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ORIGINAL PAPER

Why the quantification of modularity effects remains an issue for modular product families

Jakob Meinertz Grønvald[1] · Morten Nørgaard[1] · Carsten Keinicke Fjord Christensen[1] · Niels Henrik Mortensen[1] · Alberto Urueña[2]

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Abstract

This study examines the challenges regarding the quantification of modularity effects, focusing on data quality, availability, and management practices within four industrial production companies in Denmark. While the literature identifies many effects of modularity, a substantial gap persists regarding data availability and quality for accurate and practical quantification. This study reveals that less than half of the modularity-related effects have sufficient data for analysis. Furthermore, critical data such as bill-of-material have observed frequent inconsistencies with far-reaching consequences that further undermine data reliability. Silo effects also hinder knowledge sharing and limit holistic assessments of modularity effects. Traditional cost accounting methods often overlook indirect costs, leading to underestimations of modularity's economic impact, while this study finds that even direct costs lack accuracy and consistency. The results in this paper imply that the Danish industry, and likely other sectors too, may benefit from more rigorous data practices, including tracking time expenditures in overhead departments, to facilitate modularity quantification. Future research may include how accounting systems impact data management, developing structured data management frameworks, including artificial intelligence, to enhance data quality, improve quantifiability, and encourage knowledge sharing within and across departments. Ultimately, these advancements would support informed, data-driven decisions regarding modular product development and support bridging the gap between research and successful industrial application.

Keywords Modularity · Data-driven design · Life cycle analysis and design · Decision support · Data quality

1 Introduction

In an age of artificial intelligence (AI) and big data, why is the quantification of modularity effects still an issue for modular product families? The modularization of product portfolios comes with many documented benefits, and though it has some broad implementation in the industry, it has not been without its fair share of resistance [1]. Many reasons have been proposed to answer why, but the lack of quantifiable evaluations of the effects of modular product families and platforms might seem to be a foundational one [2].

There seems to be great difficulty convincing decision-makers of the benefits of reduced indirect cost when compromising direct cost [3]. This may be due to the difficulty of properly quantifying or measuring the expected gains or savings using conventional methods [4], as traditional accounting schemes often favor expensive specialized designs due to distorted cost-carrying figures [5]. If the total savings and gains cannot be properly quantified, how can

[z,2] Corresponding author.

✉ Jakob Meinertz Grønvald
jamgr@dtu.dk

Morten Nørgaard
mornor@dtu.dk

Carsten Keinicke Fjord Christensen
ckfjch@dtu.dk

Niels Henrik Mortensen
nhmo@dtu.dk

Alberto Urueña
alberto.uruena@upm.es

[1] Department of Civil and Mechanical Engineering, Technical University of Denmark, Koppels Allé, 404, 207, Kgs. Lyngby 2800, Denmark

[2] Department of Industrial Engineering, Business Administration and Statistics, ETSI Industriales, Universidad Politécnica de Madrid, Calle de José Gutiérrez Abascal, 2, Chamartín, Madrid 28006, Spain

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decision-makers be persuaded? There is a need for a holistic framework to evaluate all the effects of modular product development and quantify these effects in monetary terms. This need is emphasized by research showing that decisions made in product design can account for up to 70% of a product's life cycle cost [6].

Many researchers have made great efforts to identify relevant effects of modularity, but they often focus on a few specific parameters rather than adopting a holistic perspective [7]. Likewise, many metrics have been identified to evaluate platforms, but only a few – and most still reliant on qualitative measures - have attempted to combine them into a holistic framework for proper evaluation [8]. Some attempts have been made to develop holistic frameworks for evaluating the benefits and consequences of modular product development solely using quantitative measures, but broad applicability in the industry remains to be seen [9].

After reviewing the literature on the subject, an underlying and underappreciated factor came to light. Many studies and evaluation schemes appear to run into issues due to a lack of detailed information and data. Often, researchers compensate by relying on experienced opinions. However, key questions arise: Which quantitative data are actually available in the company? Which data are measured? Which areas offer the greatest potential for impactful insights when evaluating modularization effects?

These questions shed light on an overlooked topic in modularity research. The answers presented in this paper may prove useful in future research. They might provide some guidance in the design of new evaluation schemes and provide insights into when data availability can or cannot be expected. Such foundational knowledge may also prove useful for the construction of large data models using AI, for instance. In addition, observations regarding specific behavioral patterns and data management practices – such as inconsistencies in bill-of-materials (BOMs) and silo effects observed in this study – may be useful for other companies and may also be fruitful areas of research in the future.

This paper presents findings from the literature on the effects of modularity and product variety, how these effects may be evaluated, and what challenges the existing evaluation methods may experience. To address a fundamental challenge for these methods, data availability was analyzed in a sample of companies consisting of three SMEs and one larger corporation. These companies are part of a larger research project called AIMO (AI-Supported Modular Design and Implementation Project), which aims to study a sample representative of the Danish industry. According to [10], two out of three companies in Denmark are small- and medium-sized enterprises (SMEs), defined as having less than 250 employees.

A total of 113 interviews have been conducted across the case companies to study their processes, data flows, data management practices, and databases, in order to determine their data availability. The findings reveal that less than half of the effects found in the literature have data available for quantification. Additionally, the available data may be less useful than the literature commonly indicates. Finally, if the bulk of effects are to be quantified in any company, time expenditures in overhead departments may need to be considered. This paper aims to support bridging the gap between research and industrial application by investigating a possible root cause of why the quantification of modularity effects remains an issue for modular product families.

2 Methodology

This study consists of two main parts: a literature review and a case study. The literature review takes its offset in previous literature studies, doctoral theses, and books addressing the effects of variety and modularity and their economic evaluation [2, 4, 5, 7, 8, 11–18]. These sources laid the foundation for defining the search strings used in Web of Science and Scopus. The initial search applied the following Boolean string:

TITLE-ABS-KEY("complexity cost" OR "complexity costs" OR "product complexity costs" OR "variety induced complexity" OR "complexity assessment" OR "product architecture costing" OR "quantification of product complexity" OR "modular product families" OR "modular product platform" OR "product modularity" OR "product platform development" OR "impact model" OR "extended impact model" OR "platform assessment matrix" OR "component part commonality" OR "design commonality" OR "commonality opportunity").

The search was restricted to peer-reviewed journal articles, conference papers, and review papers written in English, and limited to the subject areas of engineering, business, economics, and operations management. This search yielded a total of 8,766 publications across the two databases. The search results were restricted to publications from 1990 to 2024, ensuring contemporary relevance. Subject areas were limited to Engineering (ENGI), Business (BUSI), Economics (ECON), and Decision Sciences (DECI) to focus on fields aligned with modularity, product architecture, and complexity-cost research. Only scholarly and peer-reviewed document types were included—articles, conference papers, books, reviews, conference reviews, etc.—to ensure academic quality and methodological transparency. After filters were applied the search result was reduced to 2,729 sources. Titles were screened for relevance, resulting in 337 papers selected for abstract review. After screening, 173 references were excluded because they did not address the identification or quantification of the effects of product modularity or complexity, nor the challenges and barriers associated with these topics. Works focusing solely on specific methodologies for modular product development, or those unrelated to modularity research, were also excluded. Following full-text screening, 24 studies were included from this search.

