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# Measure it to manage it – quantitative review of product family complexity metrics

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**ABSTRACT:** Product variety increases complexity across product, process, and organizational domains, yet existing complexity measures offer limited guidance for design decisions. This study implements established metrics within a framework to enable consistent assessment across domains. The results reveal substantial redundancies among these metrics - with the notable exception of modularity, emphasizing its central role in complexity management. The consolidated measure set provides practitioners with a systematic basis for evaluating design strategies and managing complexity in product families.

**KEYWORDS:** product families, complexity, modularisation, simulation-based design

## 1. Introduction

Product variety has become a central challenge for companies seeking to satisfy diverse customer needs and maintain competitive positions in global markets. The variety inherently generates complexity that manifests across multiple domains of the system architecture (Mertens et al., 2023): in the product architecture itself, where abstract functions are mapped to the physical components that realise them (Ulrich, 1995), in the processes required to manufacture the product variants, and in the organization, which must coordinate the necessary resources. When unmanaged, this complexity typically leads to inefficiencies and increased costs, whereas excessive reduction may cause firms to miss market opportunities - making the management a widely recognized and crucial challenge in engineering and operations management (e.g., Hackl et al., 2020; Labro, 2004; Trattner et al., 2019). The principle of 'measure it to manage it' applies directly: valid and reliable measures are essential to assess the impact of design decisions on operational performance. Prior research has therefore proposed a wide range of metrics to quantify complexity. However, despite this richness, the multitude of available measures complicates the situation, as their individual merits are unclear and generalization is often limited to case studies (Blecker & Abdelkafi, 2006; Hennig et al., 2022; Sinha & Suh, 2018). In addition, engineering literature focuses on capturing complexity in the physical domain, which may neglect the system-wide perspective (Mertens et al., 2023). To address these limitations, Hennig et al. (2022) proposed a framework to systematically validate proposed measures. While this marks progress toward establishing valid and reliable measures, the field remains fragmented across the distinct aspects of complexity within the system architecture.

This study addresses the fragmentation by seeking to consolidate the multitude of metrics across the system architecture, extending the work of Hennig et al. (2022). Specifically, we identify and categorize measures from the literature, and implement these measures within a computational framework that generates varying system architectures, enabling a neutral evaluation (Hennig et al., 2022).

To this end, we build on the Extended Axiomatic Design (EAD) framework (Mertens, 2020; Meßerschmidt, 2025; Suh, 1998), which allows for representing system architectures of product families across four domains - *functional*, *physical*, *process*, and *resource* - along with their intra- and inter-connections (i.e., within and in between domains). This framework enables the generation of synthetic product family designs with diverse properties reflecting different design strategies, such as emphasizing commonality, modular kits, or platform-based approaches (Krause & Gebhardt, 2023). In doing so, it overcomes the limitations of studies restricted to one or a few case studies, thereby enabling more generalizable conclusions. Within this framework, we operationalize 15 widely cited complexity measures and evaluate them through a large-scale numerical experiment, followed by a correlation analysis to examine relationships among the metrics.

We contribute with three main results. (1) By reviewing and categorizing complexity measures proposed in the literature, this study sheds light on the large variety of existing approaches and provides an overview for future research. We find that most existing work focuses narrowly on product architecture, which motivates an examination of whether these metrics capture distinct aspects of complexity. (2) We reveal redundancies among existing measures within the EAD framework and advocate for a consolidated set of metrics (Hennig et al., 2022). Rather than a shortage of measures, the challenge lies in embedding this aggregated knowledge into strategies for system architecture design. We find significant correlations, especially for intra-domain measures, indicating that most of them act as proxies for each other; except for the modularity metric, which captures a distinct aspect of complexity by reflecting specific coupling patterns within the physical domain. Additionally, it shows negative correlations with most structural and count-based measures, consistent with modular product architectures being associated with lower complexity (e.g., Hackl et al., 2020). (3) Physical design is often used as a proxy for complexity in engineering studies (e.g., Hennig et al., 2022; Sinha & Suh, 2018); however, multiple domains contribute to the conceptual layer of complexity. Building on EAD, we operationalize complexity measurement in a standardized and replicable way across the system architecture (Mertens et al., 2023). In doing so, we contribute to the development of a framework for evaluating complexity measures and pave the way to assess their impact on operational performance (Hackl et al., 2020; Hennig et al., 2022). In turn, the framework enables the generalization of previous findings on complexity effects on operational performance, while its application and the resulting comprehensive view can directly support practitioners in design decision-making.

