Design Elements of a Platform-Based Ecosystem for Industry Applications

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Abstract

Many companies in the Industry 4.0 (I4.0) environment are still lacking knowledge and experience of how to enter and participate in a platform-based ecosystem to gain long-term competitive advantages. This leads to uncertainty among firms when transforming into platform-based ecosystems. The article presents a structuralist approach to conceptualize the platform-based ecosystem construct, giving an overview of the literature landscape in a model bundled with unified terminology and different perspectives. The holistic process model aggregates the findings of 130 papers regarding platform-based ecosystem literature. It consists of 4 phases and 16 design elements that unify different terminologies from various research disciplines in one framework and provide a structured and process-oriented approach. Besides, use cases for different design elements were developed to make the model apply in an I4.0 context. Use Case I is a methodology that can be used to model and validate usage hypotheses based on usage data to derive optimization potential from identified deviations from real product usage. By collecting and refining data for analyzing different manufacturing applications and machine tool behavior the importance of specific data is shown in Use Case II and it is highlighted which data can be shared from an external perspective. Use Case III deals with strategic modeling of platform-based ecosystems and the research identifies control points that platform players can actively set to adjust their business models within alliance-driven cooperation to create and capture value jointly. Use Case IV investigates the status quo and expectations regarding platform-based ecosystems in the field of laser technology with the help of structured expert interviews. Overall, this chapter presents a framework on industrial platform-based ecosystems that gives researchers and practitioners a tool and specific examples to get started in this emerging topic.

1 Introduction

The rise of interconnected businesses participating in a platform-based ecosystem has induced a redesign of existing business models in various industries and technology sectors. Starting with telecommunication networks, platform-based business models are prevalent in many industries today; especially in the online gaming industry (Boudreau and Jeppesen 2015) or social networks (Li and Agarwal 2017). As per our understanding ecosystems consist of independent yet interdependent actors who interact to generate a joint value proposition. Actors include (multiple) platforms, users, and complementors. A platform is the technology that allows the efficient creation of many options by producers and/or users. Platforms act as an intermediary facilitating exchange/transactions between different actors and/or serve as a foundation on top of which other firms develop complementary technologies, products, or services (Adner et al. 2020; Jacobides et al. 2019; Parker and van Alstyne 2018). Many companies lack knowledge and experience of how to enter, participate, and position themselves in a platform ecosystem to gain long-term competitive advantages. The promises of Industry 4.0 lead to increased cross-domain collaboration and industrial data sharing within an open ecosystem based on underlying platform business models. For example, when shifting from a product system to a platform-based ecosystem, firms lack knowledge of how resulting value is captured and shared in the ecosystem. To cope with interdependencies in the ecosystems, firms need to assess whether they must build up new competencies (Stonig et al. 2022). So far, only a few companies in an Industry 4.0 environment have experience in platform design, leading to uncertainty among firms regarding platform-based ecosystems.

The literature on platforms and ecosystems has grown enormously in recent years. However, the existing literature is currently very scattered across many disciplines (Rietveld and Schilling 2021). Researchers have mostly investigated terms of platform and ecosystems isolated within their disciplines, delivering insights from an isolated point of view. Especially in management, information systems, and engineering disciplines, the research is further based either on platform or ecosystem literature, with a lack of integrating platform and ecosystem aspects. Further, existing research does not give a holistic overview of platform-based ecosystems, as researchers mostly focus on specific aspects. This work fills the gap by combining research from different disciplines, defining and organizing relevant aspects of platforms and ecosystems from the perspectives of the ecosystem, the platform organizer, and the complementor and placing them in a process-oriented framework. We combine these research strings, giving a holistic overview of relevant literature related to platform-based ecosystems. Past platform and ecosystem literature usually discusses specific aspects, either of platforms or ecosystems. McIntyre and Srinivasan (2017) focus on the view of industrial organization economics, technology management, and strategic business perspectives of platform-mediated networks. The research of Hagiu (2014) analyzes four strategic challenges regarding multisided markets that are the number of sides to bring on board, design, pricing structure, and governance rules. Jacobides (2019) deals with the emergence of ecosystems and clarifies the differences from other forms of governance. The work of Rietveld and Schilling (2021) provides a literature review focusing on platform competition and providing an overview of key questions around network externalities, platform ecosystems on corporate level, heterogeneity, and value creation and capture. Rietveld and Schilling (2021) cover individual aspects on both, platform and ecosystems, yet not classified within a holistic process model. Our process model builds on the paper of Rietveld and Schilling by adding further important aspects to their described key themes as well as showing how individual elements are interrelated and fit into an overall process.

2 Description of the Process Model for Platform-Based Ecosystems and Industry Applications

The process model was developed using a hybrid approach combining both common literature analysis and new machine learning methods for further verification. Using a Boolean search query string regarding titles and publication outlets, a comprehensive list of around 400 academic papers could be identified via Web of Science. To be included in the list, at least one of the following words had to be in the title: "ecosystem," "platform," "network effect," "complementor," "sided market," "network externality," "network effect" or a combination between the phrase's "innovation" and "ecosystem" or "platform," "strategy" and "ecosystem*" or "platform," "open" and "ecosystem" or "platform." To ensure an interdisciplinary approach, we included journals known for their research on platforms and ecosystems from management, information systems, and engineering disciplines. Subsequently, all papers were manually reviewed in aspects of relevance and contextual fitness. For a further verification of the literature, we used the machine learning software ASRreview which deploys learning techniques for an efficient screening of titles and abstracts (Van de Schoot et al. 2021). The software was given a training set of 40 relevant and 10 irrelevant articles which was used to learn and select the most relevant articles. The result was 130 relevant papers, which were the basis for our model. From the literature selection, we synthesized 16 design elements for platform-based ecosystems and allocated at least one design element per paper. To ensure a structured process, we defined four phases, namely "Strategy," "Design & Entry," "Within-platform competition," and "Between-platform competition" and assigned each design element to one of the four phases. Starting point for the definition of our phases and design elements were the four structural factors from Gawer (2014) and Parker and van Alstyne (2018): "governance," "organizational form," "capabilities," and "interfaces." The "organizational form" and "capabilities" are in our "Strategy" phase, in which firms need to clarify questions of how to play and use an ecosystem. The governance dimension is central part for all phases after the strategy was clarified. The last factor "interfaces" was divided into the phases "Within-platform competition" and "Between-platform competition."

