AI-enabled business-model innovation and transformation in industrial ecosystems: A framework, model and outline for further research

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Introduction

AI is commonly defined as "…activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment" (Nilsson, 2009, 13). Firms are increasingly relying on artificial intelligence (AI), and managers are trying to identify and manage new business models around it (Li, 2010; Wellers et al., 2017). The outlook is promising. PWC (2017) estimates that forty-five percent of work processes can be automated and that such automation could lead to annual workforce cost savings of up to two trillion US dollars. However, in general, large manufacturing firms have failed to create an AI-based growth agenda (Björkdahl, 2020) because of problems integrating AI into the business model (Wuest et al., 2016).

Although AI is linked to changes in business models, few studies have investigated whether and how AI leaves its mark. According to Teece (2010, 172), a business model is defined as the "design or architecture of the value creation, delivery, and capture mechanisms" of a firm. Teece (2018) explains that AI is an enabling technology that can be integrated throughout a network of products and systems and can provide a beneficial service for customers in various parts of the value chain. Understandably, the integration of AI innovations may cause what Foss and Saebi (2017, 201) refer to as "designed, novel, non-trivial changes to the key elements of a business model and/or the architecture linking these elements". For example, manufacturing incumbents who have implemented AI innovations have managed to lower maintenance and inspection costs and reduce the number of expensive production stoppages (Björkdahl, 2020). However, such improvements aim for optimization rather than profit-generating opportunities. Further studies are needed in this area (Baines et al, 2009).

A large body of research has highlighted the positive consequences of AI (Björkdahl, 2020). However, it would appear that using AI in transformed business models may not be that straightforward. Even if companies with transformative business models have superior AI solutions, traditional players may still prevail because of a slow market adoption rate, for example. Therefore, incumbents need to transform not only the technology but also the wider network of business relationships. Indeed, manufacturing incumbents typically perform technology development in collaboration with external stakeholders in innovation ecosystems (Adner, 2017; Björkdahl, 2020). During AI development, such collaboration requires the flow of data between stakeholders in the ecosystem. Hence, it is important to study the linkages between AI, business models, and industrial ecosystems.

We address this gap in the literature by proposing that the determining impact of AI on business models is best understood from the perspective of industrial ecosystems. As defined by Moore (1993, 76), "in a business ecosystem, companies co-evolve capabilities around a new innovation: they work cooperatively and competitively to support new products, satisfy customer needs, and eventually incorporate the next round of innovations". Understandably, as value is created in innovation ecosystems (Adner and Kapoor, 2010). Business-model transformation is a matter of inter-firm coordination. Nonetheless, we lack firm-level business-model insights that adopt an ecosystem perspective on AI development/integration in the manufacturing industry (cf. Björkdahl, 2020).

Previous research looked at the general influence of AI on work processes as an indicator of its impact. However, this research has resulted in limited insights into the larger transformation mechanisms involved in business-model innovation and the substantial changes in ecosystems. Our research suggest that such knowledge is crucial. This paper draws on the research question: *How do manufacturing incumbents use AI to enable business-model innovation in industrial ecosystems?* We approach our research question by using a qualitative method to study four large global manufacturing incumbents that have been transforming their business models through AI. We performed more than 30 semi-structured in-depth interviews with key strategic personnel to understand how they succeeded in implementing AI and transformed their business models. Our results provide considerable support for how AI enables business-model innovation in industrial ecosystems. We connect organizational micro-elements with ecosystem macro-dimensions and provide an evolutionary model envisioning how incumbents attempt to promote strategic transitions in their firms and ecosystems.

2. Theoretical framework

In line with Chen (2014), this study takes a process perspective on change. In this spirit, we first describe a development that is strongly indicative of AI-based business-model innovation. As recommended by Ritter and Letti (2018), we then combine two different streams of literature in order to expand existing knowledge on business-model innovation. We establish a connection between business-ecosystem theory and business-model innovation theory, discussing value-creation, value-delivery, and value-capture mechanisms. We specify our research focus in relation to each business model dimension.

This study focuses specifically on manufacturing incumbents. For the most part, we use practical examples to describe the effects of AI because there is scant research connecting AI and business-model innovation in industrial ecosystems. Generally, studies of innovation ecosystem structures are rare, and none of them focuses explicitly on the manufacturing industry (cf. Sant et al., 2020).

2.1 AI and business model innovation

The lion’s share of previous AI studies typically take a descriptive approach, portraying the use of AI in different industries. However, we argue that these examples also signal possible business-model innovation in the manufacturing industry. For example, AI has, in general, penetrated various industries and has had an effect on business models (Brynjolfsson & McAfee, 2017; Davenport & Dreyer, 2018; Davenport & Ronanki, 2018; Hoffman, 2016; Kolbjørnsrud et al., 2016; Matzkevich & Abramson, 1995; Ng, 2016; Ransbotham et al., 2017; Wang et al., 2018; Wilson et al., 2017). These studies address AI as a tool, enabling paradigmatic shifts in business practices. Of course, such development is of interest to manufacturing incumbents. However, changes in business models due to technological progress is related to high levels of uncertainty (Hess et al., 2016).

Although limited in scope, research shows that AI can have an impact on strategic work (Agrawal et al., 2017; Anandarajan, 2002; Fedyk, 2016; Oliver, 1996; Ransbotham, 2016), influence competence development (Gaines-Ross, 2016; Chamorro-Premuzic et al., 2018), and impact business team interaction (Lawler & Elliot, 1996; Wilson et al., 2016).

There is also a process aspect to business-model innovation. It is likely that AI will become more pervasive as time goes by and key stakeholders learn more about the pros and cons of AI (Li, 2010; Wellers et al., 2017). Indeed, firms are trying to learn how to predict and explore the radical use of AI solutions (Wellers et al., 2017; Yeomans, 2015). Specific studies on manufacturing firms have demonstrated that incumbents find it difficult to integrate new technology into their business models (Kong et al., 2019; Meijer et al., 2019; Zeng et al., 2019). There have been some advances – for example, in the areas of automation/robotization (Duan et al., 2016; Leigh, Kraft, & Lee, 2019) and product development, visualization systems, and predictive maintenance (Björkdahl, 2020, 5).

