Int. J. Production Economics 253 (2022) 108573

Contents lists available at ScienceDirect

International Journal of Production Economics

journal homepage: www.elsevier.com/locate/ijpe

Identification of aftermarket and legacy parts suitable for additive manufacturing: A knowledge management-based approach

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ARTICLE INFO

Keywords:
Additive manufacturing
3D print
Part identification
Aftermarket parts
Legacy parts
Knowledge management

ABSTRACT

A research stream identifying aftermarket and legacy parts suitable for additive manufacturing (AM) has emerged in recent years. However, existing research reveals no golden standard for identifying suitable part candidates for AM and mainly combines preexisting methods that lack conceptual underpinnings. As a result, the identification approaches are not adjusted to organizations and are not completely operationalizable. Our first contribution is to investigate and map the existing literature from the perspective of knowledge management (KM). The second contribution is to develop and empirically investigate a combined part-identification approach in a defense sector case study. The part identification entailed an analytical hierarchy process (AHP), semi-structured interviews, and workshops. In the first run, we screened 35,000 existing aftermarket and legacy parts. Similar to previous research, the approach was not in sync with the organization. However, in contrast to previous research, we infuse part identification with KM theory by developing and testing a "Phase 0" assessment that ensures an operational fit between the approach and the organization. We tested Phase 0 and the knowledge management-based approach in a second run, which is the main contribution of this study. This paper contributes empirical research that moves beyond previous research by demonstrating how to overcome the present challenges of part identification and outlines how knowledge management-based part identification integrates with current operations and supply chains. The paper suggests avenues for future research related to AM; however, it also concerns Industry 4.0, lean improvement, and beyond, particularly from the perspective of KM.

1. Introduction

Aftermarket services are a stable revenue stream. Deciding on the appropriate manufacturing technology and sourcing model for aftermarket services and spare-part management is a critical managerial decision (Sgarbossa et al., 2021). Designing optimal supply chain flexibility for: (i) procurement and sourcing; and (ii) reengineering of legacy parts and spare parts, is extremely important for original equipment manufacturers (OEMs) and the entire supply chain's operations (Chaudhuri et al., 2019, 2020; Delic and Eyers, 2020; Knofius et al., 2019). The traditional model primarily uses conventional subtractive or formative manufacturing processes. In addition, the conventional model places parts and tools into stock, requiring long-term storage as stock-keeping units (SKUs). Aftermarket services tie up capital, and physical SKUs often remain unused for long periods because anticipating demand patterns can be challenging (Eyers et al., 2018).

AM, an innovative group of technologies (Beltagui et al., 2020), enables geometric freedom and highly customized parts without high costs (Gardan, 2017; Weller et al., 2015). Reengineering or redesigning parts for AM using topology optimization enables the enhanced performance of in-service parts (Flores Ituarte et al., 2020; Knofius et al., 2019). From a supply chain perspective, AM has the potential to eliminate or reduce the stock of tools, molds, dies, or casts (Holmström et al., 2010) while digitalizing the supply chain of spare parts (Khajavi et al., 2014). Furthermore, AM adds a new level of flexibility to existing supply chain models (Eyers et al., 2018). In both subtractive and formative methods, CM incurs high upfront costs and longer lead times when production volumes are low because of tooling (Weller et al., 2015). Thus, AM allows for capturing new service markets through localized on-demand manufacturing and the provision of spare parts tailored to

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https://doi.org/10.1016/j.ijpe.2022.108573
Received 31 May 2021; Received in revised form 11 July 2022; Accepted 13 July 2022
Available online 19 July 2022
0925-5273/

small customer demographic groups and niche markets (Kleer and Piller, 2019; Steenhuis and Pretorius, 2017).

However, AM has yet to gain traction as a mainstream application for manufacturing end-use parts (Beltagui et al., 2020; Schniederjans, 2017), even though it can disrupt supply chains. The literature identifies multiple technological and business factors that slow down the adoption of end-use applications, such as costs, education, materials, finishing, and intellectual property rights (Ballardini et al., 2018; Baumers et al., 2016; Thomas-Seale et al., 2018). Furthermore, the technology is not entirely ready, and supply chains have not yet been fully developed to encompass AM (Chekurov et al., 2018; Kretzschmar et al., 2018). Mellor et al. (2014) emphasized strategic and organizational alignment concerning AM's feasibility, including its manufacturing and research and development (R&D) strategy. Table 1 summarizes the benefits and obstacles presented above.

AM adoption challenges necessitate the identification of the most promising candidates for successful AM adoption within extensive inventories. The organization's digital preparedness and prior knowledge are decisive factors to consider. Two approaches for identifying AM part candidates exist:

- The *top-down* approach uses codified data and explicit information extracted from information and communications technology systems, including enterprise resource planning (ERP) and product data management (PDM) systems. The top-down approach calculates AM feasibility algorithmically, thereby providing spare-part candidate scores.
- The *bottom-up* approach is mostly user-driven and extracts information from a user's experience and tacit knowledge. It requires different organizational units to identify possible AM candidates. It also uses a ranking method to select spare-part candidates, but the ranking methods rely mainly on expert input.

Frandsen et al. (2020) concluded that research on part-identification methods for AM is limited, although industry identifies this as key to technology adoption. Existing research combines preexisting methods in various AM approaches but lacks theoretical considerations relevant to companies facing challenges trying to operationalize these approaches. One main challenge concerns the data availability required for top-down screening. Data availability and quality are general concerns amid the emergence of Industry 4.0, but KM can help overcome these barriers (Schniederjans et al., 2020).