Our process model bundles and aggregates the findings of selected papers regarding platform-based ecosystem literature. It consists of 4 phases and 16 design elements that unify different terminologies from various research disciplines in one framework (Fig. 1). Each design element is backed up with relevant articles and key questions for three different perspectives are elaborated, namely the ecosystem, the platform orchestrator or complementor. The first "Strategy"-phase consisting of five design elements defines how to play and use an ecosystem. Key questions are described per design element which should be asked before companies enter the ecosystem, either as a platform orchestrator or complementor. The second phase "Design & Entry" describes the design and scale of a platform within in ecosystem by bringing others on board and is based on three design elements. The "Within-platform competition"-phase deals with the competition and collaboration with

Fig. 1 Platform-based ecosystem process model

complementors on the platform to maximize value creation and capturing of one's ecosystem. The last phase "Between-platform competition" which consists of five design elements clarifies questions of how to compete and collaborate with other platforms to ensure platform attractiveness and survival.

2.1 Strategy

Being part of a platform-based ecosystem is a strategic action, opening new ways of capturing value. To be successful in a platform-based ecosystem, actors of the ecosystem therefore need to define a shared value proposition with their future stakeholders. Both, the platform orchestrator and the complementors, need to outline how to capture value for themselves while serving the focal value proposition of the ecosystem (e.g., Autio and Llewellyn 2015; Zhang et al. 2020; Clarysse et al. 2014). Role positioning refers to the organizational governance on an ecosystem level. Platforms take different roles to follow the value proposition. The positioning (dominant vs. niche) of the platform in the overall ecosystem needs to be addressed by the platform orchestrator. From the complementor's point of view, the number of platforms should be discussed as part of the overall ecosystem strategy (Chen et al. 2021). The pre-defined shared value proposition of a platform-based ecosystem requires resources and capabilities to be implemented successfully. All players of the ecosystem should bring needed capabilities to support the overall value creation. They also need to identify capabilities that already exist, and capabilities that need to be assured by other actors (e.g., Hagiu 2014; Henfridsson et al. 2021). Part of the overall ecosystem strategy is the question of which existing intellectual property or industry standards can be leveraged by the platform orchestrator as well as the complementors. Value co-creation in an ecosystem builds on interdependencies as well as complementarities of the respective goals of the participants (Bogers et al. 2019). Defined interdependencies and complementarities shape the ecosystem strategy and the outcome of value capture. Participants of the ecosystem question how to influence complementarities and interdependencies in the ecosystem (e.g., Alexy et al. 2018; Autio and Thomas 2018).

2.2 Design and Entry

The degree of openness chosen by participants of an ecosystem defines the level of cooperation with external players. Hence, ecosystem resources can be shared in order to foster cooperation, using, e.g., an open-source license approach. However, shared ecosystem resources are vulnerable to being strategically exploited. The platform orchestrator must balance the optimal degree of openness to spur innovation while still ensuring control. Complementors need to manage the adequate access and decision rights that are crucial to be successful on the platform (e.g., Ondrus et al. 2015; Cenamor and Frishammar 2021). Network effects describe how the number of participants of a platform can impact the value generated for the participants of the platform. The question for both platform orchestrator and complementors is how to induce new network effects or, if not possible, how to use existing ones (e.g., Panico and Cennamo 2019; Markovich and Moenius 2008; Kim et al. 2014; Allen et al. 2022; Gregory et al. 2021). The decision of pricing accounts for the dynamic interaction between each side of the ecosystem. The pricing structure of platform-based ecosystems should balance the value captured for each player, in order to keep all players on board. The platform orchestrator, on one hand, specifies which side to subsidize by themselves to bring all sides on board. Complementors, on the other hand, need to be clear about which pricing structure and pricing mode to accept (e.g., Economides and Katsamakas 2006; Dushnitsky et al. 2020).

2.3 Within-Platform Competition

Vertical integration addresses the decisions of which activities are performed by the platform provider and which by the platform complementors, then defining how the efforts of the players are integrated into a coherent whole (Wang 2021). To achieve platform health over time, fast and sustainable growth is shaped by the decision of how to share profit for the platform with multiple stakeholders. As a platform orchestrator, the challenge lies in determining the maximum share of profit for the platform without alienating complementors. Complementors will determine the minimum share of profit that is still acceptable (Oh et al. 2015). Boundary resources play a critical role in managing the tension between an ecosystem owner and independent external players. The main challenge for the platform orchestrator is how to obtain a competitive advantage with strategic openness. Complementors set which kind of boundary resources can be used (e.g., Woodard 2008; Eaton et al. 2015; Ghazawneh and Henfridsson 2012).

2.4 Between-Platform Competition

To orchestrate outbound communication and cooperation with external players, platform owners should define which kind of bottlenecks can be removed in order to foster progress and growth (e.g., open innovation by removing technological bottlenecks). Therefore, control points are crucial to secure profits and competitive advantages, managing how the network operates and how other players can participate in the ecosystem. The main challenge for the platform orchestrator and the complementors is to identify bottlenecks that can be resolved (Hannah and Eisenhardt 2018). The importance of the number as well as the nature of complements (heterogeneity) are crucial in terms of shaping the ecosystem structure. Leveraging complementor dynamics plays an important role in gaining a competitive advantage. Hence, the platform orchestrator needs to solve the trade-off of focusing on many complements vs. securing exclusive marquee complements (e.g., Rietveld and Eggers 2016; Panico and Cennamo 2020). Multi-homing describes the decision about the exclusiveness of complementors and/or users on one hand, and the affiliation with other platforms on the other hand. From the perspective of a platform orchestrator, the question of how multi-homing can be prevented plays a central role. Complementors need to think about how costly it is to affiliate with other platforms. The main challenge of platform envelopment describes how actors of different platform markets can combine their functionalities to leverage existing user relationships and expand into other markets. The platform orchestrator as well as complementors need to address the question with whom to compete and cooperate (e.g., Adner et al. 2020; Ansari et al. 2016). Cooperation and competition need to be balanced over time. Therefore, it also has to be specified if competition takes place on specific layers and/or in between platforms.

To transfer the process model into an I4.0 context, four different research topics are defined as use cases for different design elements.

3 Use Case I: Use of Product Usage Information to Identify Innovations

Product development in the machinery and plant sector is currently facing a variety of challenges. As in many other industries, the entry of new competitors and the emergence of overcapacities have led to an increase in the intensity of competition. Accompanied by an increase in price pressure, this has led to a shift in market power to the customer side (Schuh and Riesener 2018). At the same time, the lifetime of a product on the market is decreasing. While this used to be the case primarily for consumer goods, the lifetime of industrial products, as in machinery and plant engineering, is also becoming shorter and shorter (Michels 2016). For the companies in the market, it is important to take the impact on a necessary reduced time-to-market and shorter innovation cycles into account (Schuh and Riesener 2018). In addition to price and quality, the short innovation time thus evolved into the criterion for success (Ehrlenspiel and Meerkamm 2013). In this context, the development costs for products with overloaded product functions or product functions that are rarely used in the usage phase raise exponentially (Schuh et al. 2020). Based on the initial situation described above, the aim is to increase the effectiveness and efficiency of research and development (Schuh 2013). Particularly in the context of the innovation process, companies are more than ever confronted with the challenge of completing the activities from idea generation to market launch as quickly as possible and with scarce resources, while at the same time ensuring the highest possible probability of success (Gommel 2016). The rapid translation of an identified customer need into a market-ready solution has become one of the key success factors in competition (Michels 2016). Development activities, especially for new products, must therefore be focused on those product functions that have a positive influence on the fulfillment of customer needs.

