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Looking back and forward

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Testing service infusion in manufacturing through machine learning techniques: looking back and forward

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Abstract

Purpose – Responding to calls for deeper analysis of the conceptual foundations of service infusion in manufacturing, this paper examines the underlying assumptions that: (i) manufacturing firms incorporating services follow a pathway, moving from pure-product to pure-service offerings, and (ii) profits increase linearly with this process. We propose that these assumptions are inconsistent with the premises of behavioural and learning theories.

Design/methodology/approach – Machine learning algorithms are applied to test whether a successive process, from a basic to a more advanced offering, creates optimal performance. The data were gathered through two surveys administered to USA manufacturing firms in 2021 and 2023. The first included a training sample comprising 225 firms, whilst the second encompassed a testing sample of 105 firms.

Findings – Analysis shows that following the base-intermediate-advanced services pathway is not the best predictor of optimal performance. Developing advanced services and then later adding less complex offerings supports better performance.

Practical implications – Manufacturing firms follow heterogeneous pathways in their service development journey. Non-servitised firms need to carefully consider their contextual conditions when selecting their initial service offering. Starting with a single service offering appears to be a superior strategy over providing multiple services.

Originality/value – The machine learning approach is novel to the field and captures the key conditions for manufacturers to successfully servitise. Insight is derived from the adoption and implementation year datasets

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for 17 types of services described in previous qualitative studies. The methods proposed can be extended to assess other process-based models in related management fields (e.g., sand cone).

Keywords Service infusion, Manufacturing, Quantitative analysis, Machine learning, Pathways
Paper type Research paper

1. Introduction

For the past 3 decades, scholars have studied manufacturing firms that have routinely added services to their core product offerings (Rabetino *et al.*, 2021). Service infusion, often synonymous with servitization (Kowalkowski *et al.*, 2017), represents the progressive augmentation of service offerings within a company's portfolio (Brax and Visintin, 2017) and may be accompanied by the restructuring of firms' resource allocation, organisational structures and competencies (Bustinza *et al.*, 2017). Service infusion is fuelled by firms' attempts to improve their competitiveness, secure longitudinal revenue streams and exploring avenues for further expansion (Rabetino *et al.*, 2021; Davies *et al.*, 2023). For example, two-thirds of large manufacturers have shifted to hybrid product-service offerings as a way to develop and sustain competitive advantage in their industry (Martinez *et al.*, 2017); and the number of servitized global manufacturing multinationals with annual revenues higher than $1bn exceeds 7,000 organisations (Bustinza *et al.*, 2019). Importantly, service infusion requires manufacturers to undergo a critical organisational transformation (Kohtamäki *et al.*, 2018; Kowalkowski *et al.*, 2015; Rabetino *et al.*, 2018). Chase (1981) developed an initial framework for firms transitioning from pure manufacturing to pure service-based business models, identifying various stages in the service system where decoupling was possible. Using Chase's framework as a starting point, most scholars frame service infusion as a product-service continuum (see Table 1) where service transition follows a stage model (Baines and Lightfoot, 2013; Oliva and Kallenberg, 2003) or series of strategic service pivots [1] (Kirtley and O'Mahony, 2020; Gomes *et al.*, 2021). A comprehensive body of research has conceptualised the stages that form the sequential product-service pathway (Oliva and Kallenberg, 2003; Tukker, 2004; Kowalkowski *et al.*, 2015; Brax and Visintin, 2017).

In the service infusion process, it is generally posited that companies traverse a continuum, either through evolutionary progression or discontinuous leaps, from rudimentary product-centric services towards more advanced service-oriented provisions (Kowalkowski *et al.*, 2017). Consequently, most models typically advocate a gradual expansion in service offerings, starting with base services and progressing towards intermediate and advanced offerings, as proposed by Baines and Lightfoot (2013). Whilst some evidence supports this by recommending a balanced mix of base and advanced services (Sousa and da Silveira, 2017), others argue that factors like industry, firm size and age influence the optimal path for service infusion, challenging this linear progression (Valtakoski and Witell, 2018). Research has explored a counter trend termed "service dilution" (Kowalkowski *et al.*, 2017), disrupting the assumed unidirectional movement. Further, despite the expected linear increase in profits with service infusion (Tenucci and Enrico, 2020), studies by Kohtamäki *et al.* (2013), Suarez *et al.* (2013) and Visnjic and Van Looy (2013) found non-linear relationships between service infusion and profitability across various industries.

Although prevailing theoretical research supports a linear product-service sequence, recent empirical studies challenge this idea, conflicting with established behavioural and learning theories (e.g., Argote and Epple, 1990; Surdu *et al.*, 2021). This discrepancy might arise from limitations in empirical designs to assess service integration, which often rely on parametric approaches (Wang *et al.*, 2018). Given the complexity of service infusion, success in developing new service offerings seems reliant on the path of service infusion (Lexutt, 2020). To effectively analyse such complexity, regression models should encompass all relevant observable variables to reveal genuine predictive interactions (Lindner *et al.*, 2022). However, due to the complexity of firm service infusion (Rabetino *et al.*, 2021), it is unlikely all critical variables are

Types of services	Baines and Lightfoot (2013)	Oliva and Kallenberg (2003)	Tukker (2004)	Wang *et al.* (2018)
Documentation	Base services	Basic installed based services	Product-oriented	Services supporting products
Transport	Base services	Basic installed based services	Product-oriented	Services supporting products
Installation	Base services	Basic installed based services	Product-oriented	Services supporting products
Product/Equipment provision	Base services	Basic installed based services	Product-oriented	Services supporting products
Spare parts	Base services	Basic installed based services	Product-oriented	Services supporting products
Warranty	Base services	Basic installed based services	Product-oriented	Services supporting products
Scheduled maintenance	Intermediate services	Maintenance services	Product-oriented	Services supporting products
Helpdesk	Intermediate services	Maintenance services	Product-oriented	Services supporting products
Condition monitoring	Intermediate services	Maintenance services	Product-oriented	Services supporting products
Training	Intermediate services	Professional services	Product-oriented	Services supporting clients
Process-oriented engineering & R&D	Advanced services	Professional services	Product-oriented	Services supporting clients
Process/Business oriented consulting	Advanced services	Professional services	Product-oriented	Services supporting clients
Outsourcing/Rental	Advanced services	Professional services	Use-oriented	Services supporting clients
Activity management	Advanced services	Operational services	Use-oriented	Services supporting clients
Support agreements	Advanced services	Operational services	Result-oriented	Services supporting clients
Revenue through use contract	Advanced services	---------------	Result-oriented	
Risk and reward sharing contract	Advanced services	---------------	Result-oriented	

SERVICE INFUSION CONTINUUM

Source(s): Authors' own creation

Table 1.
Services classification and different service continuum/trajectories

included. Current trends in the literature favour regression models with numerous explanatory variables, but these amplify multicollinearity issues and affect result stability (Kalnins, 2022). Non-linear and bidirectional relationships between variables compound the stability challenge (Johnston *et al.*, 2018). Innovative methodologies, such as machine learning (ML) methods, have been developed to address these complexities and enhance research outcomes whilst alleviating multicollinearity concerns inherent in traditional regression models (Kalnins, 2018, 2022; Tonidandel *et al.*, 2018). ML encompasses the development and implementation of algorithms that facilitate computer learning through the identification and analysis of statistical regularities and patterns inherent within datasets (Hammann, 2024). Importantly, ML models can discern intricate interrelations (Choudhury *et al.*, 2021). The fundamental aim of ML is to construct a model that is able to precisely forecast outcomes by leveraging a specified collection of potential predictor variables (Bowles, 2015). ML offers solutions to identifying patterns that could serve exploratory inductive or abductive research purposes, or facilitate post hoc analysis of regression outcomes to reveal potentially overlooked patterns (Choudhury *et al.*, 2021).

Some voices highlight the importance for management studies to seek new quantitative approaches that extend beyond regression analysis. For instance, in a recent editorial in the *Journal of International Business Studies*, Lindner *et al.* (2022) propose that broadening the methodological pallet will produce better empirical models, adding ML techniques that, amongst other advantages, avoid significant bias in model coefficients. Verbeke *et al.* (2012) and Chuang *et al.* (2021) also advocate for enhanced prediction models that complement operations management principles with ML tools. Pagell *et al.* (2019) and Chou *et al.* (2023) encourage the use of new approaches for building operations and supply chain management theory based on, amongst other emerging approaches, ML techniques.

This study clarifies the nature of service stage development and pathways leading to superior performance by applying ML techniques (Verbeke *et al.*, 2011). The first research question investigates whether service infusion in manufacturing adheres to a step-by-step developmental pathway, examining if it aligns with the "Base → Intermediate → Advanced" sequence (Baines and Lightfoot, 2013; Kohtamäki *et al.*, 2020; Oliva and Kallenberg, 2003) and exploring deviations from this linear progression. The second question investigates the linear association between service integration and enhanced performance, seeking to understand if a rise in the proportion of service sales consistently leads to improved performance, regardless of the initial service sales level.