To mitigate the risk of missing relevant contributions, supplementary searches were performed using backward and forward citation tracing of the included works, as well as targeted searches based on known key authors and references identified through conference participation and professional contacts. This iterative process ensured that both seminal and recent contributions were captured, and that the literature base reflected the full spectrum of research on modularity effects, product complexity, and their implications across the value chain. In total, 76 references were ultimately included in this paper.

The literature reviewed revealed that the effects of modularity and variety are well established. What is lacking is the quantification and holistic assessment of these effects so that the overall profitability of modularity may be investigated properly. In the works by [7, 9, 19], the impact model of modular product families (IMF) was developed and validated on a qualitative basis. The IMF presents over 70 effect chains derived from the five generic design properties of modularity [20], as described in [9]. In combination with additional effects found in the literature reviewed for this paper, the effects found in the IMF lay the foundation for the analysis presented. These effects are shown in the results section from Tables 3, 4, 5, 6 and 7 according to the life cycle phases in which they occur. For this paper, similar effects have been combined, while other effects have been removed if their monetary effect would be a sum or result of other effects. For example, the monetary effects of the increased reuse of designs cannot be measured in reuse itself but through other effects derived thereof, such as the reduction in setup changes and larger lot sizes in purchasing. The IMF has been quantitatively validated by [21], though mainly in large corporations. According to [22], nine out of 10 companies in the European Union are SMEs. Thus, one might argue that it is important to investigate what options exist in this setting. Additionally, only a few studies point to data availability as one of the main barriers or bottlenecks to implementing modular product structures [1, 5]. Therefore, the case study aims to investigate the data available for quantifying the effects of modularization in monetary terms using a different sample of case companies [23].

In these case companies, workflows throughout the value chain were examined through semi-structured interviews [24] with relevant personnel from various departments, including sales, engineering, research and development (R&D), production, supply chain management, delivery, installation, after-sales services, and accounting. Interviews were conducted with employees at all organizational levels. During each interview, the interviewee would describe the activities they conducted both in a general order flow setting and in specific cases involving particular orders or projects (see Table 1). They were asked to explain which data they generated, handled, or transferred in their daily work, and which systems or databases supported these processes. This approach made it possible to map company-specific data flows across departments, identify existing data sources at different life cycle stages, and determine where gaps or inconsistencies occurred. The identification of available data sources was carried out in close collaboration with company representatives, who provided detailed knowledge of their respective IT systems and data structures. Consequently, the classification of data availability was based on mutual agreement with the participants, and no discrepancies were observed between respondents within each case company.

Hundred and thirteen interviews (each between 45 and 75 min) were conducted with 69 people (In Table 1 some positions are held by the same person and for some positions multiple people were interviewed). The interviews provided a comprehensive understanding of day-to-day operations and validated findings from the database investigations by clarifying how recorded data were actually used in practice. Together with the review of IT systems and supporting databases—including product data such as bills of materials (BOM) and computer-aided design (CAD) models (see Table 2) —these insights enabled a detailed understanding of the relationship between data availability, data management practices, and the quantification of modularization effects. In this study, data are deemed available for an effect if relevant information could be located in the companies' SQL databases, IT systems, or shared folder structures, and was maintained in a form that allows potential quantification for the existing product portfolio.

The companies selected for this study are three SMEs and one larger enterprise in Denmark from across various industrial sectors and span a broad range in size and complexity regarding both their organizations and products. All four companies have already investigated or are investigating how to implement modular product structures into their portfolio. Two companies are ETO (product design is finalized after an order is placed [25]), one is primarily MTO (production starts after an order is placed [26]), and the last is CTO (product design finalized when an order is placed from pre-defined options [27]). They manage their entire value chains, including sales offices, production sites, suppliers, and customers domestically and internationally. Moreover,

Table 1 Overview of interviews, participants, objective, etc. For companies, A, B, C, and D

Position	No. Of Int. in Co.				Objective (I/O = data input/output)
	A	B	C	D	
CEO		2	1		Understand company objectives, strategy, and challenges
CTO		1			Explain general order/workflow, challenges, and department interfaces
Head of Sales	1	1	2	1	Explain general order/workflow, challenges, strategy, and department interfaces
Sales Representative	3	3		3	Explain order/workflow activities (general and specific), data flow, and I/O
Project Manager	1			2	Explain project flow, external/Internal requirements, data flow and I/O
Head of Mechanical Engineering	1	2		2	Explain general order/workflow, challenges, department interfaces, and verification of results
Modular Architect				5	Understand product structure and strategy
Product Manager			3	5	Explain order/workflow activities (general and specific), strategy, data flow, and I/O
Product Manager Technical				7	Understand product sustainment cost
Mechanical Engineer	4	3		1	Explain order/workflow activities (general and specific), data flow, and I/O
Head of R&D			3	3	Understand challenges, department interfaces, development strategy, and verification of results
R&D Project Manager			2	2	Explain order/workflow activities (general and specific), data flow, and I/O
R&D Engineers			2		Explain order/workflow activities (general and specific), data flow, and I/O
Head of Automation	1				Explain general order/workflow, challenges, and department interfaces
Software Architect				2	Understand software structure and strategy
Software Lead				1	Explain general order/workflow, challenges, and department interfaces
Electrical Engineer				1	Explain order/workflow activities (general and specific), data flow, and I/O
Software Engineer				2	Explain order/workflow activities (general and specific), data flow, and I/O
Systems Engineer				1	Explain order/workflow activities (general and specific), data flow, and I/O
Head of Production	1	1	2	1	Explain order/workflow activities (general and specific), department interfaces, data flow, and I/O
Production Engineer	2			2	Explain order/workflow activities (general and specific), data flow, and I/O
Head of Procurement	1	1	1	1	Explain order/workflow activities (general and specific), department interfaces, data flow, and I/O
Head of Sourcing				1	Explain general order/workflow, challenges, and department interfaces
Purchaser	1				Explain order/workflow activities (general and specific), data flow, and I/O
Head of Quality				1	Explain general order/workflow, challenges, and department interfaces
Head of Order Handling				1	Explain general order/workflow, challenges, and department interfaces
Head of Installation and Service	1	1			Explain order/workflow activities (general and specific), data flow, and I/O
Head of Spare Part Sales	1	1			Explain order/workflow activities (general and specific), data flow, and I/O
Head of Accounting	1		1		Explain current accounting practices, challenges, and data I/O
Accountant		1			Explain current accounting practices, challenges, and data I/O
Head of IT	3		3		Identify relevant SQL Tables and data management practices
Production Technologist			5		Explain order flow (general and specific), data flow and I/O, IT system interfaces, data practices, architecture, department interfaces, and verification of results
Configuration Specialist			2		Explain order/workflow activities (general and specific), data flow, IT system interfaces, data practices, architecture, and I/O
IT Solutions Provider		2			Identify relevant SQL Tables and data management practices

the companies rely heavily on engineering competencies, dedicating substantial resources to support product design and development. This description portrays companies with relatively high organizational and product complexity, where overhead costs become pronounced enough to make modularization initiatives relevant [8].