In contrast, product development faces the challenge that companies lack knowledge about which product functions the customer actually needs and to what extent. While the range of functions in most products is constantly increasing, it is still the task of humans to anticipate and develop them (Michels 2016). Similarly, a consultation of future customers does not prove to be effective, since they usually do not yet know how the product will be used in the specific application. Development activities and focus are therefore based on assumptions about later product usage and the corresponding customer needs. If customer feedback is taken and used to focus product development, it is usually unstructured and isolated feedback from distributors or service partners based on warranty cases, complaints, or product recall (Abramovici and Lindner 2011).

With regard to the initial situation and challenges presented, the transformation of machines and plants from mechatronic to cyber-physical products offers enormous potential. Cyber-physical machines enable information from product usage to be generated, recorded, stored, and evaluated by means of sensors (Hellinger 2011). The recorded information can be used to examine how the functions of the machine are used in order to derive valuable findings for innovations in the next product generation. Assumptions about later product usage, which were made due to a lack of knowledge during product development, can be verified by the recorded product usage information.

This potential was exploited in the presented use case by developing a methodology for identifying innovation potential through the analysis of product usage information. The methodology pursues the objective of systematically formulating product development assumptions as hypotheses and testing them based on recorded product usage information to derive innovation potential for the next product generation.

In the context of the platform-based ecosystem process model, the methodology can be assigned to the "Strategy"-phase and specifically to design elements "Value creation & Capture" and "Resources & Capabilities," as it deals with general added value that can be derived from usage data. This is particularly evident in the development and elaboration of the individual phases of the methodology presented later. Value is generated on the part of the machine and plant manufacturer by the possibility of better addressing the customer needs, which can lead to an improved market positioning and an increased competitiveness. Simultaneously, the customer receives a product with an improved cost-benefit ratio in the long term, as fewer or even unused functions and the associated higher costs are eliminated. Due to the level of detail of the methodology it is shown what kind of information and capabilities are required and could be provided by stakeholders in a platform-based ecosystem to generate the value. In general, it can be stated that within the implementation of the methodology in the context of a platform-based ecosystem, further design elements and their contents need to be elaborated. Nevertheless, primarily in terms of an exemplary use case, the method illustrates a way to generate value from data that can be shared via a platform.

The methodology consists of four steps (Fig. 2). In the first step, the usage cycle of the machine is systematically described and it is determined where the user can influence the machine during usage. Based on this, relevant product usage information to be recorded is derived in the next step. In the third step, the assumptions about the product usage are formulated as so-called usage hypothesis

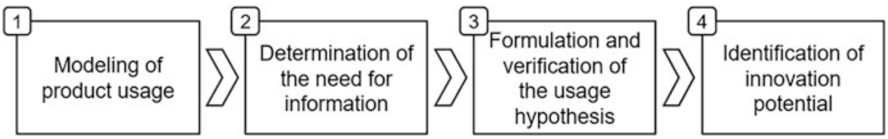

Fig. 2 Four steps of the methodology for the identification of innovation potential

and verified by recorded product usage information. Finally, innovation potentials for the next machine generation are derived from deviations between the usage hypothesis and real product usage. The four steps are explained in detail below.

The aim of the first step is to model the usage cycle of the machine as a basis for the further methodology. In accordance with systems theory, the usage cycle is defined as a structural system in which the elements of the system are not considered detached from the context, but only in their interdependencies with other system elements (Ropohl 2009). In order to develop a suitable method for modeling these elements, at first various requirements for the modeling were developed. In addition to other requirements, the modeling of the usage cycle should represent the states of the product functions, their functional attributes, and the transitions between the product functions, the so-called transitions. Various existing modeling methods, such as state machines, Petri nets, and UML, were analyzed with regard to these requirements, and suitable elements were adopted.

Subsequently, different types of variability were identified, which means the changeability of the modeled elements due to external influence by the user. It was determined that the user can influence the duration of the functions, control the characteristics of the functions and select between different functions or transitions. Based on modeled elements as well as types of variability, the need for relevant product usage information to be recorded was derived. The minimum, average, and maximum attributes, the frequency of use of various functions and transitions, and the usage duration of functions were among others identified as relevant information.

Afterward, the usage hypothesis can be defined based on the modeled usage cycle, the identified variabilities, and required information. The usage hypothesis comprises the assumptions about the respective information that describe the state of the modeled elements in usage. The one-sample t-test was identified as a suitable test procedure for the subsequent verification of the usage hypothesis on the basis of recorded product usage information (Hedderich and Sachs 2018). This test can be used to identify significant deviations between the usage hypothesis and the actual usage of the machine in the usage cycle.

In order to convert the identified deviations into innovation potential, it was first assumed in the sense of the finality and causality of human action that the user pursues a specific goal in use with all deviations (Hartmann 1951). Deviations between usage hypothesis and real product usage were therefore first clustered into generic use cases and linked to possible targets in the usage of the machinery. From the analysis of the use cases, various innovation potentials could be derived, such as the elimination of a function, the change of a solution principle, or the expansion of the possible attribute value. In order to enable efficient processing in the subsequent product development, a recommendation for action was elaborated for each innovation potential.

With these four steps, the methodology addresses the challenges presented above in the development of machines and plants. Through the targeted recording of relevant product usage information, innovation potentials can be efficiently derived and the speed and success in the development of innovations can be increased.

4 Use Case II: Potentials of Knowledge Sharing with Platform-Based Ecosystems in the Context of Machine Tools

For the analysis of various manufacturing applications in machining, data can be collected and refined from different sources along the digital process chain. Manufacturing execution systems (MES) are widely used in industry to document discrete-event information on production such as throughput times, set-up times, or possible quality problems and their respective causes. However, to gain specific insights into the behavior of the machine tool, its components, and the manufacturing process itself, the acquisition of continuous and high-resolution data is required. Modern CNC machine tools allow accessing data from machine internal sensors in the control cycle. This involves recording high-frequency sensor data from the machine controller such as axis positions, drive currents of the axis, spindle speeds and spindle positions, as well as discrete-event messages as the active tool or NC line (Brecher et al. 2018).

