Data Analytics Services for Additive Manufacturing Ecosystems

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Completed Research

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Abstract

Additive Manufacturing (AM) promises to redefine production by enabling unforeseen product designs, new degrees of customization, or transformative approaches to spare parts management. However, the radical degree of innovation of AM also incurs unprecedented changes to production planning and control with a plethora of new technical and managerial decisions to be made. As a new bridge between the physical and digital world, the technology is inherently suited to address these issues in a data-driven, analytics-based manner. We argue that it is advisable to look at this subject with a business ecosystem lens. Based on a series of interviews and workshops, we derive a set of analytics services for AM that can be embedded into such ecosystems. For each service, we define the benefit, the analytics potential, the involved roles, the data provision, and the information generation. Our results suggest that an analytics-driven ecosystem approach helps unlock the true AM potential.

Keywords

Additive Manufacturing (AM), Ecosystem, Data Analytics Services, Business Intelligence and Analytics (BIA), Predictive Analytics, Reporting.

Introduction

With the increasing integration of information technologies into manufacturing processes, new possibilities to collect and exploit data emerge (Tao et al. 2018). This opens the door to new options for the *servitization* of industrial processes (Hunke and Engel 2018), such as moving from the mere transactional exchanges of products to the relational provisioning of services. This changes the division of labor and gives rise to manufacturing *ecosystems* with a multitude of players. Data facilitates planning, connecting, monitoring, steering, allocating, and optimizing the involved resources and processes (Martín-Peñ et al. 2018; Schüritz et al. 2017). All these managerial processes can benefit from analytics in general and advanced and predictive analytics in particular, enabling competitive advantages (LaValle et al. 2011; Rymaszewska et al. 2017). In fact, conducting analyses can itself be defined as a self-contained service – an *analytical service*.

Against this background, technologies for *Additive Manufacturing (AM)* are of special interest, as they increase the level of digitalization in manufacturing to a new level (Petrick and Simpson 2013). With its inter-organizationally distinct value creation, AM is an exciting domain for undertaking research on manufacturing ecosystems (Hiller et al. 2022). In AM, products are created by incrementally adding material in a layer-wise fashion, following the specification of 3D CAD models (Gibson et al. 2021). AM being once used primarily for design prototypes, it is now applied to produce parts with unforeseen product designs (e.g., for the aerospace industry or medical products), individualized articles with a high degree of customization (e.g., for fashion articles, automotive interior, or whole buildings), or to enable transformative approaches to spare parts management (Pfähler et al. 2019; Gibson et al. 2021; Ahmed et al. 2022). A recent example for the potential of AM has been the rapid fabrication of ventilators during the early stages of the COVID pandemic in 2020 (Wohlers et al. 2021).

However, in AM not only the manufactured results (parts) are different, but also the processes for designing and managing production (Thiesse et al. 2015). Moreover, alongside these changes come new types of decisions – on all managerial levels. Examples for the operational level include the choice of the material composition, the positioning and orientation of the products to be printed in one printing process, and decisions regarding adequate printing parameters. On a tactical level, the issue of the optimal printing technology comes up (e. g. material jetting, material extrusion, powder-bed fusion, or vat polymerization), as does the need to select a suitable AM machine, or to design and manage printing material replenishment (Khajavi et al. 2014; Abduhlahmeed et al. 2019). Strategically, enterprises need to decide on the right scope and scale of their AM applications (Klahn et al. 2015; Bikas et al. 2019). All this feeds into the need to design specialized decision support systems (DSS).

