Pricing Models for Data Products in the Industrial Food Production

Calvin Rix, Jana Frank, Volker Stich, Dennis Urban

Pricing models for data products in the industrial food production

Calvin Rix[1], Jana Frank[1], Volker Stich[1], Dennis Urban[2]

[1] Institute for Industrial Management (FIR) at RWTH Aachen University, Campus-Boulevard 55, 52074 Aachen, Germany
[2]Lindt & Sprüngli Germany GmbH, Süsterfeldstraße 130, 52072 Aachen, Germany

Abstract. In the food industry, a very large potential of data ecosystems is seen, in which data is understood, exchanged and monetized as an economic asset. However, despite the enormous economic potential, companies in the food industry continue to rely on traditional, product-oriented business models. Existing data in the value chain of industrial food production, e. g., in harvesting, logistics, and production processes, is primarily used for internal optimization and is not monetized in the form of data products. Especially the pricing of data products is a key challenge for data-based business models due to their special characteristics compared to conventional, analog offerings and multiple design options. The goal of this work is therefore to solve this issue by developing a framework that allows the identification of pricing models for data products in the industrial food production. For this purpose, following the procedure of typology formation, essential design parameters and the respective characteristics are derived. Furthermore, three types for pricing models of data products are shown. The results will serve not only stakeholders in the food industry but also manufacturing companies in general as input for an orientation of their data-based business models.

Keywords: Pricing models, Data products, Food production, Typology

1 Introduction

The increasing use of networked machines is generating ever greater volumes of data [1]. In the manufacturing industry the value was 3.5 zettabytes in 2018 and is estimated to grow to 21 zettabytes by 2025 [2]. Against a backdrop of evolving capabilities in the areas of data analytics and storage, as well as artificial intelligence, this data holds continuously growing economic potential [3]. The value of the European data economy, for example, is estimated to grow to 827 billion euros in 2025 [4]. This data is generated across the entire food production value chain: starting with the selection of raw materials, through international transport and production activities, to real-time market analyses [5]. Through intelligent aggregation and processing by data-analytic services, this data can deliver significant added value and become an economic good itself, the so-called data product. As a result value creation is increasingly shifting to data-driven business models that provide unique value to the customer [6]. Nevertheless, the cross-manufacturer use of data in a data economy is still in its infancy [7]. Despite a focus on data monetization of manufacturing companies today, few mechanisms exist to price data products [3]. This can be attributed to characteristics that complicate the choice of a pricing model compared to tangible goods [8]. It is difficult to accurately determine the value of data prior to purchase as the value lies in the derived information, which is intangible and difficult to measure [9]. In addition, data products have a unique cost structure: The fixed costs of building the infrastructure and aggregating the first data product are often substantial ("first copy cost") while the marginal costs of copying and disseminating are negligible [10]. The provisioning costs are composed of the specific value creation process: data extraction, data preparation, information extraction, information provision and information usage [11]. Data products can develop very heterogeneous values for buyers depending on the value creation stage and the specific type [12]. They can be sold directly, as a supplement to existing products and services or as enabler of an entire new value proposition composed of a bundle of services [13].

Due to the above mentioned characteristics and design options, data product pricing is a central challenge of digital business models [14]. Traditional cost- and competition-oriented pricing methods are not sufficient to achieve optimal pricing for data products [15], so that innovative pricing models have become established [8]. Since there can be no universally valid price model for all data products and price models are basically composed of several elements, we addressed the following research question in this paper: *How can pricing models for data products in industrial food production be designed?* Therefore we provide a design framework for the price parameters of data products in the industrial food production. Therefore, we performed a typology formation through workshops with pricing, digitalization and food production experts.

2 State of Research

Since pricing of data products has attracted lot of attention, there has been an increase in recent publications. Nevertheless, research in this area is still in its infancy.