To demonstrate the importance of using an ML approach to build new theory, contrast theoretical assumptions, and complement previous development, this research administered a survey to US manufacturing firms at various stages of their service infusion journey. The survey captures a training sample of 225 firms and a testing sample of 105 firms and shows that the antecedents of higher service performance include the development of advanced services in isolation, with firms later adding less complex offerings, no matter the service type, base or intermediate. Our contributions are fourfold. First, the study reviews different consolidated sequence pathway models in operations management literature and demonstrates the relevance of applying ML techniques for identification of the optimal sequence of path stages. This provides an example of the application of ML techniques to test the assumption of service infusion in manufacturing literature. Using supervised ML techniques, assumptions of unidirectional progress through the product-service sequence pathway are tested using rule induction algorithms, and linearity assumptions are tested using decision tree algorithms. Second, the study contributes to the debate on how manufacturing firms infusing services learn (e.g., Sousa and da Silveira (2017) vs Valtakoski and Witell (2018)) by asking firms for the adoption and implementation date of various services. Collecting chronological data establishes the service implementation pathway and suggests there are more heterogeneities in the implementation pathway than process-based models would predict. Third, the study shows that results from ML techniques align with management theories. For instance, our finding that manufacturers need to start their service infusion journey at the most complex stage of service offering (i.e., Advanced services) is consistent with behavioural theory (Surdu *et al.*, 2021), learning curves (Argote and Epple, 1990) and absorptive capacity (Zahra and George, 2002). This suggests ML techniques are a useful addition to the methodological techniques for theory testing (Chou *et al.*, 2023). Finally, in showing the importance of ML techniques in assessing the assumptions of a consolidated theoretical sequence pathway model, we open a new avenue of empirical research, evaluating the assumptions behind other dominant stage pathway-based models in management, e.g., sand cone of manufacturing capabilities development (Ferdows and de Meyer, 1990); internationalisation model (Johanson and Vahlne, 1990); manufacturing competitiveness (Wheelwright and Hayes, 1985); knowledge lifecycle management (Siemieniuch and Sinclair, 2004); innovation-oriented operations stage-based model (Nair and Boulton, 2008); and the context, content, and process framework (Baines *et al.*, 2017).

2. Background literature

2.1 Machine learning techniques in management

Mantere and Ketokivi (2013) elucidate three modes of reasoning prevalent amongst managers and researchers in the field of organisation science: deduction, induction, and abduction.

Deductive reasoning operates by employing established rules and explanations as a premise to derive specific observations. Inductive reasoning involves synthesising observations and explanations to infer overarching rules, progressing from the specific to the general. Abductive reasoning commences with both rules and observations; the explanation is then inferred if the observations can be rationalised within the framework of the rules. In this context, ML methodologies present researchers with a novel and robust approach to observation that facilitates the theory-building process, adopting either an inductive or abductive method (Choudhury *et al.*, 2021). For instance, in management research, ML has been applied to theorise in different contexts (Leavitt *et al.*, 2021): how the diversity of organisational cultures influences both the ability to innovate and execute effectively; the impact of observable personality traits of CEOs on market perceptions of firm risk and shareholder returns; the dual nature of recombination in breakthrough innovation; and the temporal dynamics involved in team shifts from transition processes to action processes.

In the field of operations management, there are several studies using ML techniques for different research topics. For instance, Cui *et al.* (2018) utilised ML models to predict the demand for fashion products by leveraging information from social media. Feldman *et al.* (2022) undertook a comprehensive field experiment on Alibaba to identify the optimal assortment of products to present customers with on arrival at Alibaba's online marketplace. Ferreira *et al.* (2016) employed ML to estimate the demand for new products during promotional events for online fashion retailers. Liu *et al.* (2021) examined methods to minimise delays in last-mile delivery services through the analysis of delivery data and the utilisation of ML models. Kinra *et al.* (2020) investigated the potential for devising a national logistics performance assessment methodology grounded in textual big data analytics. Zhang *et al.* (2023) offered a framework for future operations management research by employing a ML approach to construct the determinant model of CSR performance. Finally, Chou *et al.* (2023) reviewed the application of supervised ML in operations management research and identified opportunities for theory development and empirical testing; and Rana and Daultani (2023) mapped the role and impact of ML applications in the digital transformation of supply chains using bibliometric analysis. ML now plays a prominent role in theory development and empirical testing within operations management. Regarding technique implementation, ML employs algorithms that learn patterns within attributes to predict outcomes (Lindner *et al.*, 2022; Verbeke *et al.*, 2012). In supervised ML, models are trained on labelled data, enabling predictions for new, unseen examples based on learnt patterns, whilst unsupervised learning explores unlabelled data, discovering inherent patterns and relationships. Supervised learning predicts outcomes; unsupervised learning unveils data relationships. ML utilises training datasets to create a prediction model, refining techniques and algorithms until an optimal "learner" is achieved (Hastie *et al.*, 2009). Various techniques and algorithms are employed to identify the most effective "learner" (Verbeke *et al.*, 2012). These methods encompass: *decision trees*, using a top-down divide-and-conquer approach that selects attributes and partitions datasets to create subsets reflecting homogeneity, assessed via entropy (C4.5 algorithm) or Gini criterion (CART algorithm); *decision rules*, offering rules based on a single attribute (1R algorithm), employing top-down separate-and-conquer approaches (e.g., RIPPER algorithm) or a blend of divide-and-conquer and separate-and-conquer strategies (e.g., PART algorithm); *ensemble methods* that utilise various learners (e.g., random forest, employing base learner and bagging and boosting through decision trees) weighted to derive a final prediction; *nearest neighbours*, classifying attributes based on Euclidean distance (e.g., lazy IBk algorithm); *Support Vector Machines*, crafting hyperplanes to maximise margins between classes and employing kernel functions to establish decision boundaries; *statistical classifiers* such as logistic regression for probability estimation, Naïve-Bayes estimating class-conditional probabilities by assuming attribute independence, or Bayesian networks specifying attribute independence; and *neural* *networks* based on the perceptron convergence theorem, constructing networks of neurons and determining class fitting, functions and associated weights aligned with training data (Chiu and Xu, 2023; Hastie *et al.*, 2009; Witten and Frank, 2005).

The evolution of ML literature has focused on developing new algorithms that maximise accuracy metrics on isolated datasets, yet addressing the real impact of these techniques remains an open issue (Wagstaff, 2012). Valizade *et al.* (2022) advocate for the incorporation of new analytical tools and advanced statistical modelling based on null hypothesis significance testing, emphasising the need for a more balanced methodological approach. ML offers a balanced avenue for theory generation and testing research, which is particularly beneficial for scrutinising and potentially providing robust evidence against prevailing assumptions and expectations (Tonidandel *et al.*, 2018). Unlike traditional statistical models like regression or SEM, ML techniques excel in unravelling complex phenomena by deciphering non-monotonous and non-linear effects between model variables (Kalnins, 2022; Leavitt *et al.*, 2021). For instance, Valizade *et al.* (2022) applied ML techniques to predict outcomes in a European innovation survey, comparing parametric approaches like logistic regression with a range of algorithms. ML outperformed logistic regression by reporting variable importance scores, identifying non-linear relationships and effectively addressing multicollinearity issues typically encountered in regression analyses.

2.2 Service infusion in manufacturing: models

Chase (1981) pioneered the grouping of service offerings into categories according to an incremental tracing variable, in his case, customer contact. He proposed a linear classification such that with increasing customer contact a firm moved from manufacturing, through a varying product-service mix, to offering pure services. Building on this, the service infusion literature adopted an assumption of unidirectionality and linearity (Baines and Lightfoot, 2013; Kowalkowski *et al.*, 2015; Oliva and Kallenberg, 2003). The unidirectionality stems from the product-service continuum introduced by Oliva and Kallenberg (2003), which proposes that manufacturers move along a continuum from product to service as they seek to offer more advanced or customer-orientated services. As providers move in a unidirectional manner toward providing Advanced services, literature postulates that profits and revenues increase linearly (Tenucci and Enrico, 2020). Since the inception of Oliva and Kallenberg's (2003) product-service continuum, many variations have emerged. Within these, whilst the type of offering differs in their degree of product/service mix, definition and general categorisation, the underlying logic remains the same: organisations participate in a strategic repositioning along the product-service continuum, as shown in Figure 1.

In an early example of product-service transitions, Tukker (2004) takes an ecological perspective to highlight how a unidirectional shift from selling products to selling services improves a firm's economic and environmental impact. The continuum moves from offerings on the left side, where value is primarily added by products, to the right-hand side, where value is primarily added by services. Between each end of the continuum is a varying degree of product/service mix. Helander and Möller (2007) and Windahl and Lakemond (2010) present similar continuums to one another, with the former identifying three categories of offering along the continuum (equipment supplier, availability provider and performance provider) and the latter identifying maintenance provider, operational provider and performance provider. Despite slightly different definitions, both research studies identify a general move along the continuum from services supporting products to services supporting customers.