In this research, the main hypothesis stipulates that part-identification strategies are heterogeneous and that relying merely on a bottom-up vs. top-down approach or redesigning aspects for part identification is not enough. New AM part-identification strategies need considerations related to the organization's KM practices (i.e., is AM knowledge embedded in the organization and how can the data foundation help identify AM part candidates?). Therefore, organizations adopting AM must adjust part-identification strategies by examining the organization's KM regarding data availability and AM knowledge. We explore KM in the context of AM part identification from two angles: (i) What is the organization's strategic alignment regarding AM knowledge? (ii) What is the organization's data foundation (i.e., ERP and SKU data quality and codified data availability for analysis, including PDM

Table 1
Benefits and obstacles to AM adoption.

Benefits	Obstacles
Reduction of tools, molds, dies, or casts	Cost
Geometric freedom/customization	Education
Typology improvement of part	Material
Adding flexibility to the supply chain	Finishing/surface quality
Cost-effective for entering new or niche markets	Intellectual property rights
Cost-effective for serving low and intermittent demand	Technology and supply chain maturity

systems, part inventory computer aided design (CAD) models, demand patterns, and part procurement strategies)?

The available literature on part identification for AM introduces relevant key concepts for business case screening and part identification for AM. However, Chaudhuri et al. (2021) questioned whether a "one-size-fits-all" approach is applicable, and both Chaudhuri et al. (2021) and Frandsen et al. (2020) have called for further research to establish guidelines for designing a suitable approach to identify AM candidates. Therefore, this paper defines and tests an overarching strategy for part identification of existing aftermarket and legacy parts that ensures that the approach is operationalized and tailored to the organization, rather than just applying a potentially unsuitable preexisting approach. Our first contribution is to investigate and map the existing literature from the perspective of KM (Figs. 1 and 2). Our second contribution is to develop and empirically investigate a combined part-identification approach in a defense sector case study. Our third and main contribution is to infuse part identification with KM theory by developing and testing a Phase 0 assessment that ensures an operational fit between the approach and the organization.

The paper is structured as follows: Section 2 investigates and maps the theoretical background on part identification and KM. Section 3 outlines part identification and KM synthesis. Section 4 presents the methodological choices for developing and executing the part-identification approach conducted in this study. Section 5 presents the results and a discussion of testing the approaches and Phase 0. Finally, Section 6 concludes the paper with implications, limitations, and future research directions.

2. Theoretical background

The theoretical background section includes two subsections. The first concerns the various top-down and bottom-up part-identification methods included in this research, and the second concerns KM.

2.1. Top-down and bottom-up part identification

Top-down and bottom-up part-identification approaches differ because quantitative and data-driven elements are dominant in top-down approaches. In contrast, qualitative and user-driven elements dominate bottom-up approaches. However, bottom-up approaches include potential top-down elements regarding data extraction and the calculation of scorecards. Similarly, top-down approaches include bottom-up elements, particularly validation and screening technique inputs. Validation in the top-down approach necessitates a few people discussing and ensuring that the part is printable. However, the bottom-up approach includes several people discussing more than just printability. Table 2 presents an overview of the different part-identification approaches.

Generally, bottom-up approaches have in common the element of

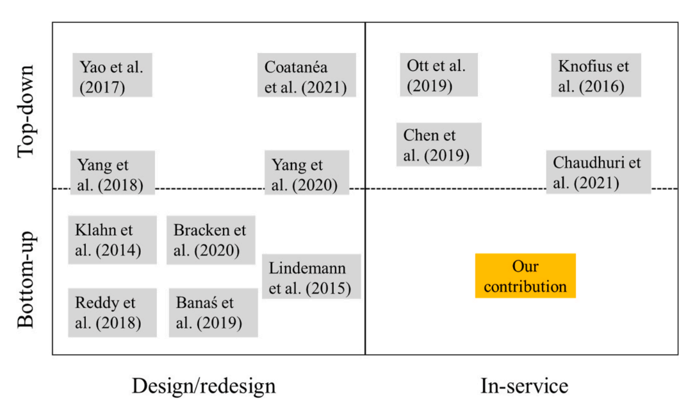

Fig. 1. Framework for part-identification approaches.

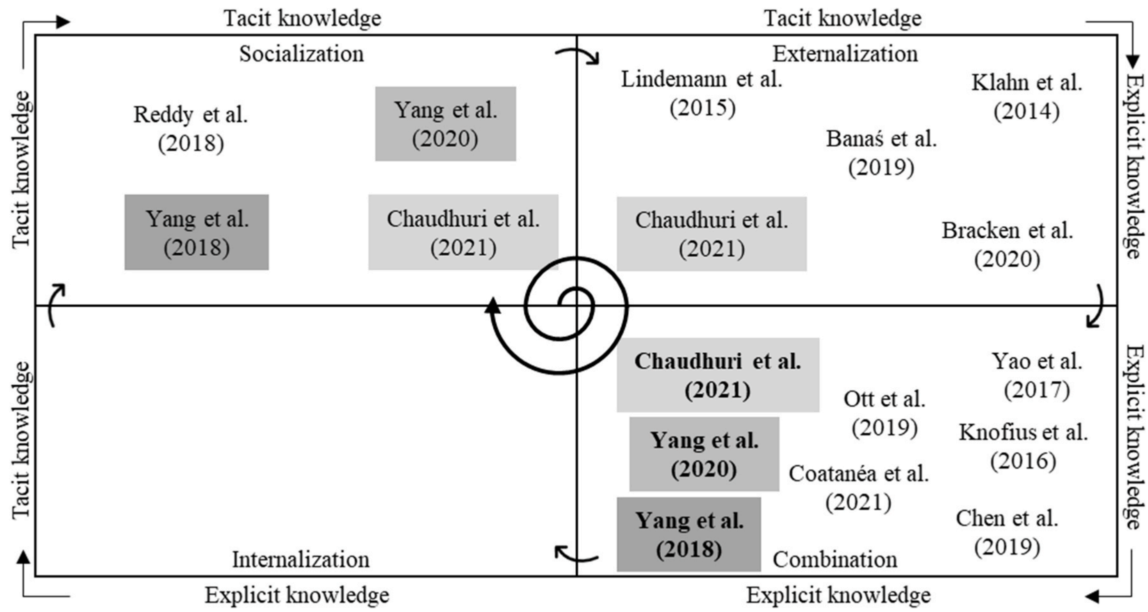

Fig. 2. The SECI framework with individual approaches.