There are publications examining the selection of pricing models as well as the evaluation of prices on data marketplaces [8, 14, 16, 17]. However, these works focus primarily on pure information goods and leaves out data-based service bundles that generate direct added value for the customer. Furthermore, no design factors for the respective data products are shown. Frohmann [15] presents five overarching pillars of pricing models of digital products in his work. The framework provides a precious basis, but refers to digital products in general, whereby the results are on a high level and important design factors for the pricing of the addressed data products in this paper will not be considered. In addition, Buxmann and Lehmann [18] present a model for the pricing of pure software products. Even though many of the design factors can also be applied to this work, it does not cover the entire spectrum of data products due to the focus on pure software products. Liang et al. [8] categorize pricing strategies in terms of different market structures and identify their limitations as part of the Big Data lifecycle. The focus is on setting an appropriate price for the data product. However, as pure digital offers are prioritized, the results are of limited use. In addition, there are scientific approaches that address a systemic overview of design factors of data-based business models and services as well as data marketplaces in particular [3, 19, 20]. In these works, the business models are considered holistically and thus no detailed attention is paid to the respective pricing models.

This shows that even if the current state of research provides building blocks to answer the research question, no framework for the design of pricing models of data products in the industrial food production has been developed yet. Accordingly, there is a research gap not only for the food industry, but also for the entire manufacturing sector.

3 Methodology

Due to the heterogeneous characteristics of data products and diverse design options of pricing models, the method of typology formation is used for designing and building a framework to describe characteristics of data product pricing models within the industrial food production. The development process is based on the well-established approach provided by Welter [21]. With the help of typology an area of investigation can be systematized and thus made comprehensible. Furthermore, it serves to uncover correlations and to support design recommendations [21].

The typification is ideally suited to structure the area of investigation and to offer an application-oriented tool. This includes all relevant characteristics, which are presented holistically as well as the subsequently developed types. When identifying the features as well as their characteristics, the following criteria must be taken into account in order to ensure that the types are meaningful and meet the requirements [22]: First of all, each characteristic must have at least two expressions, whereby an upper limit is not prescribed. In addition, each characteristic must have a certain meaningfulness, which means that there must be a causal and a preferably relationship between the purpose of the examination and the characteristic. Further the differentiability requires that only characteristics that contribute to the differentiation of types are used. The procedure for the formation of the typology is based on a five-step approach (see Fig. 1).

Step 1	Step 2	Step 3	Step 4	Step 5
Delimitation of the investigation area	Selection of suitable features	Determination of meaningful feature characteristics	Formation of types by combinations of characteristics	Graphical representation of the obtained types

Fig. 1. Procedure of the type formation process [21]

In the first step, the definition and appropriate generalization of the given problem takes place, in which primarily the area of investigation is delimited and discussed. Subsequently, the derivation of suitable features (step 2) as well as their characteristics (step 3) takes place. These were derived factually and logically through the experience of the authors and the experts of the EVAREST project team, considering existing literature approaches and requirements from operational practice. This is followed by the identification of typical feature combinations (step 4). Following Grosse-Oetringhaus [22], a combination of progressive and retrograde typing is chosen as an iterative procedure. For this purpose, relevant literature was used as a basis. In addition, consistent combinations of the characteristics were determined according to the configuration theory. Afterwards, the developed combinations were validated by case studies from the food industry. Finally, the results are presented graphically (step 5).

4 Results

The results were developed during the research project EVAREST (see Chapter 6). In the following the steps of typology formation and the achieved results are described.

4.1 Investigation Area (Step 1)

In addition to the delineation of the scope of the study shown in chapter 1, the retrograde approach requires the consideration of the targeted types in advance. In the literature different approaches can be found that describe and categorize data products.
Tempich [23] defines three different types: Firstly, "Data as a Service", i.e. data are made available by providers and used to generate direct revenue (data * price = revenue). Secondly, "Data as Insights" where data is used to improve product marketing and achieve higher economic results. Thirdly, for "Data-enhanced Products", data enrich physical or virtual products. Hereby, increasing revenue of the enhanced physical product corresponds to the revenue generated by data. Wixom and Ross [24] distinguish data products as follows: "Selling data", "optimize existing products or service" or "improving internal processes". Liozu and Ulaga [13] add "new business models and revenue streams" to these types. Laney [25] defines data products based on economic value which they capture for businesses: "direct exchange with goods, services or monetary resources"; "use to increase income, or reduce risks and expenses". To date, there is no consensus on the definition of data products, so a distinction of data product types has been made using the approach described in Chapter 3.