Baines and Lightfoot (2013) provide a perspective on the transition from products to services that is widely used in the literature (e.g., Sousa and da Silveira (2017), Story *et al.* (2017), Davies *et al.* (2023)). Their model proposes three categories of service: Base, Intermediate and Advanced. Base services focus on outcomes for product provision (e.g.,

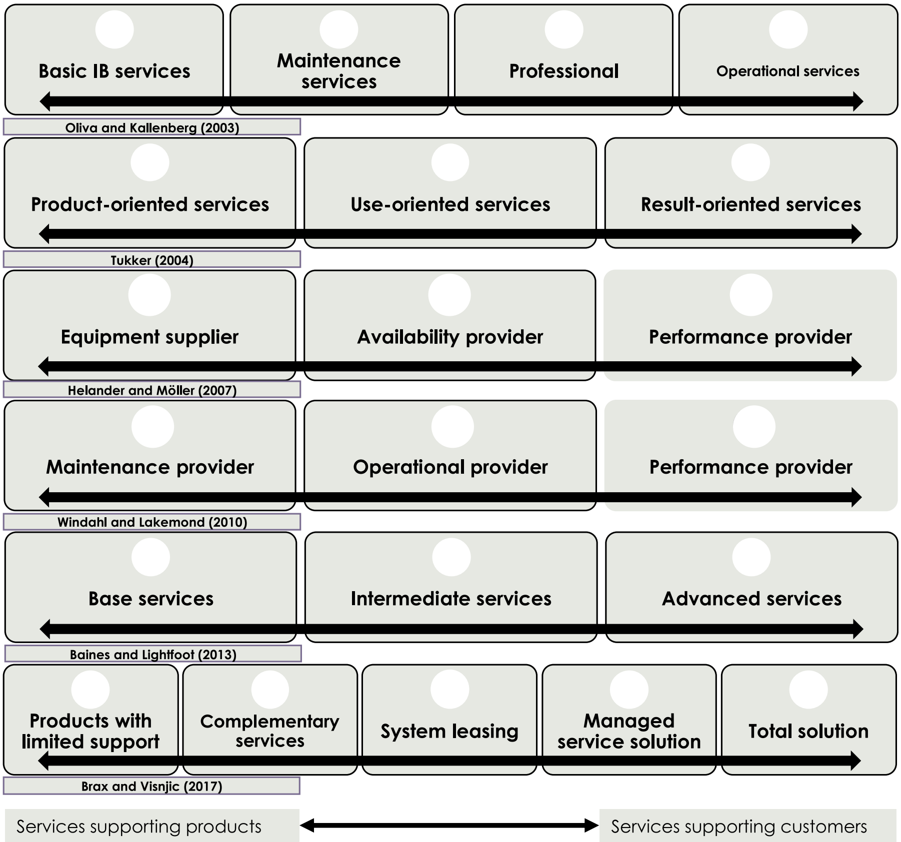

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Figure 1. Service continuum models from literature

warranty). Intermediate services focus on outcomes for maintenance of the product condition (e.g., condition monitoring). Advanced services focus on outcomes for capability and thus product performance (e.g., an availability contract). As manufacturers move from Base to Advanced services, the degree of customer orientation increases, and profitable revenues linearly increase for the provider. Finally, Brax and Visintin (2017) presented eight generic value constellations [2] derived from a literature analysis. These constellations extend from products with limited support, through systems leasing, concluding with total solutions as the highest level of service identified. In a similar vein to other continuums, the degree of value added by the product is highest at the low end of the continuum and the degree of value added by services increases as manufacturers move toward total service providers.

3. Challenging underlying assumptions about service infusion in manufacturing

The studies described in Figure 1 represent an extensive body of research rooted in the assumption of a unidirectional progression from product sales to service offerings. Despite variations in categorisations across articles, the fundamental assumptions persist: unidirectionality and linearity. Whilst widely accepted in literature, these studies have limitations. Our examination begins with a theoretical inquiry, followed by an exploration of qualitative and quantitative evidence challenging these foundational assumptions.

3.1 Theoretical critique

Previous research has scrutinised process-based models; Valtakoski and Witell (2018) contended that the capabilities necessary for specific service types do not align with the traditional incremental sand cone model, which assumes cumulative capabilities in a sequence of dependent layers (Ferdows and De Meyer, 1990). However, previous work has not thoroughly articulated or probed the assumptions underpinning process-based models beyond contextual considerations. We advance three interrelated theoretical arguments.

First, managerial decision-making, inherently shaped by human behavioural conditions, dictates firms' risk tolerance and strategic preferences (Surdu *et al.*, 2021). Diverse behavioural conditions may drive certain firms to embrace higher risk, perhaps selecting an advanced service offering from the outset.

Second, the concepts of bounded rationality and satisficing come into play (Schwarz *et al.*, 2022) as limitations prompt managers to utilise heuristics in decision-making (Huikkola *et al.*, 2022). Motivated by perceived marginal cost/effort, managers may exhibit varied motivations for implementing Base versus Advanced services.

Third, the sequencing of actions can influence a firm's learning curve. Employing a learning curve approach (e.g. Argote and Epple, 1990), starting with Advanced services, may facilitate adoption of Base or Intermediate services. Correspondingly, the absorptive capacity approach argues that learning from advanced services makes an organisation more receptive to further service innovation (Zahra and George, 2002). Together, these propositions challenge assumptions of unidirectionality and linearity in service adoption pathways.

3.2 Challenging unidirectionality

Recent qualitative enquiries challenge the established notion of linear progression along the product-service continuum. Some servitised manufacturers have shifted focus, moving from services to product offerings (Finne *et al.*, 2013). These trajectories, labelled "deservitization" or "service dilution" (Kowalkowski *et al.*, 2017), highlight how technological advancements and regulatory changes in industries influence the nature and level of services provided (Finne *et al.*, 2013). The concept of "reverse" product-service trajectories, or deservitization, has gained prominence, particularly since the special issue of *Industrial Marketing Management*. Guest editors Kowalkowski *et al.* (2017) challenge the prevailing unidirectional assumption of service infusion, urging researchers to revise established theories to accommodate the bidirectional aspects of service dilution. Gomes *et al.* (2021) further illustrate how service infusion not only shapes new business models for individual manufacturers but also for entire industries. This suggests that whilst firms may experience service dilution to re-evaluate previous business models, they might reinstate intensive service infusion approaches when conditions align with their resources, or a suitable environment emerges for new business models. Consequently, service infusion facilitates flexible business models that enable manufacturers and competitors to adapt to contextual demands, creating entry points for service infusion that aren't initially Base service offerings.

To comprehensively explore how manufacturing companies integrate services into their offerings, this study employs ML techniques to challenge the unidirectional assumption prevalent in service infusion and addresses the following research question:

RQ1. Does service infusion in manufacturing adhere to a sequential pathway of service development? Alternatively, within the framework of the Baines and Lightfoot (2013) service continuum model, does it progress in the sequence: Base → Intermediate → Advanced?

3.3 Challenging linearity

Initial quantitative studies supported a presumed linear correlation between increased service provision and enhanced firm performance (Homburg *et al.*, 2003; Skaggs and Droege, 2004). However, recent contributions challenge this assumption. Kohtamäki *et al.* (2013) and Suarez *et al.* (2013) revealed a U-shaped relationship between service infusion and firm performance, showcasing revenue and profit recovery after an initial decline, marking the attainment of a critical mass of services. Visnjic *et al.* (2016) similarly highlighted an initial detrimental impact on firm financial performance from product innovation and service business model innovation, followed by long-term improvements when both are developed simultaneously. Visnjic and van Looy (2013) demonstrated how servitised manufacturers experienced a surge in profitability upon service introduction, followed by a period of stagnation until economies of scale in service offerings were achieved, signifying an S-shaped relationship between service introduction, revenue, and profit generation.

In summary, quantitative research has challenged the assumed linear correlation between service infusion and firm performance, revealing a generally positive yet non-linear relationship (Wang *et al.*, 2018). The multiple alternative explanations for this relationship can be attributed to the constraints inherent in empirical designs. The prevalent use of regression analysis may limit consideration of interactions between non-monotonic and non-linear effects and service infusion and firm performance (Kalnins, 2022; 2022; Lexutt, 2020). Better suited to such analyses (Leavitt *et al.*, 2021), ML techniques are applied to address the research question testing the linearity assumption in the literature on service infusion and firm performance:

RQ2. Is service infusion linearly associated with superior performance? Alternatively, does an increase in the relative weight of service sales consistently lead to improved performance, irrespective of the initial level of service sales before the increase?