The domain of AM seems to be particularly suited for DSS as AM is by design a digital technology that is fed with digital inputs (CAD models), is controlled by software, and generates digital outputs that allow to embed it into digital production environments. One could assume that it should be straightforward to collect suitable data that can be explored and exploited with both reporting-oriented, descriptive analytics, like reports or interactive dashboards as well as with model-oriented, predictive techniques, esp. based on statistics and machine learning. However, due to the AM orientation towards small lot sizes and the problem that a single AM part producer can only provide a small excerpt of the data needed for meaningful analytics applications, the availability of relevant data is hampered both in scale and scope. We argue that by widening the view to the business ecosystem in which the printing takes place, it becomes possible to envision cooperatively designed and operated, value-generating analytical services based on a rich and broad data foundation. Based on these assumptions, we tackle the following research question (RQ): *What types of value-generating analytical services for AM can be designed for a business ecosystem environment and what partners benefit from it?*

This RQ calls for an explorative and qualitative approach that focuses on systematizing the analytical services at the intersection between smart service, systems engineering, and ecosystem research. We *contribute to the ecosystem research* by shedding light on AM as a dynamic IS field and providing insights into Business Intelligence and Analytics across enterprise borders. Our results also *contribute to practice,* as our services can support identification, specification, and design of analytical services for AM ecosystems.

Background and Related Work

The following section provides an overview of the conceptual foundations of our research. After a short introduction to AM and AM ecosystems, we discuss analytical services and their embedding in business systems. Finally, we present the results of a literature review on state of the art in analytics for AM.

Additive Manufacturing and Additive Manufacturing Ecosystems

A common structure for an AM process includes five phases: First comes a design phase that generates the digital product model (usually a CAD model enriched with construction-related data). Secondly, during pre-processing, single or multiple product models are arranged into build jobs that fixate the relevant production parameters (e.g., layer thickness, position, and orientation). Thirdly, the actual printing takes place. This is followed by a fourth phase comprising the post-processing of the fabricated part and eventually its actual application. Figure 1 illustrates this process (Hiller et al. 2016).

AM is considered to be predestined for an ecosystemic value creation (Piller et al. 2015; Kwak et al. 2018; Rong et al. 2018), as most AM applications are characterized by as being highly collaborative bringing together multiple partners. Examples for partner are the product designers, the customers as potential co-creators or co-producers, the actual manufacturers applying AM to produce parts, specialized AM service providers (e.g., for spare parts on demand services), marketplaces, and AM platform providers (AM platforms) (Piller et al. 2015 and Pfähler et al. 2019).

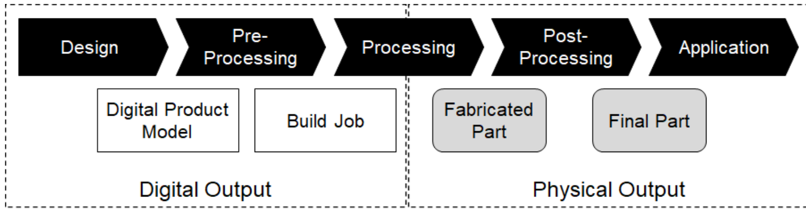

Figure 1. Additive Manufacturing Process (Hiller et al. 2016)

In business ecosystems, multilateral and loosely coupled actors pool their resources to materialize value, which is usually enabled by complementarities and interdependencies (Hannah and Eisenhardt 2018). Additionally, they are typically characterized by a coopetitive stance of the involved actors, as they can collaborate and compete on different products or services (Dagnino and Padula 2002; Ritala 2012). This is also true for AM-based manufacturing (Kwak et al. 2018; Hiller et al. 2022).

Data Analytics Services

Data Analytics subsumes all forms of data transformations to support or automate decisions and, therefore, the enablement of fact-based decisions (Davenport and Harris 2007). This includes both descriptive, report-based as well as model-based approaches, which are also known as "Advanced and Predictive Analytics" (Bose 2009). The aspect of *prediction* also goes along with an embedding of a running model into a business process, the *model operationalization* (Halper 2016). Predictive Analytics has garnered some attention due to the recent progress made in machine learning (ML), that is, the derivation of models from data (Mitchell 1997). ML is primarily applied for solving problems of classification (predicting a class label), regression (predicting a continuous variable), clustering, outlier analysis, and association rule mining. Recent advances in the field of deep learning (ML with large, multilayered neural networks) allow application of ML to unstructured content (images, audio, speech, text, etc.) (Schmidhuber 2015).