4.2 Development of the framework (Step 2 to 3)

Within step 2, the following features could be derived: price determination, price discovery, measurement unit, payment flow, timing of price determination, bundle components, bundling type, degree of integration, differentiation, price dynamic, value creation. The features and feature characteristics (step 3) developed are described below.

Basically, there are three different ways for the *price determination* of data products [12]: cost-based, competition-based and value-based. In the traditional cost-based approach, the supplier costs are calculated and a price is determined for the customer by adding up an amount (cost-plus) [26]. The cost-plus approach is considered ineffective due to the aforementioned cost structure, as the customer's willingness to pay can significantly exceed the costs including the target margin, especially for digital offers and services [15]. Nonetheless, there is widespread use for digital products, due to higher acceptance, simple and quick determination as well as no necessary data regarding demand structures and willingness to pay [12, 27]. In competition-based pricing, expected or observable price levels of the market serve as the main source of pricing [28]. Thus, competition-based approaches have severe limitations due to the lack of data-based offerings, as it requires the existence of an active market where prices can be continuously observed and compared [12]. Basically, cost and competitive situation are important influencing factors for any pricing model, but the isolated use of both methods is neither sufficient to achieve optimal pricing for analog nor intangible assets [15, 27]. It is also necessary to assess the actual value of data products to the customer especially in the industrial sector [27]. Thus, in the value-based approach, the price is no longer based on the provider's internal variables (e.g., costs) or competitive prices, but on the added value that the offered solution generates in the customer's business environment [28]. The added value of the data product is determined on the basis of the benefits that arise over the entire data product lifecycle [29]. Even if value-based pricing is considered to be an superior approach, paradoxically, cost-based and competitive approaches continue to play a dominant role in industrial pricing [30]. One of the main problems in business practice is to gain access to essential data to quantify the value of the offers to the customers [31]. Another aspect is the so-called fixed-pie bias. Even though value-based pricing has the potential for win-win situations, the dominant assumption is that what the company gains, the customer loses and vice versa (zero-sum game) [32].

Price discovery is a key function of marketplaces as it allows suppliers and demanders to set a price at which both agree to the transaction [33]. Firstly, it can be determined by one of the two sides, supplier or demander [20]. In this case, the other side only has the option to accept or reject the offer at this price. Secondly, the price can be determined by the platform provider. Therefore, provider and buyer must accept the determined price to be part of the marketplace [20]. A third option are negotiations between buyers and sellers, which are primarily relevant for goods of higher value [20].

The *measurement unit* of a price model specifies the service the customer pays for [15]. A basic distinction is made between usage-independent and usage-dependent pricing models [15]. In addition to the one-time payment, subscription payments count as usage-independent measurement unit. Usage-dependent pricing models are dependent on the usage phase of the customer. These pricing models are becoming increasingly important, especially for digital goods. The customer pays for the actual use or even the outcome or economic success achieved by the data-based solution [15, 34].

There are three variants for the *payment flow* [15]: single payment, recurring payment and a hybrid combination of both variants.

The *timing of price determination* can be either ex-ante or ex-post the service provision [26]. Ex-ante market pricing is particularly relevant for standardized products and services [15]. Ex-post price determination is based on the actual performance provided by the supplier and is particularly advantageous for individual services [15].

Another elementary part of the pricing model are the *components* that are bundled into the offer [35]. For the considered data products, the data itself, the analytic services used, and the enhanced products and services are the main items to be considered. Furthermore, a holistic data-based solution can also be offered.

Depending on the *bundling type*, three categories are possible [18]: unbundling, mixed bundling and pure bundling. In unbundling, products can only be purchased individually [36]. If the customer can choose whether to purchase the entire bundle or the included products individually, this is termed as mixed bundling. For pure bundling, the products are offered exclusively in the bundle defined by the provider.

Furthermore, the products in the bundle can also be described in terms of their *degree of integration*. The partial services can be independent to each other or have a substitutive or complementary relationship to each other [37].