In addition to machine-internal data, external sensors such as force, acoustic emission, or vibration sensors can be applied to the machine tool to monitor machining operations. Especially the measurement of the occurring process forces is of crucial importance due to the high sensitivity and rapid response to changes in cutting states (Teti et al. 2010). In practice, it is not the data from machine-internal or external sensors during the machining process itself that is of interest, but the underlying knowledge that is worth sharing from an external perspective. Therefore, raw data must be refined into characteristic values to share them between different participants within a platform-based ecosystem. This form of data exchange enables participants to map correlations based on this knowledge without having to generate the underlying raw data themselves. Sharing this knowledge in the form of recommendations in turn offers potential for optimizing machining processes. In this context, combining raw data from the machining process with domain-specific models enables the necessary data refinement by addressing known issues in machining as quality defects, wear condition of tools or components and creating a Digital Shadow of the respective object of observation (Brecher et al. 2021a).

Brecher et al. (2019) and Königs and Brecher (2018) describe an online material removal simulation that generates a Digital Shadow of the workpiece based on process parallel recorded machining data and available manufacturing metadata. This digital workpiece can be used to assess the manufacturing quality and derive further information about the engagement situation during machining. Based on the resulting availability of information on the engagement situation and process forces this information is mapped on the used tools to monitor the wear condition during machining (Brecher et al. 2022; Xi et al. 2021). Monitoring the wear condition facilitates maintenance measures by estimating the remaining service life. In addition, findings on correlations between the usage of tools in machining processes achieved workpiece quality and the resulting tool wear can be leveraged for a more efficient and sustainable use of tools.

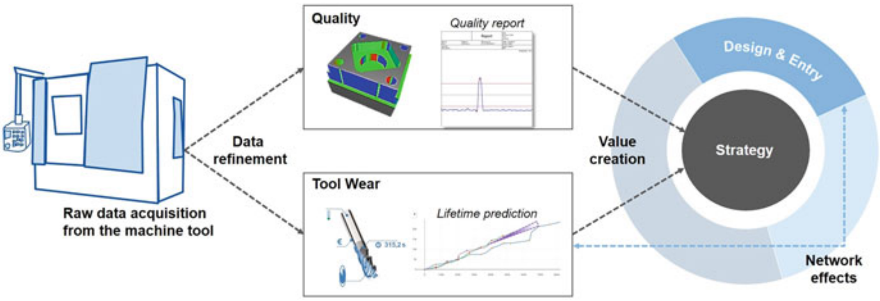

Fig. 3 Integration of the machine tool context in the platform-based ecosystem process model

The described use case for collecting and refining data in context of machine tools can be assigned to the “Strategy”-phase of the platform-based ecosystem process model. Refining raw data from machining processes creates added value by gaining knowledge with regard to parameters relevant to practice and thus enables leveraging existing resources and capabilities in the machine tool environment. After this form of value creation, the characteristic parameters can be used across platforms and thus network effects from the “Design & Entry” phase can be exploited. The integration of the machine tool context into the process model is shown in Fig. 3 on the example of workpiece quality and tool wear.

The success and crisis resistance of digital business models is demonstrated in particular by examples from the media and entertainment industry (Vonderau 2017; Winter 2017). Adapting these digital business model approaches on the machine tool industry raises different challenges. Companies underline their high customer orientation and focus on technology and product. Therefore, the central value proposition is still the physical machine tool. In some cases, digital add-on applications are offered as services for machine tools, but these are not integrated into a service-oriented value chain and thus often cannot lead to additional financial benefits. In conjunction with a high level of complexity in the provision of services in machine tool manufacturing, this results in a further cause for the lack of digital business models such as platform-based approaches (Copani 2014; Kamp et al. 2017).

To address the stated challenges, Brecher et al. (2021b) name two enablers for successfully implementing a digital business model. Examples from industry show that the basic technological enablers are in principle already in place. However, these individual solutions must evolve to cross-company platforms through standards and guidelines. Although companies face technological problems due to a lack of competencies in the digital domain, this is not the main obstacle for the implementation of these business models. Prevailing mindsets at the management level of manufacturers and users within the machine tool industry are of greater importance, particularly in the direction of the central value proposition and thus human enablers. In this regard, expert interviews conducted at the Laboratory for Machine Tools and Production Engineering (WZL) of RWTH Aachen University show that central questions regarding data security, cost transparency and calculability, liability and risk assessment, and dependence on third-party companies must be answered before using platform-based business models on the machine tool industry.

Generally, the pure adaption of digital business models from other industry on the machine tool context is not possible, as the stated challenges are not solvable this way. The platform-based ecosystem process model creates a methodological framework to develop possible solutions to face these challenges.

5 Use Case III: Strategic Modeling of Platform Ecosystems

Industry 4.0 as the fourth industrial revolution is based on the digitization of manufacturing processes. Collecting data throughout the processes not only create ample opportunities to improve efficiency and quality, but also enables the possibility to advance business models, e.g., through selling value-added services based on data generated at customers, or by creating new subscription models for machines based on this data. For instance, insights gained through using a machine tool at a company can be played back to the manufacturer to improve future machine generations. With these new business models, data-driven platforms emerge that trade machine data as good. However, these platforms pose major challenges for existing market participants. Not only do they have to update their machine parks to incorporate new smart functionality and deal with large amounts of data on the first place, but they do have to take strategic decisions on the fate of their organization's business model. Existential questions are, for instance, whether they should participate in the nascent data market, or whether they should create a data platform themselves, or join an existing data platform, possibly from a competitor. Data availability in platforms also opens opportunities for new members as complementors such as startups specializing in artificial intelligence (AI) products, as there is a low entry-barrier without investments in industrial hardware. Examples are service-oriented business models with multi-angular relationships between companies (Pfeiffer et al. 2017).

Yet, data-related ecosystems are highly complex regarding their operational and technical level of data management, service exchange, and IT security mechanisms. To shed light on these opportunities, we observed and analyzed the positioning of market players in the agricultural industry. The farming sector is dominated by a few large manufacturers with two market players in Europe and North America, respectively. In the 2010s, the market leader began with setting up its platform-based ecosystem including players in its supply chain as well as customers. Based on an extensive study incorporating the analysis of the strategy of an agricultural machine manufacturer (Van Dyck et al. 2020), we identified several control points that influenced their data strategy. We combine the findings of the study with strategic modeling with the conceptual modeling language iStar (i*) and the setting of control points (Koren et al. 2021). In the following, we present the resulting model. We then show how the strategic model can help organizations in finding their strategy in dealing with new data-driven ecosystems, by actively setting control points.

