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Defining a Flexible Value Framework for Digital Products and Services Using Systems Engineering and AI Approaches

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Abstract. As digital transformation reshapes business practices across numerous industries, a growing need exists to systematically characterize the intrinsic value of digital products and services (DPS). Value comparisons are central to prioritizing project backlogs for groups constrained by budget, headcount, or time. Rationalizing ongoing work also requires assessments of project value to support the decision to discontinue efforts, including those associated with long-duration R&D. A survey of recent literature reveals several proposed DPS value frameworks to address this business need. However, no unified set of value elements collectively defines the utility of individual DPS activities. This paper addresses whether a coherent framework can be derived from multiple disparate DPS value models within the publication record. The problem space is evaluated through a multi-disciplinary lens, using concepts from systems engineering, computer science, and project and portfolio management. Results from optimizing a design structure matrix (DSM), contextual clustering using a natural language processing (NLP) model, and evaluating a hybrid DSM with NLP-derived similarities all reveal the potential for a hierarchical value framework. Each level defines a different granularity of value decomposition. Firms may identify the framework complexity that best suits the needs of their organizations, enabling management to balance DPS portfolios and resources more optimally. Furthermore, the approach allows for flexible updates as additional publications come to light, shifting the focus away from a rigid framework and toward an evergreen perspective on work item valuation.

Keywords. Value Engineering, Design Structure Matrix, Machine Learning, Systems Thinking, Product Design and Development, Portfolio Management

Introduction

Organizations across many industries have strategically embraced digital transformation over the past decade to remain competitive during the latest industrial revolution, coined Industry 4.0 [1]. As opportunities for new or improved digital products and services (DPS) grow, companies pursuing digitalization must prioritize and select among many potential initiatives under the constraints of a limited budget and available talent. These decisions are further complicated by in-flight project work, including long-duration R&D projects with strong commitment bias. Adopting a consistent and comprehensive value framework flexible enough to cover the breadth of in-scope work for the organization could unblock decision-making. However, firms not traditionally associated with digital delivery lack the core functional experience to establish such a

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framework. Furthermore, no single value system for DPS work has attained universal consensus as a best practice across industries.

Recent publications on digital product management offer several proposed conceptual models covering the contemporary understanding of DPS value creation for an organization (Table 1). In one literature review, researchers identified 38 benefits of

Table 1. Digital Products and Services (DPS) value themes and elements in the literature.

Theme	Value Elements	Source
Customer	Relevance among customers, innovative products and services, customer interaction convenience, drive customer behavior, product and service quality, customer experience, customer-tailored solution, customer conversion	[2]
Business Model	Enlarge customer pool, profitability, increase returns, expand to digital channels, competitive advantage, enhanced promotion, new competitive models, advance to new business fields, increased sales, risk mitigation, cost reduction, enable innovations, efficiency	[2]
Business Processes	Increase productivity, reduced product time to market, operational excellence, smart workflow integration, gain external network synergies, process flexibility, speed of service proposition, process automation, process improvement	[2]
Application Systems & Services	Improved information base, new delivery model, knowledge management, real-time information, use of customer data, use of internal data, customer insights	[2]
Infrastructure	Smart technologies	[2]
Organizational Knowledge	(Competency): Organizational agility, transparency; (Process): accidental innovation, innovation productivity, sustainability	[3]
Product/Service	(Product Functionality) Frugality, customization; (User) consumer perceived value, willingness to pay	[3]
Human Capital	(Empowerment) Employee empowerment, reduced path dependence; (Structural) organizational identity, teamwork performance	[3]
Collaboration	(Networked) User contribution; (Pooled) External knowledge absorption, collaboration	[3]
Competition	(Holistic) Resource efficiency, improvisational capabilities, mobilizability; (Start-up) Customer adoption, user base scaling	[3]
Direct Commercial Benefits	Direct revenue, direct cost reduction	[4]
Indirect Commercial Benefits	Core product sales, employee effectiveness, process speed and quality, equipment utilization, customer satisfaction/retention	[4]
Goodwill / Intangible Benefits	Brand awareness, employer branding, agile culture & organizational learning, technology & data expertise, ecological & social sustainability, strategic bets, equity story	[4]
Profitability	Direct cost savings, direct revenue	[5]
Boosting Core Business	Customer satisfaction, core business sales, asset & infrastructure utilization, process speed & quality, employee efficacy, enhanced promotion	[5]
Long-Term Success	Technology expertise, threat/risk mitigation, leveraging of alliances, employer branding, strategic long shot	[5]