## 2. Related work

Complexity, arising from internal and external sources, requires effective complexity management for staying competitive and for improving operational performance (Trattner et al., 2019; Vogel & Lasch, 2016). While external sources include market variety or technological change, product family complexity is an internal source driven by the system architecture (Mertens et al., 2023). Complexity has many definitions (see Jacobs & Swink (2011)), often tailored to the specific research discipline in which complexity is of relevance. One of the earliest definitions originates from complex systems research, where Simon (1962) characterizes complexity as a property of systems composed of a large number of parts that interact in a non-simple manner. In general, the literature agrees that complexity is driven by two fundamental dimensions (e.g., Summers & Shah, 2010): element variety (or system size) and relational variety (coupling), reflecting interdependencies and change propagation within the system.

Modularity, by contrast, represents the structural system characteristic that counteracts complexity by reducing element variety and confining coupling to modules while minimizing inter-module coupling (Ulrich, 1995). Similarly, Newman (2006) conceptualizes modularity as the extent to which connections within a subgroup exceed those expected across the overall network, representing the system as a matrix of intra-network connections. In product family design, modular architectures enable external variety with limited internal variety (Salvador, 2007) by decomposing systems into relatively independent, combinable modules with standardized interfaces and clearly defined functional assignments. The degree of modularity is determined by the *characteristics* of function binding, interface standardization, decoupling, and overdesign, which jointly promote the *properties* of commonality and combinability (Hackl et al., 2020). Commonality facilitates reuse and economies of scale through standardized modules, while combinability enables the efficient generation of product variants, thereby allowing complexity to be managed without sacrificing product variety. The literature discusses numerous effects on firms' economic objectives across the product lifecycle (e.g., Hackl et al., 2020; Mertens et al., 2023), highlighting a central trade-off between higher direct costs, for example due to overdesign, and lower indirect costs, for example resulting from reduced process variety and other complexity-related effects. In sum, product family complexity is fundamentally well understood, prompting recent calls for integrated frameworks that enable the evaluation of its impact under varying design scenarios

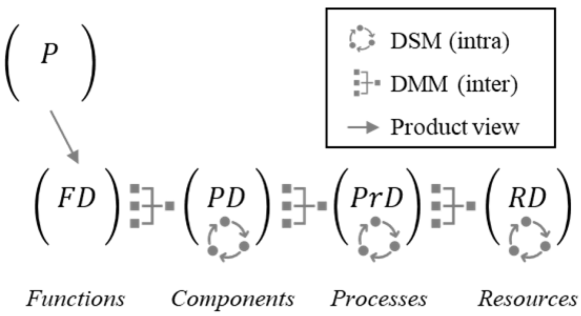
(Hackl et al., 2020; Nørgaard et al., 2025). For the purpose of modelling, numerous metrics have been proposed to capture multiple aspects of complexity and modularity, as summarized in major surveys (Hennig et al., 2022; Sinha & Suh, 2018; Summers & Shah, 2010; Trattner et al., 2019); however, little consensus exists on what constitutes an appropriate metric. Hennig et al. (2022) review part of the literature and conclude that measures are sensitive only to specific aspects and do not capture complexity across all domains of the system. Mertens et al. (2023), in a systematic review of engineering design literature, also note fragmentation, alongside growing interest from operations and management perspectives. They call for stronger integration across disciplines to establish a more unified research agenda. Furthermore, several studies report that the operationalization of economic consequences of product family complexity remains underdeveloped (Hackl et al., 2020; Hennig et al., 2022). With this work, we make a step towards the development of such an integrated model by operationalizing complexity metrics from various studies within the EAD framework and by providing a consolidated set of metrics to account for variety and coupling across the system architecture.

# 3. Method

## 3.1. Extended axiomatic design

To operationalize product family complexity in a structured and reproducible way, this study builds on the EAD framework (Mertens, 2020; Meßerschmidt et al., 2020; Meßerschmidt, 2025; Meyer et al., 2019). EAD extends the well-established Axiomatic Design theory (Suh, 1998), originally focused on complexity within product architecture (Ulrich, 1995), by adding the resource domain to include an organizational perspective (Mertens et al., 2023). Dependencies within and across these domains are modelled using Design Structure Matrices (DSMs) and Domain Mapping Matrices (DMMs). DSMs capture intra-domain relationships, such as component interdependencies, while DMMs represent inter-domain relationships, for example linking components to manufacturing processes and required resources. As illustrated in Figure 1, the EAD framework models product families by representing product variants as unique combinations of domain elements within the underlying system architecture, spanning four interconnected domains.