4. Methodology

4.1 Sample

Data was collected through Qualtrics on behalf of the research team. We provided a set of exclusion criteria to ensure respondents met the study requirements. First, we focused on US firms, excluding respondents affiliated with manufacturing companies outside the US. The US was chosen due to its prominent role in digital technologies and service business model development (Standing and Mattsson, 2018; Teruel *et al.*, 2022; Vendrell-Herrero *et al.*, 2017). Second, our study excluded companies with fewer than 500 employees, aligning with Kohtamäki *et al.* (2013), as smaller enterprises are less likely to offer advanced manufacturing-based services. Firm size was categorised into four groups: 500–999, 1,000–4,999, 5,000–9,999 and over 10,000 employees. Third, firms without a Standard Industrial Classification (SIC) code between 35 and 37 (identifying them as industrial and commercial machinery (SIC-35), electronics and other electrical equipment (SIC-36) and transportation equipment (SIC-37)) were excluded. Finally, responses from individuals below the management level within the relevant service business unit of the manufacturer were excluded to maintain data consistency within our model (Sousa and da Silveira, 2017).

The initial data collection was in December 2021, resulting in 225 valid responses, constituting the training dataset. This dataset displays balanced representation across industries, with 75 companies in each industry. Firms with fewer than 1,000 employees have a higher representation, accounting for 55%. The second data collection round in October 2023 formed the testing dataset, including 105 additional firms meeting the same criteria. Based on the ORBIS database, the total population comprises 935 firms that meet these criteria. Combining the training sample of 225 firms (70% of the total sample) with the testing sample of 105 firms (30% of the total) results in a combined sample of 330 firms. The training sample represents 24.06% of the total population, whilst the entire sample accounts for 35.29%, signifying representative samples within the target population. With a 95% confidence level ($Z = 1.0 + 1.96$), the training sample is representative with a sampling error of 5.7%, whilst the overall sample maintains a 4.4% sampling error, both of which are deemed acceptable levels (Juslin *et al.*, 2007; Okoye *et al.*, 2021).

4.2 Variables

Our analysis concentrates on a small set of variables. Here we discuss their average values for the training database, noting that the values for the testing database are quite similar. Our dependent variable is performance change. We asked companies *'On average, how did your firm's profit margin change over the period 2015–2020?'* The 5 Likert-scale options and their weighting in our database are as follows: *Decreased considerably* (2.2%), *Decreased slightly* (5.8%), *Remained flat* (7.6%), *Grown slightly* (52.4%) and *Grown considerably* (32%).

We have three other explanatory variables alongside industry and class size. First, we asked companies about their main client. 58.2% of firms said their main client was another business (B2B); 40.4% said their market orientation is towards final consumers (B2C); the remaining 1.3% declared they give equal importance to B2C and B2B relationships. Second, we employed the percentage of service sales, a measure used extensively in service infusion literature (e.g., Crozet and Milet, 2017; Visnjic and Van Looy, 2013; Suarez *et al.*, 2013). To construct this variable, we asked managers to describe the company's portfolio composition (as a percentage), e.g., products/services split 60% product, 40% services. The range of the resulting variable is between 6% (min.) and 80% (max.) with a mean of 43% and a median of 45%. Finally, we employed a list of 17 standard services offered in manufacturing and, as detailed in Table 1, divided into Base, Intermediate and Advanced services [3]. For each, we asked whether the company has adopted the service, and if the answer was affirmative we asked for the implementation year (see Appendix). This information enabled us to construct a variable related to the process of service implementation.

As specified in Table 2, we coded service stages following a sequential Base-Intermediate-Advanced service pathway development. Codes 1 to 11 represent manufacturers where service development pathways began from Base and/or Intermediate services, codes 12 to 17 are manufacturers with service development journeys from Advanced services, and codes 18 to 22 include manufacturing firms that began service infusion simultaneously with Advanced services and any other type of service combination.

4.3 Stylised facts

Based on descriptive evidence shown in Figure 2 and Tables 2 and 3, we present four stylised facts about the connection between the explanatory variables and the objective variable.

First, service stages do not seem to follow the service continuum (see Columns 3 and 4 in Table 2); only 41% of firms in the training sample and 55% of firms in the testing sample started their service journey with Base or Intermediate services, whilst 44% of firms in the training sample and 35% in the testing sample started their service journey with Advanced services. The remaining firms started their service journey by implementing a combination of Advanced and less advanced services simultaneously.

Second, service sales are only slightly correlated with the product-service sequence pathway. Figure 1 (left horizontal axis) exhibits the mean value of percentage of service sales by each service stage cohort. Whilst there is a positive association between the service stage and the level of service revenues for firms starting to servitise from Base services (S1-S6), there is no association between the service stage and relative level of service sales for firms

Code	Service stages	Training sample Number of firms (%)	Testing sample Number of firms (%)	Explanation
1	BASE	8 (3.5)	5 (4.8)	Service development paths beginning from Base and/or Intermediate services (e.g., Code 2 reflects that manufacturing firms developed first Base services and later in time Intermediate services; Code 8 reflects that Intermediate services was firstly developed, later Base services, and finally Advanced services)
2	BASE→INTERMEDIATE	1 (0.4)	0 (0.0)	
3	BASE→INTERMEDIATE→ADVANCED	9 (4.0)	3 (2.9)	
4	BASE→ADVANCED	22 (9.8)	13 (12.4)	
5	BASE→ADVANCED→INTERMEDIATE	20 (8.9)	10 (9.5)	
6	BASE→INTERMEDIATE&ADVANCED	6 (2.7)	0 (0.0)	
7	INTERMEDIATE	2 (0.9)	1 (0.9)	
8	INTERMEDIATE→BASE→ADVANCED	11 (4.9)	2 (1.9)	
9	INTERMEDIATE→ADVANCED	0 (0.0)	0 (0.0)	
10	INTERMEDIATE→ADVANCED→BASE	3 (1.3)	0 (0.0)	
11	BASE&INTERMEDIATE→ADVANCED	10 (4.4)	7 (6.7)	
12	ADVANCED	28 (12.4)	17 (16.2)	
13	ADVANCED→BASE	40 (17.8)	20 (19.0)	Service development paths beginning from Advanced services (e.g., Code 17 reflects that manufacturing firms developed first Advanced services and later in time and simultaneously Base and Intermediate services)
14	ADVANCED→BASE→INTERMEDIATE	17 (7.6)	16 (15.2)	
15	ADVANCED→INTERMEDIATE	6 (2.7)	0 (0.0)	
16	ADVANCED→INTERMEDIATE→BASE	3 (1.3)	1 (0.9)	
17	ADVANCED→BASE&INTERMEDIATE	5 (2.2)	0 (0.0)	
18	ADVANCED&BASE	22 (9.8)	10 (9.5)	Paths beginning simultaneously from Advanced services plus any other type of service (e.g., Code 19 reflects Advanced and Base services jointly developed and later in time Intermediate services)
19	ADVANCED&BASE→INTERMEDIATE	5 (2.2)	0 (0.0)	
20	ADVANCED&INTERMEDIATE	2 (0.9)	0 (0.0)	
21	ADVANCED&INTERMEDIATE→BASE	2 (0.9)	0 (0.0)	
22	ADVANCED&INTERMEDIATE&BASE	3 (1.3)	0 (0.0)	

Source(s): Authors' own creation

Table 2.
Stage coding

starting to servitise from Intermediate or Advanced services (S7-S22). The percentage of service revenue for these firms ranges between 40 and 70%, but from the descriptive analysis it is unclear how service sales connect with service stage evolution cohorts. This result is central to our thesis as it suggests that the value of service revenues as a proxy for the service strategy adopted has decreased over time since more firms are starting to servitise from Intermediate or Advanced services. This was initially an effective method to indirectly deduce the level of service infusion in firms (e.g., Suarez *et al.*, 2013; Visnjic *et al.*, 2016), but our descriptive results indicate it may not be a good proxy anymore.