3 Literature review

The literature review is structured to progressively address three interrelated aspects of modular product development. First, it identifies the effects of modularity and product variety described in existing research, illustrating how these effects extend across the value chain and often manifest within indirect cost pools. Second, it discusses the inherent challenges and trade-offs that make such effects difficult to quantify—particularly the limitations of traditional accounting systems and the interdependencies inherent to modular product architectures. Third, it examines existing models and tools developed to evaluate modularization effects, assessing their capabilities and limitations in achieving reliable, data-driven quantification. These three subsections are designed to move from what is known about modularity's effects, to why quantification remains problematic, and finally to how existing approaches attempt—but often

Table 2 Description of case companies and data sources included in the study

	Company A	Company B	Company C	Company D
Sector	Heavy Machinery	Waste Management	Construction	Defense
Product type	Manufacturing equipment for asphalt and concrete	Mechanical waste compression machinery	Ventilation aggregates	Radars and other systems for defense related equipment
Main manufacturing principle	Engineer-to-order(ETO)	Make-to-order (MTO)	Configure-to-order (CTO)	ETO
Employees	151	41	185	1704
Data sources	Project folders (CAD, BOM, Sales doc.), ERP, sales logs, purchase logs, production logs, warehouse logs, pre- and post-calculations of projects	Product data (CAD, BOM, Sales doc.), ERP, sales logs, purchase logs, production logs, warehouse logs, pre- and post-calculations of orders	Configurator data (CAD, BOM, other product doc.), ERP, sales logs, purchase logs, production logs, warehouse logs, pre- and post-calculations of orders	Product data (CAD, BOM, etc.), ERP, sales logs, purchase logs, production logs, warehouse logs, pre- and post-calculations of orders, CRM data

fail—to address these issues. Together, these subsections provide a structured overview of the current state of knowledge and highlight the persistent difficulties in translating modularity's effects into measurable economic outcomes. The findings from each subsection are summarized before diving into the case study analysis.

3.1 The effects of modularity

Modularity has been described and defined in many ways by many authors throughout the years. While a universally accepted definition of the concept is difficult to reach, there is a common understanding throughout the literature: The grouping or clustering of functions into modules with standardized interfaces, allowing them to be used and shared across multiple product variants within a product platform, family, or architecture. The most prominent benefit of doing so is the reduction of internal complexity while still delivering a high external variety to the market [28].

Increasing variety will initially improve sales as the company's portfolio becomes more attractive to customers [2]. However, the increase in product complexity will also affect the entire value chain from increased quotation times in sales [11], increased documentation and part management in construction [7], increased setup changes in production [29], and worse purchasing conditions in procurement [18] to expensive spare parts inventory and tools investment in service and maintenance [17]. Furthermore, variety impacts product quality [30], lead times [31], learning curves [18], economies of scale [32], automation possibilities [33], and much more [32]. It is observed in the literature that variety influences all types of costs across all life cycle phases. This means that if the complexity cost is broken down into single cost objects, there is a risk of underestimating it [4].

According to [4], lowering the internal complexity of an organization through modularization will turn the negative cost effects of variety positive – at least on a qualitative basis. Jiao et al. [2] further found that if added variety falls within the range of the defined product family, then it has no additional complexity cost. The positive effects of modularization include reduced development risk [2], inventory holding cost [34], and documentation efforts [7], as well as increased predictability in planning [17], product and process quality [35], flexibility [36], and responsiveness [37]. In the work by [7, 9], over 70 effect chains (positive and negative) were identified as derived from or caused by the five generic design properties of modularity identified by [20], namely commonality, combinability, loose coupling, interface standardization, and function binding. An overview of all effects found in the literature can be seen in Results. The benefits gained through modularity are largely reductions in overhead cost pools [29].

The problem with indirect and overhead cost pools is that they are, by definition and in opposition to direct cost, difficult and impractical to allocate directly to product variants [38]. Despite the subtle differences in the definition of indirect and overhead costs, they will be used interchangeably in this article. They are commonly allocated evenly across product variants, even though indirect costs are actually distributed so that high runners attract the least amount of cost and slow runners the most [39]. Furthermore [5], found that the amount of overhead resources products consume also depends on how technically complex they are. They argued that technically complex products may demand more time in overhead departments (sales, engineering, etc.), and traditional cost accounting does not make this obvious. Consequently, this may decrease the likelihood that sales prices account for the increased overhead costs, leading to poor decision-making. It is reasonable to extrapolate that this will favor expensive special designs, as they seemingly create the highest profits, though the reality may be entirely different [5]. In that sense, traditional accounting systems act as barriers to the implementation of modularization initiatives [29]. In summary, the literature establishes that modularization can transform the negative cost impacts of product variety into positive ones, primarily through reductions in overhead and indirect cost pools. However, because these cost categories are difficult to trace and allocate accurately, their quantification remains a persistent challenge—an issue further explored in the following subsection.

3.2 The challenges of standard models

In their book, Cost-Efficient Design [5], described the economic activities of a company as a black box with resources and associated costs coming in and products and associated revenue coming out with the objective to maximize their difference (i.e., the profit) as its optimal measure of success. Cost accounting is described as the activities within that black box. This analogy seems to be rather fitting in the case of indirect cost. The box is truly black and untransparent, and one might argue that it can only be illuminated if the inputs and activities within are clearly defined. Traditional accounting systems will usually have detailed data on the direct cost for each product but will evenly spread the indirect cost as a fixed percentage across the portfolio. According to [2], this will create distorted cost-carrying figures.

Some cost accounting methods may help shed more light on the quantification and allocation of indirect costs, such as activity-based costing (ABC) or its variant, time-driven ABC [40]. These methods have been used in previous work with some success as seen in [28, 30, 41], though [2] criticized both traditional accounting and ABC, arguing that these methods have issues properly supporting the separation of cost elements. In their view, traditional accounting is especially ill-suited to estimate the true economic consequences of design decisions throughout the value chain [2]. Hence, many decisions are made based on production cost alone, as the conventional approaches cannot measure the impact of other effects [4]. Another challenge of cost accounting is that every company uses its own costing schemes, which vary greatly in the extent and content of their cost accounting, and especially smaller companies often rely on incomplete accounting systems [5].

In traditional accounting systems, cost responsibility often falls on departments, teams, or individual projects, making it difficult to track cross-project cost savings like from modularization [5]. Many companies use accounting systems that focus on individual projects or product variants' performance, where common components may have different costs than unique ones, benefiting some projects and disadvantaging others [29]. When such a single-product mindset is used instead of considering the entire product family, there is a monetary disadvantage to modular products, as previously described.

Another factor as to why the cost effects of modularization are hard to quantify was described in [29]. They argued that at least four categories of cost cannot be determined in general due to opposing factors. First is the unit cost impact, as oversizing consumes more materials and labor, but this may be mitigated through economies of scale (i.e., procurement discounts and learning curve effects). Second, there are batch cost effects. They argued that more technically complex modules may demand more setup and test costs, but these may be moderated by fewer total batches since fewer subassembly variants need to be produced. Third, modular product development has an extra upfront investment cost due to more design efforts, though this may be mitigated by fewer modules designed. Lastly, they argued that there is an information cost in determining the module options and cost estimates.