This structure enables the generation of diverse product family designs and supports the consistent application of complexity measures across the functional domain (FD), physical domain (PD), process domain (PrD), and resource domain (RD) (Mertens et al., 2023). The functional product view $P_{FD}$ - which itself is not considered a DMM - builds on the idea that products can be mapped as unique combinations of functional requirements. The product views of the subsequent domains are then derived by successive multiplication with the preceding DMMs, for example $P_{PD} = P_{FD} \cdot DMM_{FDPD}$.




*Note.* **P** represents the product family, with its variants mapped as unique combinations of domain elements.

**Figure 1.** Schematic representation of the EAD framework

## 3.2. Product family complexity measures

A large number of complexity measures have been proposed in the literature. We reviewed existing work, including major surveys (Hennig et al., 2022; Sinha & Suh, 2018; Summers & Shah, 2010; Trattner et al., 2019), and identified a pool of candidate measures. After screening for applicability, the metrics reported in Table 1 were selected for implementation, covering a representative spectrum of complexity aspects.

Not all measures identified in the literature are listed, as we excluded those that were not suitable for operationalisation within the EAD framework - either because they require additional information such as expert judgment, are limited to squared matrices, or could not be reproduced. This restriction limits direct validation against certain practice-oriented metrics; however, it enables a transparent and internally consistent comparison of complexity measures within the modelling framework. As such, the results provide a structured basis for future extensions of EAD-based models and support the development of integrated approaches to assess the cost implications of design decisions.

**Table 1.** Complexity measures from the literature

| Matrix | Name | Authors | Variable | Low Values | High Values |
|---|---|---|---|---|---|
| DSM | Modularity | Blondel et al. (2008); Newman (2006) | Q | random couplings | clustering of couplings |
| | Structural Complexity | Hennig et al. (2022); Kim et al. (2016); Sinha and Suh (2018) | SC | centralized design | distributed design |
| | Neumann Entropy | Anand et al. (2011); Passerini and Severini (2009) | NE | low degree of disorder | high degree of disorder |
| | Cyclomatic Complexity | McCabe (1976) | MCC | low number of closed loops | many closed loops |
| | Halstead's Volume | Halstead (1977); Prather (1984) | HVM | few elements and couplings | many elements and couplings |
| | Interface Complexity | Hölttä-Otto (2005) | HIC | low number of interfaces | many interfaces |
| DMM | Total System Size | various in Trattner et al. (2019) | TSS | lower sum of domain elem. | higher sum of domain elem. |
| | System Design Complexity | Guenov and Barker (2005); Modrak and Bednar (2015); Suh (1998) | SDC | uncoupled design | more coupled design |
| | Jung's System Design Complexity | Jung et al. (2022) | JSDC | uncoupled design | more coupled design |
| P | Diversification Index | Brahm et al. (2017); Gollop and Monahan (1991) | D | low product diversification | high product diversification |
| | Proportion of Product Variants | various in Trattner et al. (2019) | NPV | restricted variety | free feature combination |
| | Option Variability | MacDuffie et al. (1996) | OV | low variation of options | high variation of options |
| | Commonality Index | Martin and Ishii (2002) | CI | high degree of standardization | products share common parts |
| | Product Line Commonality Index | Kota et al. (2000) | PCI | high degree of standardization | products share common parts |
| | Density | Anand et al. (2019); Balakrishnan et al. (2011) | DNS | low non-zero fraction | high non-zero fraction |

## 3.3. Design of experiments

We adopt a Design of Experiments (DOE) approach (Lorscheid et al., 2012) to generate synthetic product family designs within the EAD framework. The objective is to evaluate the metrics listed in Table 1 across a range of design alternatives. Linear (Pearson) and non-linear (Spearman) correlation analyses are then conducted to identify redundant metrics and select suitable proxy measures, thereby simplifying the model (Robinson, 2008). The resulting consolidated set of measures provides a foundation for future assessments of product family complexity, particularly in EAD-based studies.