Third, firm size seems unrelated to product-service continuum evolution. If they are remotely related, our results would suggest that larger firms start their service infusion journey by implementing Base services (S2) whilst smaller firms start their service infusion journey by implementing Advanced services. Significantly, according to the results for the training sample (see Figure 2), amongst the six cohorts representing different points in the service continuum evolution with a mean class size ranging from 500 to 1,000 employees for

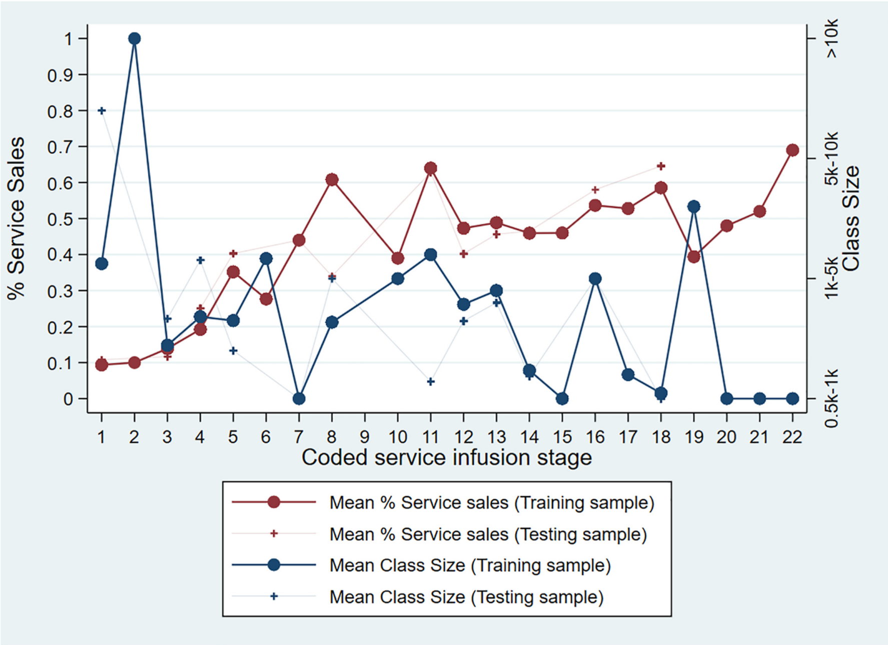

Figure 2.
Percentage of service sales and class size by service continuum evolution point

Source(s): Authors' own creation

all firms (S7, S15, S18, S20, S21 and S22), five are associated with firms commencing their service journey with the most advanced service offerings. This suggests service infusion strategic choices are not constrained by firm resources.

Finally, whilst the relationship between service sales and profit growth seems non-linear, the relationship between service stage cohorts and profit growth does appear linear. Table 3 splits the full sample in three based on the level of profit growth, separated by non-positive (including considerable decrease, slight decrease and flat), slight positive and considerable positive. The results from the training data indicate average service sales are around 50% for both non-positive and significantly positive categories, but 37% for slightly positive; figures for the testing sample are nearly identical. This descriptive result is consistent with previous literature finding a U-shaped relationship between service sales and performance (Suarez *et al.*, 2013; Visnjic and Van Looy, 2013): initially, profit rises with a fall in service sales, but at higher levels of profitability, profit rises with a rise in service sales. However, the evolution between service stage cohorts and performance seems linear. For the training sample, the percentage of firms with considerable profit growth is 0% for firms that start to servitise through Base services, 15% for firms that start to servitise through Intermediate services, 38% for firms that start to servitise through Advanced services in combination with other services, and 55% for those starting to servitise through Advanced services without offering any other service. For the testing sample, we find the same trend, but they seem dichotomised. 0% of cases have considerable growth if they start with Base or Intermediate services, whilst 40% of cases show considerable growth if they start with advanced services.

	Training sample			Testing sample		
	No positive(*) (%)	Moderate/ slight (%)	Considerable (%)	No positive(*) (%)	Moderate/ slight (%)	Considerable (%)
% Sample	15.6	52.4	32	28.6	47.6	23.8
% Service sales (Mean)	50.9	36.7	49.3	49.8	35.0	46.7
% Start by Base (S1-S6)	15.1	84.9	0.0	29.0	71.0	0.0
% Start by Intermediate (S7-S11)	23.1	61.5	15.4	70.0	30.0	0.0
% Start by Advanced simultaneously (S18-S22)	32.3	29.4	38.2	50.0	10.0	40.0
% Start by Advanced (S12-S17)	8.1	36.4	55.6	16.7	44.4	38.9
% B2B	19.9	54.9	25.2	34.8	50.7	14.5
% B2C	6.6	50.5	42.9	16.7	41.7	41.7
% SIC-35 Industrial Machinery	8.0	52.0	40.0	4.0	64.0	32.0
% SIC-36 Electronics	25.3	64.0	10.7	42.9	46.9	10.2
% SIC- 37 Transportation equipment	13.3	41.3	45.3	25.8	35.5	38.7
% Number of Employees 0.5k-1k	20.8	44.0	35.2	39.3	32.1	28.6
% Number of Employees 1k-5k	4.2	72.2	23.6	2.6	81.6	15.8
% Number of Employees 5k-10k	12.5	75.0	12.5	75.0	25.0	0.0
% Number of Employees >10k	25.0	25.0	50.0	57.1	0.0	42.8

Note(s): (*) Category no positive include considerably decrease, slight decrease and flat profit growth categories

Table 3. Explanatory variables by profit growth categories and subsamples

5. Results

5.1 ML applications

ML techniques can be categorised as supervised, predicting the value of an outcome variable based on a specific number of input measures, or unsupervised, where the goal is describing the particular associations amongst a set of input measures: association learning problems (Hastie *et al.*, 2009). As our objective is to predict considerable performance growth, the supervised category of ML algorithms is used. The majority of ML studies evaluate new algorithms applied to isolated benchmark datasets but their assessment is unrelated to their real impact on the larger world (Wagstaff, 2012). ML studies have focused on finding the best learner for a specific context (Holte, 1993) but have not applied ML techniques to answer the study's research questions. Applying the set of different ML algorithms to the data collected, and taking the Zero-R algorithm as baseline, [4] we can see the accuracy (percentage of correct

Algorithm	Description	10-Fold CCI	Improvements (*statistically sig.)
ZeroR	o-R classifier: Predicts the mean or the mode	52.47	Basic classifier
Decision tree and CART (Classification and Regression Tree) approaches			
Hoeffding	Incremental, anytime decision tree algorithm	58.05	10.63%
J48	Pruned or unpruned C4.5 decision tree	*88.22*	*68.13% (*)*
SimpleCart	Implements minimal cost-complexity pruning	90.25	72.00% (*)
Rule induction techniques			
One-R	Uses the minimum-error attribute for prediction	*75.56*	*42.16% (*)*
JRIP/RIPPER	Implements a propositional rule learner	86.29	64.46% (*)
PART	Builds a partial decision tree in each iteration	89.80	71.34% (*)
Nearest neighbours			
Lazy IBk	K-nearest neighbour classifier	81.51	55.35% (*)
Ensemble methods			
RandomForest	Forest of random trees	93.74	78.65% (*)
LMT	Logistic model trees	92.11	75.55% (*)
Bagging	Bag a classifier to reduce variance	86.05	64.00% (*)
AdaBoostM1	Boost IBk as classifier to improve performance	91.84	75.03% (*)
Neural Networks			
Ml.Perceptron	Uses backpropagation to learn a perceptron	88.02	67.75% (*)
RBFNetwork	Implements a normalised function network	76.06	44.96% (*)
Support Vector Machines (SVM) base techniques			
LibLinear	A wrapper SVM classifier	68.74	31.01% (*)
LibSVM	A wrapper SVM classifier	80.64	53.69% (*)
Statistical classifiers			
Logistic	Multinomial logistic regression model with ridge	72.20	37.60% (*)
NaiveBayes	Bayesian classifier	79.10	50.75% (*)
BayesNet	Bayes Network classifier	68.64	30.82% (*)

Source(s): Authors' own creation

Table 4.
Comparison of machine learning algorithms

predictions over total instances) of the different ML approaches to classify instances using tenfold cross validation, and if the improvement in accuracy is statistically significant (Table 4). Notably, training via n-fold cross-validation is employed for the predictive model, derived from the initial sample of 225 firms.

Following Valizade *et al.* (2022) suggestion to apply ML techniques specific to the research questions posed, in their case identifying the best predictors for innovation outcomes, and Chou *et al.* (2023) procedures outlining the key variables that give information that predicts outcome, we computed the attribute contribution function (similar to the function 'tuneRanger' for hyperparameter tuning used by Chou *et al.*, 2023) for the random forest algorithm, as this algorithm proved most accurate (see Table 5). Random forest is a consolidated procedure for effective detection of input predictors through a bootstrapped sample strategy (Witten and Frank, 2005). The importance of predictors based on the average impurity decrease procedure was found to be: stage (0.53), percentage of services (0.31) and market (0.16). Following this analysis, we selected rule induction to test the unidirectional assumption (RQ1) and decision tree to test the linearity assumption (RQ2) behind service infusion. For both analyses we trained the data with the initial sample of 225 firms and re-evaluated the model using the second sample of 105 firms.