Table 2
Overview of part-identification approaches.

Approach	Bottom-up	Top-down	Combined (top-down)
Type of knowledge	Mainly tacit	Mainly explicit	Mainly explicit
Type of data	Mainly qualitative	Mainly quantitative	Mainly quantitative
Data collection	Mainly workshop and interview	Mainly data extraction from ERP	Mainly data extraction from ERP
Level of data availability	Low to medium	Medium to high	Medium to high
Sample of parts (size of part inventory)	Small to medium	Medium to high	Medium to high
Methodology (own wording from references)	Workshop, interview, scoresheet, and criteria-based approach	AHP, ANP, hybrid machine learning, machine learning, part clustering, part classification, and activity-based costing model	TOPSIS, cluster analysis, workshop, interview, PCCD, algorithms, and machine learning
Main references	(Banaś et al., 2019; Bracken et al., 2020; Klahn et al., 2014; Lindemann et al., 2015; Reddy et al., 2018)	(Chen et al., 2019; Coatanéa et al., 2021; Knofius et al., 2016; Ott et al., 2019; Yao et al., 2017)	(Chaudhuri et al., 2021; Yang et al., 2018, 2020)

getting a group of experts together in a workshop format (Banaś et al., 2019; Bracken et al., 2020; Klahn et al., 2014; Lindemann et al., 2015; Reddy et al., 2018). Banaś et al. (2019), Bracken et al. (2020), and Lindemann et al. (2015) used a scoresheet to assess and rank part candidates. Both Klahn et al. (2014) and Reddy et al. (2018) applied a purer form of the bottom-up approach by selecting critical parts in which they saw AM potential. However, they did not specify whether other part candidates were relevant. The scope of parts that the user can assess is limited because all bottom-up approaches rely on users' knowledge and less on codified data. All of the bottom-up papers focused on identifying either design or redesign AM features.

The top-down-focused papers use a data-driven approach with automatic score calculation, and are split between either identifying design and redesign features (Coatanéa et al., 2021; Yang et al., 2018, 2020; Yao et al., 2017) or identifying in-service spare parts (Chaudhuri et al., 2021; Chen et al., 2019; Knofius et al., 2016; Ott et al., 2019). Knofius et al. (2016) and Ott et al. (2019) used AHP and analytical network process (ANP), respectively. Chen et al. (2019) clustered parts using traditional classification schemes. Chaudhuri et al. (2021) combined both top-down and bottom-up elements using clustering, AHP, a workshop for introduction, and an interview for validation. Yang et al. (2018) used a part consolidation candidate detection (PCCD) algorithm, and their second follow-up study (Yang et al., 2020) incorporated other components besides part consolidation. Yang et al. (2020) applied machine learning to address these added components. Yao et al. (2017) and Coatanéa et al. (2021) also applied machine learning in their approach, and Yang et al. (2018) and Yang et al. (2020) applied bottom-up elements in their approaches. The top-down approach enables the screening of a large inventory but relies heavily on codified data availability.

Overall, combining top-down and bottom-up approaches utilizes the best of both worlds, for example, screening a large inventory, followed by in-depth analysis and discussion concerning the highest-ranking candidates. However, limited research is available in the literature. Early on, Knofius et al. (2016) mentioned that combining their top-down approach with Lindemann et al. (2015) could be valuable for enabling more effective screening in a bottom-up approach. However, ensuring the availability of the right people with proper knowledge is the primary concern of the bottom-up approach. These people need sufficient knowledge about AM as well as the spare parts. Furthermore, the data volume and quality required to apply data-driven screening are concerned with the top-down approach. For example, five out of eight papers using top-down elements either had to reduce the amount of data they intended to use or recognize it as a potential issue (Chaudhuri et al., 2021; Knofius et al., 2016; Ott et al., 2019; Yang et al., 2020; Yao et al., 2017). Furthermore, we observed that the approaches did not consider the organization's AM knowledge and data availability.

Fig. 1 maps the identified literature based on the top-down or bottom-up approaches and their focus on either design/redesign or in-service parts. Three papers (Chaudhuri et al., 2021; Yang et al., 2018, 2020) fall somewhere between the top-down and bottom-up approaches. Furthermore, Fig. 1 illustrates the scarcity of research on bottom-up-based approaches that focus on in-service parts. Therefore, one contribution of this paper concerns the development of a part-identification approach that focuses on bottom-up elements for in-service parts.

2.2. Knowledge management considerations for part identification

The literature on part identification outlines general issues in top-down and bottom-up approaches that we relate to the relevant elements of KM. KM theory overlaps with knowledge transfer theory and entails "the individual and organizational activities by which organizations develop or leverage their knowledge base" (Kalling, 2003, p. 116). KM distinguishes between tacit and explicit knowledge. Language does not capture tacit knowledge. Tacit knowledge concerns experienced action and accumulated insights (Polanyi, 1966). Tacit knowledge can have cognitive (mental models and beliefs) and technical (know-how) dimensions (Nonaka and Konno, 1998; Søberg and Chaudhuri, 2018). However, explicit knowledge "can be expressed in words, numbers, and shared in the form of data" (Nonaka and Konno, 1998, p. 42). Bottom-up approaches require tacit knowledge from users and experts. Top-down approaches require explicit knowledge in the form of codified data and information. We assume that the bottom-up approach will always be viable to a certain extent because the organization either has some in-house knowledge or can source it from outside the organization. However, this is not necessarily the case with the top-down approach.