We define independent parameters to control element variety, represented by the number of domain elements, and coupling characteristics in DSMs and DMMs, allowing systematic variation of complexity across designs. Density (DNS) is defined as the ratio of non-zero entries to the total number of entries and provides a normalized and easily comparable measure (e.g., Anand et al., 2019). Increasing values of DNS indicate stronger coupling, but provide no information on specific entry arrangement patterns, a limitation addressed by metrics such as System Design Complexity (SDC) metric (e.g., Modrak & Bednar, 2015). Based on Shannon entropy, SDC can be interpreted as an operationalisation of the Information Axiom (Suh, 1998) and has been applied across a range of research contexts. Generally, modular designs are expected to exhibit reduced density in the physical DSM, as they form clusters of strongly coupled components with minimal inter-cluster coupling. To explicitly generate modular structures within DSMs, an a priori specification of the desired pattern is required. The model enforces this using a greedy optimization algorithm that arranges matrix entries into the targeted structure while maintaining a given density (Clauset et al., 2004). The parameter Q controls how strictly this structure must be achieved. Values near zero indicate no clear patterns; with high values near one the pattern becomes more pronounced. The model generates distinct patterns, corresponding to modular strategies, with high-density clusters along the diagonal with weak couplings between clusters (e.g., Newman, 2006). Arguably, an a priori definition is not well suited for practical application to an existing product family. Hölttä-Otto and de Weck (2007) propose a metric based on the decay of singular values, which could, for instance, be applied in this context but is not included in the present study. Modular architectures distribute information more broadly across the system and a larger number of eigenvectors is required for complete representation, resulting in a slower decay of singular values.
To ensure structural realism and diversity, parameter ranges are bounded by empirical limits reported in published DMM and DSM studies (Meßerschmidt, 2025). Within these bounds, random designs are generated to match predefined target values for the independent parameters, using uniform sampling. All designs are represented as binary matrices. The main parameter settings are presented in Table 2.

**Table 2.** Simulation protocol

| Variable | Description | Range |
|---|---|---|
| *Independent variables: product family design* | | |
| $DNS_{FD}$ | Density of the functional product view | U[0%;50%] |
| $DNS_{DSM}$ | Density of DSMs | U[0%;35%] |
| $Q_{DSM}$ | Weight of modular/randomly matrix entry arrangement | U[0;1] |
| SDC | System design complexity of DMMs (normalized entropy) | U[0%;8%] |
| $N_P$ | Number of product variants | U[50;100] |
| $N_{FR}$ | Number of elements in FD | U[8;12] |
| $N_{PD}$ | Number of elements in PD | U[14;20] |
| $N_{PrD}$ | Number of elements PrD | U[30;40] |
| $N_{RD}$ | Number of elements in RD | U[60;80] |
| *Control variables* | | |
| seed | Random seed to reproduce the results | 1234 |
| RUNS | Number of runs | 8.000 |
| *Dependent variables: complexity measures (Table 1) across relevant domains* | | |

*Note*. U[X;Y] uniform distribution between X and Y.

Using the DOE, approximately 8,000 synthetic product family designs were generated. For each instance, all 15 complexity measures were calculated across relevant domains. DSM and DMM metrics are applied to each domain as illustrated in Figure 1. While Option Variability (OV) and the Proportion of Product Variants on total possible Variants (NPV) are defined only for the functional product view, DNS and the commonality and variety indices (PCI, CI,D) are applied to product views of each domain (Jacobs & Swink, 2011). This results in 43 observations per generated product family.

## 4. Simulation results

### 4.1. Correlation analysis

The correlation analysis shows that several metrics are highly interrelated within their respective domains, broadly confirming concerns in the literature (e.g., Trattner et al., 2019) that many metrics proposed in isolation are not independent constructs but alternative representations of the same underlying complexity aspects. Notably, the observed independence across domains reflects the DOE, which defines independent parameters for $P_{FD}$, DSMs, and DMMs to account for the fact that complexity emerges system-wide from multiple, distinct sources (Hennig et al., 2022; Mertens et al., 2023).

Table 3 reports the results for the functional (FD) and physical (PD) domains. For clarity, DMM metrics were excluded, and the analysis focused on product architecture, since similar correlation patterns were found in the other domains. Untabulated results indicate that the total system size TSS is largely uncorrelated (with the notable exception of .31 with $PCI_{PD}$), whereas System Design Complexity $SDC_{FDPD}$ and the version of Jung et al. (2022) $JSDC_{FDPD}$ show a strong correlation (.82). All three metrics remain uncorrelated across domains. Similarly, most DSM metrics show near-identical behaviour within their respective domains. Another reason for the focus on product architecture is the impact of modularity, captured by the $Q_{PD}$ metric in the physical domain. Its correlation values remain insignificant, indicating independence from other $DSM_{PD}$ metrics. The latter are primarily structural and count-based, yet their small negative correlations with $Q_{PD}$ reflect that modular product architectures can mitigate complexity by decoupling elements within the physical domain (e.g., Hackl et al., 2020), that is, by combining components into modules.