Both reporting and model-oriented systems support the generation of information (which later is distributed). This is only possible with a pertinent, high-quality *data provision*, leading to requirements for dedicated data repositories (data warehouses or data lakes) and data processing. Considering the increasingly distributed and heterogeneous data sources, analytical tools and applications, infrastructure, and data analytics are provisioned as sets of complex services with multiple players (Horakh et al. 2008; Ereth and Baars 2020). This is particularly true for an AM setting. Data across multiple ecosystem partners is supposed to be accumulated and combined to provide an adequate data foundation for analytical services. Drawing on the smart service definition, data analytics services apply data analytics to the physical product and process data to create and monetize added-value (Hunke et al. 2018; Koldewey et al. 2020). Similarly, analytics can be applied to the data from all the AM process stages to design data analytics services.

Data Analytics Services for Additive Manufacturing: State of the Art

For deriving the state of the art of data analytics services for AM we conducted a literature review according to vom Brocke et al. 2009. We focused on two databases that cover both more the IS and the IT angle (the AIS eLibrary and IEEE Xplore). As a filter criterion, we selected only peer-reviewed articles where the following key-strings can be found in the abstract: Additive Manufacturing AND data-driven service(s) (AIS: 0 results; IEEE: 2 results, 1 relevant); Additive Manufacturing AND analytics (AIS: 2 results, 0 relevant; IEEE: 21 results, 5 relevant); Additive Manufacturing AND data sharing (AIS: 0 results; IEEE: 10 results, 0 relevant); Additive Manufacturing AND machine learning (AIS: 0 results; IEEE: 45 results, 27 relevant) and Additive Manufacturing AND data (AIS: 5 results, 0 relevant; IEEE: 265 results, 9 relevant).

We evaluated the titles, the abstracts of all the articles and most of the full-texts. All relevant papers present algorithms or application ideas, software designs or software frameworks esp. for monitoring AM-processes and quality assurance. A dominant focus was fault detection and prediction with various methods from simple classification tree to complex deep learning systems for analyzing image, geometry, or even acoustic data. A conceptualization and systematization of analytics services (from the perspective of service science or information systems) are missing. Some papers are also considering aspects of data selection, preparation, augmentation, and labeling. The full list of screened and selected relevant papers is available online: https://bit.ly/3Hu4Sq3.

Research Design

Given the results of our literature review, we consider the subject of AM data analytics services an under-researched field that suggests an explorative and qualitative research design (Yin 2018). For eliciting in-depth results, we decided on conducting interviews and workshops with potential AM ecosystem partners. We were able to acquire these partners from three research projects on the subjects of AM ecosystems, data sharing and analytics in ecosystems, and IT-based decision support for the industrial use of AM.

Our research instruments' design (questionnaire / workshop guidelines) and the data analysis were based on the conceptual framework depicted in Figure 2 (Ravitch and Riggan 2011). The framework is built around our RQ and embeds categories drawn from the foundations presented above: For each potential ecosystem, we derived (and for the most part gathered) the involved partners, their roles, and the value these partners attributed to AM analytics. We abstracted these configurations to *scenarios for AM ecosystems*. Each scenario is realized with one or several distinct *data analytics services* that is specified by the data sources (usually distributed among several partners), requirements for data provision (e.g., a data lake for shape files), and the model-oriented or reporting-based information generation (e.g., an ML-based classification of printing outcomes). The analyses are designed to support distinct AM processes, thereby realizing the value for the partners.