The large-scale study follows the suggestions for rigorous case study research by Yin (2018). To derive the model, we identified several stakeholders participating in the smart agricultural data platform and their goals. First, the Manufacturer delivers products and services to the farm. The Dealer provides, sells, and leases farm machines to a Contractor, that in turn cultivates the fields. The Farmer commissions the Contractor to efficiently raise living organisms for food or raw materials. A Farm Management Platform as new actor in the agricultural value chain integrates data from the farm. It also provides the entry point for complementors to offer new, innovative services to other stakeholders.

Figure 4 shows the conceptual model of the stakeholder relationships in the described agricultural data ecosystem following the iStar 2.0 modeling notation. It presents a view on the dependencies between the stakeholders. For instance, from center right to center left, a Farmer depends on a Manufacturer for machines. An example for a non-physical asset displayed in the model is machine data, which the Farm Management Platform depends on from the Contractor.

For organizations in a platform-based ecosystem, it is of high strategic importance to anticipate their future decisions at an early stage. Strategically, this is best done top-down, as actively placed management decisions. We therefore combine our strategic modeling with control points. They can be set to grant access or impose certain behavior (Eaton et al. 2015). Organizations can, for instance, set up control points, by adhering to certain technical standards. Platform operators, on the other hand, could introduce multi-homing costs to promote their own platform. A detailed discussion of the proposed control points is out of scope, the reader is kindly referred to an earlier publication (Van Dyck et al. 2020).

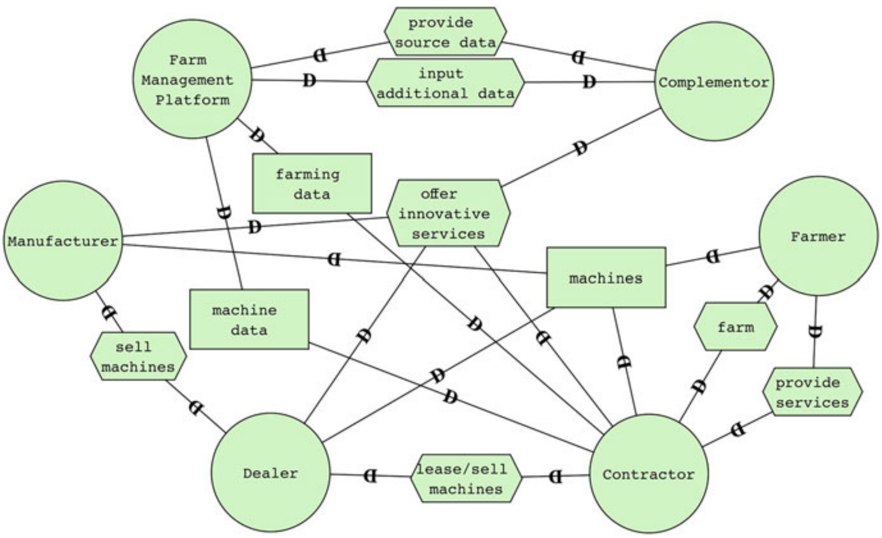

Fig. 4 Strategic dependency view of stakeholder relationships

The technological basis for autonomous data exchange between companies are interfaces. The platform thereby embraces standards that manage the interdependencies in the ecosystem (Thomas et al. 2014). While, for instance, the International Data Spaces Association introduced an architecture for data sharing between its members, it does not impose a specific format for the data objects. In the Internet of Production, we are exploring the notion of Digital Shadows as conceptual abstractions (Becker et al. 2021).

Platform ecosystems in industrial environments are challenging in terms of technology layers (Sisinni et al. 2018) and relationships (Schermuly et al. 2019). Potentials and risks need to be recognized in time, so that companies can take strategic decisions in advance. Our research portrayed above introduces two tools that can deal with the complexities: modeling using the i* language and control points. They are decision-making instruments to plan the next step within platform ecosystems. Regarding our process model for platform-based ecosystems, they are therefore tools located in the strategic core. Decisions on this strategic level have radiating effects toward the other phases. For instance, providing data access to industrial machines result in a strategic openness, with APIs as possibly boundary resources that platform players can actively set to adjust their business models to create and capture value jointly. The challenge is to identify and assess these opportunities early on. As a next step, we plan on providing an initial repository of available graphical representations and code structures to facilitate automated decision support for stakeholders. These design patterns could allow organizations to discover missing links and potential obvious options.

6 Use Case IV: Laser Material Processing Market Pull for Digital Platforms

Laser material processing is particularly predestined for close coupling to digital value chains. This is due to the unique properties of laser light (Poprawe et al. 2012). Like no other tool, laser light can be controlled extremely quickly and extremely precisely in space and time based on digital data (Hinke 2017). With the various laser-based subtractive and additive manufacturing processes (e.g., laser beam cutting, laser beam surface structuring, or laser-based additive manufacturing), it is thus possible to realize highly individualized components in very small quantities directly from digital data (Hinke et al. 2015; Gu et al. 2021; Poprawe et al. 2017).

Figure 5 shows the concept of Digital Photonic Production. The entire laser-based manufacturing process is directly controlled by digital data. Digital data or the digital shadow of the component to be produced (left) controls the entire laser processing system. This allows raw material (lower right) to be ablated, applied, or locally modified in the smallest 2D or 3D surface or volume units (lower center). Essentially, (i) laser beam source (power, time distribution), (ii) optical system (focal length, spot size), and (iii) beam guiding system (spatial distribution x, y, z) are controlled by digital data (Poprawe et al. 2018).

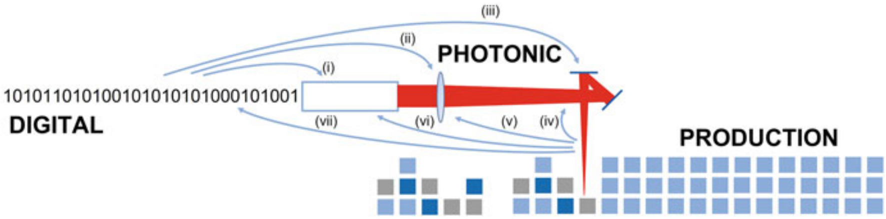

Fig. 5 The concept of Digital Photonic Production

At the same time, laser-based manufacturing processes can be adjusted and thus corrected extremely quickly and precisely during the manufacturing process. Typically, with optical sensors, large amounts of data can be recorded in high spatial and temporal resolution during laser manufacturing processes. Based on process understanding represented in Digital Shadows (reduced real-time process models) or on trained AI methods, it is possible to control the entire laser processing system and therewith the laser-based manufacturing process in real time. The blue arrows (iv–vii) in Fig. 5 represent these closed control loops (Knaak et al. 2018).