digital transformation that fall into five broad value themes: customers, business model, business processes, application systems and services, and infrastructure [2]. An alternate study covering nearly two decades of literature found 21 distinct DPS value dimensions that fall either inside or outside an organization, each associated with the value theme of organizational knowledge, product/service, human capital, collaboration, or competition [3]. DPS value creation has also been presented as a wheel with direct, indirect, and intangible benefits in concentric layers of elements, totaling 14 value drivers [4]. This framework was later revised to comprise 13 elements that contribute to profitability, boosting the core business, or the long-term success of an organization [5]. Deciding which framework to apply is a non-trivial choice, further complicated by alternative value models from other publications, internal sources, or business consultants.

There is a need to identify the salient drivers of DPS value from multiple frameworks, ideally at the level of granularity desired by an organization. This paper approaches the problem using a traditional systems-engineering approach and compares it to using state-of-the-art artificial intelligence (AI). We show that the combination of multiple DPS value frameworks can be achieved at a custom level of complexity, and the value drivers identified show good alignment between the methods. Furthermore, we define a hybrid approach that retains the key benefits of both end-member techniques and is flexible enough to incorporate additional frameworks as they come to light for an evergreen view of what constitutes DPS value.

1. Methods

1.1. Design Structure Matrix Analysis

In systems engineering, complex system analysis can be accomplished by representing a system with an $N \times N$ matrix, where each of the N unique components is listed along the diagonal. This representation, known as a Design Structure Matrix (DSM), models the system like a directional graph such that the value within a cell described by any (row a, column b) pair corresponds to a relationship from component b to component a of the system [6]. In its simplest form, a unit flag marks the connectedness between any two elements, and all relationships are assumed to be bi-directional. This binary DSM is symmetric in structure and contains only zeros and ones.

When applied to the problem of combining multiple frameworks, a DSM model formally catalogs thematic matches between individual framework elements like those listed in Table 1. In some cases, different DPS value frameworks share the same element (e.g., *direct revenue*), while in others, the close relationship between elements requires a human-identified match based on contextual similarity (e.g., *customer perceived value* and *relevance among customers*). DSM construction begins with zero-filling the matrix and reviewing value element pairs along the lower triangular, marking with a one (1) where there is a thematic relationship. The upper triangular then mirrors the lower triangular entries for symmetry. Matrix transformations may be performed to highlight strongly connected components [7]. Lastly, a clustering algorithm is applied to rearrange related value elements to appear close to each other along the diagonal. The resulting clusters reveal the salient value drivers spanning the combination of all input value frameworks. The choice of target cluster count comes from visual inspection of the DSM or by optimizing spatial statistical metrics applied to the clusters.

1.2. Generative AI Clustering

Advances in AI applied to human language reached a critical milestone with the release of ChatGPT in late 2022. ChatGPT uses the GPT-3.5 model series released by OpenAI trained to generate novel conversational replies to natural language text prompts [8]. While the underlying architecture is beyond the scope of this paper, generative AI models like ChatGPT have demonstrated the ability to recognize semantic context and summarize text [9], both of which are needed for combinatory value framework analysis.

To test the applicability of generative AI to this problem space, the value elements listed in Table 1 were passed into ChatGPT with user prompts to aggregate the value elements into non-overlapping clusters. Results were provided in the chat replies, requiring no further preparation or analysis from the authors.

1.3. Intelligent Design Structure Matrix Analysis

Large language models like those underlying ChatGPT function by transforming text into a reduced representation called an embedding vector [10]. Measures like cosine similarity can then be applied to any two embedding vectors to quantify the degree of contextual similarity between the associated original text phrases. Using this approach on each pair of value elements noted in Table 1, one can construct a similarity DSM that catalogs the degree of connectivity within and across the original value frameworks.

Clustering methods could be applied directly to this Intelligent DSM or I-DSM (named for its association with AI models); however, DSP value elements will naturally have a high degree of similarity due to their shared relationship in defining the business value of digital products and services. Matrix preconditioning for greater differentiation of the value elements is achievable by applying a similarity threshold, replacing entries below this value with zero (0) and those above the threshold with one (1). As with traditional DSM analysis, clustering this matrix will shuffle the value elements into groups representing broader value drivers, ultimately forming the basis for a combined value framework. The optimal number of clusters can be derived directly from the products of specific clustering methods, as illustrated in the next section.