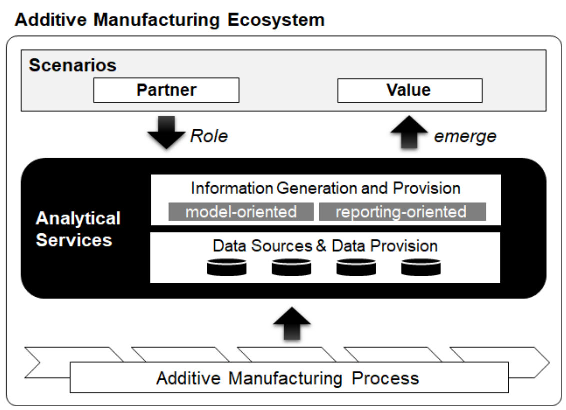

Figure 2. Conceptual Framework

To ensure high-quality results, we selected only cases in which the involved partners were actively pursuing an institutionalization of the ecosystem and the realization of actual services. In total, we conducted two interviews and seven series of workshops (duration approx. 1h), in which the potential ecosystem partners interactively fleshed out the respective contents of the framework (which we also used as categories). Within a workshop, possible services were discussed in more detail with several partners at the same time, each in a different composition. In addition, four meetings were held in addition to the workshops, in which bilateral exchanges took place with individual partners. Our data was collected over a period of approximately ten months (May 2021 until February 2022).

For the data analysis phase, we either recorded interviews and workshops or made memory protocols afterwards. Recorded interviews were transcribed. With the help of the protocols and transcripts, we conducted a qualitative content analysis – the category system served as a guide (Gläser and Laudel 2010). Our research approach is visualized in Figure 3.

In our interviews and workshops, the following AM ecosystem roles were represented: *AM part producer* (service provider who actually applies AM in order to create parts), *AM part customer* (user of finished AM parts, for example another manufacturer), *AM material supplier, AM system provider* (provisioning of AM machinery), *online AM order platform* (a middleman who routes orders to AM part producers), *AM-specific IT-solution provider* (IT-solutions for different roles alongside the AM process), as well as *AM certifiers* as providers for AM standardization and AM certification (concerning AM parts and AM processes) – a role we only discovered for one scenario as critical during the workshops.

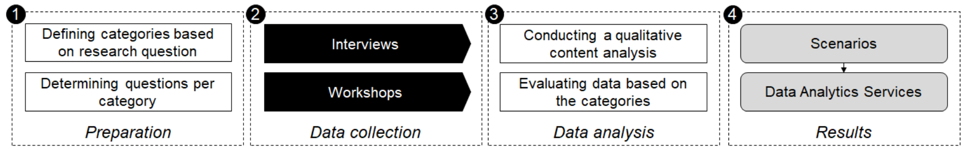

Figure 3. Research design

Results

In the following section, we first present the five identified scenarios (see Figure 4), followed by a detailed analysis of the derived analytical services.

Identified Scenarios

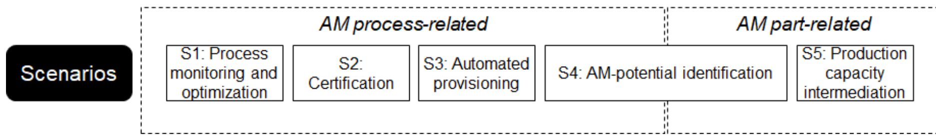

Figure 4. Identified scenarios

We divide the scenarios according to their main subject – either AM process-related or AM part-related. In case of process-related scenarios, the actual AM-process is analyzed: In the center is the logic of the process, in which the actual printing is embedded, and that follows the basic structure depicted in Figure 1. The relevant data comes from the various steps of this process. In part-related scenarios, the focus is on analytical services that consider the AM components itself. The relevant data captures the design idea, the finished part or its application.

As scenario S1, we identified is *process monitoring and optimization*. Here, the data analytics services provide benefits for the involved partners by a) creating transparency about process instances and/or b) by generating insights on where and how to improve the process structure. In scenario S2 (*certification*), data analytics services generate information for 3rd parties. An example is the test, demonstration, and documentation that the AM part producer complies with the rules, standards, and specifications required by the AM part customer. Scenario S3, *automated provisioning*, is characterized by analytical services which focus on the steering of AM materials from an AM material supplier. In the context of scenario S4 (*AM-potential identification*) we see services that focus on supporting decisions regarding the scope and the scale of the application of AM (both ad-hoc/operational and fundamentally/strategic). For example, an AM part customer needs to decide whether or not to produce spare parts with AM technologies – and to what degree. Scenario S5 (*production capacity intermediation*) focuses on data analytics services which help partners of the AM ecosystem with matching AM orders and capacities, e.g., via an AM online order platform. Usually in AM, packing multiple parts (regardless of their geometry) into one build job leads to scale effects. As a result, capacity intermediation (e.g., via market places) offers value to AM service providers by supporting cost-benefits and respective pricing advantages.