Price differentiation is based on the optimal exploitation of heterogeneous customers' willingness to pay through different prices [37]. Price differentiation is particularly important for suppliers of purely digital goods, as inexpensive modification greatly facilitates the application [18]. Basically there are three different forms of price differentiation [38]: self-selection, segmentation and willingness to pay. With self-selection, the customer decides for himself which product-price combination he wants to choose [39]. A distinction is made between quantity-based, time-based and performance-based self-selection [40]. In this context, versioning is considered to be very advantageous for digital goods [41]. Often, data product providers offer extensive versions and likewise offerings with reduced functionalities to achieve better market penetration, also for less solvent customers. In segmentation, the provider decides how to differentiate prices on its own criteria [37]. The price can be determined, for example, based on the size of the customer's company, the country or region in which the customer operates [40]. Finally, there is the differentiation that tries to skim off the customer's actual willingness to pay, which, however, is the biggest challenge of the differentiation types [42].

Dynamic pricing is based on adjusting the price over time [18]. For the addressed data products, the penetration and skimming strategy as well as supply & demand and result-orientation are of importance. The penetration strategy has the objective to use low prices in order to maximize market penetration [18]. The skimming strategy aims at skimming off customers with a high willingness to pay with initially high prices and then reducing prices to win further customers. Supply & demand models depend on the buying behavior of market participants [8]. It can be used to balance peak periods with very high demand and to make purchasing more attractive in less busy periods [8]. A strategy that is dynamically oriented towards the achieved result aims to continuously increase the performance for the customer and thus create a positive lock-in effect.

The way in which *value is created* by the data product can be distinguished by three types: product/service sales, barter and achieved performance. A monetary added value can be achieved through the traditional sale of products and services. In addition, bartering plays an essential role for data products [25]. This means the exchange of generated data for added value, like products or better business conditions. The generated and exchanged data represent an indirect value, as it can be resold to interested parties in the ecosystem (e. g. drinking behavior for beverage producer) (see Section 4.3). In addition, the monetary added value can also be based on the performance actually achieved for the customer, accounted by a suitable measurement unit [34].

4.3 Pricing models for data product types (Step 4 to 5)

In the final step, pricing models were derived for the identified data product types and presented graphically by using the developed framework (see Fig. 2).

The first type of data product is the *data product as insight (blue)*. It is composed of raw data and analytical services aggregated into a data product that aims to answer business-critical questions for the customer. The price of this data product is measured by the potential added value that the additional insights bring to a business decision. In addition to basic criteria such as quality and relevance in the business context, the degree of analytical maturity plays a major role for the added value. The value increases from a descriptive data product over a diagnosis to forecasts or even decision support that shows direct guidance for action in the future [43]. Since it is not possible to clearly allocate the added values for the customer, the value can be determined and estimated ex-ante based on of existing value attributes. The price can be paid once or on a subscription basis, e.g. for the purpose of updating the data. In food production data products as insight can add great value to a wide range of areas. In addition to classic price panels, sales forecasts are particularly valuable because they are very volatile and are influenced by various external factors such as weather, seasonality, constantly changing customer needs and political influences. This has a positive impact on inventory management throughout the food production value chain, from retailers to distributors to producers and farmers. Stocks can thus be reduced, and capacity limits improved, thereby reducing the loss due to overcapacity.