As presented in the previous section, multiple papers present challenges concerning data availability. The lack of data challenges the digitalization of the supply chain (Schniederjans et al., 2020). In our view, two factors impact the top-down approach: data availability and inventory size. A large spare-part inventory makes the top-down approach more desirable. Still, top-down screening is not feasible if only limited codified data are available or if the data has insufficient quality. Thus, we view data availability as a deciding factor and an enabler of the top-down approach. In this study, we define high and low data availability as follows:

- High data availability = AM knowledge and data are codified and of high quality (i.e., both explicit codified knowledge and tacit knowledge are available).
- Low data availability = AM knowledge and data are not codified and are available only from specific users (i.e., only tacit knowledge is available).

This paper applies the SECI framework (Nonaka and Konno, 1998) for KM analysis and as a starting point concerning tacit and explicit knowledge. In the SECI framework, knowledge is transferred from the individual to the organization through four conversion patterns in a knowledge spiral:

- Socialization transfers tacit knowledge from one individual to another through direct interaction.
- Externalization converts tacit knowledge into explicit knowledge through interactions among individuals in a group.
- Combination codifies explicit knowledge created in the "externalization" pattern, transcending knowledge from being known by the individual to being known by the group.
- Internalization operationalizes new knowledge and takes it into practice, creating new tacit knowledge for the individual and restarting the continuous circular process.

Fig. 2 maps the different approaches identified in the literature in the SECI framework's four conversion patterns, indicating the tacit and explicit knowledge levels. The two upper conversion patterns mainly focus on tacit knowledge, whereas the two lower conversion patterns mainly focus on explicit knowledge.

The bottom-up papers start in the socialization pattern and move into externalization because they use workshops where individuals contribute their tacit knowledge. Reddy et al. (2018) is the exception because their research involved only a few individuals and used a less structured approach. All the top-down papers belonged to the combination pattern because they collected explicit knowledge. The colors in Fig. 2 highlight the papers that fall somewhere between the top-down and bottom-up approaches. Yang et al. (2018) and Yang et al. (2020) extend into the socialization pattern because they sought user input. Similarly, Chaudhuri et al. (2021) also extend into externalization because they included a workshop. The bold text represents the studies' primary placements. Although not depicted, all papers enter the internalization pattern because they operationalize and test their approaches (i.e., inducing new knowledge).

Further research on the SECI framework has pinpointed which of the phases provide more creative output (Schulze and Hoegl, 2008) and criticism on the foundation of the framework (Gourlay, 2006). More importantly, Nonaka and Konno (1998) defined tacit and explicit knowledge using insufficient detail. They did not define AM knowledge or data availability levels; therefore, we need to amend one aspect to use the SECI framework in this study. The distinction between tacit and explicit knowledge leaves too much ambiguity about the form in which knowledge is available (Søberg and Chaudhuri, 2018). Nonaka and Konno (1998) definition of explicit knowledge does not specify whether explicit knowledge is documented (i.e., codified). In this respect, the Information Space model (Boisot and Child, 1999; Søberg, 2011) provides more clarity because it includes the codification dimension. Codification gives form to data by assigning categories (Boisot and Child, 1999). The degree to which knowledge is documented or expressed fully in writing determines the extent to which it is codified (Hansen, 1999). This otherwise-negligible detail carries vast implications for part identification in the sense that most top-down approaches presume the availability of high-quality codified data. Therefore, we go beyond the SECI framework and develop an assessment connected to part identification.

3. Synthesizing part identification with knowledge management

We call the assessment "Phase 0" (presented in Fig. 3); it comprises themes extracted from the literature on part identification and KM. Phase 0 allows practitioners to assess the organization's essential factors before designing the part-identification approach. The Phase 0 assessment is our main contribution and our suggestion to ensure that the part-identification approach for aftermarket and legacy parts is operationalizable and fits the organization.

Phase 0 includes ten factors, as outlined in Fig. 3. The left side of Phase 0 favors the bottom-up approach, and the right side favors the top-down approach. As presented previously, we assume that the bottom-up approach is always possible but that the top-down approach is not. The top-down approach requires specific factors, such as codified data availability and explicit knowledge (Factors 2 and 3). Although we previously defined data availability as codified data of sufficient quality, we wanted to distinguish between the two factors in the Phase 0 assessment and measure them separately (Factors 4 and 5). A large part inventory, Factor 6, is the only factor in Phase 0 that demands top-down elements. The alternative solution would be to divide the inventory into manageable subsections for bottom-up scrutiny. Factor 7, a redesign, necessitates bottom-up elements. The bottom section of Fig. 3 contains additional factors without any affiliation or favoritism toward either top-down or bottom-up approaches. The AM equipment (Factor 8) and AM capabilities (Factors 9 and 10) assess whether the organization can make the CAD drawings and print the parts internally or if outside assistance is needed.