Data Analytics Services for Additive Manufacturing

Table 3 gives an overview of the data analytics services we identified for our five scenarios. The results are structured according to the categories of our conceptual framework.

Benefits	**Analytics potential**	**Roles**	**Data provision**	**Information generation and provision**
Service 1: AM printing monitoring (assigned to S1)				
Timely communicating problems and failures, bases for production improvements	Data-based reporting on and monitoring of AM processes	AM part customer; AM part producer	Machine data; build job data; production planning data (integrated by process instance) provided and prepared near real-time	Primarily report-oriented (e.g., dashboards); can be supported by model-based techniques (e.g., a clustering of failure types, or a classification-based prediction of severity)

Service 2: AM material handling (assigned to S1, S3)				
Improving the production environment; Shortening time-to-market	Data-based monitoring of material and AM-production	AM material supplier; AM part customer	Machine data (material); manufacturing capacity (integrated in a logistics-oriented data repository)	Report-oriented (e.g., inventory monitoring); can be supported by model-based solutions (e.g., a regression-based forecasting of stock turnover)
Service 3: Quality inspection (assigned to S1)				
Production improvement	Data-based identification of quality deficits	AM part customers* AM part producers*	CAD-data; production planning data from multiple producers; inspection data (ideally provided in a data stream)	Model-based (e.g., image analysis) in combination with report-oriented (can feed the AM printing monitoring service)
Service 4: Automated report generation for external stakeholders (assigned to S1, S3)				
Transparency about state of production for third parties / compliance	Data-based reporting	Authorities; AM part customer; AM part producer	Machine data; manufacturing volumes and capacities	Report-oriented (e.g., daily / weekly / monthly reports)
Service 5: Identification of certification opportunities (assigned to S2)				
Better quality estimation by AM part customers; expansion of the services provided by a certification organization	Data-based identification of requirements	AM certifier; AM part customers*	Production planning data; build job data; CAD-data, annotations and meta-data provided collected in the AM process (collected in a versatile data storage like a data lake)	Model-based (e.g., clustering in combination with text mining in annotations)
Service 6: Active certification service (assigned to S2)				
Standardization of AM; increased customer safety and customer acceptance	Data-based monitoring of business activities	AM certifier; AM part customer; AM material supplier; AM part producer	Production planning data; machine data	Report-oriented (e.g., daily / weekly / monthly reports)
Service 7: Component identification (assigned to S4, S5)				
Shortening time-to-market; prioritization of activities; transfer of existing know-how	Data-based identification of cost-efficient and qualitative adequate parts for AM production; data-based identification of (similar) parts to predict opportunities and risks of extending AM	AM part customers*; AM part producers*; AM-specific IT solution provider; online AM order platform	CAD-data; master data of components from multiple partners (collected in a versatile data storage like a data like)	Model-based (e.g., clustering component types, classification of component parts, or similarity analysis on top of dimensionality reduction techniques; application of geometric deep learning); descriptive, reporting-oriented (e.g., with an ABC-/XYZ-analysis)
Service 8: Tracking know-how development (assigned to S4)				
Improved strategic planning; targeted consulting services; higher added value; shortened time-to-market	Data-based development of AM-specific know-how	AM part customers*; AM part producers*; AM-specific IT-solution provider	CAD-data; knowledge database; Project data	Report-oriented (e.g., weekly reports based on a balanced scorecard)
Service 9: Prediction of manufacturing capacity (assigned to S5)				
Optimize production capacity; manage manufacturing demand	Data-based prediction of capacities of AM service Providers	AM part producer; online AM order platform	Production planning data; build job data; inventory data (part of a logistics-oriented data repository)	Model-based (e.g., regression and timeseries analysis, classification)
Service 10: Cost estimation (assigned to S5)				
Shortening time-to-market	Data-based estimation of costs per part (with regard to current AM capacity)	AM part producer; online AM order platform	Enrichment of "component identification" with order data and AM capacities	Model-based (e.g., classification)
* potentially multiple				