2. Results

2.1. Design Structure Matrix Analysis

The results of the traditional binary DSM analysis are illustrated in Figure 1. Background banding in Fig. 1A highlights the original value frameworks included in the matrix, and dark gray cells indicate pairwise contextual connections between value elements in the corresponding row and column. Figure 1B depicts the outcome of an agglomerative clustering routine executed with a goal of 11 clusters. This choice in count comes from the analysis shown in Figure 1C. The agglomerative routine used here starts with all value elements in individual clusters and merges them based on a minimum inter-cluster variance criterion. The circled peaks in the plot show large changes in cluster width as clusters are merged for the subsequent decrease in cluster count, suggesting 3, 7, or 11 as practical levels of granularity for a combinatorial value framework.

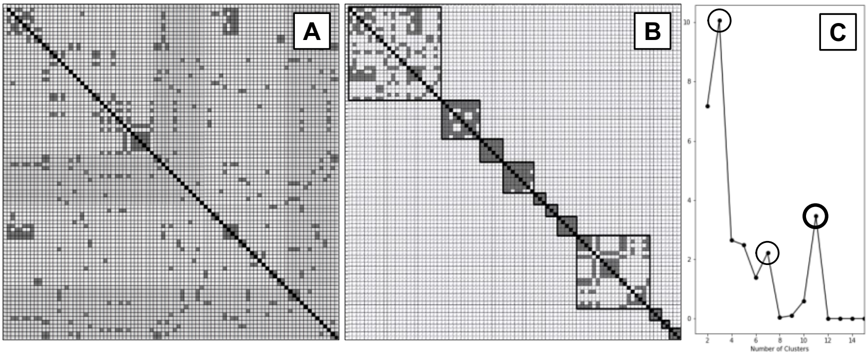

Figure 1. A. Design Structure Matrix (DSM) of the 86 value elements in Table 1. Light and medium gray bands illustrate groups of rows and columns corresponding to the four original value frameworks referenced in this paper: [2-5]. Dark gray cells denote thematic connections between elements in the row-column pair. B. Agglomerative clustering results for the DSM using 11 clusters as the target. Value driver themes are presented in square boxes. C. Preferred cluster counts are identified by considering the change in cluster variance with increasing aggregation. The peaks at 3, 7, and 11 highlight optionality in lumping or splitting value drivers for a combined value framework.

2.2. Generative AI Clustering

Defining value drivers by requesting proposed value element clusters from ChatGPT produces results with minimal effort. The drivers listed in Figure 2 were captured by asking, in a clear chat with no history, "*cluster the following phrases into non-overlapping groups:*" followed by quoted-surrounded keyword descriptions in a comma-separated list. The keyword descriptions were the 86 short phrases listed in Table 1. Recognizing that the brevity of these phrases may lack important context for ChatGPT, the authors expanded each into a longer-form phrase based on human intuition of the appropriate level of detail. For example, "*equity story*" was revised to "*increasing a company's value potential, market potential, success drivers, strategy, culture, and stability*." Figures 2A-B illustrate one example of the ChatGPT-proposed clusters using the keyword descriptions and expanded phrases, respectively. By default, responses tended to be 3-4 clusters in number, although the specific count of clusters, elements within each cluster, cluster title, and even the structural style of the response varied each time ChatGPT was asked to perform the task. Furthermore, the responses inexplicably leave some value elements out of the reply text, as noted by No Cluster in the figure. Prompts using human-augmented phrases result in more value element drop-outs in ChatGPT replies than prompts with keyword descriptions.

Figures 2C-D illustrate how the proposed value drivers change when the prompt is updated to "*cluster the following phrases into eleven non-overlapping groups…*" Exactly 11 value drivers are defined, but the outcomes are non-unique, and the number of dropped elements increases compared to when the cluster count was not pre-defined. ChatGPT responses consistently end mid-statement for the expanded phrase case. Importantly, large language models have a limit that applies to both the input prompt and output generated. For GPT 3.5, this limit is 4096 tokens or approximately 3000 words. This can be overcome with a simple follow-on prompt of "*continue*" to ChatGPT, although the combination of the two partial responses still demonstrates phrase drop-out.