Finally, this study focuses explicitly on how AI functions such as forecasting, monitoring/controlling, optimizing, and autonomy (cf. Davenport & Ronanki, 2018) are used for business model innovation in the manufacturing industry. We propose that such functions are intimately connected to a firm's strategic development (Bharadwaj et al., 2013) and its value offer (Teece, 2010). In terms of business-model innovation, value offers have three distinct parts – "design or architecture of the value creation, delivery, and capture mechanisms" (Teece, 2010: 172). Although some preliminary evidence exists, there is little development of theory on the topic of AI, business models, and ecosystems in the manufacturing industry. Our study, therefore, investigates how manufacturing incumbents go about generating value-creation, value-delivery, and value-capture mechanisms by innovating AI business models. These mechanisms are discussed below.

2.1.1 AI, Value Creation, and Business Model Innovation

The value-creation dimension concerns the final offer to the customer, comprising the products and services offered by the incumbents. We believe that AI, as a form of digital technology, can play a vital role in configuring new advanced products and services.

Most importantly, researchers (Gebauer et al., 2005; Gerpott & May, 2016) emphasize that any value offers created on digital technologies must be created from the standpoint of customer need. Just as with any other product or service, incumbents must work systematically and understand market needs in relation to the technology at hand (Gerpott & May, 2016). Indeed, incumbents should map technological applications and the potential value that they bring (Sjödin et al., 2018). Failing to address the relationship between technologies, values, and the business model can be very costly for the firm (Dijkman et al., 2015; Kiel et al., 2017).

Research has revealed that incumbents can extend their product/service portfolios through digitalization and that, by extending them in this way, they can identify new customer segments (Cenamor et al., 2017; Hasselblatt et al., 2018). Furthermore, the possibility exists for incumbents to use digital technologies to complement products and services, reduce transaction costs, and adapt to market needs (Gerpott & May, 2016; Laudien & Daxböck, 2016). Nevertheless, using AI to drive value creation is faced with numerous challenges. Incumbents must learn to match new technologies such as AI with resources that already exist (cf. Krotov, 2017; Luz Martín-Peña et al., 2018).

This study has a specific focus on how AI is used by manufacturing incumbents to access and understand customer needs, identify new customer segments, and achieve a higher degree of customization in the manufacturing industry. Existing research examining advances in AI data-driven manufacturing provides suggestions on how manufacturing incumbents could create new value offerings that confer certain competitive advantages. For the benefit of customers, manufacturing incumbents can enhance quality control by using digital technologies that make the manufacturing process more intelligent and deliver superior data. For instance, by using AI technologies to access real-time and historical data, manufacturing incumbents can automatically respond to unexpected events such as machine faults and quality defects (c.f. Tao et al., 2018; Li et al., 2019). Moreover, AI is well placed to facilitate mass customization because AI-powered technologies can provide incumbent manufacturers with the prospect of offering products that serve individual customer needs whilst bordering on mass production efficiency (c.f. Jiao et al., 2007; Tseng and Jiao, 1996). For instance, user demographics, demands, preferences, and behaviors can be gathered from multiple sources including the Internet of things (IoT), and they can be precisely quantified using AI so that more personalized products and services can be designed (Tao et al., 2018). This enables manufacturers to carry out customer-centric or 'smart' design to extend their product and service portfolios.

2.2.2 AI, Value Delivery, and Business Model Innovation

The value-delivery dimension of the business model is concerned with how processes and activities are configured to deliver the value promised. For an incumbent, it could relate to front-line and back-line service staff, and technological support systems, for example (Shallmo et al., 2017). Indeed, such processes may be interdependent in terms of both internal and external firm resources (Bharadwaj et al., 2013; Gorissen et al., 2016).

A major challenge for incumbents in configuring AI-based value-delivery systems concerns the identification and development of new technology-based capabilities and employee competences (Raichinger et al., 2019). Such capabilities are most often developed in an incremental manner (Parida et al., 2015; 2019) since key activities and processes such as support services, technology development, and skills development are interdependent and spread across the entire organization (Parida et al., 2015; Cenamor et al., 2017; Gauthier et al., 2018). Incumbents are dependent on their innovation culture when trying to match new technologies to novel value-delivery systems (Laudien & Daxböck, 2016; Sjödin et al., 2018; Kiel et al., 2017). Due to the complexities of creating value-delivery systems, incumbents can be expected to use AI in a limited, experimental manner in order to configure value-delivery systems for the business model.

Another challenge for incumbents is to match local organizational capabilities with a global value-delivery system (Sambamurthy et al., 2003), two essential ingredients in the business model. In order to match these effectively, incumbents need to develop practice-based routines enabling stability in data flow and service provision (Parida et al., 2015; Sjödin et al., 2018). Such matching is commonly co-created by various stakeholders in the value-delivery system (Kuula et al., 2018). Here, AI technologies can play an important role in supervising product flows, process flows, and maintenance processes (Reim et al., 2016, 2018).

In this study, we concentrate on how manufacturing incumbents use AI to develop new delivery routines (internally) such as developing service-delivery organizational units, developing practices to interact with customers, and establishing new strategic partnerships for value-delivery partners. Research on manufacturing incumbents indicates that, through collecting, storing, processing, transmitting, visualizing and applying data using AI technology combined with new technologies such as IoT and cloud computing, they can deepen their understanding of customers, competitors, products, equipment, processes, services, employees, and suppliers (c.f. Jiao, 2017 Tao et al., 2018). Large volumes of data can be collected across the entire manufacturing value chain and product life cycle (Tao et al., 2018). This should help to improve existing internal routines – with the potential to develop new ones both at the front end and the back end – and to strengthen collaboration with partners in value delivery. For instance, AI technology can enable the development of digital procurement systems that benefit manufacturers, suppliers, and customers through enhanced tracking and tracing of customer orders and better integrated value-chain activities (cf. Björkendahl, 2020). Manufacturers obtain access to previously unavailable data and analytics, which they can share with customers, suppliers, and other stakeholders to improve value delivery.

2.2.3 AI, Value Capture, and Business-Model Innovation

The value-capture dimension of the business model relates to elements such as cost structures, potential revenue streams, and revenue-model and financial viabilities. New technologies such as AI have the ability to affect all these elements.