Table 3. Data Analytics Services in AM

The first data analytics service is the *monitoring of the AM production process*. This service is intended to monitor the actual AM production's functioning, identify errors, and detect them in time. For this purpose, data must be collected along the AM production process, integrated on the level of a process instance, and be provided near real-time. The collected data may include sensor data from the AM machines, the build job data, and production planning data to compare the actual and target status. Regarding the roles, this type of service is initially mainly relevant for the AM part customer and the AM part producer which need to share their respective data. Information can be generated either report-oriented (e.g., with a dashboard that visualizes production outcomes and deviations from target values) or model-based (e.g., a clustering of failure types, or a classification-based prediction of problem severity). The actual failure identification can build up on the quality inspection service discussed below.

AM material handling is the second data analytics service. Unlike the first service, it is focused not on quality but on logistics. Monitoring the order situation and the ongoing AM production allows tracking material consumption. Based on the service, systems of the AM part producer can automatically order required materials from the responsible AM material supplier (as another crucial role we identified in our workshops). This can save time and costs. Additional similar services for AM material handling (e.g., machine-related) are conceivable.

As a third service, we identified *AM quality inspection*. In the center, there is a *detection* of errors and goes beyond a simple reporting of descriptive numbers. However, the results can be fed into a reporting-oriented AM production monitoring service. The service primarily benefits the AM part producer by improving the quality of its production. While this can mean a simple comparison of measurements with specifications, this usually requires more advanced, model-based analytics, e.g., a deep-learning-based analysis of photographs of the produced parts for failure classification (e.g., with convolutional neural networks).

Our fourth derived service is *automated report generation for external stakeholders*. Similarly, the monitoring service integrates data from the entire AM process. The difference to the first service is that the recipients of the reports are external stakeholders (e.g., external auditors or government authorities) – who usually do not need the information in real-time. The goal is to generate transparency for those stakeholders and to meet compliance requirements. For instance, monthly reports on the utilization of an AM machine can be used to derive the level of environmental sustainability of production.

The fifth service comes from a certification perspective. Due to the novelty of the AM technology, certification is an important component that contributes to the development and maturity of the application of this technology, especially for using AM in high-risk domains like aerospace or healthcare. In contrast, for AM machines certifications already exist, those do not cover the whole AM process and the full range of requirements by the AM part customers and AM part producers. A collection of heterogeneous content on design, manufacturing, and processes – possibly enriched with metadata and annotations by diverse involved partners in a data lake – is regarded as a treasure trove for identifying new standardization and certification opportunities. The information generation is challenging as it requires a strongly open-ended, creative and explorative approach, possibly supported by text mining, clustering, or outlier detection.

Once certifications are in place, data analytics services for an *active certification* become relevant. Here, the data is used for services that check if certification requirements are met. An example would be that the certifier analyzes machine data and – depending on the results – grants a certificate to the AM part producer (or not). An efficient certification fosters AM acceptance by a parts customer and therefore benefits the AM part producer (plus it generates income for the AM certifier). The analysis here is simpler than in the service before as it is based on fixed decision rules and comes down to a mostly reporting-oriented solution.

In the center of *component identification* as our seventh data analytics service is the decision what to produce with AM technologies as well as with what specific technologies and machinery. These types of decisions arise on a day-to-day operational level (when deciding on how to realize a specific print job) as well as on a strategic one (when to decide on the scale and scope of an AM application). A first approach here is a descriptive ABC-/ XYZ-analysis that takes costs and quantities into account. In our workshops we learned, that beyond that, a crucial part of such a service would be the identification of similar parts in order to transfer accumulated AM knowledge. This service depends on complex and heterogenous product data (geometry, AM process, material, etc.) that needs to be kept in a versatile data storage like a data lake and requires extensive data preparation and harmonization before conducting the actual analyses. The analytical techniques that can be applied encompass clustering of component types, a classification of component parts, or a similarity analysis on top of dimensionality reduction techniques. Also, geometric deep learning might be applied here to identify problematic geometries (e.g., unfeasible folds).