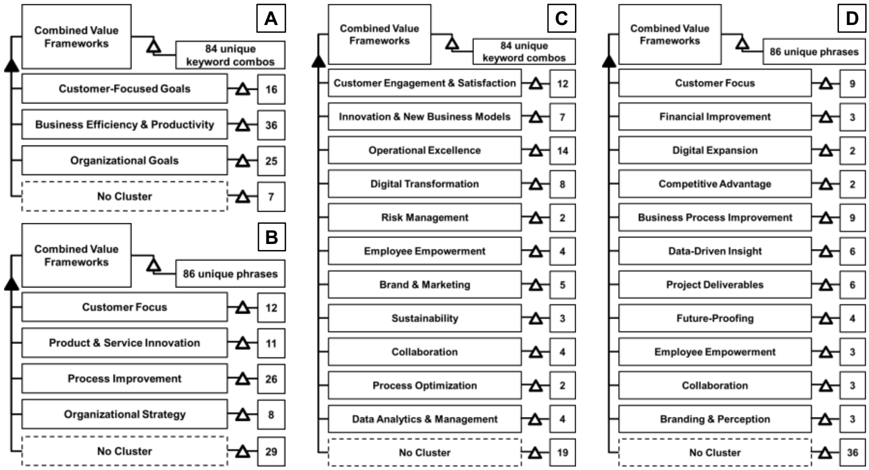

Figure 2. Examples of ChatGPT v. Feb13 responses presented using Object Process Model representation. Results vary with each chat session due to model randomness. Unlabeled numbers indicate the count of value elements assigned to the connected higher-level value driver. A. ChatGPT identifies three value drivers, clustering 77/84 (92%) of the unique keyword descriptions. B. Use of human-augmented value element phrases in the prompt leads to four value drivers covering 57/86 (66%) of the inputs. C. Suggested value drivers when prompted for 11 clusters using keyword descriptions. 77% of the inputs are in the response. D. Results when pairing the 11-cluster prompt with human-augmented phrases. Only 58% of the input elements are in the reply.

2.3. Intelligent Design Structure Matrix Analysis

A pre-trained model to transform text inputs into embedding vectors is fundamental to the I-DSM workflow. The authors identified the all-mpnet-base-v2 (MPNet) model from the sentence-transformers Python library [10] and the text-embedding-ada-002 (Ada) model from OpenAI GPT-3 [11] as well-suited for this task. Taking an ensemble approach for results enhancement, the embeddings from the MPNet and Ada models were concatenated into an extended embedding for all value elements before comparing them pairwise using the cosine similarity measure. Figure 3A illustrates the raw I-DSM created using the keyword descriptions in Table 1, compared to the I-DSM for expanded phrases in Figure 3D. To introduce greater contextual meaning before generating embedding vectors, ChatGPT was asked to express each of the keyword descriptions in paragraph form, which led to the I-DSM in Figure 3G. Visually, all three DSMs show different similarity measure responses. The keyword version has a more homogenous image character than the human-augmented phrases version, and the AI-augmented paragraph version shows the most variation in pairwise similarity patterns.

Before clustering the similarities, each matrix was transformed into a binary DSM. The threshold used for the transform comes from the maximum curvature point of the upper curve in the cumulative distribution function for all matrix values. Agglomerative clustering produced poor results, so spectral clustering was used to rearrange the matrices, as shown in Figures 3B, E, & H. A valuable artifact of spectral clustering is the generation of Laplacian eigenvalues (λ) in the process, which can be plotted for further analysis (Figure 3C). The count of zero-value λs corresponds to a natural separation of the value elements into separable clusters, in this case totaling 6. In addition, large relative steps in successive eigenvalue magnitudes can highlight alternate cluster counts, such as seen for 12 clusters in Figure 3C. Results for the phrase version of the value elements suggest a single optimal cluster count of 8 (Figure 3F), whereas the paragraph version identifies 9 and 12 as the best number of clusters to target (Figure 3I).