Other tradeoffs have also been described in the literature. Modularization is often described as lowering safety stock levels and, thereby, holding cost, but it also increases material cost, which holding cost is dependent on [28]. Thyssen et al. [28] further noted that the cost of support activities (design cost, procurement overhead, production overhead, quality cost, and after-sales service cost) may be reduced because they are called upon fewer times. However, again, due to overspecification and increased technical complexity, they might be more expensive each time they are called. In addition, there is a tradeoff between the lost revenue from product cannibalization due to increased commonality and the cost savings from commonality [2]. Furthermore, the effects of variety and commonality are product- and company-specific and do not seem to impact all product families to the same degree [4].

Some authors also pointed out that there is a lack of data in the development of and decision-making about modular product families, though it is often only mentioned as a side note in the discussion. However [1], pointed to this as one of two main challenges for modularization implementation success in their investigation of why modularization initiatives stall in ETO companies. Ripperda et al. [4] commented that they must exclude some effects and that they must rely on guestimates from seasoned experts to calculate the complexity cost in their case study due to a lack of available detailed information. Ehrlenspiel et al. [5] argued that poor availability of information can create bottlenecks in product development and are worsened by silo effects in a company, particularly when it comes to modularization projects [42]. From these accounts, it would seem a very foundational issue with far-reaching impact that it is not possible to describe the necessary aspects of operations and costs in a company.

It is clear that sharing modules creates cost interdependencies between participating products, affecting how companies account for the economics of individual projects within a portfolio. Simple allocations are often insufficient [29]. Most sources analyze the impact of modularity on specific cost categories, such as design and production costs, but its overall effect on profitability remains unproven [4]. Often, only individual cost factors are considered, while the full complexity cost is overlooked. Neglecting to consider the combination of all effects may lead to faulty decisions with limited credibility. In fact, many of the cost-saving benefits attributed to modularization are based on rough estimates, intuition, or subjective opinions rather than verified data [12]. Overall, the reviewed studies indicate that while traditional and activity-based costing approaches can offer partial insights, they remain insufficient to capture the full economic implications of modularization. These limitations have motivated the development of alternative models and evaluation tools, which are examined in the next subsection.

3.3 Tools to evaluate modularization effects

As the challenges with traditional accounting systems have been made clear, what proper evaluation schemes exist to assist in decision-making and to evaluate the effects of modularization? In this section, specific proposals will be investigated to better understand how the challenges described earlier have been handled by researchers.

One interesting proposal comes from [28]. They cleverly avoided calculating the expected cost of new modules by determining how much material and assembly costs can increase to break even with the average costs of the substituted modules. However, their analysis is limited, primarily focusing on inventory costs. While initially including other effects, they ultimately deemed them negligible, and they overlooked the uneven cost distribution between low-volume and high-volume variants. Additionally, they argued that internal changes to the product assortment would not cannibalize sales, but this only holds true if the features and functions of the different modules are either not what customers specify or are clearly distinct from one another.

The PAMatrix was presented in [8] is a tool applicable across industries and platforms, evaluating both pre- and post-use phases. It uses seven "views" to assess platform effects, categorized into two groups: platform effects on surroundings and vice versa. These views are qualitatively graded, which introduces uncertainty, as noted in [8]: "*A score of −1 for one stakeholder*, *might be a −3 for another*, *without them actually disagreeing in the platform evaluation*." Using monetary values could reduce uncertainty regarding users' subjectivity. Furthermore, the framework also relies on users' prior knowledge of modularity's effects, requiring them to evaluate their impact on each value chain step. This may not be realistic, as decision-makers might lack broad knowledge of modularization effects. Additionally, the framework's scope is limited by the user's expertise.

Weiser et al. [34] also relied on seasoned personnel to conduct their quantification of complexity cost. In their methodology, personnel from each department are asked to evaluate the effects of complexity during the early product development phases. The more experienced the employee is, the better the estimates they can provide, and though this may be true (if the employee also has a deep understanding of the effects of variety), it does become a rather costly approach if the manager or other senior staff of each department is to be included in every product development project. Additionally, the estimates will still suffer from uncertainties, as they will most likely be guestimates in practice unless detailed and relevant information and data are available.

Other authors have used decision support tools like the analytical hierarchy approach [43]. This tool has the benefit of being compatible with both quantitative and qualitative inputs and relies only on what sort of data is available to determine the values of chosen decision criteria. Again, the user will need a deep understanding of modularity and complexity to holistically evaluate alternatives when choosing decision criteria. Siddique et al. [44] developed the Product Family Architecture Index, which is the weighted sum of six modularity properties: materials, variety, manufacturing, late-point differentiation, assembly, and commonality. Each property is scored on a 0 to 1 scale. While this approach is interesting, it only accounts for material costs.

Another line of research has focused on developing structural indicators to evaluate the degree of modularity and standardization within product architectures. Among these, two widely recognized measures are the Product Commonality Index (PCI) proposed by Kota et al. [45] and the Generational Variety Index (GVI) developed by Martin and Ishii [46]. The PCI assesses the extent to which non-differentiating components are standardized across a product family by comparing geometry, materials, manufacturing processes, and fastening schemes, thereby indicating the level of achievable commonality. The GVI, in contrast, estimates the redesign effort required for future product generations by identifying components most sensitive to changing customer or engineering requirements based on inputs from relevant employees or product experts. While both indices provide valuable insights into architectural robustness and potential improvement areas, they primarily capture structural rather than economic effects of modularization. Consequently, they serve as useful complements to—but not substitutes for—data-driven approaches aimed at quantifying resource consumption and cost impacts of modularity.

As mentioned previously [7], developed an impact model called the IMF, and in [9], the IMF contains over 70 effect chains found in the literature. The effects found are then coupled to the five generic design properties of modularity

[20]. Furthermore, the effects are linked to the impact they may have on a company's economic objectives. These chains have been validated by a survey of eight large enterprises (above 10,000 employees) and one smaller enterprise (100–250 employees). At this stage, there are no quantifiable measures in the framework yet, and desires to enrich it with formulas are expressed in future research. It was also stated that the list of effects is not considered exhaustive.

In [21], several KPIs were added to the IMF along with different calculation methods/formulas (some clearer than others). Economic targets like time, costs, quality, and flexibility are also added to the framework, and it is possible to address different boundary conditions corresponding to the company's individual circumstances and interest areas. However, the degree to which the framework is complete with quantifiable KPIs is unclear, as they often waver back and forth between what is possible to quantify now and what will be quantifiable in the future. They finished their paper with a case study and showed a table with 19 distinct KPIs (out of 60 distinct KPIs presented). Eight of these are quantified in monetary terms, seven in units of time, and the rest as percentages. They also mentioned that some of their KPIs cannot be quantified, such as automation, effects on implementation, and process time savings in sales and marketing due to faster quotation generation, though they do not explain why. As mentioned, the IMF is validated and tested on large corporations. However, what is possible in large corporations may not be possible in SMEs [47]. The newest additions to the IMF come from [48]. They investigated the effects of personalization (customization to individual customers) in modular product architectures, and as mentioned in the article, "*the effects are mostly the same*" [48]. There is no additional contribution toward better quantifications or evaluations of the effects.