As mentioned, knowledge is developed through the collection of experiences from accomplished AM projects. By documenting the findings in a structured way, this can be made accessible and used to generate information for future projects. We see *know how development* as another data analytics service which can be assigned to the fourth scenario. This service is also characterized by supporting strategic decisions, for instance for offering consulting services as AM producer for AM component users.

Predicting manufacturing capacity represents our ninth service. Efficient manufacturing processes depend on a precise prediction of manufacturing capacities. Such analyses could be based on historical machine capacity data as well as order and production volumes and apply regression and time series analysis. The prediction quality could be enhanced by enriching the data with data on the supply chain, the manufacturing personnel, quality assurance, etc.

Our tenth and last analytical service is *cost estimation*. A rule-based cost estimation can be based on the materials employed, the machinery used, and the spatial volume and the weight of a given AM component. A solid cost optimization is of value for gaining and keeping AM part customers as well as for identifying new AM opportunities. It can also support a component identification service (see above) and be used to derive and execute new pricing strategies. For example, a flexibility in terms of delivery time allows AM producers to fill poorly charged AM build jobs and therefore could be incentivized with respective feeds.

It is noteworthy that particularly the services for quality inspection, the identification of certification opportunities, and the tracking of know-how development can benefit from combining data from multiple and potentially even competing AM part producers and/or AM parts customers, to provide a solid data foundation both for gathering statistically robust insights and/or for a solid model training. This requires carefully preparing data with pseudonymization or anonymization techniques and integrating that data at a neutral ground to ensure the acceptance of data sharing.

Discussion and Outlook

Until now, the research on data analytics services missed out the AM domain. In this paper we argue that there are good reasons to close that gap and to do it with an ecosystem lens. In a series of interviews and workshops with forming AM ecosystems that represent five different types of scenarios, we derived ten analytics services for five different scenarios. We highlighted involved roles, benefits as well as aspects of data provision and analysis/information generation. The results capture the specifics and the novelty of the AM field and provide an answer to our respective central RQ.

Considering their practical use, our findings may support business development in both AM-oriented and data analytics companies to create domain-specific offerings for AM ecosystems and integrate analytics capabilities in the AM domain. Our results not only guide the development of services, they also highlight the partners and roles that are needed to form ecosystems that support them and to provide the necessary data. The knowledge of the actors and their roles and the alignment of their complementary capabilities is considered crucial for ecosystem management (Lingens et al. 2021). Therefore, our results might be of interest for potential ecosystem orchestrators, which currently seem to be missing in AM (Hiller et al. 2022). Besides, all of the ten delineated data analytics services rely on inter-organizational data sharing and exemplify how AM can be extended by the data ecosystem concept in line with (Abbasi et al. 2016; Oliviera and Lóscio 2018). The findings also enrich the body of knowledge on analytics, esp. regarding analytics use cases and analytics across organizational borders.

We acknowledge that the results still need further validation, particularly as none of the infant ecosystems has yet been institutionalized, and the described data analytics services have only been realized partially and prototypically. More research is needed here, especially for the more sophisticated approaches discussed for services like component identification, tracking know-how development, or identifying certification opportunities. From the service engineering perspective, we suggest mapping our services with frameworks such as the service blueprinting framework (Lim and Kim 2014) or the DIN SPEC 33453 (DIN SPEC 33453 2019). Additionally, the derived service concepts can be integrated into smart service innovation methods adding AM-specific patterns for the pattern-based innovation and fostering the smart service ideation (Koldewey et al. 2020; Ebel et al. 2021). Besides, the derived service concepts can be used by future research to build archetypes of analytics services, which represent generic conceptual prototypes and usually consist of different service configurations. Additional research also needs to be done regarding the aspect of data sharing and the provision of reliable and trusted data spaces. An interesting approach here is the establishment of a cooperative as an institutionalized unit for the ecosystem (Baars et al. 2021).

Acknowledgement

Parts of this research were funded by the Ministry of Economy, Labor and Tourism Baden-Württemberg within the project "Digitale Datenräume zur Kooperation von KMUs".

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