The assessment done during Phase 0 serves as the input for the design considerations presented in Fig. 4, which presents the key top-down and bottom-up elements identified in the literature (Chaudhuri et al., 2021; Knofius et al., 2016; Lindemann et al., 2015), as well as our case study. If possible, we suggest combining top-down and bottom-up approaches to

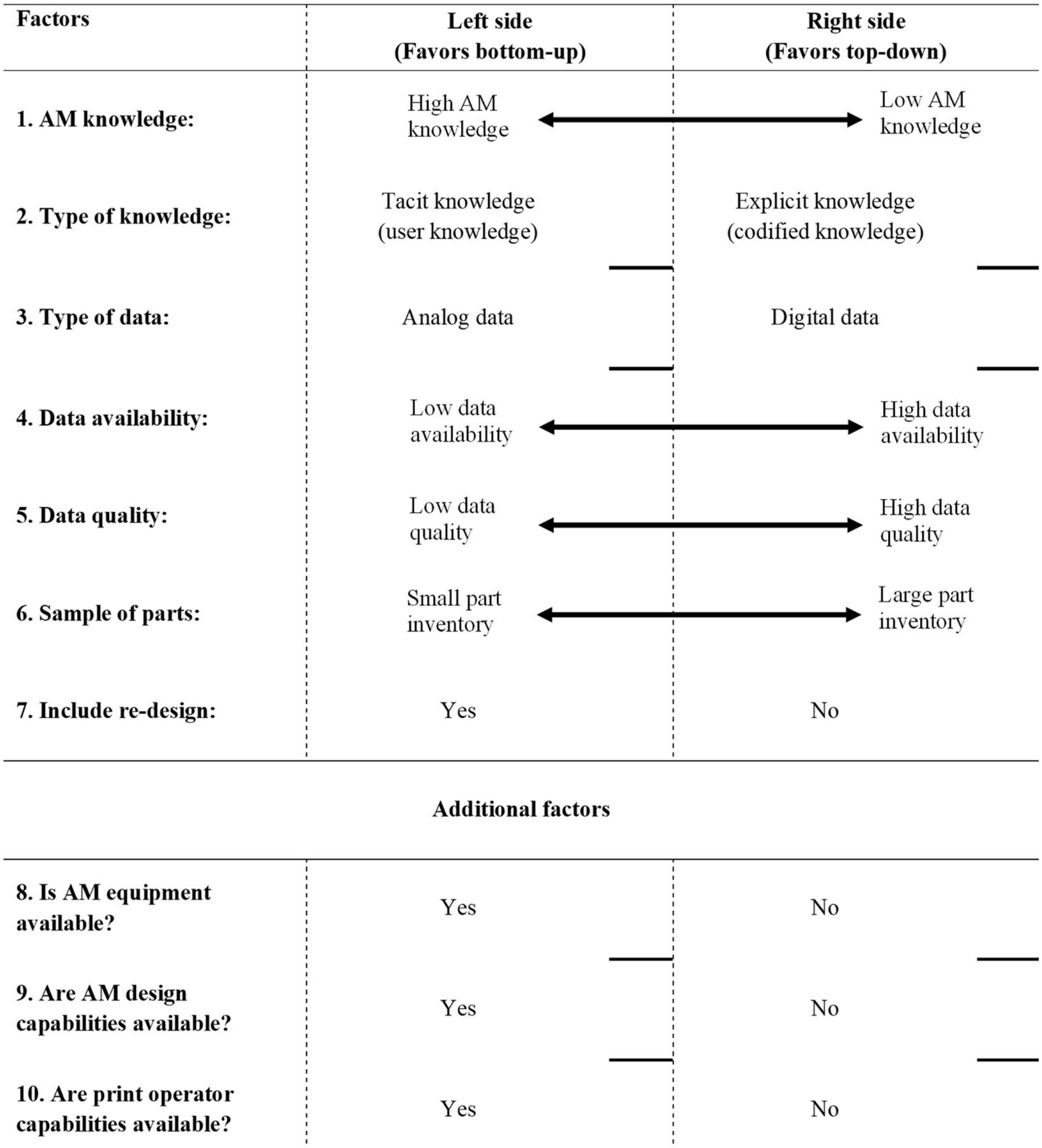

Fig. 3. Phase 0 assessment.

exploit their strengths (i.e., an initial top-down screening followed by a deep-dive discussion with experts about the best candidates). The bottom-up and top-down approaches overlap; for example, the bottom-up approach most often includes top-down elements, such as scorecards and other analytical steps with limited human interaction. Similarly, a top-down approach often includes human interaction (bottom-up elements) required to extract weights for the screening method (AHP or TOPSIS) and to validate the screening. However, these various elements are necessary to make the approach work. Thus, they remain labeled top-down and bottom-up.

If top-down screening encounters low discrimination between the parts, adding bottom-up elements or conducting a cluster analysis can solve the problem, as Chaudhuri et al. (2021) demonstrated with the latter. Someone using the bottom-up route can conduct the last three processes in the bottom-up route as often as necessary. Fig. 4 excludes redesign considerations, but one of the bottom-up routes can incorporate redesigns. The added requirement is more AM knowledge and knowledge of conventional manufacturing. The main difference between choosing the top-down approach or a combination approach is the scope of the approach and moving beyond what is necessary to make the approach work. For example, if the bottom-up approach is combined with the top-down approach, bottom-up elements are not just meant to validate the top-down screening. Instead, the purpose is to include workshops, thoroughly discuss the parts, and select parts based on users' experience and tacit knowledge that includes more than the parts' numerical values.

4. Methodology

This research applies an abductive case study strategy for three reasons: (i) we sought a deeper understanding of the process of part identification for AM; (ii) the process of part identification entails going back and forth between data collection and analysis; and (iii) collaborative participation from both researchers and organizations was sought (Dubois and Gadde, 2002, 2014; Yin, 2009). The case study's purpose was twofold: (i) identify AM part candidates using a case organization; and (ii) link part identification with KM as a theoretical framework. The unit of analysis concerns the process of part identification in the case organization. Qualitative data are relevant when investigating processes within organizations (Merriam, 1998).