In this regard, researchers (Dijkman et al., 2015; Kiel et al., 2017) emphasize that product development processes and the creation of IT infrastructure are the most common cost drivers. On the other hand, researchers (Zhou et al., 2015; Cheah & Wang, 2017) have established that implementation of new technologies can lead to the development of more cost-efficient processes. Such development is commonly performed with stakeholders outside the boundaries of the incumbent firms (Sensi Zancul et al., 2016). Indeed, such development is critical to improve the business model (Gauthier et al., 2018). One challenge that needs to be managed when co-creating technology-based processes is to find a balance between the cost of collaboration and the financial benefits (Kuula et al., 2018). Incumbents, therefore, need to create a flexible risk management system that can capture the risk arising from shared development (Dellerman et al., 2017; Ehret, and Wirtz, 2017). Thus, there are substantial cost-saving effects to consider when fine-tuning the business model using AI-based solutions.

The other element to consider is the revenue model. Research has established that new technologies such as AI can improve the revenue streams of incumbent firms (Rachinger et al., 2018) and create more transparent supplier/customer relationships (Zhou et al., 2015; Zheng & Wu, 2017). Novel technologies can be used to create more flexible revenue models (Kiel et al., 2017) that accommodate customized solutions (Zhou et al., 2015) and promote increased customer satisfaction (Kotarba, 2018). Thus, there are substantial revenue-enhancement effects to consider when fine-tuning the business model through AI-based solutions.

In this study, we are primarily concerned about how manufacturing incumbents use AI to reduce the cost structure by using data analytics, improving risk assessment, and creating new revenue streams. A recent study suggests that manufacturing incumbents have used AI to seek cost advantages through efficiency improvements, while initiatives using AI to drive revenue growth have been far fewer (Björkendahl, 2020). For growth-driven innovation, these incumbents must initiate a fuller business model transformation because problems may need to be solved in novel and more creative ways. However, radical transformation exposes them to higher levels of uncertainty. This study will, therefore, investigate how AI enables manufacturing firms to capture value.

2.2 AI, Value, and Business Ecosystems

On several occasions in this text, we have pointed out that value is created, delivered, and captured beyond the boundaries of incumbent firms. That is to say, value-creating activities and processes are configured in a business ecosystem. Jacobides et al. (2018) explain how business ecosystems differ from other forms of business arrangement such as markets, alliances, networks, and supply chains. They argue that business ecosystems are non-hierarchically managed, with unique interorganizational interdependencies enabled through modularity and characterized by collective investments that cannot be replicated elsewhere.

The business ecosystem is defined by the alignment structure of a multilateral set of partners that need to interact so that a focal value proposition can materialize (Adner, 2017, 42; Winter et al., 2018). In addition, Adner (2017, 47) defines the alignment structure as "the extent to which there is mutual agreement among the members regarding positions and flows". The objective, pursued through a firm's "ecosystem strategy", is to "secure its role in a competitive ecosystem".

Researchers (Jacobides et al., 2018; Rong et al., 2018) have further proposed that the business ecosystem supports the creation of unique value propositions. Added value is created through complementary sets of roles, guided by the shared rules of the game, inviting various stakeholders to enter into more or less formalized and customized contractual agreements. This approach connects to, and extends, the business innovation research that asserts the need for incumbents to develop and utilize external networks in order to renew the business offer (e.g., Lazerson & Lorenzoni, 1999; Huang et al., 2013; Hao-Chen et al., 2013). In other words, customer value can be developed in-house but also in collaboration with external stakeholders. However, ecosystem alignment structures are not static and may need to be reconfigured as new value-creation opportunities are unveiled. It is important that such reconfiguration should be studied because it changes the interplay between value-creation stakeholders in the manufacturing industry.

In business-ecosystem research, stakeholders are commonly referred to as hubs, complementors, or suppliers. Teece (2018) observes that the literature on complements is confusing and complex. Nonetheless, these firms play different roles in the ecosystem (Teece, 2018). The hub is usually a large firm with exceptional value assets and capabilities. However, hubs need complementary assets to run their businesses. Additional complexity is added by the different types of complementary assets. These assets are of varying importance for the hub. Some complementary assets may be so important for the hub that the business would not run without them (Teece, 2018). Examples can be found of manufacturing firms obtaining competitive advantage through ecosystem development. The Swedish manufacturing firm Assa Abloy has revitalized its ecosystem to capitalize on the AI promise. It has partnered with Google and Apple to develop digital/smart door locks. This collaboration with tech companies has provided critical complementary assets enabling Assa Abloy to transform its business model and attain substantial growth in revenues (Björkendahl, 2020). Clearly, when using digital technologies such as AI to change business models, incumbents will need to change the roles, structures, and processes in their ecosystems (cf. Matt et al., 2015). Such change is needed in order to revitalize the ecosystem. Having said that, studies of such revitalization are lacking.

Finally, a recent paper advises that, when renewing manufacturing ecosystems, stakeholders should aim to create resilience (Ghazinoory et al., 2020). It counsels that hubs should take long-term responsibility by creating an ecosystem that can manage market turbulence. In the main, however, such AI studies that cover the ongoing interplay and change between hubs and complementors in the manufacturing industry are in short supply.

In this study, we focus on how manufacturing incumbents use AI so that ecosystems can be reconfigured, revitalized, and made resilient.

To summarize, by tying together the central organizational elements of AI – business-model innovation and macro-related ecosystem dimensions – this study contributes to an understanding of how manufacturing incumbents use AI to enable business-model innovation in industrial ecosystems.

3. Method

In this section, we discuss our research approach, data collection methods, and data analysis.

3.1. Research approach and case selection

This study is based on an exploratory multiple case study of four large incumbent firms that have successfully implemented AI-enabled business-model changes leading to ecosystem innovation. The multiple case study is a commonly used approach in research within the industrial marketing domain (Halinen & Törnroos, 2005). Case studies make it possible to mobilize many observations on complex real-life processes (Eisenhardt, 1989; Eisenhardt, & Graebner, 2007). They are particularly useful in developing new insights into theoretically novel phenomena (Edmondson & McManus, 2007), such as extending our understanding of how large incumbent firms implement AI business models to achieve commercial success.

Our sample included large, globally active Swedish providers that have used AI capabilities to drive internal efficiency and competitiveness. To justify the generalizability of our findings, we followed the guidelines of Eisenhardt (1989) in selecting cases from different industries and product categories. Accordingly, the selected companies represent diverse industries – namely, manufacturing and mining industries – providing an opportunity to contrast various industrial perspectives on relational processes. Building on the recommendations advanced by Glaser and Strauss (1967), we opted for theoretical sampling to select cases that would illuminate how companies successfully implement AI business models and gain from ecosystem innovation (Suddaby 2006; Eisenhardt, & Graebner 2007).