In many cases, manufacturing defects can be controlled before they lead to defective components. This is because the time scale with which a laser beam can be controlled is typically an order of magnitude smaller than the time scale with which the molten material typically moves. An incorrect energy- or heat-input during laser-based additive material processing can thus be corrected, for example, before the liquid melt solidifies in its final geometry (Knaak et al. 2021). However, the enormous technological potential of Digital Photonic Production can only be fully exploited if corresponding digital business models and platform-based ecosystem are developed and implemented. The photonics industry, which is characterized by many small- and medium-sized companies, is still struggling with the development of corresponding digital business models and platform-based ecosystem though (Poprawe et al. 2018).

Against this background, a survey was conducted in 2020 with 34 companies from the photonics sector. In addition, two workshops were held with senior representatives from these companies in 2020 and 2021. The various obstacles to the development and implementation of digital business models and platform-based ecosystems were discussed and analyzed in six small groups in each case. Based upon this, recommendations for the design of such digital business models and platform-based ecosystems were developed.

The study shows that a large majority of company representatives see a medium to high potential of artificial intelligence (80%) and digital services (74%). At the same time, a vast majority of companies complain of having no or too little in-house expertise and appropriately trained personnel in these areas. Especially in the field of AI, the internal acceptance of this technology is not yet very high. The study shows a very indifferent picture regarding the internal acceptance, particularly in the field of AI: the company's internal acceptance of AI is estimated to be low and

Table 1 Results of a survey on the topics artificial intelligence (AI), digital services, and the according platforms

Question	Low and rather low (%)	Neither low nor high (%)	Rather high and very high (%)
How do you assess the potential of AI for your company?	20	20	60
What is your level of interest in participating in a collaborative AI platform?	20	40	40
What is your level of interest in AI education and training formats?	15	20	65
How do you assess the acceptance of AI within your company?	35	30	35
How do you assess the potential of digital services for your company?	26	5	69
What is your level of interest in participating in a collaborative digital services platform	26	10	64
What is your level of interest in education and training formats regarding digital services?	21	37	42
How do you asses the acceptance of digital services within your company?	26	22	52

rather low (35%) as well as high and rather high (35%) with the same percentage. However, the internal acceptance of digital services is significantly better and is rated as medium to high (74%) by a majority of the surveyed companies (Table 1). Accordingly, the overwhelming majority has a medium to high level of interest in education and training formats in the field of AI (85%) and digital services (79%).

In the following expert workshops, two main challenges were identified, and corresponding solutions were proposed. The companies have broad domain know-how (laser technology), but according to their own statements hardly any AI-know-how or any know-how about platform-based ecosystems. Secondly, besides interest and expectations of the companies in the topics of digitization and artificial intelligence are great, AI and platform-based ecosystems are seen as a great opportunity, but also as a potential threat. On this basis, the following recommendations for the design of such digital business models and platform-based ecosystems were developed: (1) Analysis of examples from other industries on the use of AI and platform-based ecosystems and analysis of transferability to laser technology. (2) Development of transferable design and behavioral rules for dealing with platform-based ecosystems. (3) Development of transferable design and behavioral rules for dealing with multiple platforms simultaneously in the role of non-dominant designer. In a next step, we plan a detailed elaboration of our derived recommendations to facilitate the design and development of such digital business models and platform-based ecosystems in laser material processing.

7 Conclusion

Our process model provides an overview of the relevant literature regarding important design factors of platform-based ecosystem. Building up on the framework, academia can identify relevant areas for future research. Furthermore, a structured and process-oriented approach is given due to the division into phases, specific design elements, and key questions for different perspectives. The holistic process model helps managers to tackle all relevant aspects before entering in a platform-based ecosystem as platform orchestrator or complementor. Practical examples in the context of I4.0 are developed for different design elements and/or phases to make the model easy to understand and apply. The methodology from Use Case I can be assigned to the Strategy phase and specifically to the design elements “Value creation & capture” and “Resources & Capabilities,” since it deals with general added value that can be derived from usage data. At the same time, it generally shows how field data can be used in product development, but also which capabilities are needed. Research of Use Case II can be integrated into the “Strategy”- and “Design & Entry”-phases. In addition to showing which data can be shared from an external perspective, Use Case II demonstrates whether digital business model approaches from other industries can be transferred to the machine tool industry under the condition of data availability and expected challenges. Strategic modeling of platform-based ecosystems is shown in Use Case III and can therefore be understood as the connection of the central “Strategy” phase, with effects that radiate toward the other phases. Use Case IV can be assigned to the “Strategy”- and “Design & Entry”-phases. The research identifies the future potential and possible obstacles regarding platform-based ecosystems in the field of laser technology.

8 Cross-References

▶ 3 Use Case I: Use of Product Usage Information to Identify Innovations
▶ 4 Use Case II: Potentials of Knowledge Sharing with Platform-Based Ecosystems in the Context of Machine Tools
▶ Use Case III: Strategic Modeling of Platform Ecosystems
▶ Use Case IV: Laser Material Processing Market Pull for Digital Platforms

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References

Abramovici M, Lindner A (2011) Providing product use knowledge for the design of improved product generations. CIRP Ann 60(1):211–214

Adner R, Chen J, Zhu F (2020) Frenemies in platform markets: heterogeneous profit foci as drivers of compatibility decisions. Manag Sci 66(6):2432–2451

Alexy O, West J, Klapper H, Reitzig M (2018) Surrendering control to gain advantage: reconciling openness and the resource-based view of the firm. Strategic Management Journal 39(6):1704–1727

Allen BJ, Gretz RT, Houston MB, Basuroy S (2022) Halo or cannibalization? How new software entrants impact sales of incumbent software in platform markets. J Mark 86(3):59–78

Ansari S, Garud R, Kumaraswamy A (2016) The disruptor's dilemma: TiVo and the US television ecosystem. Strateg Manag J 37(9):1829–1853

Autio E, Thomas LD (2018) Tilting the playing field: towards an endogenous strategic action theory of ecosystem creation. In: World Scientific reference on innovation: volume 3: open innovation, ecosystems and entrepreneurship: issues and perspectives. World Scientific Publishing, Hackensack, pp 111–140

Baldwin CY, Woodard CJ (2009). The architecture of platforms: A unified view. Platforms, markets and innovation, 32:19–44

Becker F, Bibow P, Dalibor M et al (2021) A conceptual model for digital shadows in industry and its application. In: International conference on conceptual modeling. Springer, Cham, pp 271–281

Bogers M, Sims J, West J (2019) What is an ecosystem? Incorporating 25 years of ecosystem research. Acad Manag Proc 2019(1):11080

Boudreau KJ, Jeppesen LB (2015) Unpaid crowd complementors: the platform network effect mirage. Strateg Manag J 36:1761–1777