Taken together, the reviewed tools demonstrate notable progress toward structured evaluation of modularization effects, yet most remain reliant on qualitative assessments or expert judgment rather than verifiable quantitative data. This reinforces the underlying challenge identified throughout the literature: despite conceptual advances, the quantification of modularity effects continues to be constrained by data availability and methodological limitations.

3.4 Summary

By investigating the literature, it has become clear that effects from product variety have an impact on all types of costs and all life cycle phases of a product. Furthermore, the negative effects of variety can be mitigated by modularization. However, modularization impacts the direct cost of a product, and its positive effects are mostly seen in overhead and indirect cost pools. This becomes an issue since traditional accounting systems do not handle overhead and indirect costs sufficiently to account for the effects of variety, and this will often favor single-product mindsets where doing special design seems more profitable than designing product families with some degree of commonality and shared modules.

Other challenges regarding the quantification of modularization effects come from inherent tradeoffs in modular designs and interdependencies created through module sharing and increased commonality. When investigating the literature regarding the evaluation of modularization effects, it becomes clear that the challenges found by [5] and [8] almost 20 years ago remain unsolved. Most of the evaluation schemes fail to include anything other than direct production costs and rely on qualitative assessments from users who may or may not have the required understanding of the effects of variety and commonality. Only the IMF introduces quantifiable evaluations of modularity effects, though not all in monetary terms, and it has mainly been tested in large corporations, leaving the question, "What is possible in a different sample of companies?"

It seems that one challenge, in particular, does not get much attention and is often only mentioned as a side note, if at all. It seems clear to the authors that an area worth investigating is the apparent lack of available cost data to evaluate modularization effects adequately. If tradeoffs and interdependencies are to be properly investigated, there is a need for detailed information and data describing how large the individual impacts are. If the profitability of modularity is ever to be proven, then proper cost data and cost descriptions are needed. These data may need to come from many different systems, life cycle phases, and company departments. Hence, this study will investigate in four case companies which data are available for these types of calculations, and which effects are possible to quantify in these cases.

4 Results

To investigate which data are available for the quantification of modularity effects, the data and process flows of each company for all functions along the value chain and life cycle were analyzed through semi-structured interviews. Furthermore, the databases and IT systems of each company were investigated. This provides the necessary information to determine whether the data needed to quantify the modularity effects are present in the company. In the following tables, an "X" indicates that relevant data were found in the company's databases, IT systems, or shared folder structures. Furthermore, the data should be available in a form that allows the quantification of the effect in question. Some effects are denoted with a "(X)", this indicates that data is partially available. Comparing the number of Xs (including partials) and blanks gives a crude score for how large a percentage of the effects data exist for. In this article, that will be called a data availability score. The effects will mainly be referred to by their numerical ID going forward. Furthermore, the effects are separated by which life cycle phase they occur in (development, procurement, production, sales, or service and maintenance); though some effects may be relevant across lifecycle phases, they are presented here according to where the literary sources describe them. The way modularity impacts an effect is denoted by a "+" or a "-," indicating whether modularity is reported to have a positive, negative, or both positive and negative impact on the effect. This list is not deemed to be exhaustive.

In Table 3, the effects found in the product development life cycle phase are listed. Across the companies, data availability varies from 15% to 23% in product development. It is mainly the same sort of data that is available in the companies, which is mainly data from direct cost or otherwise traditional accounting schemes, relevant to effects 12, 13, 18, 19, and 20, with a few exceptions. Company C keeps track of 4 as sales figures for specific upgrades to its products, and in Company D, the cost of 15 referring to documentation is recorded both in terms of time spent per type of documentation and the number of documents for each product. However, in most cases, the necessary information is simply not available. There is no information to assess 1—the cost of outsourcing development tasks—no data for 2, 3, 11, 14, 16, 17 regarding time consumption for design-related activities, and no data on 5, 6, 7, 8 regarding risk assessments either. Effect 9 may prove difficult to define both in terms of what innovation is and in terms of the value creation of said innovation [49]. According to the interviews conducted, freedom of design, 10, may be very dependent on how much the customer is willing to pay, and there are no formalized data or policies in place in the companies.

As mentioned, data are available for effects regarding direct cost. However, the quality of the data may need to be brought into question. All the companies have issues with their BOM. The structure of their BOM varies notably, even for similar products. Parts in one order are considered parts of one subsystem, while in another order, they may be part of a different subsystem. The naming of parts and subsystems may also vary from one BOM to the next, both due to typos when staff input data into the systems and because different employees call the same things different names. This gives rise to uncertainties when estimating and comparing the direct material cost of subsystems. Furthermore, the BOMs are a central type of data that is passed on through subsequent steps through the entire product life cycle—as a specification list in sales, an engineering BOM in construction, a purchase list in procurement, a manufacturing BOM in the production, and a list of possible spare parts in service and maintenance. This implies that uncertainties and inconsistencies in the BOM have consequences in every department and every value chain step. Additionally, the companies experience silo effects not only between departments but also within departments. For instance, in the companies' engineering departments, engineers only reuse existing designs if they have done it themselves previously

Table 3 Modularity effects found in the literature occurring in the development life cycle phase

ID	Effect		Source	A	B	C	D
1	Outsourcing of development task	+	[2, 15, 21, 50, 51]				
2	Parallel development/prototyping	+	[16, 21, 35, 48, 52–55]				
3	Ease of product updating (functional modules)	+	[17, 35]				
4	Adaptability/upgradeability	+	[16, 35, 56]			X	
5	Reliability of product	+	[20, 21, 57–60]				
6	Probability of spreading error	-	[17, 19, 21]				
7	Failure rate	+	[19, 21, 32, 60]				
8	Decoupling of risk (module sharing)	+	[2, 12, 20]				
9	Product innovation	+/-	[14, 20, 21, 32, 35, 61]				
10	Freedom of design/product differentiation	-	[14, 19, 21, 35, 61]				
11	Variant derivation	+	[21, 35, 54, 57, 60, 62]				
12	Initial development investment	-	[21, 48, 60, 61, 63, 64]	(X)	(X)	X	X
13	Development cost per unit	+	[2, 4, 5]	(X)	(X)	X	X
14	Time for part search	+	[19, 21]				
15	Documentation and coordination effort	+	[17, 19, 21, 65]				X
16	Part administration	+	[8, 21, 53]				
17	Implementation of new processes	+	[17, 35]				
18	Product volume/size	-	[21, 35, 56, 61, 66, 67]	X	X	X	X
19	Product weight	-	[21, 35, 56, 61, 66, 67]	X	X	X	X
20	No. of unused features	-	[21, 35, 56, 61, 66]	X	X	X	X
Percentage of effects where data are available (data availability score):				15%	15%	23%	15%

(and if they remember doing it). There are no procedures in place within any of the companies to provide an overview of existing designs. This may be one reason for the observed variance in the BOMs, even for similar products.