Three key reasons underpin our selection of these cases. First, these large firms have recently placed much emphasis on AI-based business models, indicating that they have numerous ongoing initiatives related to offering AI functions to commercial customers. Second, these incumbent firms have a well-established, traditional ecosystem that has been challenged and innovated by implementing a new, AI-enabled business model. Moreover, recently, all case firms have publicly reported mergers and acquisitions, partnerships, and pilot projects with new and existing ecosystem partners. Finally, we selected cases where we had established good contacts with diverse respondents due to the ongoing nature of the research project; this made for rich data collection.

3.2. Data collection and analysis

Data for the present study was gathered primarily through individual, in-depth interviews with participants in the four Swedish firms. We developed a semi-structured interview tool for our interviews. The unit of analysis was at firm level due to the focus on business strategy and business model changes. Therefore, we carried out interviews with numerous managers and senior staff members. In total, 30 respondents were interviewed from all cases. The respondents were selected because they were actively involved in AI business-model development and commercialization. Interviewees were identified by snowball sampling where key informants were asked to recommend people who had an active role in AI business-model development initiatives. To capture a multifaceted view of the process, we interviewed participants exercising various functional roles in the firms. This was deemed necessary since new business-model implementation is not the responsibility of one unit but requires complex interaction between various units within an organization. The respondents interviewed included business developers, R&D managers, product managers, and service managers. This allowed us to obtain a wider understanding of the cases from different perspectives. Table 1 gives an overview of the cases and the positions held by the company respondents interviewed.

Company name	**Revenue/Employees**	**AI-enabled business-model case**	**Respondent positions**
Alfa	6,550 m EUR/ 14,000	AI-enabled fleet management solution	R&D manager, 2 technology managers, procurement managers, IT manager, service portfolio manager
Beta	3,240 m EUR/ 7,800	Advanced AI services for operational control system	Senior manager, business development manager, technology engineer, vice president technology, and service manager
Gamma	3,100 m EUR/ 13,000	AI services for autonomous solution	Digitalization lead, business development manager, sales and services manager, line manager, and digitalization director
Delta	98,000 m EUR/41,000	Mine optimization and AI services	IT manager, sales manager, business development manager, and autonomation manager

Table 1. Cases and the positions of company respondents interviewed

Respondents were asked open-ended questions with the support of an interview guide. The guide was developed based on themes about AI and digitalization, business models, ecosystem innovation, and value co-creation. For example, respondents were asked to consider questions relating to broad themes such as *'How did the AI business model evolve?'* and *'Which activities are critical in facilitating AI business development?* In seeking answers to these overarching questions, we encouraged informants to base their answers not only on the relationships studied but also on their broader experience so that empirical comparisons could be made. Follow-up questions were asked for clarification and to obtain further details, which allowed further exploration of relevant themes. Interviews lasted approximately 50 to 115 minutes each, and were held either face to face or through online conference calls. Due to the sensitivity of the information related to business models and future strategy, we were unable to record all the interviews. Thus, we relied on a mix of transcripts and extensive notes for our data analysis.

We triangulated our data by applying various data-collection techniques, including interviewing and reviewing documents (Jick, 1979). We performed document studies, which included reviewing company reports, agreements, and project documents to validate and contextualize our respondents' views, thus enabling empirical triangulation. To increase reliability, enhance transparency, and provide scope for replication, a case-study protocol was constructed along with a case-study database. The database included case-study notes, documents, and analysis.

This study takes an abductive approach (Dubois and Gadde (2003; 2014). The data analysis was based on a thematic analysis approach, which provides ways to identify patterns in a large and complex dataset (Braun & Clark, 2006). Following Dubois and Gadde (2002), we systematically matched data with theory. This approach provided the means to effectively and accurately identify analytical themes. Through a series of iterations and comparisons, it is possible to identify themes and overarching dimensions so that a framework grounded on both empirical observations and theory can be developed. In doing so, we followed a three-step process similar to that described in recent literature. Data was coded into categories following a thematic analysis approach to find relevant themes and patterns (Braun & Clarke, 2006). These were clustered into second-order themes, which were then converted into aggregate dimensions (Braun & Clarke, 2006; Gioia, Corley, & Hamilton, 2013).

4. Findings

The analysis revealed that successful manufacturing incumbents performed AI-enabled business-model innovation in a dynamic fashion where various AI functionalities impacted value-creation, value-delivery, and value-capture processes. Analysis also showed that incumbents typically developed AI solutions in global networks consisting of interdependent partners, complementors, suppliers, and customers. Thus, business-model innovation in terms of making changes to value-creation, value-delivery, and value-capture processes meant transforming their industrial ecosystems.

4.1 AI business functionalities

We found that manufacturing firms can perform business-model innovation by applying AI capabilities. Not all firms are able to move quickly along the maturity ladder of AI functionalities; it depends on how well they are able to align AI technological development with business applications. In sum, we find four early functionalities related to AI that are key in driving business-model innovation.

Forecasting tends to be a low-hanging opportunity to use AI algorithms to generate reports and new insights for customers in the ecosystem. All case companies saw this function as the first concrete step in utilizing AI for commercial gains. As most products have been installed with sensors and improved connectivity, they had, over time, generated large amount of data. In most cases, this operational data has not been used to generate customer insights due to data messiness and the lack of appropriate analytical models. But with technological advances in AI, case firms were able to develop algorithms to auto-generate reports. These forecasting reports tend to provide an overview of the operational KPIs related to the product or fleet of products. They also project how the equipment would operate in future and what its likely maintenance needs would be. The commercial gains related to the auto-generated reports per se are quite low but AI functionalities allow the capture of new patterns related to customer usage of equipment, which drives innovation towards more advanced AI-enabled digital offerings and ensures a better fit for customers' operational needs.

"We did AI analysis on our large database which includes operation data from the last five years for certain product categories. To our surprise, we were able to find new patterns of insights related to customer operational usage which our sales and service unit has totally missed. The initial idea for doing the analysis was to create some summary reports for customers, but we ended up with much more." (Technology manager, Alfa)

Monitoring and control represented the second step towards AI utilization of business applications by manufacturing firms finding a match in their ecosystem. This meant an increasing capacity to forecast case firms' ability to develop routines for improved checking of their equipment's installed base across customer sites and at country level. The key customer value proposition associated with AI-enabled monitoring and control is being able to provide a detailed overview of the equipment's health and performance. Thus, firms started to commercially offer preventive maintenance contracts enabled by AI functionalities. Such service contracts include early warning, reduction in the number of breakdowns, and productivity gains. An AI-based simple digital dashboard for customers has given them an enhanced ability to monitor and control their equipment performance. To better support this offering, case firms developed a dedicated team that provided back-end support to the customer and informed them about any irregularities and potential problems. We found that AI significantly reduced the extend of human resources needed to provide back-end monitoring and control. Thus, individuals can now monitor much more equipment because many of the basic customer interactions are automated through AI.