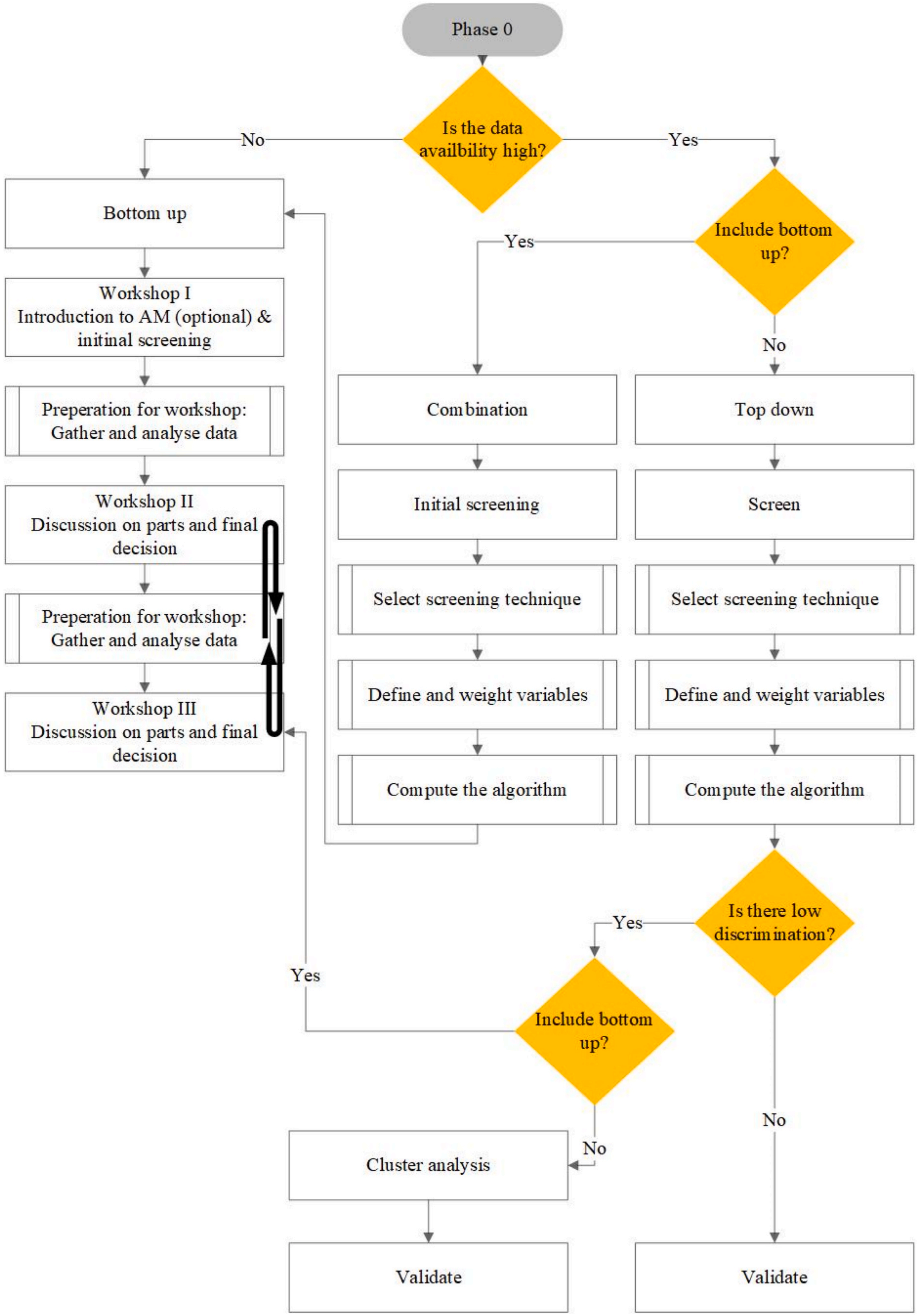

Fig. 4. Design considerations for developing an approach for AM part identification.

The case organization falls within the defense and military sectors, and it primarily sources its parts. Organizations within the defense and military sectors usually use a wide variety of equipment for extended periods (Louis et al., 2014). Obsolescence, long lead times, and high costs are common supply chain elements in this industry, rendering AM a beneficial production method. Furthermore, the military often operates in remote locations where AM capacity enhances mission readiness with print-on-site and print-on-demand (3dprintingindustry.com). However, AM still requires further development before deploying it "in theater". Aside from post-processing requirements, cybersecurity is a sensitive topic for the military industry (Louis et al., 2014; militaryaerospace.com). Furthermore, exploring polymer and metal 3D printing possibilities is necessary (additivecenter.com). To explore the options, we found that identifying the most suitable part candidates for AM is relevant because the technologies and business cases are not clear or feasible for all parts.

Fig. 5 presents the timeline and iterations of the research. Initial discussions with the organization revealed a large spare-part assortment, limited data availability, and limited AM knowledge. The organization is in the early stages of its AM journey, in which individuals identify and print part candidates under local initiatives (i.e., a bottom-up, user-driven approach). In the first run, we started by obtaining an overview of the AM part-identification approaches and then developing an identification approach and testing it in the case organization. We encountered obstacles with the organization's data foundation, forcing us to adjust our top-down screening. The data were of questionable quality and codified only to a limited extent. We encountered these obstacles because we failed to tailor our approach to the organization. Upon revisiting the literature, we identified similar barriers. In the second run, to cope with the mismatch between the part-identification approach and organization, we developed and tested a Phase 0 assessment that assessed the organization's KM as an initial input. The appendix contains information on the methodological steps of the part-identification approaches. Further inspiration for part identification can also be found in the research by Chaudhuri et al. (2021), Knofius et al. (2016), and Lindemann et al. (2015).

5. Results and discussion

5.1. The initial part-identification approach

During the first run in the organization, manual screening and AHP ranking shortlisted 30 out of 35,000 aftermarket and legacy parts for the workshops. High cost, long lead time, and low demand were factors in the scoring. Table 3 presents the results where all the parts, except Rank 1, are ranked based on lead time. This resonates well with the organization ranking lead time as the most important factor. Table 4 presents the lowest and highest values and the means and standard deviations for the entire dataset. A few extreme values affected the numbers concerning cost and demand (such as Rank 1), whereas only having ten lead times for the whole data set affected lead time numbers. The dataset's questionable quality highlights the necessity for a pre-assessment of the organization's KM as an input to design the part-identification approach (with relevant bottom-up and top-down elements).