Table 4 shows the effects relevant for procurement. Effects are fewer here, but data availability is also higher, scoring 44%. The data available here usually comes from traditional operations management methods. Effects 21 and 22 regarding stock levels are kept in check by ERP systems, and effects 24 and 26 regarding criteria for quantity discounts are known with their main suppliers, but only for the most commonly purchased parts and subsystems. In Companies A and B, this is especially simple, as their prices are determined per kilo of steel with set thresholds. When it comes to 23 regarding predictability, then the economic impact of forecast precision may be dependent on many variables, such as last-minute changes to production and purchase to name a few. While 25, 27, and 28 may be calculated using time-driven approaches, none of the companies utilize such practices. In this lifecycle phase, there is no data for 29 regarding risk assessments.

In Table 5, the effects impacting production are presented. Data availability is even higher here, between 44% and 69%, which might be expected, as labor hours are measured here. In general, it would seem that control is high in production departments in this sample at first glance. All companies have data on 38 regarding tool inventory from purchase logs and are, for the most part, well aware of their actual manufacturing cost regarding effects 32, 42, and 43. Furthermore, all the companies have, at one point or another, investigated or implemented some degree of automation in their manufacturing systems, giving them formalized or partial data on 39 (in Company A, this is mainly done as back-of-the-envelope calculations). They also keep track of 40—their machine utilization. Three out of four companies have data on 41 regarding setups, though this information is allocated as overhead for Company C. For Companies B and D, the data are allocated directly to the order or product. Companies C and D both have data regarding 35, as sales probabilities could be used to estimate the impact of postponement, though neither company has any formalized procedures for doing so. Effect 31 is not stored

Table 4 Modularity effects found in the literature occurring in the procurement life cycle phase

ID	Effect		Source	A	B	C	D
21	Safety stock levels	+	[2, 17, 19, 21]	X	X	X	X
22	Stock levels	+	[21, 51, 61, 65, 68]	X	X	X	X
23	Predictability	+	[21, 61]				
24	Purchasing conditions (economy of scale)	+	[21, 32, 35, 53, 60, 61, 67]	(X)	(X)	(X)	(X)
25	No. of purchase orders	+	[21, 35, 53]				
26	Purchase of prefabricated modules	+	[2, 8, 20]	X	X	X	X
27	No. of suppl./ease of suppl. management	+	[15, 19, 21, 61, 69]				
28	Repetition rate/less clarification w. suppl.	+	[19, 21]				
29	Dependency on suppl. performance	-	[17, 19, 21]				
Percentage of effects where data are available (data availability score):				44%	44%	44%	44%

Table 5 Modularity effects found in the literature occurring in the production life cycle phase

ID	Effect		Source	A	B	C	D
30	Outsourcing of manufacturing steps	+	[2, 19, 21]	X	X		
31	Parallel testing	+	[15, 19, 21, 35, 53, 71]				
32	Parallel manufacturing processes	+	[15, 19, 21, 35, 53, 71]	X	X	X	X
33	Time to start of production planning	+	[8, 19, 21]				
34	Production planning and control	+	[2, 8, 21, 35]				
35	Postponement in production	+	[13, 15, 19, 54, 61]			(X)	(X)
36	Time for failure detection	+	[19, 21, 35]			X	X
37	No. of errors/rework/rejected parts	+	[19, 21, 35, 65]				X
38	Tool inventory (inventory holding cost)	+	[19–21, 62, 63, 67, 72]	X	X	X	X
39	Potential for automation	+	[2, 19, 21]	(X)	X	X	X
40	Balance of machine utilization	+	[2, 19, 21]	X	X	X	X
41	Setup changes (setup times/Quing delays)	+	[19, 54, 61–64, 67, 73]		(X)	X	X
42	Manufacturing cost per unit	+/-	[20, 21, 35, 63, 67, 71, 72]	X	X	X	X
43	No. of unnecessary manufacturing steps	-	[21, 56, 64]	X	X	X	X
44	Production flexibility	+	[2, 8, 21, 35]				
45	Learning curve gradient	+	[8, 19, 21, 35]		(X)	(X)	(X)
Percentage of effects where data are available (data availability score):				44%	56%	63%	69%

in any product-specific sense and is allocated as production overhead evenly among orders and products. Similarly, 33 and 34 regarding the time for planning and control is not available for quantification. Two of the companies have outsourced all bending and cutting work and, therefore, have data on 30. In three of the companies, it may be possible to estimate learning curves, but inconsistencies in BOM may make direct comparisons less credible. In Company A, the unit volume is simply too low to estimate learning curves. Effect 37 is only recorded in Company D. This is because errors in the other companies are not recorded. They are fixed as they occur, according to the interviewees. Additional material may be recorded, but deep knowledge of the production and product would be required to identify it. Effect 44 regarding production flexibility is a complex multidimensional measure [70] and cannot be measured directly in any of the cases in this study.

In sales, there is only a 20% data availability score for each of the four case companies. None of the companies tracks the time consumption of sales-related activities. This means that 46, 47, 52, 53, and 54 in Table 6 are difficult to quantify. Effects 48, 49, and 50 may be evaluated through customer surveys and market analysis, but the companies in this sample do not have the resources, human or otherwise, to conduct formalized investigations, and their perceptions of these measures are mostly based on experience, intuition, and their interactions with customers. In the companies, there are no data on 51—how many sales are cannibalized by one or the other product. Although one may estimate this based on sales and technical product data, it will ultimately be an estimation reliant on intuition and experience, hence this has been marked as partially available. Quantifying the impact of Effect 55 may come from regular sales data, such as the number of lost sales from not having the variant relative to the cost saved. However, effects from cannibalization may also apply.

Another issue regarding direct cost estimations is the pre-calculations made in the sales departments. The companies have different approaches to these. Company B finds the most similar order and bases its cost calculations of direct material and labor on this. This may be an acceptable approach if the product in question is ordered with high regularity, but if the product is specialized, then it may be sold less frequently, and prices and labor hours may be obsolete. In one extreme example, such an approach reduced the expected contribution margin ratio by 23.9%, mostly due to obsolete material cost figures from the previous order. Company A lies on the other end of the spectrum. For it, every order is unique and far apart, so under no circumstances can it rely on previous calculations. It copes by spending much of its resources in sales on keeping the pre-calculations for each project up to date by gathering prices from the suppliers multiple times during the order process. Through the interviews, it is estimated that sales personnel spent about 15% of their time on keeping prices up to date during the order process. In Company C, orders are more regular and are created in a sales configurator. However, the configurator does not have any link to procurement. Supply chains have been described as unsteady in the interviews, and the parts commonly used are often unavailable. This means that procurement must get different parts that may have different price points but may also create issues in production when interfaces suddenly change. This means changes to both material and labor costs at the company's expense.