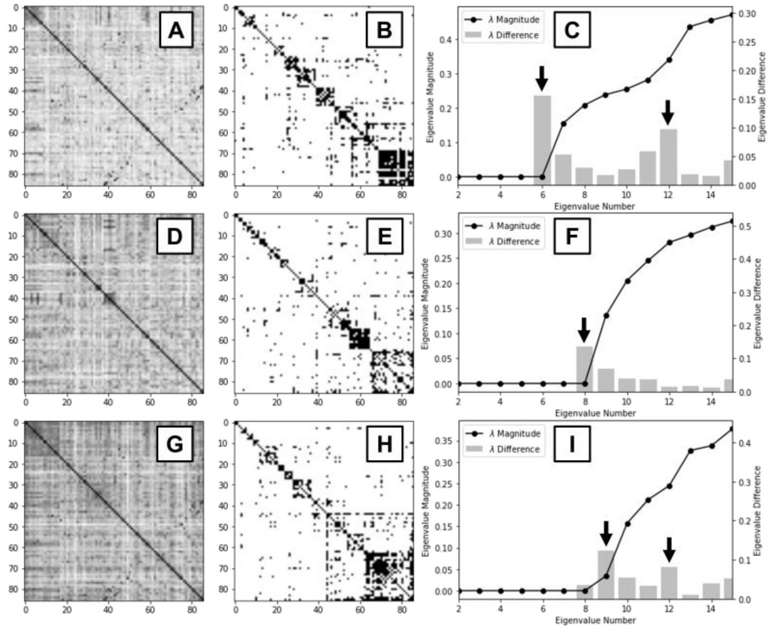

Figure 3. A. I-DSM constructed from pairwise similarities of embedding vectors for value element keyword descriptions in Table 1. B. Keyword I-DSM after converting to a binary form and spectral clustering for 11 value drivers. C. Laplacian eigenvalues (λs) for the binary I-DSM (as points) and running eigenvalue differences (as bars) illustrate a natural cluster count of 6 and an alternate option of 11, noted by the arrows. D.-F. Same analysis as A.-C. except using human-augmented phrases for the value elements when generating embedding vectors. G.-I. Same analysis as A.-C. except using ChatGPT-derived paragraphs for the value elements as input into the embedding models.

2.4. Value Framework Comparison

A comparison of the different results sets described in Sections 2.1-2.3 is shown in Table 2. For the Generative AI outcome, the authors selected value drivers identified using keyword descriptions of the value elements over the expanded phrase results due to observed element drop-out count in responses for the latter. The I-DSM value drivers derive from the ChatGPT-generated paragraph versions of the value elements and a 12-cluster target, as suggested by the eigenvalue optima in Figure 3I. The Consistent Drivers column notes value drivers observed across most results sets and defines a suggested combinatorial value framework on the scale of 12 drivers in complexity.

3. Discussion

This study used multiple methods to integrate elements from alternate DPS value models into a cohesive set of drivers to facilitate DPS work valuation and portfolio management. The first approach grouped elements using a DSM, where value theme linkages were identified through human cognition. Specifically, 3655 pairwise comparisons were made to construct the matrix, each requiring a decision on whether the similarity between two

Table 2: Comparison of combined value frameworks identified using the methods described in this paper. The Consistent Drivers column highlights value drivers consistent with two or more results sets.

Binary DSM	**Generative AI (keywords)**	**Intelligent DSM (para.)**	**Consistent Drivers**
Process Optimization & Agility	Process Optimization	Process Optimization	Business Process Improvement
Financial Performance & Cost Management		Profitability & Growth	Financial Performance
Digital Transformation & Market Expansion	Digital Transformation	Organizational Agility	Digital Transformation
Collaborative Teamwork	Operational Excellence	Collaborative Teamwork	Operational Excellence (Teamwork Focus)
Branding & Sustainability	Brand & Marketing	Employer Branding	Brand & Identity
Strategic Innovation	Innovation & New Business Models	Innovation Strategy	Innovation Strategy
Employee Productivity & Development	Employee Empowerment	Employee Effectiveness	Employee Effectiveness
Customer-Centric Solutions & Satisfaction	Customer Engagement & Satisfaction	Customer Engagement	Customer Focus
Partnership & Collaboration	Collaboration	Network Synergies	External Partnership
Risk Management & Sustainability	Risk Management	Risk Mitigation	Risk Management
Technology Expertise & Data Management	Data Analytics & Management	Data-Driven Efficiency	Data & Technology Management
	Sustainability	Business Efficiency	Sustainability and Utilization

value elements warranted a flag for connectedness. This method required multiple iterations to arrive at the result in Figure 1. However, data preparation was unnecessary because the human brain can intuit context from keyword descriptions and determine thematic relatedness without formal calculations. For smaller data sets, the simplicity of this method makes it favorable, but the traditional DSM method does not scale well as the number of value frameworks included in the analysis grows.

Generative AI tools like ChatGPT challenge norms associated with language-related problem solving, partly because of their extreme efficiency with tasks considered laborious for a human to complete. Figure 2 shows that ChatGPT can successfully group a list of concepts and even provide meaningful labels for each group. Nonetheless, both consistency and completeness remain opportunities for improvement. The value drivers identified from keyword descriptions differ from those derived with phrases, even when a target cluster count is specified (Figure 2). As a conversational AI model, ChatGPT relies strongly on details provided within a chat session. More information in the prompt could fill contextual gaps, but input detail trades off with output completeness. Several value elements were missing in the reply for keyword descriptions, and that number grew by a factor of 2-4 for human-augmented phrases. In addition, model randomness reduced reproducibility within or between chat sessions, even for the same user. The close match in value drivers in Figure 2 with those in Table 2 suggests an alternative use case for generative AI: validating value frameworks derived using more consistent techniques.

