^k_{ij}]$, and W^k_{ij} represents the weight of the link between nodes i and j in the network $k, k = A, C$ We then define $A_{ij} = W^A_{ij}/(\sum_{i,j} W^A_{ij}/2)$ and $C_{ij} = W^C_{ij}/(\sum_{i,j} W^C_{ij}/2)$ so that A_{ij} (so that C_{ij}) represents the proportion of total links from subsystem i to subsystem j in the product architecture (in the coordination) network. Finally, we define β_i as the coordination deficit for node (subsystem) i as

$$\beta_i = \sum_j \max\{A_{ij} - C_{ij}, 0\} \tag{1}$$

Note that we have included only links where $A_{ij} - C_{ij}$ is positive (i.e., the connection between nodes i and j is stronger in the product architecture network than in the coordination network) in order to capture under-coverage of linkages within the product. Since problems from lack of coordination cannot be reduced below zero, we would not expect excess coverage along one link to offset inadequate coverage along another. Hence, we omit links where $A_{ij} - C_{ij}$ is negative. We illustrate these calculations for a subset of the nodes in the vehicle development system in Figure 3.

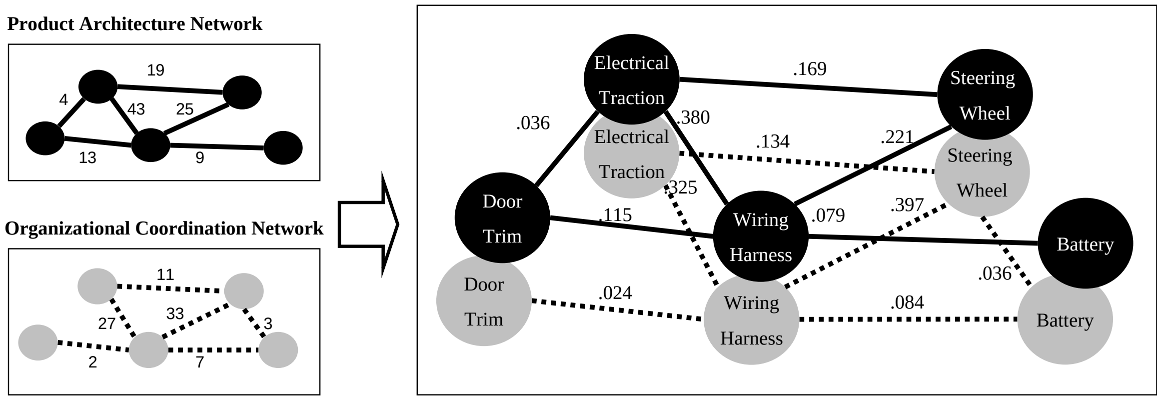

Figure 3 **An example of calculating coordination deficit for a subset of nodes**

Figure 3 illustrates the coordination deficit metric. In this example, the Wiring Harness subsystem has four links in the product architecture network, with weights of 13, 43, 25 and 9, to other subsystems (see Figure 2). Since the total weight of all the links in the network is $4 + 19 + 13 + 43 + 25 + 9 = 113$, these links represent the following fractions of the total: 0.115, 0.380, 0.221, 0.079. In the organizational coordination network, the Wiring Harness subsystem has four links to Door Trim, Electrical Traction, Steering Wheel, and Battery, respectively, with weights of 2, 27, 33, and 7. These represent the following fractions of the total: 0.024, 0.325, 0.397 and 0.084. For each link, we compute the difference between the fraction of weight in the product architecture network and the fraction of weight in the organization network (inserting a zero if this difference is negative). This yields a coordination deficit for the Wiring Harness subsystem of $(0.115 - 0.024) + (0.380 - 0.325) + 0 + 0 = 0.146$. Once we have computed coordination deficit for all subsystems, we can use it as an independent variable in our model.

Following the logic we used to derive Hypothesis 3, we conjecture that higher coordination deficit will lead to more quality problems. Hence, we make the following hypothesis:

Hypothesis 4. *Quality of a product subsystem is negatively correlated with coordination deficit of that subsystem.*

We again used IPTV (incidents per thousand vehicle) as the dependent variable. In addition to coordination deficit, which is the main independent variable in this model, we included the number of problematic ECO's and the fraction of new parts in a subsystem as control variables, similar to Section 4.1.1.

4.2.2. Results and Insights After checking to makes sure that correlations between the independent variables were acceptable (less than 0.41), we ran the regression to generate the results in Table 4. As in the previous model, both the number of problematic change orders and fraction of new parts are significant and positively correlated with the number of warranty claims. More importantly, we note that the coordination deficit is also significant and positively correlated with the number of warranty claims.

Table 4. OLS Regression Analysis of Warranty Incidents For Product Subsystems

Variable	Model
number of problematic ECOs	0.02935***
fraction of new parts	0.04898**
coordination deficit (β)	2.9161**
R^2	15.9%
adj R^2	15.6%
F	47.56***
n	3,159

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

This result is of direct managerial importance. Unlike the observation of the previous section, which noted that, in general, subsystems of intermediate centrality are prone to quality problems, this result pinpoints the specific subsystems likely to present quality issues. It also directly suggests an improvement strategy. By adding appropriate people to the distribution lists for key components within the potentially problematic subsystems, management can reduce or eliminate coordination deficits. Our result indicates that this would reduce the number of future warranty claims.