Table 3
Results of the top-down screening.

Part name	Price (DKK)	Lead time (days)	Total demand (three-year period)	Part overall score	Rank
Armor plating (set)	662,014.00	7	1	0.00263	1
Ceiling light	303.90	180	16	0.00233	2
Screw nuts (set)	176.74	180	10	0.00233	3
Water tube, gasket	5.70	140	1	0.00181	4
Cylinderpipe	428.00	130	1	0.00168	5
Radiator grill	6730.00	120	3	0.00158	6
ABS hydrounit	3573.53	120	1	0.00157	7
Engine starter	2787.60	120	2	0.00156	8
Brake caliper	1627.20	120	1	0.00156	9
Headlamp	1525.65	120	20	0.00156	10
Engine brake	1480.00	120	1	0.00156	11
Tool kit	812.50	120	6	0.00156	12
Valve magnet	615.00	120	3	0.00156	13
Glow plug	552.12	120	12	0.00156	14
ABS sensor	490.00	120	1	0.00156	15
Hubcap	475.00	120	1	0.00156	16
Oil cooler, gasket	431.80	120	1	0.00156	17
Cylinder tube, gasket	428.00	120	1	0.00156	18
Safety bumper	398.41	120	1	0.00156	19
Timing chain	320.07	120	1	0.00155	20
Tail light (left)	292.00	120	2	0.00155	21
Tail light (right)	286.00	120	2	0.00155	22
Mounting unit	282.30	120	1	0.00155	23
Brake pad	241.22	120	3	0.00155	24
Wiper blade (set)	238.89	120	90	0.00155	25
Shaft	235.57	120	1	0.00155	26
Brake pedal	211.85	120	2	0.00155	27
Sensor ring	198.68	120	1	0.00155	28
Adjusting collar	183.40	120	1	0.00155	29
Footrest	152.83	120	1	0.00155	30

Table 4
Descriptive statistics.

	Price (DKK)	Lead time (days)	Demand (three-year period)
Min value	0.01	0.00	1.00
Max value	662,014.00	180.00	8252.00
Mean value	2055.22	7.51	26.47
Standard deviation	10,895.54	10.14	171.26

Cluster analysis (an additional top-down element) solved the data quality issue for Chaudhuri et al. (2021) to some extent. In contrast, our initial approach dealt with this issue by including bottom-up elements (workshops) following top-down screening. As presented in Fig. 5, the initial approach during the first run comprised two workshops focused

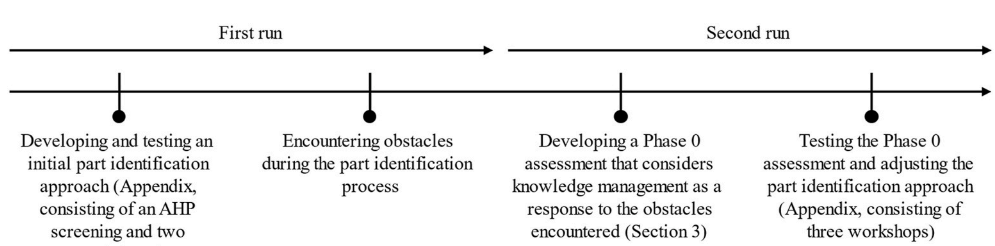

Fig. 5. Timeline of the abductive case study research.

on the candidates on the list in Table 3. The results pinpointed the need for single-material components with no mechanical or electrical properties. AM benefits, such as print-on-site and print-on-demand (to cope with low demand and long lead times), motivated most parts. However, print-on-site and print-on-demand differ in importance across parts. Some parts are more critical than others; for example, the ceiling light (Rank 2) and set of screw nuts (Rank 3) are not viewed as critical parts. Other parts are critical but not printable due to mechanical properties (e.g., engine starter, Rank 8). These restrictions, coupled with lack of criticality, led to discarding most candidates from Table 3 except for the brake pedal (Rank 27), gaskets (Ranks 4, 17, and 18), and lights (Ranks 10, 21, and 22). Further down the list, long lead time parts became cheaper and less relevant only until a lead time below two weeks was available for the remaining parts.

After discussing the remaining parts during the second workshop, the users chose the brake pedal because it is feasible to print, relatively exposed, susceptible to damage (compared with the gasket), and viewed as a critical part. Furthermore, the brake pedal is useable across different types of equipment—potentially offering more opportunities within the smaller vehicle segment. However, it is difficult to codify and provide numerical values on the part's exposure, susceptibility to damage, and potential applicability across other vehicles to include in the top-down screening. Therefore, by including workshops, we can include users' experience and tacit knowledge in the part-identification approach and add further depth to the discussion about the part candidates compared to top-down data-driven approaches (Chaudhuri et al., 2021; Knofius et al., 2016). Regardless, we hoped for better execution of the top-down screening.

As previously presented, defense and military organizations usually use a wide selection of equipment for extended periods (Louis et al., 2014). As a result, these organizations consume massive numbers of aftermarket and legacy parts to keep the equipment running. Furthermore, in this case, roughly 25,000 illegible parts were excluded. Thus, there is an increased likelihood that the parts inventory included other expensive and critical aftermarket and legacy parts with long lead times relevant to AM. However, insufficient data made them challenging to identify. This issue is one of the pitfalls when dealing with a large inventory and insufficient data to support the screening.