"The operational costs have been significantly reduced through AI as we have automated many interactions with customer personnel. This has led to much better quick response times and also improved monitoring and control of the equipment". (Business development manager, Beta)

Optimization represents a step to greater maturity in using AI functionalities for business applications. By gaining access to historical data and real-time data, AI algorithms can be used to optimize their utilization in the ecosystem. Often customers utilize individual products unevenly, making intense use of their equipment on some occasions and infrequent use on others. Moreover, this variability is pronounced when considering fleets of equipment. By employing AI, equipment usage can be optimized to ensure that the "right machine is ready for the right work". Manufacturing firms have also used the optimization features to provide prescriptive maintenance contracts. By using data across customer sites and benchmarking across global markets, it was possible to develop simulation models for certain types of use, and this insight was used to instruct customers in how to get the most out of their machines. For example, this could take the form of scheduling maintenance at appropriate intervals or suggesting what action to take to improve machine performance. In addition, optimization increases flexibility within customer operations because, with changing demands or contexts, the machine can be optimized to achieve the outcomes required. For example, the intervals between maintenance can be increased or reduced in line with optimization conditions. Thus, AI-enabled optimization creates greater value for customers in terms of higher productivity and greater cost savings.

"Our customers were not very receptive to our AI-enabled optimization-based services as they thought it was costly. But with many successful customer cases, we can show the numbers of how our other leading customers managed to gain from such an offering." (Digitalization lead, Gamma)

"At the end, with AI power, we can truly utilize the extensive data that we have been generating for higher customer value. When we moved into optimization services, we became fully engrained into customer operations, and their operational performance became our priority." (IT manager, Delta)

Autonomy represents the final step in developing AI functionalities in the ecosystem to ultimate maturity. At this stage, the key challenge for manufacturing firms is to conduct analysis not only of their own data but also the data generated by the equipment of ecosystem partners. By integrating data across the ecosystem and using AI functionalities, manufacturing firms can provide semi- or fully-autonomous solutions. Deep learning and self-learning can allow for automated improvements in operations. Since data connected to customer operations is generated via autonomous equipment, AI functions facilitate decision making and corrections that generate greater value for the customer. Thus, an autonomous solution helps to reduce deployment costs associated with offering customized solutions. With greater access to data and higher processing power, AI functions can become a critical part of customer operations and performance.

"AI has been a game changer. It has allowed us to take the next step towards autonomy with confidence. We know very well the customer operational environment and usages and, by using AI, we develop suggestions for customers and take proactive action, when necessary." (IT manager, Alfa)

4.2 AI-enabled business-model innovation based on ecosystem fit

We find that AI functionalities show great potential for business growth in manufacturing firms once a fit with their ecosystem is established. When firms begin to develop AI capabilities, they also initiate experimentation with innovative business models. To better understand how AI can successfully drive business-model innovation, we looked specifically into how AI enabled changes to business activities and how business activities fitted in with the ecosystem. By applying a business-model lens, we were able to categorize AI-enabled activities related to value creation, value delivery. and value capture.

AI-enabled value creation in ecosystems

Value creation largely depends on a firm's ability to assess customer needs. Powered by AI, manufacturing firms are able to more deeply understand customer operational needs. Analytics allow firms to crunch a large amount of data and identify hidden patterns that would be difficult to find using traditional analysis. AI provides the possibility to look deeper into data and, over time, develop insights into customer intelligence.

Manufacturing firms are also better able to configure their offerings for different customer segments. Through digitalization and AI, customers can be offered a much wider array of digital services than the standard product offering. To do that successfully, however, it is critical to target the right customer segment with the right offering. Our case companies were increasingly successful in matching their offerings to customers. Compared to earlier practice, AI-enabled models can use many more variables for segmentation, which produces more precisely defined segments.

"For a global organization as ours, we are constantly struggling with ensuring a good fit between what we sell and to which customer segment. Through AI analysis which build on our global database, we could find hidden segments and better target our offering. This has resulted in higher sales and customer satisfaction." (Sales manager, Delta)

Finally, AI-enabled insights became highly appreciated by market-facing units because the sales and service staff obtained more accurate information on what to offer based on the analysis of customer operational data. We increasingly found that sales and service staff used AI-based insights to package the offering in more appropriate ways for customers, allowing for greater customization. For example, certain customers might use a product less frequently in certain months, allowing them to take advantage of a cheaper service agreement. In higher usage months, the service agreement would revert to the more comprehensive package.

"Offering customized solution is expensive and often lead to higher costs for our delivery unit. Through AI, we have become much better as customizing the offering based on data-driven insights. This significantly reduces the guessing part and make the sales process more accurate. At the end, we generate higher value to the customer, which is the most important factor." (Vice president technology, Beta)

AI-enabled value delivery in ecosystems

Delivering value to the customer requires the development of new routines. But due to capability gaps in the ecosystem between the customer-facing front end and back end, the delivery process can be unproductive. Often the front end is well informed about customer needs and wants, whereas the back end has the technological capability to develop the products and services. In global organizations, such capability gaps are even more widespread and vary from marketer to marketer. Through AI analytics, we found that the back end was increasingly connected to market and customer operations. Using market insights allowed the back end to be more aligned with front-end needs and to provide appropriate support for value delivery. Many respondents stressed that the roles and responsibility distribution between the front end and the back end were significantly improved due to digitalization.

"Historically, you will have a smart engineer in the headquarters who takes product or service development decisions with limited market-oriented information. But now, we are able to work with data and conduct deep analysis, which has led to a reduction in the knowledge gap between market and R&D units." (Line manager, Gamma)

Service delivery routines were also improved due to AI-enabled monitoring, control, and optimization. Front-end staff found themselves better equipped with operational insights than in the past and more responsive to customers. For example, predictive maintenance was possible because the service technician could foresee which spare parts would be needed in certain customer sites. With improved delivery routines, the service organization expanded the business to include service contracts for smaller customers that own less equipment. Many respondents stated that this shift to services was also a cultural change for front-end staff because they now had to rely on technology rather than their gut feeling.