Brecher C, Epple A, Knape S, Schmidt S (2018) Netzwerkarchitekturkomponenten auf Werkstattebene: Anforderungsgerechte Netzwerkarchitektur für das Internet of Production. Z Wirtsch Fabr 113:342–345

Brecher C, Eckel H-M, Motschke T, Fey M, Epple A (2019) Estimation of the virtual workpiece quality by the use of a spindle-integrated process force measurement. CIRP Ann 68:381–384

Brecher C, Biernat B, Fey M, Kehne S, Lohrmann V, Spierling R, Wiesch M (2021a) Data science in production. In: Bergs T, Brecher C, Schmitt R, Schuh G (eds) Internet of Production – turning data into sustainability: 30. Aachener Werkzeugmaschinen-Kolloquium 2021, 1st edn. Apprimus Verlag, Aachen, pp 202–236

Brecher C, Butz F, Kaever M, Nagel E, Neus S, Rettich T, Steinert A, Welling D (2021b) Sustainable business models for machine tools. In: Bergs T, Brecher C, Schmitt R, Schuh G (eds) Internet of Production – turning data into sustainability: 30. Aachener Werkzeugmaschinen-Kolloquium 2021, 1st edn. Apprimus Verlag, Aachen, pp 395–420

Brecher C, Lohrmann V, Wiesch M, Fey M (2022) Clustering zur Bestimmung von Werkzeugverschleiß: Hybride Modellierung durch automatisches Clustering von Prozessverhalten zur Vorhersage von Werkzeugverschleiß bei der Fräsbearbeitung. Z Wirtsch Fabr 117:218–223

Cenamor J, Frishammar J (2021) Openness in platform ecosystems: innovation strategies for complementary products. Res Policy 50(1):104148

Chen L, Tong TW, Tang S, Han N (2021) Governance and design of digital platforms: a review and future research directions on a meta-organization. J Manag 48(1):147–184

Clarysse B, Wright M, Bruneel J, Mahajan A (2014) Creating value in ecosystems: crossing the chasm between knowledge and business ecosystems. Res Policy 43(7):1164–1176

Copani G (2014) Machine tool industry: beyond tradition? In: Lay G (ed) Servitization in industry. Springer, Cham, pp 109–130
Dushnitsky G, Piva E, Rossi-Lamastra C (2020) Investigating the mix of strategic choices and performance of transaction platforms: evidence from the crowdfunding setting. Strateg Manag J 43(3):563–598
Eaton B, Elaluf-Calderwood S, Sørensen C, Yoo Y (2015) Distributed tuning of boundary resources: the case of Apple's iOS service system. MIS Q 39:217–243
Economides N, Katsamakas E (2006) Two-sided competition of proprietary vs. open source technology platforms and the implications for the software industry. Manag Sci 52(7):1057–1071
Ehrlenspiel K, Meerkamm H (2013) Integrierte Produktentwicklung: Denkabläufe, Methodeneinsatz, Zusammenarbeit, 5th edn. Carl Hanser Verlag, München/Wien
Gawer A (2014) Bridging differing perspectives on technological platforms: toward an integrative framework. Res Policy 43(7):1239–1249
Ghazawneh A, Henfridsson O (2012) Balancing platform control and external contribution in third-party development: the boundary resources model. Inf Syst J 23(2):173–192
Gommel H (2016) Transparenz über den Innovationsprozess mithilfe der Wertstromanalyse. In: Abele T (ed) Die frühe Phase des Innovationsprozesses: Neue, praxiserprobte Methoden und Ansätze. Springer Gabler, Wiesbaden, pp 142–161
Gregory RW, Henfridsson O, Kaganer E, Kyriakou H (2021) The role of artificial intelligence and data network effects for creating user value. Acad Manag Rev 46(3):534–551
Gu D, Shi X, Poprawe R, Bourell DL, Setchi R, Zhu J (2021) Material-structure-performance integrated laser-metal additive manufacturing. Science 372(6545):eabg1487
Hagiu A (2014) Strategic decisions for multisided platforms. MIT Sloan Manag Rev 55:92–93
Hannah DP, Eisenhardt KM (2018) How firms navigate cooperation and competition in nascent ecosystems. Strateg Manag J 39(12):3163–3192
Hartmann N (1951) Teleologisches Denken. de Gruyter, Berlin
Hedderich J, Sachs L (2018) Angewandte Statistik: Methodensammlung mit R, 16th edn. Springer Spektrum, Heidelberg
Hellinger A (ed) (2011) Cyber-physical systems: Innovationsmotor für Mobilität, Gesundheit, Energie und Produktion. Springer, Heidelberg
Hinke C (2017) Beam sources for metal additive manufacturing – Status quo and requirements. In: 2017 IEEE High Power Diode Lasers and Systems Conference (HPD), pp 5–6. https://ieeexplore.ieee.org/document/8261077
Hinke C, Merkt S, Eibl F, Schrage J, Bremen S (2015) Additive manufacturing: perspectives for diode lasers. In: Proceedings of the 2015 High Power Diode Lasers and Systems Conference (HPD): Co-located with Photonex 2015, Ricoh Arena, Coventry, United Kingdom. IEEE, Piscataway, NJ pp 39–40. https://ieeexplore.ieee.org/document/7439684
Jacobides MG (2019) In the ecosystem economy, what's your strategy? Harv Bus Rev 97(5):128–137
Jacobides MG, Sundararajan A, Van Alstyne M (2019) Platforms and ecosystems: enabling the digital economy. World Economic Forum White Paper February
Kamp B, Ochoa A, Diaz J (2017) Smart servitization within the context of industrial user–supplier relationships: contingencies according to a machine tool manufacturer. Int J Interact Des Manuf 11:651–663
Kim JH, Prince J, Qiu C (2014) Indirect network effects and the quality dimension: a look at the gaming industry. Int J Ind Organ 37:99–108
Knaak C, Thombansen U, Abels P, Kröger M (2018) Machine learning as a comparative tool to determine the relevance of signal features in laser welding. Procedia CIRP 74:623–627
Knaak C, von Eßen J, Kröger M, Schulze F et al (2021) A spatio-temporal ensemble deep learning architecture for real-time defect detection during laser welding on low power embedded computing boards. Sensors 2021(21):4205
Königs M, Brecher C (2018) Process-parallel virtual quality evaluation for metal cutting in series production. Procedia Manuf 26:1087–1093

Koren I, Braun S, Van Dyck M, Jarke M (2021) Dynamic strategic modeling for alliance-driven data platforms: the case of smart farming. In: Nurcan S, Korthaus A (eds) Intelligent information systems. Springer, Cham, pp 92–99

Li ZX, Agarwal A (2017) Platform integration and demand spillovers in complementary markets: evidence from Facebook's integration of Instagram. Manag Sci 63:3438–3458