In Table 7, the effects occurring in the maintenance and service phase are shown. Data availability varies from 44% to 63%. The high score is mainly due to a low number of effects, which mostly rely on direct cost or standard operations management practices. The case companies monitor the spare parts inventory cost and cost of service, as service packages are part of their business models. These costs are handled in the same way as traditional direct costs (material and labor; 57 and 58). Effect 59 regarding the cost of tools can also be found in purchase logs, but it is difficult to tie them onto specific products or parts and demands deep knowledge of the assembly and manufacturing processes and the products. None of the companies are concerned with end-of-life processes; therefore, there is no data for Effect

Table 6 Modularity effects found in the literature occurring in the sales life cycle phase

ID	Effect		Source	A	B	C	D
46	Time to offer preparation	+	[19, 21]				
47	Price calculation	+	[17, 35]				
48	Customer satisfaction	+	[2, 19, 21, 65]				
49	Consumer-based configurability	+	[2, 19, 21, 35]				
50	Acquisition of new customers	+	[17, 35]				
51	Cannibalizing sales	+/-	[2, 8, 19, 21]	(X)	(X)	(X)	(X)
52	Targeted reacting to customer requirements	+	[2, 19]				
53	Cost related to training employees (customers)	+	[19, 21]				
54	Responsiveness	+	[2, 19, 21, 35]				
55	Exotic product variants	-	[5, 12, 19, 21]	X	X	X	X
Percentage of effects where data are available (data availability score):				20%	20%	20%	20%

Table 7 Modularity effects found in the literature occurring in the service and maintenance life cycle phase

ID	Effect		Source	A	B	C	D
56	Risk of replacement of intact module parts	-	[19, 21]				
57	Service, maintenance, and repair cost	+	[5, 19, 21, 35, 65]	X	X	X	X
58	No. of stock items	+	[2, 35, 65]	X	X	X	X
59	No. of specialized tools for repair/service	+	[2, 19, 21]	X	X	X	X
60	Learning curve for training staff	+	[8, 19, 21]		(X)	(X)	(X)
61	Failure diagnosis/Reactivity	+	[19, 21]				X
62	Re-use, recycling, and disposal due to dis-ass. effort	+	[2, 19, 35]				
Percentage of effects where data are available (data availability score):				44%	56%	63%	69%

62. One might use production times and the time on site to determine learning curves in service, but these are difficult to compare fairly across orders and projects due to the observed inconsistencies in the BOMs. Time-driven approaches may be useful for Effect 61, but as previously mentioned, the companies do not keep detailed records of the time consumption of specific activities, such as failure diagnosis, except Company D.

Looking at all 62 identified effects, the data availability score varies from 32% in Company A to 43% in Company D. Almost a third of the effects—19 to be precise—in this study might be evaluated using time-driven approaches, though none of the case companies track the time consumption of their employees for specific activities except in manufacturing. Another third of the effects are covered by standard operations management or traditional accounting systems. However, even when the data are considered available, the data quality and how they are managed may indeed create problems for the type of evaluations in question. Silo effects challenge data flow from department to department and make some analyses difficult to conduct.

For instance, Company A has issues with traceability across different departments in its SQL database. Identifiers such as project IDs, purchase IDs, sales IDs, and production IDs are only rarely transferred from one department's data table to another. As an example, this makes it necessary to do complicated workarounds when trying to assign specific purchase orders to specific projects. Furthermore, the company's sales volumes are low, which makes any statistical analysis difficult to trust. Company B uses many identifiers to identify the same item. In one SQL table, a product may be referred to by an "item ID," but in another, it may be referenced by a different type of ID, such as a "table ID" or "line ID." This creates unnecessary complexity and makes the system less transparent. Company C has issues with conflicting data across different IT systems, such as its ERP and configuration systems. Additionally, data points are often left blank in Company C's databases.

In Company A, data are stored in separate folders for each project, both in its ERP system and in its shared Windows folders. Furthermore, its ERP system is not set up to extract data like BOM, sales order information, production orders, or any other project-relevant data across projects. This makes it challenging to analyze the portfolio's performance, as product data are stored in many different folders, and data mining becomes a time-consuming and tedious task with a high potential for errors. Company A has very complex portfolios, as most or every project is engineered specifically for the individual order. Most projects are one of a kind, and data are not stored or recorded consistently. Hence, data recording and storage have also become one of a kind for many of its projects, and comparisons between them have become increasingly difficult.

5 Discussion

In this section, the results of the study will be discussed and compared to the findings from the literature. The most important observations will be elaborated further, and the areas that may have the largest impact on the companies are also discussed here. The credibility, applicability, and future perspectives of this work will also be investigated in more detail.

The literature review concluded that little attention has been given to the issue of data quality and availability in the research area of modularity. Many sources identified the importance of indirect cost when evaluating modular product structures, but few have been able to quantify these holistically. The results of this study show that data are only available for quantification for less than half of the identified effects of modularity in the cases investigated. Another finding in this study is that even the data points commonly assumed to be of adequate quality in the modularity literature, such as direct materials and labor, are riddled with inconsistencies and errors. One example of this is the BOMs, which have far-reaching consequences, as these data are passed on from department to department, impacting the comparativeness of several effects throughout the value chain.

Apart from data quality and availability, certain data management practices and behavioral patterns were also observed to hinder the evaluation of modularization effects. The literature often describes silo effects between departments as a challenge for many companies [42]. However, in the cases investigated here, it was also observed that siloes exist within the siloes. Particularly in the engineering department, this creates challenges regarding the reuse of modules or subsystems that other engineers may have developed. The silo effects may, in turn, be amplified if all product data are stored in separate project folders with no convenient way of extracting the relevant knowledge across different projects, as observed in Company A. An additional observation regarding the silo effects between departments is that they neglect to examine how they manage and share data, which IDs (item ID, purchase ID, sales ID, etc.) to track across departments, and how to keep different systems aligned and up to date. Future research could investigate whether addressing these issues will make the quantification of modularization effects more credible and convenient.

The interpretation of the interview data further strengthened the analysis by providing context to the quantitative findings. While the database investigations revealed what data were present, the interviews clarified how these data were generated, maintained, and applied across departments. This made it possible to interpret observed data gaps and inconsistencies in light of actual work practices, such as informal routines or siloed data management. The qualitative insights from the interviews thereby complemented the quantitative observations and increased the robustness of the conclusions regarding data availability, data quality, and the underlying challenges in quantifying modularization effects.

As mentioned, less than half of the identified effects have data available for quantification, and most of these effects are related to traditional accounting and operations management schemes. This is also reflected in the data availability scores, where manufacturing and procurement are the lifecycle phases with the highest percentages, with means of 58% and 44%, respectively. The life cycle phases with the lowest scores were in sales and development, with means of 20% and 17%, respectively. This suggests that accounting systems might be associated with the types of data being collected, though more research is necessary to test this hypothesis. Traditional accounting systems have often been criticized in the literature for unfairly favoring specialized, “one-of-a-kind”-type of product strategies [5], without regarding the consequences to the rest of the value chain. This study might add to that picture that a link to life cycle costs is missing in all four companies. Particularly, a link to product development is missing, meaning that product developers in the case companies have little to no knowledge of how their decisions impact the rest of the organization. Future research may investigate whether establishing these links through more detailed accounting schemes can enable modular product families to be evaluated more fairly.

An interesting observation from the results is the consistency of data availability patterns across the four case companies, particularly evident in Tables 2 and 6. This similarity does not necessarily indicate that the companies share identical organizational structures but rather that they exhibit comparable data management and accounting practices. All four rely on similar ERP-based systems and conventional volume-based costing schemes, which shape how and where data are collected along the value chain [74]. Consequently, the same types of data are often available (or lacking) across companies. Effects identified in the literature but not observed in any of the cases should therefore not be interpreted as irrelevant but as insufficiently supported by existing data structures. Their absence reflects limitations in measurable information rather than the nonexistence of the underlying mechanisms. Conversely, effects observed across all companies point to areas where data recording is more mature, typically related to direct costs, underscoring the persistent imbalance between the effects discussed in the literature and those that can currently be quantified in industrial practice.