"We have witnessed a shift within our distributors' capabilities as they integrated technology as a part of their delivery process. They rely on AI and analytics for ensuring smooth and efficient delivery processes for customers. They have become better at inventory planning, making contact with customers, and service experience." (Service manager, Beta)

AI-enabled value capture in ecosystems

AI-enabled systems enhances the ability of manufacturing firms to devise activities to capture value. Digital technologies exert a positive influence on cost reduction – for example, manpower costs and the elimination of inefficient processes. We found that AI helped firms make better use of limited resources. For example, an AI-powered system in the front end allowed a handful of individuals to optimize the delivery process for customers. They were much more responsive given the greatly improved monitoring and control system. In addition, AI helped to eliminate service contracts that were potentially risky or costly. Often the front end unit had a portfolio of contracts that were a mix of good and bad contracts. By using AI algorithms, the front-end unit could undertake better analysis of the pricing level of service contracts, allowing for higher profitability in the service business.

"We used to take unnecessary risks related to our service contacts and offer similar conditions to all customers. With AI, we can do a better risk analysis of customers and create a service contact based on their previous track record. Changes to contracts can also be introduced if we see a deviation towards usage of equipment in relation to the contact conditions. This helps in reducing conflicts and creates transparency and accountability between partners." (Senior manager, Beta)

AI was also found to be a catalyst for creating new service businesses, which delivered new revenue streams. All the case firms acknowledged that their service businesses would not be profitable or even possible without AI development. AI has become the core that drives service business development from forecasting to monitoring, optimization, and autonomy. Although product-oriented sales continued to be an important revenue generator, the future outlook clearly shows that the service business would come to dominate the business model. Manufacturing firms also saw the benefit of moving from CPAX to OPAX revenue streams because this allowed for greater resilience in fluctuating market conditions. The most advanced AI-enabled revenue model was based on the concept of performance contracts, where manufacturing firms retained ownership of the equipment and promised a certain outcome, such as the availability of equipment or a specific productivity gain.

"In the past, we lacked the technological capabilities which made the service business complex and expensive. But with AI and digitalization, we can ensure better revenue flow and also develop closer relationships with customers." (Service portfolio manager, Alfa)

Finally, incumbents described how ecosystems generally were characterized by restructuring activities. That is to say, AI-technology innovation was followed by business-model innovation where various stakeholders (partners, complementors, suppliers, customers) had to reconfigure their roles in the ecosystems. Nonetheless, incumbents had observed that, as AI technology matured, new actors entered the marketplace. These actors could benefit from existing technological advances and bring cheaper and smarter solutions to the market. Incumbents, therefore, analyzed the need to revitalize parts of the ecosystem. Such revitalization would mean a major change in ecosystem structures, processes, and roles in order to withstand competitive threats. Our observations are summarized in Table 2.

Table 2. Summary of observations

Business application usage	**Value creation impact**	**Value delivery impact**	**Value capture impact**	**Ambition levels**	**BM transformation**	**Ecosystem structural alignment**	**Ecosystem transformation**
Forecasting customer operational usage	Understanding customer operational needs	Improved knowledge sharing	Cost reduction	Improve and/or enable. No disruptive solutions.	Higher BM impact from forecasting and monitor/control functionalities. Lower BM impact from optimization and autonomy functionalities	New internal front-end and back-end interfaces. New social and technological customer interfaces. New role definitions.	A current situation characterized by ecosystem reconfiguration. An anticipated need for future revitalization and resilience.
Monitor and control equipment performance	Identify new customer segments	Improved role distribution	Transparency and accountability				
Optimize preparation and maintenance	Customized solutions	Improved service delivery routines	New service business				
Autonomous decision making and correction	Higher quality customer offerings	Improved service experience	Better revenue flow				

5. Discussion

The Artificial Intelligence paradigm has the potential to bring about many positive financial and societal effects. Nonetheless, this study shows that incumbents are still struggling to perform AI-enabled business-model innovation. One challenge for incumbents relates to the parallel transformation of AI functionalities, value processes, and ecosystems. This study sheds light on the dynamics behind this transformation process and how companies successfully introduce AI and establish a fit between the transformed business model and the ecosystem.

Whilst previous AI studies show that AI plausibly has an impact on incumbents' business models (cf. Kolbjørnsrud et al., 2016; Ng, 2016; Davenport & Ronanki, 2018; Matzkevich & Abramson, 1995; Wilson et al., 2017; Hoffman, 2016; Wang et al., 2018; Ransbotham et al., 2017; Davenport & Dreyer, 2018), this study provides insights into *how* business model innovation is achieved. Incumbents develop AI functionalities such as forecasting, monitoring/controlling, optimizing, and autonomy in parallel. However, there is a significant difference in the utilization of these business applications. Forecasting and monitoring/control applications have reached a more mature stage of development. Incumbents are exploiting both of these functionalities. In contrast, optimization and autonomy functionalities are still in the exploration stage. Thus, incumbents try to balance development between AI exploitation and AI exploration in different business areas (forecasting customer operational needs, monitoring/controlling equipment performance, preparation and maintenance, decision making and correction).

Moreover, we find that the development of AI applications makes it possible to fine-tune and extend traditional value-creation, value-delivery, and value-capture processes (cf. Bharadwaj et al., 2013; Cenamor et al., 2017; Dellerman et al., 2017; Gorissen et al., 2016; Hasselblatt et al., 2018; Zhou et al., 2015). In particular, we find that the value-delivery process is affected from the beginning to the very end of the process. This finding contradicts the idea of a linear step-by-step value-delivery process. In line with Rachinger et al. (2018), we find that incumbents experience better revenue flow with this type of business-model innovation. Nonetheless, the business-model innovation process tends to become more complex because it is integrated into partnering and customer systems. Incumbents need to learn how to manage such process complexity as the boundary between internal and external systems becomes fuzzier.