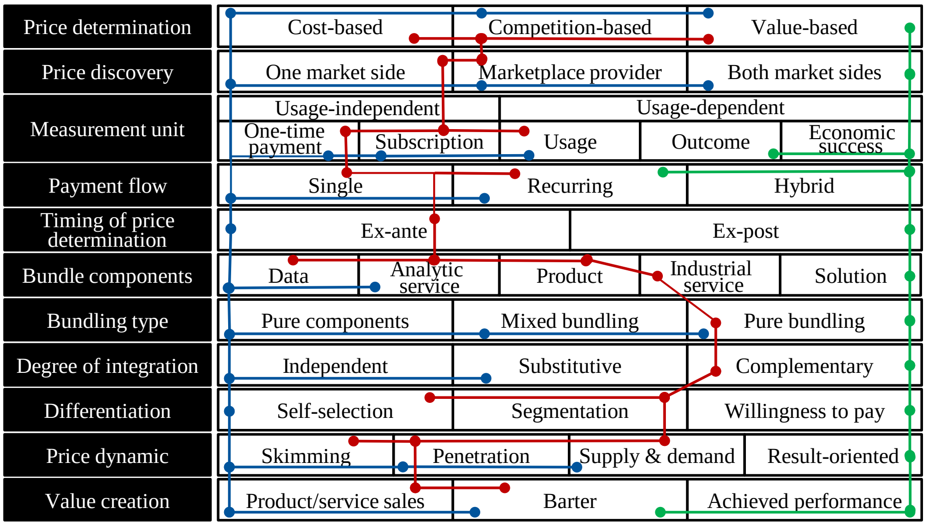

Fig. 2. Typology visualized as a morphological box

The next type is *data-enhanced product or service (red).* Compared to conventional products and services, data connectivity enables various special features. In addition to the positive economic factors, such as the possibility of charging higher prices or implementing services more cost-effectively, data connectivity enables innovations for the pricing model. The complementary bundle of services can be billed on a usage basis and even supply & demand models are possible. Furthermore, the data generated can be used to achieve additional value through bartering. Data-based features also allow the customer to select performance levels with little effort, even for hardware products. There are countless implementation possibilities for the food industry. For example Celli Group's smart dispensing systems or Bizerba's innovative weighing technology can be used to directly analyze the consumer behavior in order to optimize inventories, reduce waste or directly measure the success of marketing campaigns for the food manufacturing companies [44, 45].

Data product as performance (green) goes beyond the mere provision of insights and uses prescriptive analytics as part of a holistic solution to generate concrete benefits for the customer. This requires both data analytics and industry-specific expertise.

Through a participative business constellation of provider and customer, this data product opens the possibility of implementing performance-oriented pricing models and transferring them into a contractual framework. For this purpose, an interactive price determination with the customer is to be implemented, in which the price is ultimately determined by the result. The timing of the pricing takes place ex-post to be able to use the actual added values achieved and, optimally, to enter a long-term partnership with the customer that is result-oriented and represents a win-win situation. The data generated in the process provides the opportunity to continuously improve the offer and transform it into innovations.

5 Conclusion & Outlook

In this work parameters for pricing models of data product types within the industrial food production were derived. Three data product types were developed, determined and illustrated. The results aim to improve the systematization and classification of future research and extend the existing body of knowledge by specifying the understanding of data product pricing in the manufacturing industry. The research results are also subject to limitations. Due to the new domain of data products, the model requires frequent updating to stay relevant and to incorporate new dimensions and characteristics. Since the creation of the typology was developed with the EVAREST consortium researchers, other researchers could derive further dimensions and characteristics that they deem more significant. Although the framework of the pricing model is specified for industrial food production, further research could reuse the structure for other sectors and an extension could be made for the entire manufacturing industry.

6 Acknowledgements

The research and development project EVAREST that forms the basis for this report is funded within the scope of the “Smart Data Economy” technology program run by the Federal Ministry for Economic Affairs and Energy and is managed by the DLR project management agency. The authors are responsible for the content of this publication.

References

1. Azkan, C., Iggena, L., Meisel, L., Spiekermann, M., Korte, T., Otto, B.: DEMAND - Perspektiven der Datenwirtschaft. Fraunhofer-Institut für Software- und Systemtechnik ISST (ed.), Dortmund (2020).
2. Reinsel, D., Gantz, J., Rydning, J.: The Digitization of the World: From Edge to Core. IDC Corporate USA (ed.), Framingham, MA (2018).
3. Fruhwirth, M., Rachinger, M., Prlja, E.: Discovering Business Models of Data Marketplaces. In: Bui, T. (ed.) Proceedings of the 53rd Hawaii International Conference on System Sciences, pp. 5738–5747, Honolulu, Hawaii (2020).