It is now clear that companies need to address both their data management and data quality to gain a better understanding of the consequences of design decisions, but what type of data should be gathered remains unexplored. The results revealed that approximately a third of the covered effects could be estimated if the companies kept track of the time usage of their employees in overhead departments (sales, construction, procurement, etc.). As described by [5], the more specialized a product is, the more time it demands from overhead departments. This is also the case for the companies in this study. In some cases, interviewees expected that overhead may be as much as 50% of an order or project’s cost. This information is hidden away and unavailable for analysis and decision support when decision-makers only worry about direct costs. This indicates that much can be done by implementing time-driven ABC or similar methods despite the critiques set forth by [2]. Additionally, the effects found in product development may be the ones with the furthest-reaching impacts in the value chain, as mistakes made in the design of a product may become much more expensive to fix later [75]. However, this is where the least amount of information seems to be present, with data availability scores spanning from 15% to 23% across the companies. Effects seen in production may also have a large impact on cost, as it is here that most direct costs are commonly incurred [12]. This is where the highest data availability scores were found across the companies, spanning from 44% to 69%, although data on production overhead are lacking.

While the four cases investigated cover different industrial sectors, company sizes, and product types, the intention of this study was not to achieve statistical generalization but to identify recurring mechanisms and structural barriers influencing the quantification of modularity effects. The conclusions should therefore be understood as analytically transferable rather than universally generalizable. Similarities in the results across all four cases suggest that the observed issues (such as data inconsistencies, silo effects, and limited traceability) may be indicative of broader patterns in engineer-to-order and modularization contexts. Nevertheless, caution should be exercised when extrapolating these findings beyond the studied sample. Further studies including larger datasets or longitudinal investigations could help assess the extent to which these observations hold across different industrial settings.

These insights may prove useful for future research. The findings presented here can provide some insight into what is possible in Danish companies, which effects may be low-hanging fruits ready for quantification, and which new initiatives should be implemented to gain insights into even more effects. Furthermore, this work may provide some guidance in designing new evaluation schemes in the future, such as large data models utilizing AI. The results show quite clearly where to expect to have quantitative data and when this cannot be expected. Hence, this article may provide some guidance on when to look for quantitative data and when to rely on experts or experienced employees. This may help future schemes in finding a better balance between qualitative and quantitative measures in their evaluations making them more applicable in the industry. Furthermore, specific data management practices emphasizing data discipline and collection should be investigated in more detail to find suitable and practical methods for companies to address the issues identified in this paper. The interdependencies and tradeoffs inherent to modularity, as proposed by several authors in the literature covered for this article, should also be investigated further.

The data sources included in this study, as presented in the Methodology, comprise the main data sources within each department, including cross-departmental sources such as project folders. There remains a risk that some data sources may have been overlooked, which could introduce a degree of uncertainty to the results. However, the 113 interviews conducted make it possible to confirm that the included data sources correspond to those actively used and recognized by employees and managers in each department. If other data sources with relevant information exist, they are likely embedded deep within SQL database structures, unknown to staff, and therefore of uncertain quality and maintenance status.

The results and data mappings were also continuously validated through discussions with the participating companies. Preliminary findings were presented to representatives from all major functions—such as sales, engineering, production, and management—to ensure cross-functional agreement on the identified data and interpretations. This collaborative validation process helped confirm the accuracy of the mapped data sources and reduced the risk of bias or misalignment among respondents. The high degree of similarity in results across the four companies further supports the robustness of the findings and the reliability of the applied method.

6 Conclusion

This work contributes to the literature by highlighting the barriers that exist when trying to quantify the effects of modularization in four Danish companies. Primarily, these issues include inconsistencies in the BOM, which prevent proper comparison and analysis across variants or projects; a sole focus on direct costs, neglecting substantial overhead cost pools, particularly for specialized products [5]; and a single-product mindset, which discourages the development of common modules and instead increases the organization's complexity. Through 113 interviews and investigations of company databases this work further identifies specific and concrete areas where data quality and availability need improvements, along with the identification of specific data management practices that further challenge the quantification of modularity effects. The work also suggests promising venues for future research and brings to light a subject matter that might be well known to practitioners but which is rarely described in the scientific literature regarding modular product development.

The literature has identified many positive and negative effects of product modularity, while this study emphasized a lack of available, detailed, and high-quality data, which is a foundational challenge in making reliable quantifications of modularity effects. It was found that less than half of the modularity effects identified in the investigated literature had data available for quantification, emphasizing the gap between research and industrial application. The life cycle phases with the most data available were the ones covered by traditional accounting schemes, such as manufacturing and procurement, with mean scores of 58% and 44%, respectively. Effects relevant to overhead departments, such as sales and development, had mean scores of 20% and 17%, respectively. This observation led to the proposition of the hypothesis that accounting systems might be associated with the types of data being collected.

Additionally, silo effects within and between departments further worsen the ability to assess modularity's impact holistically. They obstruct easy access to shared knowledge and undermine the reuse of modules and subsystems, resulting in inefficiencies that might obscure modularity's potential effects. The literature mentions that traditional cost accounting methods often overlook indirect costs and, thereby, under-evaluate the total cost-saving potential of modular product strategies. This study shows that not only is indirect cost overlooked, but the direct cost figures can also not be assumed to be of high quality. Furthermore, observed common data inconsistencies in critical documents such as BOM have far-reaching impacts on the value chain, highlighting the importance of rigorous data management practices and alignment across departments.

The findings suggest that the lack of accessible and reliable data is not merely a technical issue but the result of intertwined human, technological, and organizational factors. Inconsistent practices for data entry and maintenance, often tied to personal routines or departmental habits, lead to errors and missing information in key documents such as bills of materials. Technologically, weak integration between ERP, CAD, and configuration systems prevents data from being shared seamlessly across the value chain. Organizationally, the silo effects observed both between and within departments limit visibility and hinder the reuse of information, as employees often rely on personal knowledge and no incentives for data sharing exist. These interrelated factors explain why even seemingly simple data, such as cost or time usage, remain fragmented. Addressing them requires coordinated efforts: establishing consistent identifiers across systems, improving procedural discipline, and fostering cross-functional collaboration to ensure that data are treated as shared assets rather than departmental by-products [76].

These results imply that time tracking of specific activities in all overhead departments may be necessary if the bulk of effects are to be quantified. Such a shift could make the quantification of modularity effects more feasible and credible, making it possible to perform data-driven decision-making about modular product development in companies. Future research would benefit from focusing on defining specific data management practices to support not only quantifiability but also better knowledge-sharing within and across departments. Additionally, researchers should investigate a better balance of qualitative and quantitative measures when developing evaluation schemes of modular products, which this work may provide some insights into. If more optimal data management and more detailed information on time expenditures in overhead departments are combined with proper tools for evaluation, then one might be able to finally quantify the effects of modularity.

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Declarations

Competing interests The authors declare no competing interests.

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