5.1 Ecosystem transformation

As in previous studies, incumbents explained that their AI ecosystems are constituted from a wide range of global stakeholders (cf. Björkdahl, 2020; Ghazinoory et al., 2020). In these ecosystems, stakeholders compete and collaborate at the same time. Such parallel activities bring significant challenges for incumbents initiating business-model innovation. For example, value creation is strongly coupled with the notion of collaboration, while value capture is strongly related to competition (Brandenburger & Nalebuff, 2011). Incumbents in this study expressed concerns about how best to manage such tension. For example, they relate how they are currently reconfiguring their respective ecosystems, but they recognize that, in the future, there will be a need for revitalization and resilience. Consequently, this paper discusses the implications for future AI business-model innovation from an ecosystem perspective. We illustrate two time frames: the present (short term), and the future (long term) and discuss three related strategies: reconfiguration, revitalization, and resilience.

In the present time frame, AI exploitative development activities are prevalent (see above). Incumbents act as hubs, paving the way for new technologies and creating a network of complementors and suppliers. In this network, hubs are dominant. They implant incremental AI functionalities, improving or enabling business activities (see Table 2). Thus, over time, an ecosystem of stakeholders is formed around the hub. Since the environment is relatively slow moving, the incumbent has relatively good control of the ecosystem. Therefore, the hub is in a position to deploy a strategy of reconfiguration. As this study has shown, the hub aligns processes and stakeholders, creating a more suitable ecosystem structure in which stakeholders aim to secure their position in the AI ecosystem (cf. Adner, 2017).

As indicated in this study, in the future time frame, a combination of exploitative and explorative activities can be expected to create standards and easy-to-access interfaces. AI functionalities would be integrated into new value constellations. Various stakeholders would find it easier and cheaper to create alternative AI functionalities. Thus, the ecosystem would become more attractive and vulnerable to new types of change activities, and new stakeholders would challenge the initial configuration of the AI ecosystem. At this stage, it could be expected that ecosystem stakeholders would develop and integrate disruptive AI solutions. This development poses both a threat and an opportunity for incumbents. Thus, they would turn their attention to the two strategies of revitalization and resilience creation.

Consequently, the hub would first try to revitalize the AI ecosystem by changing roles, structures, and processes (cf. Matt et al., 2015). It would, for example, renew value chains by switching collaboration partners in order to remain in the front line of technology and business AI solutions. The hub could also, in a cross-industrial manner, enter new markets. The hub would then move to a more disruptive phase of ecosystem transformation, ensuring that it remains in a top market position. Nonetheless, as it becomes clearer how stakeholders can invest in profitable AI applications, the number of players will grow. Moreover, as new stakeholders strengthen their position in the market, the hub will be forced to co-exist with these new entrants. These smaller competitors are nimbler than the hubs. They may adjust more quickly or reshape the ways to benefit from AI-enabled business model innovation (cf. Chalmers et al., 2020). The hubs can try to combat this threat by acquiring startups to develop promising AI technology initiatives.

As the AI market matures, hubs will aim to create a resilient AI ecosystem (Ghazinoory et al., 2020) that can withstand competition. That is to say, the hub will nurture the ecosystem to ensure that the best collaboration partners remain in the ecosystem. The manufacturing incumbent will most likely turn to an AI-platform strategy (compare with IBM, Microsoft, or Apple). This platform strategy will allow the creation of easy-access and long-lasting technology and business interfaces. Nonetheless, since the core business differs from industry to industry, incumbents will have to develop their own unique platform strategy. Meanwhile, successful new entrants will try to reshape the market, diminishing the market influence of hubs.

5.4 AI business-model innovation and transformation

We illustrate our findings using a conclusive dynamic model (Figure 1). There are three lessons to be learned. First, while previous studies indicate that firms identify and develop a single AI functionality, we instead find that incumbents actively try to pursue the development of multiple AI functionalities in parallel. Each realized functionality has its own impact on the business model (Figure 1, vertical axle) related to high levels of either exploitation or exploration. Second, while previous studies typically view value creation, value delivery and value capture as more or less independent dimensions of the value management process, we find that these three complementary processes are strongly interdependent. The use of AI as a central value element disrupts traditional value processes. We note that AI-based value processes are characterized by concurrency; in other words, they appear and affect the organization simultaneously. Third, when performing AI-based business-model innovation, incumbents need to take the ecosystem dimension into account. They need to understand how to reconfigure, revitalize, and create ecosystem resilience in a timely manner. Of these three strategies, the reconfiguration strategy is of a more simple character. It is characterized by exploitation and low levels of ecosystem innovation. Thus, the reconfiguration strategy has fewer elements of complexity and uncertainty compared to the revitalization and resilience strategies that contain elements of disruption.

This means that manufacturing incumbents face a situation where they must manage a dynamic environment that combines low levels of innovation with high levels of innovation (Figure 1, horizontal axle). Hence, we find that AI business-model innovation strongly relates to three interdependent transformation sub-processes: AI functionalities transformation, AI value transformation, and AI ecosystem transformation. Through these three transformation processes, manufacturing incumbents connect intra-firm micro-elements with ecosystem macro-dimensions.

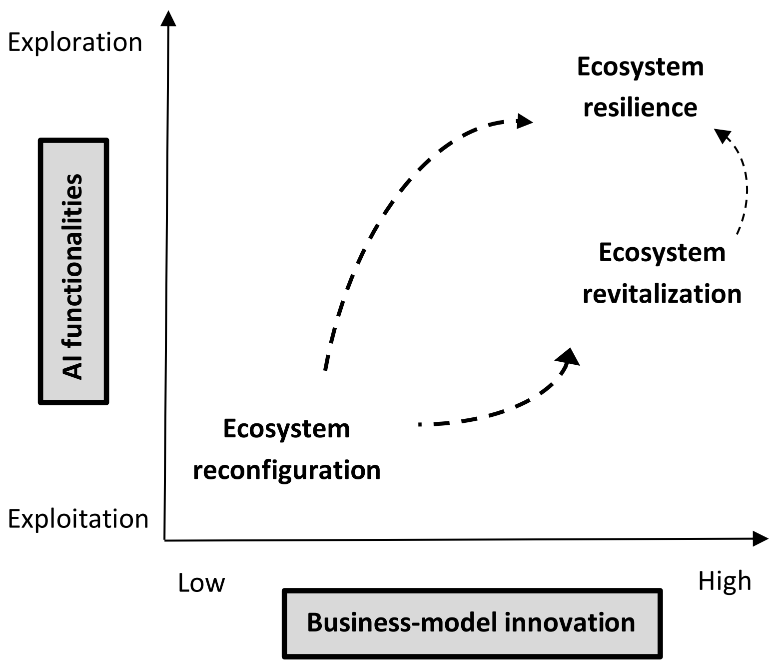

Figure 1. Business-model innovation

6. Conclusions

We contend that AI-enabled business-model innovation can be best understood as a dynamic process. Drawing on Ritter and Leitl (2018), we argue that business models are suitable connection points between different streams of literature. We, therefore, combine two types of literature: business ecosystem literature and business-model innovation literature. We present a dynamic model explaining the relationship between intra-firm micro-elements (AI functions), value processes, and AI ecosystem macro-dimensions (reconfigure, revitalize, and resilience). Our study makes its principal contribution to ecosystem and business innovation theory.