Among the methods considered, the I-DSM approach requires the most data preparation, particularly if establishing sufficient context for value element comparisons through input enrichment (either by human or AI augmentation) is desired. The additional overhead comes with substantial benefits, however. Unlike the traditional manual DSM approach, an I-DSM can capture the degree of connectedness between two elements with decimal precision on a scale of 0.0-1.0. Moreover, unlike the ChatGPT results, I-DSM outcomes are reproducible so long as the embedding model(s) remain the same. The automated nature of I-DSM construction makes it scalable to larger data sets, well past the limits of human time and patience affecting the manual DSM approach. Furthermore, I-DSM analysis supports rapid re-generation of human-interpretable clusters at any time, which allows the framework to remain evergreen as new value models are brought forward through internal or external sources.

Cluster analysis for both DSM approaches revealed an interesting hierarchical aspect to combined value framework definitions. Decomposing DPS value at different levels of complexity is a natural product of the agglomerative method, i.e., the "heights" in Figure 1C usually compose a tree-like dendrogram. Nonetheless, spectral clustering of I-DSMs also detected multiple decomposition options that roughly match in cluster count (6 and 12, see Figure 3C) with those identified for the manual DSM (3, 7, 11, see Figure 1C). ChatGPT also defaulted to 3-4 clusters when not given a target count, suggesting this may be a natural level 1 decomposition, while 6-7 or 11-12 clusters represent deeper-level frameworks. This flexibility in framework definition could be advantageous depending on the use case; the simplicity of a 3-driver value framework would enable widespread acceptance in a large organization, while one composed of more value drivers could facilitate difficult stop-work decisions for a complex DPS portfolio facing a flat or declining resource budget.

As a visual representation of all value elements at once, DSMs can also drive insights into the quality of a value framework decomposition. For example, among the clusters illustrated in Figure 1B, the first and eighth from the upper left are sparser (have more zero-valued cells) than the others. A dense cluster indicates a strong abstraction that can easily translate into a human-interpretable theme. In contrast, sparse clusters may combine value elements with partial similarity and distinct sub-themes. Referring to Table 2, clusters 1 and 8 cover "*Process Optimization and Agility*" and "*Customer-Centric Solutions and Satisfaction*"—relatively broad concepts covering multiple lower-level drivers of greater specificity. Firms could use these DSM insights to evaluate and tune a value framework to the level that best suits their needs.

Value framework flexibility, embodied in multi-level driver granularity and the ability to refresh as new information arises, reflects an essential paradigm at the heart of digital transformation. Semi-automated approaches like I-DSMs offer analysis efficiency even as data sets grow past reasonable limits for human management, and they also open opportunities for new ways of working. Rather than treating the Consistent Drivers column in Table 2 as a rigid universal framework for digital work, organizations can use the techniques described in this study to custom-tailor a framework aligned with their unique strategy and norms, increasing the chances of its adoption for prioritization decisions. Methodologies like the I-DSM approach can also enable operational excellence business practices; DPS value assignments defined today will be limited by existing knowledge, so future changes will be necessary to meet the dynamic needs of firms that are evolving and learning through time.

4. Conclusions

Portfolio management for digital products and services (DPS) relies on assigning value to work opportunities using a comprehensive and consistent framework. The results of this study show that such a framework can be derived from multiple value models using Design Structure Matrix (DSM) methods that yield high-level value drivers. Traditional DSMs involve little data preparation, but their manual construction scales poorly with many inputs. The semi-automated Intelligent DSM (I-DSM) approach overcomes scalability issues but requires context-rich inputs to replace human understanding baked into the original DSM method. Sole reliance on generative AI is not recommended due to problems with reproducibility and response completeness. Instead, I-DSMs derived from inputs augmented by generative AI efficiently reveal frameworks that honor the richness of contextual similarity across even very large numbers of value elements. Results from all methods highlight 12 consistent value drivers, although embracing framework flexibility with different levels of decomposition and regular revisions as new value models come to light is more aligned with a continuous-improvement business mindset. Future work will consider the influence of project dependencies and the socio-technical facets of an organization on value assignment and portfolio decision-making.

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