Table 5. Service infusion stages: Testing the unidirectional assumption

One-R rule induction	Service INFUSION pathways	
IF Stage < 12.5	*SEQUENTIAL STAGES THAT PREDICT*	
THEN Performance slightly growth	*PERFORMANCE CONSIDERABLY GROWTH (RULES)*	
IF Stage < 19.5	*BEGINNING BY*	*FOLLOWING BY*
THEN Performance considerably growth	ADVANCED	ANY OTHER COMBINATION
IF Stage ≥ 19.5	*SEQUENTIAL STAGES THAT PREDICT*	
THEN Performance slightly growth	*PERFORMANCE SLIGHT GROWTH (RULES)*	
IF Stage ≥ 21.5	*BEGINNING BY*	*FOLLOWING BY*
THEN Performance flat	BASE	ANY OTHER COMBINATION
	INTERMEDIATE	ANY OTHER COMBINATION
	COMBINATION THAT PREDICTS PERFORMANCE FLAT	
	BASE&INTERMEDIATE&ADVANCED	

Source(s): Authors' own creation

5.2 Testing the unidirectional assumption (RQ1)

Rule induction algorithms follow a separate-and-conquer strategy that generates one rule at a time and leads to an ordered list of rules that better predict an outcome (here this refers to the service stages order, which better predicts performance). The rule induction technique selected is a One-R algorithm that selects the best attribute predictor (service stage as expected from the random forest) that has the lowest error rate for predicting outcome (performance). This algorithm provided a set of rules shown in Table 5, and the evaluation metrics showed the results were accurate (Hossin and Sulaiman, 2015). The rule induction algorithm One-R produced no evidence for the unidirectional pathway assumed in theoretical models. Conversely, it showed that the firms performing best first developed Advanced services (Stage 13, see Table 2) or developed Advanced services first and later introduced Base and/or Intermediate services (Stages 14–19 in Table 2). This result aligns with the data, indicating that 59% of firms in the training sample and 45% in the testing sample initiated their service infusion journey by offering Advanced services, sometimes in combination with other services (see Table 2). Taken altogether, our evidence shows that the unidirectional assumption is flawed; it neither predicts the starting point of service infusion, nor provides an appropriate route to optimal performance from product service offerings.

5.3 Testing the linearity assumption (RQ2)

To test the linearity assumption regarding the relationship between predictors and the outcome, we implement the J48 algorithm, generating a decision tree graph and effectively explaining interactions between attributes (see Figure 3 for visual representation of the algorithm-generated decision tree). Table 6 shows the evaluation metrics associated with both the training sample (225 firms) and the testing sample (105 firms) using a 70–30% splitting strategy. The accuracy, Kappa statistic and entropy for the re-evaluation are higher: 90.5%, 0.86 and 0.71 respectively, compared to the initial estimation at 88.8%, 0.81 and 0.65 respectively. We also conducted a new decision tree analysis employing tenfold cross-validation and bootstrapping through bagging. This technique generates multiple data subsets for training to reduce variance and enhance stability. The results of the re-evaluated model and the bootstrapped model are nearly identical, indicating the robustness and stability of the findings. Finally, we checked the Cohen's coefficient (0.849) and the Perreault or Leigh's coefficient (0.868). Values > 0.800 suggest high alignment amongst evaluators in their assessments or ratings. These values are also included in Table 6.

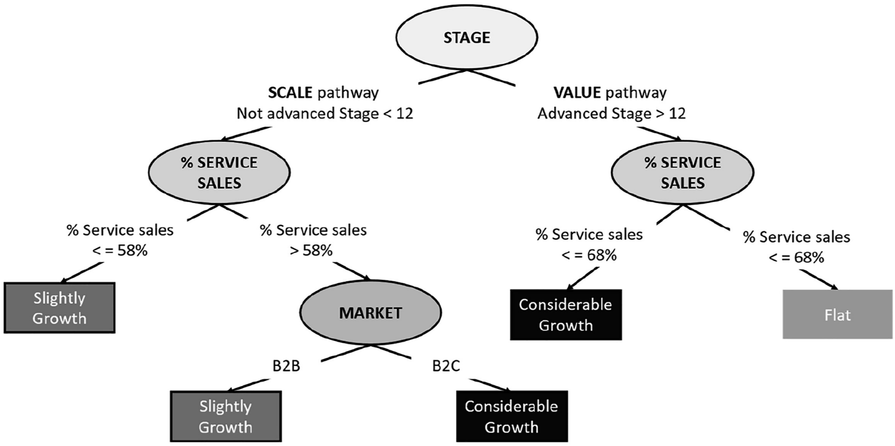

Figure 3.
Scale and value service infusion pathways to achieve superior performance

Source(s): Authors' own creation

Figure 3 shows that there are two pathways to performance. First, the *scale pathway* (left route) shows that firms that begin offering Base or Intermediate services need to achieve 58% service sales from total sales to achieve the highest level of performance from service infusion. This finding supports and complements previous studies on U-shaped and S-shaped relationships between service infusion and performance (Kohtamäki *et al.*, 2013; Suarez *et al.*, 2013; Visnjic and Van Looy, 2013) and illustrates the specific trade-off point between slight and considerable growth in profits from service infusion.

Second, the *value pathway* (right route), where firms begin by offering Advanced services, does not need a higher percentage of service sales relative to total sales to achieve considerable growth. In fact, exceeding 68% of service sales flattens performance. The existence of the two independent routes to growth is consistent with the disconnection between percentage of service sales and the level of coded service stage detected in Figure 2 and Table 3. Altogether, our evidence invalidates the linear assumption. It shows a non-linear relationship between service infusion and performance, which is dependent on the firm's strategic value proposition: scalability or value.

5.4 Robustness test

The main analysis includes one key robustness check by design: the testing sample. We also conducted analyses to ensure the consistency and clarity of our results, performing a regression analysis to demonstrate how the results presented in the decision tree can be explained using a conventional approach. Given the categorical nature of the dependent variable, we employed an ordered probit specification [5]. The model incorporated variables such as service infusion scale, percentage of service sales, main consumer type (B2B vs B2C), and industry and class size dummies. To replicate the results shown in Figure 3 generated by the J48 algorithm, we divided the sample into two subsamples based on service infusion scale: ≤12 (representing non-advanced service infusion) and >12 (including advanced service infusion). The results for the training sample are reported in Table 7. Whilst the results for the testing sample are qualitatively the same, the model does not converge in the subsample analysis due to the smaller sample size.

The results align with Figure 3. The service infusion scale has a positive relationship with performance in the full sample, but percentage of service sales is not significant. In the subsample

Model	Precision	Recall	F-MEASURE	MCC	ROC	PRC	Outcome
MODEL TRAINED AND TESTED (n-fold)	0.819	0.944	0.877	0.818	0.936	0.821	GROWTH CON.
	0.889	0.881	0.885	0.760	0.927	0.916	GROWTH SLI.
	0.750	0.706	0.727	0.706	0.929	0.677	FLAT
	0.714	0.385	0.500	0.504	0.770	0.337	DECREA. SLI.
	0.837	0.844	0.835	0.750	0.920	0.818	WEIGHTED AVG.
Summary	*ACCURACY* 88.444%		*KAPPA STATISTIC* 0.810		*ENTROPY MODULATED* 0.647		
MODEL RE-EVALUATED	0.828	0.960	0.889	0.855	0.967	0.828	GROWTH CON.
	0.920	0.920	0.920	0.847	0.928	0.898	GROWTH SLI.
	0.917	1.000	0.957	0.952	0.998	0.962	FLAT
	1.000	0.765	0.867	0.855	0.957	0.874	DECREA. SLI.
	0.912	0.905	0.903	0.859	0.949	0.877	WEIGHTED AVG.
Summary	*ACCURACY* 90.476%		*KAPPA STATISTIC* 0.859		*ENTROPY MODULATED* 0.713		
MODEL BAGGING (10-fold)	0.874	0.928	0.900	0.857	0.985	0.956	GROWTH CON.
	0.950	0.911	0.930	0.861	0.968	0.970	GROWTH SLI.
	0.788	0.929	0.852	0.829	0.994	0.942	FLAT
	0.889	0.800	0.842	0.767	0.947	0.903	DECREA. SLI.
	0.833	0.714	0.769	0.854	0.996	0.708	WEIGHTED AVG.
Summary	*ACCURACY* 90.303%		*KAPPA STATISTIC* 0.849		*ENTROPY MODULATED* 0.680		
COHEN'S COEFFICIENT 84.933%			*PERREAULT OR LEIGH'S COEFFICIENT* 86,800%				

Note(s): * Accuracy increases from 88.444% to 90.476% when transitioning from the initially trained and tested model to the re-evaluated model. However, when dealing with class-imbalanced data, such as the collected dataset, it is advisable to report Precision or specificity (the correct prediction of positive patterns amongst the total predicted patterns), Recall or sensitivity (the accurate classification of positive patterns), F-measure (the harmonic mean of recall and precision), MCC (Matthews correlation coefficient), and ROC (area under the curve showing the TP rate against the FP rate). All these metrics show improvement from the initially trained and tested model to the re-evaluated model. Furthermore, the re-evaluation involves a 10-fold cross-validation and employs bootstrapping through bagging. This technique generates multiple data subsets for training to reduce variance and bolster stability. The results between the re-evaluated model and the bootstrapped model are nearly identical, demonstrating the robustness and stability of the findings

Table 6.
Assessment metrics: Trained and tested models, 70–30 re-evaluation, and 10-fold bagging

with Scale ≤12, percentage of service sales has a positive but insignificant effect. Notably, B2C markets show a more significant impact. In the subsample with Scale >12, high service sales percentages negatively affect performance, with a significant decline after 68%. Client type does not affect these results. Our regression analysis aligns with ML predictions. Whilst it is stronger in determining effect sizes, it would have been unable to determine the threshold points. Therefore, we conclude that regression analysis and ML are complementary methods.