4. Cattaneo, G., Micheletti, G., Glennon, M., La Croce, C., Mitta, C.: The European data market monitoring tool: Key facts & figures, first policy conclusions, data landscape and quantified stories. Publications Office of the European Union, Luxembourg (2020).
5. Ji, G., Hu, L., Tan, K.H.: A study on decision-making of food supply chain based on big data. J. Syst. Sci. Syst. Eng. 26(2), 183–198 (2017).
6. Grün, O.: Datenökonomie braucht einen offenen Markt. In: Bär, C., Grädler, T., Mayr, R. (eds.) Digitalisierung im Spannungsfeld von Politik, Wirtschaft, Wissenschaft und Recht: 1. Band: Politik und Wirtschaft, pp. 127–135. Springer, Berlin, Heidelberg (2018).
7. Spiekermann, M.: Data Marketplaces: Trends and Monetisation of Data Goods. Intereconomics 54(4), 208–216 (2019).
8. Liang, F., Yu, W., An, D., Yang, Q., Fu, X., Zhao, W.: A Survey on Big Data Market: Pricing, Trading and Protection. IEEE Access 6(1), 15132–15154 (2018).
9. Stahl, F., Schomm, F., Vomfell, L., Vossen, G.: Marketplaces for Digital Data: Quo Vadis? Computer and Information Science 10(4), 22–37 (2017).
10. Shapiro, C., Varian, H.R.: Versioning: The smart wayto sell information. Harvard Business Review 76(1), 107–115 (1998).
11. BVDW: Data Economy: Datenwertschöpfung und Qualität von Daten. Bundesverband Digitale Wirtschaft (BVDW) e.V. (ed.), Düsseldorf (2018).
12. Krotova, A., Rusche, C., Spiekermann, M.: Die ökonomische Bewertung von Daten: Verfahren, Beispiele und Anwendungen. Institut der deutschen Wirtschaft, Köln (2019).
13. Liozu, S.M., Ulaga, W.: Monetizing data: A practical roadmap for framing, pricing & selling your B2B digital offers. Value Innoruption Advisors Publishing, Anthem, AZ (2018).
14. Stahl, F., Löser, A., Vossen, G.: Preismodelle für Datenmarktplätze. Informatik Spektrum 38(2), 133–141 (2015).
15. Frohmann, F.: Digitales Pricing: Strategische Preisbildung in der digitalen Wirtschaft mit dem 3-Level-Modell. Springer Gabler, Wiesbaden (2018).
16. Fricker, S.A., Maksimov, Y.V.: Pricing of Data Products in Data Marketplaces. In: Ojala, A., Holmström Olsson, H., Werder, K. (eds.) Software Business, vol. 304, pp. 49–66. Springer International Publishing, Cham (2017).
17. Cao, T.-D., Pham, T.-V., Vu, Q.-H., Truong, H.-L., Le, D.-H., Dustdar, S.: MARSA. ACM Trans. Internet Technol. 16(3), 1–21 (2016).
18. Lehmann, S., Buxmann, P.: Preisstrategien von Softwareanbietern. Wirtsch. Inform. 51(6), 519–529 (2009).
19. Hartmann, P.M., Zaki, M., Feldmann, N., Neely, A.: Capturing value from big data – a taxonomy of data-driven business models used by start-up firms. IJOPM 36(10), 1382–1406 (2016).
20. Täuscher, K.: Business Models in the Digital Economy: An Empirical Study of Digital Marketplaces. Fraunhofer Center for International Management and Knowledge Economy (ed.), Leipzig (2016).
21. Welter, M.: Die Forschungsmethode der Typisierung: Charakteristika, Einsatzbereiche und praktische Anwendung. Wirtschaftswissenschaftliches Studium 35(2), 113–116 (2006).
22. Grosse-Oetringhaus, W.F.: Fertigungstypologie unter dem Gesichtspunkt der Fertigungsablaufplanung. Duncker & Humblot, Berlin (1974).
23. Tempich, C.: Konzeption und Entwicklung von Data-driven Products / Datenprodukten. In: Haneke, U., Trahasch, S., Zimmer, M., Felden, C. (eds.) Data Science: Grundlagen, Architekturen und Anwendungen. Edition TDWI, pp. 45–64. dpunkt, Heidelberg (2018).