Markovich S, Moenius J (2008) Winning while losing: competition dynamics in the presence of indirect network effects. SSRN Electron J 27(3):346–357

McIntyre DP, Srinivasan A (2017) Networks, platforms, and strategy: emerging views and next steps. Strategic Management Journal 38:141–160

Michels JS (2016) Vom Kunden zu Lastenheft – systems engineering in den frühen Phasen der Entwicklung intelligenter technischer Systeme. In: Abele T (ed) Die frühe Phase des Innovationsprozesses: Neue, praxiserprobte Methoden und Ansätze. Springer Gabler, Wiesbaden, pp 163–189

Oh J, Koh B, Raghunathan S (2015) Value appropriation between the platform provider and app developers in mobile platform mediated networks. J Inf Technol 30(3):245–259

Ondrus J, Gannamaneni A, Lyytinen K (2015) The impact of openness on the market potential of multi-sided platforms: a case study of mobile payment platforms. J Inf Technol 30(3):260–275

Panico C, Cennamo C (2019) Strategic interactions and the nature of indirect network effects in platform ecosystems. Bocconi University Management Research Paper Forthcoming. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3473988

Panico C, Cennamo C (2020) User preferences and strategic interactions in platform ecosystems. Strateg Manag J 43(3):507–529

Parker G, van Alstyne M (2018) Innovation, openness, and platform control. Manag Sci 64(7):3015–3032

Pfeiffer A, Krempels K-H, Jarke M (2017) Service-oriented business model framework: a service-dominant logic based approach for business modeling in the digital era. In: Proceedings of the 19th international conference on Enterprise information systems. SciTePress – Science and Technology Publications, Rome, pp 361–372

Poprawe R, Gillner A, Hoffmann D, Kelbassa I, Loosen P, Wissenbach K (2012) Digital photonic production: high power ultrashort lasers, laser additive manufacturing and laser micro/nano fabrication. In: International Photonics and Optoelectronics Meetings, OSA Technical Digest

Poprawe R, Hinke C, Meiners W, Schrage J, Bremen S, Risse J, Merkt S (2017) Disruptive innovation through 3D printing. In: Supply Chain Integration Challenges in Commercial Aerospace. Springer, Cham, pp 73–87

Poprawe R, Hinke C, Meiners W et al (2018) Digital photonic production along the lines of Industry 4.0. In: Proceedings volume 10519, Laser Applications in Microelectronic and Optoelectronic Manufacturing (LAMOM) XXIII. SPIE, San Francisco

Rietveld GJ, Eggers JP (2016) Demand Heterogeneity and the Adoption of Platform Complements (No. ERS-2016-003-STR). ERIM report series research in management Erasmus Research Institute of Management. Retrieved from http://hdl.handle.net/1765/79494; https://repub.eur.nl/pub/79494/

Rietveld J, Schilling MA (2021) Platform competition: a systematic and interdisciplinary review of the literature. Journal of Management 47(6):1528–1563

Ropohl G (2009) Allgemeine Technologie: Eine Systemtheorie der Technik, 3rd edn. Universitätsverlag Karlsruhe, Karlsruhe

Schermuly L, Schreieck M, Wiesche M, Krcmar H (2019) Developing an industrial IoT platform – trade-off between horizontal and vertical approaches. In: Ludwig T, Pipek V (eds) Human practice. Digital ecologies. Our future. 14. Internationale Tagung Wirtschaftsinformatik (WI 2019), 24–27 February 2019. University of Siegen/AISeL, Siegen, p 3246

Schuh G (2013) Lean innovation. Springer, Berlin/Heidelberg

Schuh G, Riesener M (2018) Produktkomplexität managen: Strategien – Methoden – Tools, 3rd edn. Carl Hanser Verlag, München

Schuh G, Ays J, Becker A, Britz A, Dölle C, Hegener G, Hermann U, Wlecke S (2020) Always beta – devops für cyber-physische Produkte. In: Bergs T, Brecher C, Schmitt RH, Schuh G (eds)

Internet of Production – turning data into value: Statusberichte aus der Produktionstechnik 2020, pp 114–136. https://publications.rwth-aachen.de/record/810011

Sisinni E, Saifullah A, Han S et al (2018) Industrial Internet of Things: challenges, opportunities, and directions. IEEE Trans Ind Inform 14:4724–4734

Stonig J, Schmid T, Müller-Stewens G (2022) From product system to ecosystem: how firms adapt to provide an integrated value proposition. Strategic Management Journal 43(9):1927–1957

Teti R, Jemielniak K, O'Donnell G, Dornfeld D (2010) Advanced monitoring of machining operations. CIRP Ann 59:717–739

Thomas LDW, Autio E, Gann DM (2014) Architectural leverage: putting platforms in context. Acad Manag Perspect 28:198–219

Van de Schoot R, De Bruin J, Schram R, Zahedi P, De Boer J, Weijdema F, Kramer B, Huijts M, Hoogerwerf M, Ferdinands G, Harkema A, Willemsen J, Ma Y, Fang Q, Tummers L, Oberski DL (2021) An open source machine learning framework for efficient and transparent systematic reviews. Nature machine intelligence, 3(2):125–133

Van Dyck M, Lüttgens D, Piller F et al (2020) Positioning strategies in emerging industrial ecosystems for Industry 4.0: a longitudinal study of platform emergence in the agricultural industry. In: Proceedings of the 50th Hawaii international conference on system sciences

Vonderau P (2017) The Spotify effect: digital distribution and financial growth. Telev New Media 20:3–19

Wang P (2021) Connecting the parts with the whole: toward an information ecology theory of digital innovation ecosystems. MIS Q 45(1):397–422

West J (2003) How open is open enough? Res Policy 32(7):1259–1285

Winter J (2017) Europa und die Plattformökonomie – Wie datengetriebene Geschäftsmodelle Wertschöpfungsketten verändern. In: Bruhn M, Hadwich K (eds) Dienstleistungen 4.0: Geschäftsmodelle – Wertschöpfung – Transformation. Band 2. Forum Dienstleistungsmanagement. Springer Fachmedien Wiesbaden, Wiesbaden, pp 71–88

Xi T, Benincá IM, Kehne S, Fey M, Brecher C (2021) Tool wear monitoring in roughing and finishing processes based on machine internal data. Int J Adv Manuf Technol 113:3543–3554. https://doi.org/10.1007/s00170-021-06748-6

Yin RK (2018) Case study research and applications: design and methods, 6th edn. Sage, Thousand Oaks

Zhang Y, Li J, Tong TW (2020) Platform governance matters: how platform gatekeeping affects knowledge sharing among complementors. Strateg Manag J 43(3):599–626