6. Discussion and conclusions

6.1 Academic implications

Research on service infusion in manufacturing generally assumes that service development in firms follows a pathway from basic to complex (Baines and Lightfoot, 2013; Oliva and

	Full sample		Scale < 12		Scale >12	
	Main (1)	Interaction (2)	Main (3)	Interaction (4)	Main (5)	Interaction (6)
Scale	0.0950***	0.0958***				
	(0.0220)	(0.0226)				
	0.0000	*0.0000*				
% Service sales	−0.8634		1.3460		−3.5833***	
	(0.5980)		(0.8736)		(0.9094)	
	0.1488		*0.1234*		*0.0001*	
% Service sales * B2C		0.4539		2.0092		−3.2663*
		(1.1085)		(1.8144)		(1.8393)
		0.6822		*0.2681*		*0.0758*
% Service sales * B2B		−1.6946***		0.7676		−3.7549***
		(0.6190)		(0.6055)		(1.2010)
		0.0062		*0.2049*		*0.0018*
B2C	0.4459**	−0.4601	0.0087	−0.4632	0.7883**	0.5383
	(0.1829)	(0.4671)	(0.3079)	(0.6162)	(0.3310)	(1.3300)
	0.0148	*0.3246*	*0.9774*	*0.4522*	*0.0173*	*0.6857*
Electronics	−0.7539***	−0.7019***	0.2398	0.2779	−1.9995***	−1.9928***
	(0.2286)	(0.2308)	(0.2985)	(0.3115)	(0.5609)	(0.5603)
	0.0010	*0.0024*	*0.4216*	*0.3722*	*0.0004*	*0.0004*
Industry	−0.0012	0.0157	0.6828**	0.6779**	−0.4944	−0.4946
	(0.2014)	(0.2027)	(0.3350)	(0.3341)	(0.4550)	(0.4537)
	0.9952	*0.9384*	*0.0415*	*0.0424*	*0.2772*	*0.2757*
/cut1	−1.6214***	−2.0234***	−0.8048*	−1.0575***		
	(0.3909)	(0.3503)	(0.4825)	(0.3650)		
	0.0000	*0.0000*	*0.0953*	*0.0038*		
/cut2	−0.9754***	−1.3755***	−0.2956	−0.5525	−4.7381***	−4.8354***
	(0.3512)	(0.3612)	(0.4738)	(0.3742)	(0.7787)	(0.9754)
	0.0055	*0.0001*	*0.5327*	*0.1398*	*0.0000*	*0.0000*
/cut3	−0.5702*	−0.9719***	−0.1154	−0.3746	−3.7420***	−3.8373***
	(0.3154)	(0.3118)	(0.4749)	(0.3538)	(0.6208)	(0.8161)
	0.0706	*0.0018*	*0.8080*	*0.2898*	*0.0000*	*0.0000*
/cut4	1.1672***	0.7941**	3.1549***	2.8924***	−2.7965***	−2.8903***
	(0.3102)	(0.3093)	(0.6574)	(0.4871)	(0.5650)	(0.7513)
	0.0002	*0.0103*	*0.0000*	*0.0000*	*0.0000*	*0.0001*
Observations	225	225	120	120	105	105
Pseudo R^2	0.1126	0.1222	0.0807	0.0852	0.2643	0.2645
Class size dummies	YES	YES	YES	YES	YES	YES

Note(s): Robust standard errors in parentheses. p-values in *italics*. ***p < 0.01, **p < 0.05, *p < 0.1. Transport is the baseline category for electronics and industry parameters
The results are reported for the training sample and demonstrate qualitative consistency within the testing sample for the first two columns. However, the sample size is insufficient to attain model convergence for the sub-samples

Table 7. Orderd Probit specification

Kallenberg, 2003). This consolidated framework establishes that different service capabilities are needed to develop specific service offerings (often interdependent), and firm capability follows a "sand cone" model, accumulating with service stage development (Ferdows and De Meyer, 1990; Jinhui Wu *et al.*, 2012; Rosenzweig and Easton, 2010; Sousa and da Silveira, 2017). The current study is novel in testing and challenging service infusion unidirectionality and linearity assumptions.

For the unidirectionality, our results contradict the mainstream service infusion framework and show that firms that initiate the service infusion journey with Advanced services have the best performance. This is in line with Korkeamäki *et al.* (2021), who showed that Advanced services have high gross margins, and Valtakoski and Witell (2018), who established that less complex service types are not necessary to achieve higher performance. This provides theoretical grounding for a theoretically nascent field (Rabetino *et al.*, 2021) and, consistent with the absorptive capacity view (Zahra and George, 2002), shows that learning from developing Advanced services is more profitable than learning from simpler contexts.

Regarding linearity assumptions, our findings explain that profit growth is only partially associated with service sales. Particularly when firms provide Advanced services, an increase in service sales does not inherently indicate a higher level of service infusion concerning the complexity of the offering. Therefore, two different types of service infusion intensity can be identified: share of service sales due to service infusion, which has traditionally been considered the main measure of the level of service infusion (e.g., Suarez *et al.*, 2013; Visnjic and Van Looy, 2013); and the implementation of complex service-based business models, which are extensively documented (e.g., Baines and Lightfoot, 2013; Gomes *et al.*, 2021; Oliva and Kallenberg, 2003). These two conceptualisations of service infusion are disconnected in the literature and have epistemological and methodological differences. Erroneous conclusions can be reached when forcing a connection between these two concepts at a methodological level.

These results and methodological developments together point to important contributions in relation to organisational learning, behavioural decision-making and methodological advancements in operations management. In organisational learning (Argote and Epple, 1990), we envision that as service business models mature, there will be more opportunities for vicarious learning. This implies that new entrants won't need to experiment as early adopters had to and, consequently, they can embark on the service infusion journey with more advanced and complex service models that have been tested and are now considered standard (Gomes *et al.*, 2021). Our findings also support a process of absorptive capacity (Zahra and George, 2002): when firms successfully implement complex service models, they can smoothly integrate other less advanced services. The knowledge of how to transition from a product-based to a product-service-based organisation becomes crucial in this context. Current research merging service infusion and learning is lacking, with the only exception being Valtakoski (2017). Our results therefore encourage more research integrating vicarious learning and absorptive capacity as primary enhancers of complex service adoption in newly-created or late-mover manufacturing firms. This approach aligns with recent calls by Rabetino *et al.* (2021) regarding the need for more theoretical research on the field of servitization.

Concerning behavioural decision-making, our study offers insights into how ML techniques can support managers in making informed decisions, leading to fewer heuristics (Huikkola *et al.*, 2022) and more controlled risks (Surdu *et al.*, 2021). ML can streamline specialised processes, rendering them standardised and automated. Whilst decision trees have conventionally been utilised in management, their development has typically been based on qualitative strategic rather than quantitative methods. The potential to develop algorithm-informed decision trees in how services are implemented in manufacturing is significant, especially in decentralised systems (Clough and Wu, 2022). This is particularly relevant in service infusion scenarios where service departments and subsidiaries have an inherent degree of autonomy (e.g., as illustrated regarding Atlas Copco by Visnjic and Van Looy, 2013). Decision trees could potentially introduce a level of standardisation and automation in processes and decision-making within such contexts. Further research is warranted to explore the application of algorithmic decision trees in designing service business models for manufacturing firms.

Finally, in methodological approaches, as illustrated by Chou *et al.* (2023), the utilisation of ML techniques stands out in this study. These techniques consider interactive and complex variables, providing a more efficient and effective means to capture interactions between explanatory variables compared to linear regression, as highlighted by Chiu and Xu (2023). In this context, we endorse ML as a valuable methodology and address recent calls, such as Lindner *et al.* (2022), for additional statistical tools to examine consolidated assumptions, as emphasised by Kalnins (2022). The increasing prevalence of ML methods is justified by the complexity of modern business, making traditional regression analyses with treatment and control groups less relevant to explain interconnected real-world mechanisms (Lindner *et al.*, 2022). Our study illustrates an opening for more research in operations management using these methods.

6.2 Managerial implications

Our results show that manufacturing firms follow heterogeneous pathways in their service journey. Service type and the percentage of services over total offerings are critical variables to consider before embarking on a service infusion pathway. In general, firms starting with a single service offering tend to have a superior strategy to those starting with multiple services. However, the optimal starting point seems to depend on contextual factors; hence non- servitised firms should carefully consider their contextual conditions (e.g., uncertainty avoidance).