24. Wixom, B., Ross, J.: How to Monetize Your Data. MITSloan Management Review 58(3) (2017).
25. Laney, D.B.: Infonomics: How to monetize, manage, and measure information as an asset for competitive advantage. Taylor & Francis, New York, NY, Abington, UK (2018).
26. Simon, H., Fassnacht, M.: Preismanagement. Springer Fachmedien, Wiesbaden (2016).
27. Heckman, J.R., Boehmer, E.L., Peters, E.H., Davaloo, M., Kurup, N.G.: A Pricing Model for Data Markets. In: University of California Irvine (ed.) iConference Proceedings (2015).
28. Hinterhuber, A.: Customer value-based pricing strategies: why companies resist. Journal of Business Strategy 29(4), 41–50 (2008).
29. Zechmann, A.: Nutzungsbasierte Datenbewertung: Entwicklung und Anwendung eines Konzepts zur finanziellen Bewertung von Datenvermögenswerten auf Basis des AHP: Dissertation, Universität St. Gallen (2018).
30. Liozu, S.M.: State of value-based-pricing survey: Perceptions, challenges, and impact. J Revenue Pricing Manag 16(1), 18–29 (2017).
31. Töytäri, P., Rajala, R., Alejandro, T.B.: Organizational and institutional barriers to value-based pricing in industrial relationships. Industrial Marketing Management 47, 53–64 (2015).
32. Hinterhuber, A., Liozu, S.M.: Is innovation in pricing your next source of competitive advantage? Business Horizons 57(3), 413–423 (2014).
33. Bakos, Y.: The emerging role of electronic marketplaces on the Internet. Commun. ACM 41(8), 35–42 (1998).
34. Stoppel, E., Roth, S.: The conceptualization of pricing schemes: From product-centric to customer-centric value approaches. J Revenue Pricing Manag 16(1), 76–90 (2017).
35. Lehmann, S., Buxmann, P.: Pricing Strategies of Software Vendors. Bus. Inf. Syst. Eng. 1(6), 452–462 (2009).
36. Olderog, T., Skiera, B.: The benefits of bundling strategies. SBR 52(2), 137–159 (2000).
37. Diller, H.: Preispolitik. 4th edn. Kohlhammer, Stuttgart (2008).
38. Pigou, A.C.: The Economics of Welfare. 3rd edn. Macmilian, London (1929).
39. Kahin, B., Varian, H.R.: Versioning Information Goods. In: Kahin, B., Varian, H.R. (eds.) Internet publishing and beyond: The economics of digital information and intellectual property. Publication of the Harvard Information Infrastructure Project, pp. 190–202. MIT Press, Cambridge, MA (2000).
40. Skiera, B., Spann, M.: Preisdifferenzierung im Internet. In: Schögel, M. (ed.) Roadmap to E-Business, pp. 270–284. Verl. Thexis, St. Gallen (2002).
41. Viswanathan, S., Anandalingam, G.: Pricing strategies for information goods. Sadhana - Journal of the Indian Academy of Sciences 30(2,3), 257–274 (2005).
42. Choudhary, V., Ghose, A., Mukhopadhyay, T., Rajan, U.: Personalized Pricing and Quality Differentiation. Management Science 51(7), 1120–1130 (2005).
43. Amann, K., Petzold, J., Westerkamp, M.: Prädiktive Analytik. In: Amann, K., Petzold, J., Westerkamp, M. (eds.) Management und Controlling: Instrumente – Organisation – Ziele – Digitalisierung, 3rd edn., pp. 251–256. Springer, Berlin, Heidelberg (2020).
44. Bizerba: Smart Shelf Lösungen: Vernetzte Smart Shelf Lösungen mit integrierter Wägetechnologie, https://www.bizerba.com/media/themen/security_of_supply/bizerba_insight_smart_shelf_loesungen_de.pdf (2020), last accessed 2021/04/05.
45. ptc: Celli Group transformiert Nahrungsmittel- und Getränkeindustrie, https://www.ptc.com/de/case-studies/celli (2020), last accessed 2021/04/16.