This paper investigates how incumbents go about generating value-creation, value-delivery and value-capture mechanisms to innovate AI business models. We find that AI applications have not yet disrupted major parts of the manufacturing industry. Thus far, manufacturing incumbents are performing small-scale AI innovation in collaboration with various ecosystem stakeholders in order to identify a competitive edge through AI. In line with Teece (2018), we find that incumbents use AI as an improving/enabling technology. Thus, AI has not yet brought a decisive competitive advantage to incumbents in the manufacturing industry. Instead, AI is seen as a competitive requirement by the incumbents. Our core contribution establishes the need for AI business-model innovation to be aligned with ecosystem innovation.

Whereas much of the previous AI literature has discussed the positive consequences of AI (Björkdahl, 2020), we submit that there are many challenges. Using AI with transformed business models may lead to failure if transformations are not linked to established actors and other businesses in the wider set of ecosystem relationships. If companies fail to build an ecosystem around their AI-based business model that is fit for purpose, they may not succeed in the long run.

Taken as a whole, we believe our study makes several important contributions. However, it has some limitations that need to be considered. First, this research is based on insights from a qualitative analysis of incumbents in the manufacturing industry over a limited time span. It is concerned with the transformation of an industry; thus, it is vital to remember that this type of transformation tends to have an emergent and prolonged character. We can only capture a fraction of that transformation. Second, our study builds on a limited – albeit rich – set of interviews with managers in incumbent firms. Extending the study to include complementors and supplementors would have been beneficial, providing even more novel insights into the dynamics behind AI and business-model innovation. Finally, we are aware that our set of qualitative data limits the scope for generalization.

Going forward, we propose that researchers design studies reaching beyond the industrial boundaries to include stakeholders such as governments and research institutions and exploring their role in the transformation of manufacturing business models. It is reasonable to believe that governmental incentive programs would positively impact the research behavior of incumbents.

We also encourage studies using comprehensive panel data. Looking at both the firm- and industry-level effects of circular economy transformation would paint a bigger picture of global AI development and its impact on business model innovation.

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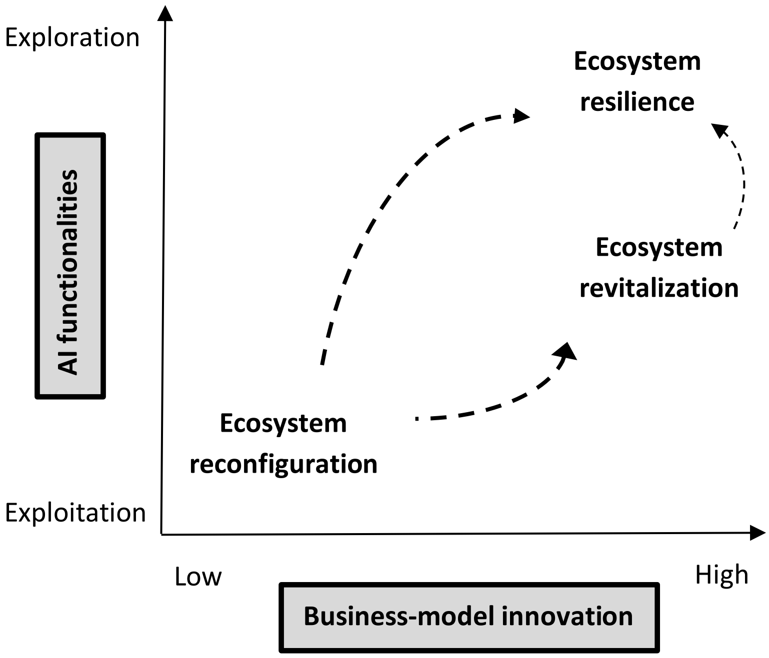

Figure 1. Business-model innovation

Company name	Revenue/Employees	AI-enabled business models case	Respondent positions
Alfa	6,550 m EUR/ 14,000	AI-enabled fleet management solution	R&D manager, 2 technology managers, procurement managers, IT manager, service portfolio manager.
Beta	3,240 m EUR/ 7,800	Advanced AI services for operational control system	Senior manager, business development manager, technology engineer, vice president technology, and service manager.
Gamma	3,100 m EUR/ 13,000	AI services for autonomous solution	Digitalization lead, business development manager, sales

			and services manager, line manager, and digitalization director.
Delta	98,000 m EUR/41,000	Mine optimization and AI services	IT manager, sales manager, business development manager, and autonomation manager.

Table 1. Cases and the positions of company respondents interviewed

Table 2. Summary of observations

<table>
<tr><th>Business application usage</th><th>Value creation impact</th><th>Value delivery impact</th><th>Value capture impact</th><th>Ambition levels</th><th>BM transformation</th><th>Ecosystem structural alignment</th><th>Ecosystem transformation</th></tr>
<tr><td>Forecasting customer operational usage</td><td>Understanding customer operational needs</td><td>Improved knowledge sharing</td><td>Cost reduction</td><td rowspan="4">Improve and/or enable. No disruptive solutions.</td><td rowspan="4">Higher BM impact from forecasting and monitor/control functionalities. Lower BM impact from optimization and autonomy functionalities.</td><td rowspan="4">New internal front-end and back-end interfaces. New social and technological customer interfaces. New role definitions.</td><td rowspan="4">A current situation characterized by ecosystem reconfiguration. An anticipated need for future revitalization and resilience.</td></tr>
<tr><td>Monitor and control equipment performance</td><td>Id new customer segments</td><td>Improved role distribution</td><td>Transparency and accountability</td></tr>
<tr><td>Optimize preparation and maintenance</td><td>Customized solutions</td><td>Improved service delivery routines</td><td>New service business</td></tr>
<tr><td>Autonomous decision making and correction</td><td>Higher quality customer offerings</td><td>Improved service experience</td><td>Better revenue flow</td></tr>
</table>