**Table 3.** Correlation table with focus on product architecture

| | Product view (P) | | | | | | | | DSM | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *var.* | **$NPV_{FD}$ 1** | **$OV_{FD}$ 2** | **$D_{FD}$ 3** | **$CI_{FD}$ 4** | **$DNS_{FD}$ 5** | **$D_{PD}$ 6** | **$CI_{PD}$ 7** | **$PCI_{PD}$ 8** | **$Q_{PD}$ 9** | **$SC_{PD}$ 10** | **$NE_{PD}$ 11** | **$MCC_{PD}$ 12** | **$HVM_{PD}$ 13** | **$HIC_{PD}$ 14** |
| 1 | 1 | .21 | −.10 | −.27 | .20 | | −.07 | | | | | | | |
| 2 | .26 | 1 | −.71 | **−.84** | **1** | −.53 | −.49 | .57 | | | | | | |
| 3 | −.05 | −.49 | 1 | .50 | **−.71** | **.68** | .28 | −.41 | | | | | | |
| 4 | −.30 | **−.83** | .33 | 1 | **−.82** | .40 | .61 | −.48 | | | | | | |
| 5 | .18 | **.95** | **−.54** | **−.77** | 1 | −.54 | −.48 | .57 | | | | | | |
| 6 | | −.48 | **.74** | .34 | −.50 | 1 | **.75** | **−.86** | .10 | −.54 | −.55 | −.55 | −.53 | −.55 |
| 7 | −.10 | −.47 | .19 | .59 | −.45 | **.67** | 1 | **−.90** | .13 | −.64 | −.65 | −.64 | −.60 | −.65 |
| 8 | | .55 | −.30 | −.46 | .56 | **−.81** | **−.88** | 1 | −.11 | **.68** | **.68** | **.68** | **.65** | **.69** |
| 9 | | | | | | | | | 1 | −.20 | −.22 | −.23 | −.26 | −.16 |
| 10 | | | | | | −.47 | −.54 | **.63** | −.21 | 1 | **.99** | **.89** | **.80** | **.99** |
| 11 | | | | | | −.48 | −.55 | **.64** | −.20 | 1 | 1 | **.92** | **.84** | **.99** |
| 12 | | | | | | −.53 | −.60 | **.70** | −.12 | **.84** | **.86** | 1 | **.98** | **.91** |
| 13 | | | | | | −.50 | −.57 | **.66** | −.15 | **.75** | **.78** | **.98** | 1 | **.84** |
| 14 | | | | | | −.51 | −.59 | **.68** | −.09 | **.97** | **.98** | **.90** | **.81** | 1 |

*Note*. All coefficients shown are significant at $p < 0.01$. The lower triangle matrix shows Pearson coefficients while the upper triangle matrix shows Spearman coefficients. Coefficients considered eminent and discussed below are shown in bold.

The product-view metric Product Line Commonality Index $PCI_{PD}$, applied in the physical domain, shows significant correlations with all $DSM_{PD}$ measures except for modularity $Q_{PD}$ - despite not being a DSM measure itself. On the one hand this again highlights component commonality as a central aspect to assess complexity (e.g., Labro, 2004). On the other hand, it emphasizes that modular architectures exhibit distinct coupling patterns in $DSM_{PD}$ whose structural characteristics go beyond what measures for commonality can capture. The ability of EAD to explicitly represent modular structures is essential for distinguishing between different modular design strategies based on their coupling patterns. In future studies, this can support the assessment of their economic impact within an integrated framework (Hackl et al., 2020; Hennig et al., 2022; Nørgaard et al., 2025).

Moreover, prior literature has particularly proposed a wide range of product-view metrics for the functional domain (see Table 1), most of which exhibit high correlations. Specifically, the density

$DNS_{FD}$ shows strong correlations with Option Variability $OV_{FD}$ and the commonality index $CI_{FD}$, while its relationship with the Diversification Index D is somewhat weaker. In our DOE, we used $DNS_{FD}$ as an independent parameter to generate different functional product views, whereas values for subsequent product views depend on the respective DMMs. Consequently, the correlations with DNS decrease along the domains (.56, .27, .06), while, interestingly, D corrects for this trend (.74, .61, .65). This suggests overlapping product family complexity aspects across domains, which, arguably, implies practical flexibility, as the measure can be consistently applied in whichever domain offers reliable data.