However, as we noted in Section 3.2, adding coordination links may slow the vehicle development process by adding delay to the time required to close ECO's. Our coordination deficit analysis also indicates that subsystems for which sum of link weights in the coordination network exceeds sum of link weights in the product architecture (which implies a *coordination excess*) can have some names removed from distribution lists without increasing coordination deficit. Hence, by judiciously selecting names to add and names to remove, management can better align the engineering organization to the vehicle architecture without increasing the total amount of coordination effort required of the engineers.

5. Predictive Power of the Model

The results of the previous section showed that warranty incidents are positively correlated with coordination deficit. However, since R^2 is quite low, the model is not an accurate predictor of the number of warranty claims to expect. But numerical accuracy is not necessary for the model to be managerially useful. What matters is that the model correctly identifies the subsystems that are likely to be most problematic from a quality standpoint.

Table 5. OLS Regression Analysis of Warranty Incidents For Product Subsystems using 12 Vehicle Programs

Variable	Model 1
number of problematic ECOs	0.02743***
fraction of new parts	0.05113**
coordination deficit	2.8159**
R^2	15.7%
adj R^2	15.4%
F	43.12***
n	2,916

*p <0.1, **p <0.05, ***p <0.01

To provide a test of the predictive power of the model, we took the data for 13 separate vehicle programs and used 12 of these programs to fit the model (see Table 5). Then we used the resulting model to predict the ten most problematic subsystems for the remaining program (the mid-sized car program).

Table 6 shows the ordinal ranking of the ten actual and predicted subsystems with the highest number of warranty incidents. Note that seven of the top ten subsystems were correctly identified by the model. Hence,

Table 6. Actual and Predicted Warranty Claims for the Mid-Sized Car Program

Actual Warranty Claims (Based on available data)	Predicted Warranty Claims (Based on our Regression Model)
Engine	Wire Harnesses
Front Brake Corner	Engine
Rear Brake Corner	Instrument Panel Trim
Wire Harnesses	Rear Brake Corner
Engine Management	Front Interior Control
Front Side Doors	Front Brake Corner
Rear Exhaust	Rear Exhaust
Power and Ground Distribution	Front Steering
Battery	Front Side Doors
Instrument Panel Trim	Front Suspension

the statistical model is capable of flagging the subsystems likely to present quality problems and therefore more amenable to remedial action, such as reducing coordination deficit.

6. Conclusions and Future Research

In this study we have presented a series of empirical models that characterize the efficiency (measured by design rework rate and engineering change order delay) and quality (measured by warranty claims) of a vehicle development process. Our results suggest that organizational factors and product architecture have a significant impact on both efficiency and quality. In particular, we find that centrality of engineers in a coordination network reduces the number of problems in their work. This centrality, however, requires communication with peers, and other coordination activities, which tend to increase task tardiness. Hence, increasing coordination links is not an unmitigated positive. Management must make judicious use of policies that foster greater communication and coordination among design engineers, to avoid overloading their design organization and slowing its output.

We have made use of emerging tools of complex networks to characterize both product architecture (a network of components) and organizational structure (a network of people). We found that vehicle subsystems with medium levels of centrality exhibit the highest risk of generating quality problems. We postulate that because these subsystems are not as “high profile” as strongly central subsystems, they may receive less attention than needed. To investigate this conjecture more deeply, we created a novel metric, called coordination deficit, which captures the mismatch between product architecture and organization structure. We showed that coordination deficit is significantly correlated with the number of warranty claims. This result provides a means for management to pinpoint architectural areas that are receiving insufficient attention by the organization and are consequently at risk of quality problems. We also showed that the resulting model that makes use of coordination deficit can predict with reasonable qualitative accuracy which subsystems are likely to present the most quality issues.

This work could be extended in several directions. First, our research exclusively relied on archival (e.g. ECO, warranty) data. While this is of substantial practical use, since it captures formal connections, it leaves out informal connections, such as communication outside the channels indicated by the distribution lists. Hence, a complementary study could make use of surveys or email/phone records to characterize informal communication for use as an additional predictor of efficiency and quality performance.

A second dimension along which our model could be refined is the granularity of the product data. We have performed our analyses at the subsystem level. This was largely due to the fact that our client only had warranty claims data at this level. But if we could obtain warranty claims at the part level, we could perform a much more detailed analysis of the impact of coordination deficit on product quality. Our expectation is that this would facilitate much more precise matching of the organization structure to product architecture. It would also enable more accurate prediction of potential quality troublespots.

Finally, we note that the ultimate managerial purpose of this type of analysis is to better adapt the design organization to the products being developed. Our results provide an approach for identifying gaps between organization structure and product architecture. But we have only analyzed vehicle programs for one model year. To get a deeper understanding of how vehicle architectures evolve over time and where the organizational coordination practices lag behind product changes, it would be useful to perform a longitudinal study. Such an analysis would represent an important step in the use of complex network methods to further the science of product development.

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