One of these contextual conditions is the industry characteristics. Our research challenges the assumption of linearity in the context of firms embarking on service infusion, particularly those venturing into complex services or operating in B2B markets. This finding delineates two distinct paths for service infusion: the service infusion intensity sales model (scalability pathway) designed for B2C environments, and service infusion involving complex service-based business models (value pathway) more suited to B2B contexts, particularly for those manufacturers commencing their service journey with sophisticated service offerings. These insights unravel the divergent conclusions found in the literature regarding the interplay between the type of service, service intensity, specific service infusion pathways, and firm performance within different business contexts. Practically, the study recommends that practitioners crafting service strategies for B2B manufacturing services consider commencing with Advanced service offerings if appropriate. Whilst base service offerings can yield profit growth, our analysis indicates that advanced service offerings have potential for superior growth.

Our study also involves the utilisation of algorithmic ML techniques to facilitate swift and meticulous decision-making processes. This becomes crucial in rapidly evolving environments characterised by abundant data, as seen in existing highly digitised and servitised manufacturing industries. Managers are encouraged to incorporate these mechanisms into their routine operations, empowering them to make decisions that are not only better informed, but also systemic in nature.

6.3 Limitations and future research

The optimal starting point for firms developing a service offering depends on various contextual conditions. This provides an opportunity for process-based research identifying pathways of adoption that consider behavioural and learning theories. Further process-based models should examine multiple starting points depending on firm context, behaviour and conditions, e.g., if the firm has the risk appetite to start with an Advanced service offering or would prefer potentially lower risk and lower return with a Base service offering. Subsequent studies should consider formulating these relationships as testable hypotheses, especially those evaluated through ML techniques, which will necessitate careful consideration of causal inference (Chou *et al.*, 2023).

The findings are consistent with most manufacturers offering use-oriented advanced services (Kohtamäki *et al.*, 2020), for instance Tesla and Roomba offer advanced services in the form of smart and autonomous products bypassing previous service stages (Porter and Heppelmann, 2014). The results are less consistent with manufacturers offering result-oriented advanced services (Baines and Lightfoot, 2013), but there is still a clear alignment if we analyse the service journey at product- and not firm-level. Companies like BAE Systems, Caterpillar and Thales position new offerings as advanced services, bypassing the previous need to initially develop base offerings for new product lines (Ng *et al.*, 2011). These advanced services reflect a pivot in the industry (Gomes *et al.*, 2021), so market newcomers may initially also offer advanced services, bypassing previous service stages. Further research based on qualitative approaches such as in-depth case studies is essential to elucidate the intricacies of the evolutionary trajectory of this learning journey for use- and result-oriented advanced services.

The ML applications proposed here suit other process-based models in related disciplines, for example we see a parallel with the Uppsala model of internationalisation (Johanson and Vahlne, 1990). It is unclear why all firms need the same approach to internationalisation; that is, on some occasions starting with higher levels of foreign market commitment (i.e., FDI) may be the superior entry mode to exporting modes of internationalisation (Surdu *et al.*, 2021).

The cross-sectional design utilised in this study serves the purpose of tracking historical patterns of service adoption within firms, aiming to validate the presence of varied pathways in adopting services. It also illustrates how ML techniques can inform decision-making processes. However, a more systematic evaluation of process-based models would benefit from the acquisition of longitudinal data. This longitudinal approach would enable exploration of the impact of critical boundary conditions, such as regulatory and technological changes. The analysis of boundary conditions could be further enhanced by employing a multi-country perspective. Whilst acknowledging the significance of the US context, future research should adopt a comparative framework encompassing various contexts, enabling assessment of whether the observed effects are contingent on the level of economic development or other macro-level factors.

Notes

1. A strategic pivot is delineated within the scholarly literature as "a change in a firm's strategy that reorients the firm's strategic direction through a reallocation or restructuring of activities, resources, and attention" (Kirtley and O'Mahony, 2020, p. 199). Gomes *et al.* (2021) study defines pivots as an established service stage within which a firm has accrued experience and remains sustainable over time, whilst pivoting refers to the firm's decision to experiment and transition into other service stages.
2. Five of eight are shown on Figure 1 for illustrative purposes.
3. Note that these three primary categories are designated specific points along the continuum, each encompassing a measurement of the degree of progress achieved and marking different levels of service infusion. Therefore, advanced services include both use-oriented services, such as smart and autonomous systems (Gomes *et al.*, 2021), and result-oriented services, such as outcome-based contracts (Ng *et al.*, 2011).
4. Zero-R algorithm chooses the most recurrent value (Choudhary and Gianey, 2017).
5. We conducted tests to ensure that the ordered probit multivariate regression adheres to its underlying assumptions, including proportional odds, normality of residuals and homoscedasticity. Our assessments revealed low VIF levels, indicating minimal collinearity amongst all direct effects. Standardised errors showed linear distribution based on residual plots, whilst Q-Q plots confirmed adherence to a normal distribution. We also verified that linear regression yielded consistent results. Due to space constraints, these comprehensive analyses are not included in the paper but are available upon request from the authors.

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Appendix

General Firm Information

Please answer the following descriptive questions in relation to your company.

Is your company based in the USA?

Yes

No

Is your company 12 years old or more?

Yes

No

Annual sales revenue in 2020

Less than £50 million

£50 < …. < £100 million

£100 < … < £250 million

£250 < … < £1,000 million

£1,000 < … < £5,000 million

Over £5,000 million

Annual sales revenue in 2015

Less than £50 million

£50 < …. < £100 million

£100 < … < £250 million

£250 < … < £1,000 million

£1,000 < … < £5,000 million

Over £5,000 million

On average, how has your firm's profit margin changed over the past five years (2015–2020)?

Decreased considerably

Decreased slightly

Remained flat

Grown slightly

Grown considerably

On average, what was your firm's annual profit margin over the past 5 years (2015–2020)?

Less than −15%

−14.9 to −5.5%

−5.4–0%

0–5.4%

5.5–14.9%

Greater than 15%

Number of employees in 2020

250 < …. < 499,

500 < …. < 999

1,000 < …. < 4,999

5,000 < …. < 9,999

Over 10,000

Number of employees in 2015

Less than 100

100 < …. < 249

250 < …. < 499

500 < …. < 999

1,000 < …. < 4,999

5,000 < …. < 9,999

Over 10,000

Please describe your main business focus (*e.g.*, B2B, B2C, other).

Please describe how your company's portfolio is composed (in percentage): (products/services, e.g. 60% product, 40% services).

(1) Industry sector
- Industrial and commercial machinery and computer equipment (35)
- Electronic and other electrical equipment and components, except computer equipment (36)
- Transportation equipment manufacturing (37)

(2) Respondent position

Senior leadership/executive

Senior manager

Manager

(3) Respondent function

Sales

Information systems

Planning and scheduling

Marketing

Manufacturing

Engineering

Finance;

Distribution;

Purchasing

Other (please type role here)

Type of service

The following list includes different services that can be offered additional to your product offerings. Please answer Yes/No if you offer this particular service and if the response if positive, please let us know when the service was offered for the first time.

Documentation: Provision of instructions, notes, etc. for using your products

[Y/N]

[If Y, Year?]

Transport: Movement of goods and logistics is the management of the inward and outward transportation of goods from the manufacturer to the end user

[Y/N]

[If Y, Year?]

Installation: Act or process of making a machine ready to be used for the end user

[Y/N]

[If Y, Year?]

Product/Equipment provision: Ensure the equipment is constructed or adapted to be suitable for the purpose it is used or provided for

[Y/N]

[If Y, Year?]

Spare parts: Provision of a duplicate part to replace a lost or damaged part of a machine

[Y/N]

[If Y, Year?]

Warranty: Writing guarantee promising to repair or replace a good, if necessary, within a specified period of time

[Y/N]

[If Y, Year?]

Scheduled maintenance: Any repair and upkeep work performed within a set timeframe

[Y/N]

[If Y, Year?]

Helpdesk: a department or person that provides assistance and information for product functioning problems

[Y/N]

[If Y, Year?]

Condition monitoring: process of monitoring a particular condition in machinery to identify changes that could indicate a developing fault

[Y/N]

[If Y, Year?]

Training: teaching or developing on your clients any skills and knowledge that relate to specific useful competencies related to your products

[Y/N]

[If Y, Year?]

Process-oriented engineering and R&D: Setting current and future processes and R&D needs to achieve business goals

[Y/N]

[If Y, Year?]

Process/Business oriented consulting: Assisting clients with their endeavours, providing management consulting to help them improve their performance and efficiency

[Y/N]

[If Y, Year?]

Outsourcing/Rental: Services to perform tasks, handle operations, or give right to use to clients

[Y/N]

[If Y, Year?]

Activity management: The recording of all activities, that is, business activities and tasks, undertaken on behalf of the company

[Y/N]

[If Y, Year?]

Support agreements: Agreement outlining what services manufacturer will provide, how manufacturer will provide them, the service levels and the associated costs

[Y/N]

[If Y, Year?]

Revenue through use contract: Agreement where clients pay per use of the product

[Y/N]

[If Y, Year?]

Risk and reward sharing contract: Contract with specific cost targets, and a shared profit pool used to cover cost overruns or accumulate additional savings

[Y/N]

[If Y, Year?]

END OF SURVEY.

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