### 4.2. Reduction of variables

We aim to consolidate the multitude of complexity measures to generate collective knowledge on how to address the multiple aspects of complexity across the system architecture, covering the functional, physical, process, and resource domains. By identifying highly correlated variables and selecting suitable proxies, we provide a comprehensive yet manageable set of metrics to support the evaluation of product family design strategies. Table 4 presents this consolidated measure set. The set includes (1) count-based indicators for system size (TSS), product variants (NPV), and density (DNS); (2) topological metrics based on specific coupling patterns in DSMs (Q) and DMMs (SDC); and (3) indices to measure commonality (PCI) and variety (D) across product variants. The PCI was chosen as a proxy for $DSM_{PD}$ measures (except $Q_{PD}$) due to its wide acceptance in the literature and its robust Pearson and Spearman correlation results.
It is important to note that the identified redundancies are specific to the EAD framework and do not imply that the excluded measures lack value outside its scope. On the contrary, these measures may be well suited to other applications where contextual knowledge, simplicity, or data availability play a greater role.

**Table 4.** Consolidated measure set

| Matrix | Name | Variable | Where to apply |
|---|---|---|---|
| DSM | Density | $DNS_{DSM}$ | All domains, each covers distinct complexity aspects |
| | Modularity | $Q_{PD}$ | Physical domain covers distinct complexity aspects |
| DMM | Total system size | TSS | All domains, each covers distinct complexity aspects |
| | System Design Complexity | SDC | |
| P | Proportion of Product Variants | $NPV_{FD}$ | Functional domain covers distinct complexity aspects |
| | Diversification Index | D | Domains cover similar complexity aspects |
| | Density | $DNS_{FD}$ | Functional domain covers distinct complexity aspects; correlation is decreasing along the domains |
| | Product Line Commonality Index | $PCI_{PD}$ | Physical domain covers similar complexity aspects as most $DSM_{PD}$ metrics |

## 5. Conclusion

This study set out to develop a joint understanding on how to address product family complexity by reviewing, operationalizing, and analysing a broad set of established metrics. Building on the EAD framework, we implemented 15 measures and applied them across a range of synthetic product family designs, thereby enabling a neutral and reproducible comparison beyond single case studies (Hennig et al., 2022). The results reveal substantial correlations among many of the proposed metrics, supporting earlier concerns that the field's diversity of metrics often reflects overlapping constructs rather than distinct complexity aspects (Hennig et al., 2022; Trattner et al., 2019). In response, we propose a consolidated and parsimonious set of metrics that captures multiple aspects across the system architecture. The degree of modularity within the physical domain emerges as an independent aspect, underscoring its unique role in decoupling system elements and mitigating complexity. Moreover, we emphasize the integration of modular structure modelling into frameworks to assess the cost implications of distinct design strategies (Hackl et al., 2020; Nørgaard et al., 2025) - such as modular kits or platform-based approaches (Krause & Gebhardt, 2023).

First, we provide a structured overview of the fragmented literature by reviewing and categorizing existing complexity measures. We extend the work of Hennig et al. (2022) by incorporating additional metrics that go beyond the physical domain, enabling a more system-wide perspective (Mertens et al., 2023). Second, by implementing the measures within the EAD framework, we operationalize complexity measurement in a standardized and replicable manner across the functional, physical, process, and resource domains. In doing so, we directly respond to recent calls for integrated frameworks capable of evaluating product family design strategies in terms of cost effects and operational performance (Hackl et al., 2020; Nørgaard et al., 2025). Third, we provide a comprehensive measure set to capture product family complexity, offering researchers and practitioners a consistent foundation for systematically deriving implications for product family design and complexity management (Hennig et al., 2022; Sinha & Suh, 2018; Summers & Shah, 2010; Trattner et al., 2019).

Like other studies, this work has limitations. The evaluation was conducted on synthetic product family designs rather than empirical data, which may limit direct applicability. However, the large number of published case studies reporting DMMs and DSMs provides additional empirical data that could be systematically processed to extend model calibration and validation. Moreover, while the selection of measures was broad, it was limited to those applicable within the EAD framework, potentially excluding relevant aspects of product family complexity. Additional statistical analyses could be conducted to evaluate how much variance the consolidated set of measures explains, thereby strengthening their validity. Future work should build on this consolidated measure set to establish links between complexity and operational performance metrics, paving the way toward a more integrated framework for assessing cost effects of product family design strategies (Hackl et al., 2020; Hennig et al., 2022; Nørgaard et al., 2025). In practice, this would enable decision-makers to directly evaluate the impact of design strategies and derive common guidelines for concrete use cases.

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