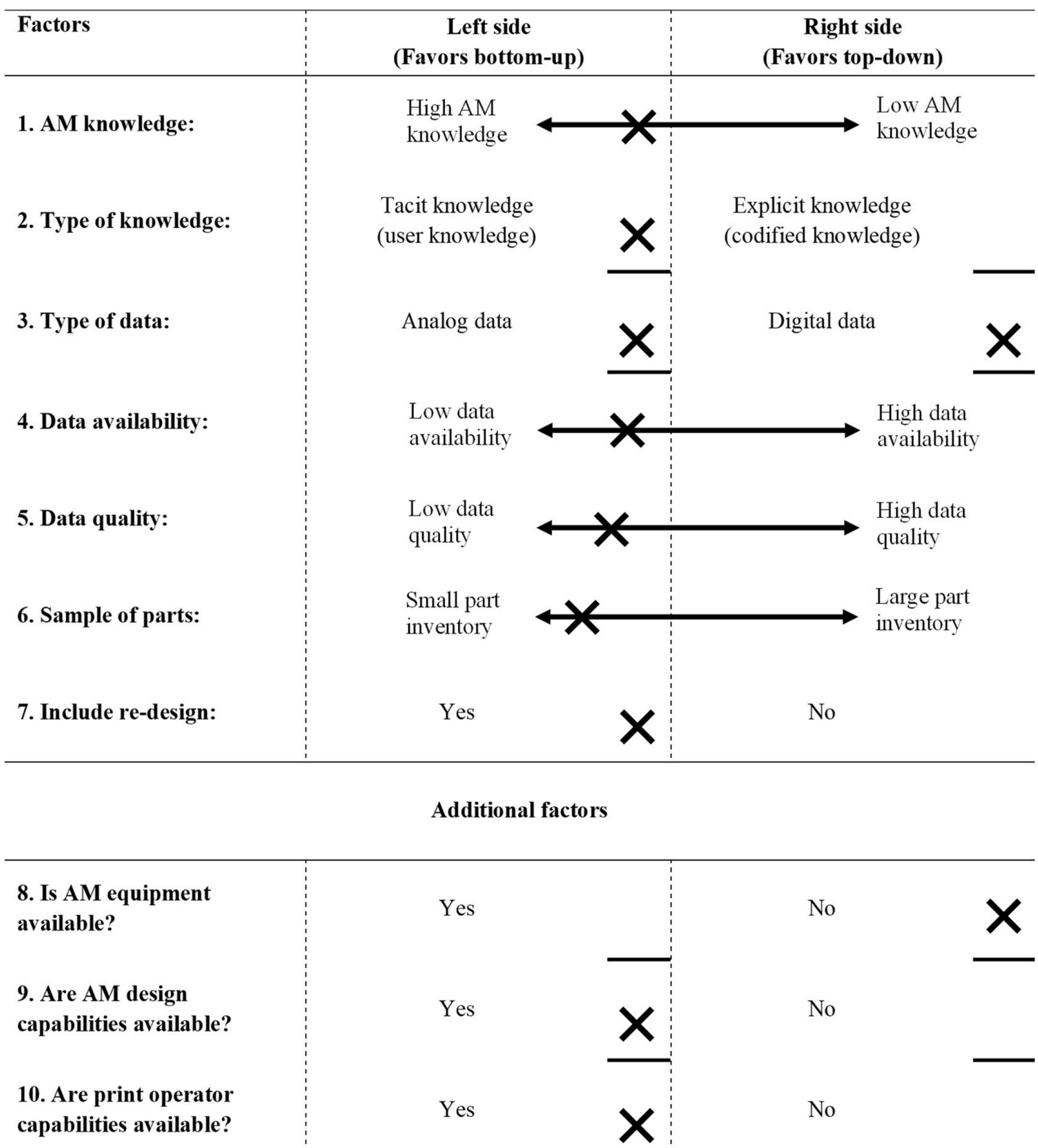

Fig. 6. Phase 0 assessment from the case organization.

5.2. The Phase 0 adjusted part-identification approach

Testing the Phase 0 assessment served two purposes: (i) to test whether the assessment would impose a new identification approach; and (ii) to validate Phase 0. We tested the Phase 0 assessment during the second run in a different unit of the organization. Fig. 6 presents the Phase 0 assessment.

The manager who helped us with the Phase 0 assessment initially preferred the bottom-up approach. The assessment provided results that were in sync with the manager's initial thoughts. Fig. 6 provides an analysis favoring an approach with many bottom-up elements in this case. Therefore, we decided to conduct three minor workshops. Comments regarding the assessment indicated that users in this unit of the organization have sufficient knowledge (Factors 1 and 2) and capabilities to design for additive manufacturing (DfAM) and operate an AM printer (Factors 9 and 10). However, that was only true for a few users, and other users tried to move beyond basic AM knowledge. However, knowledge and know-how expansion progresses slowly, considering that little time is available, it relies on limited personal training, and it is impacted by not having a dedicated printer (Factor 8). Limited codified data are available in-house, so the users use codified data based on what they discover online (Factor 3). Therefore, the data quality is questionable, and codified data are infrequently available for use (Factors 4 and 5). They reverse-engineer and design parts from scratch when no online data source for a part is available. In most cases, the part inventory is low and comprehensible by users (Factor 6). Finally, they very much wanted to include a redesign because the ability to adjust to ever-changing assignments was AM's primary benefit to them (Factor 7).

The first workshop mainly established common ground on how to assess AM. The users were quite adamant about their ability to adjust to their assignments. They did not seek solutions that would radically change their equipment, but rather the possibility of identifying low-hanging fruit for improved quality of life and lead time reduction. The users represented different areas within the organizational unit, but they all agreed that the highest potential was for the combat uniform and dummies. The combat uniform included improving quality of life and customizing solutions for users.

After a session of self-reflection for the users, the second workshop identified overall product categories. During a brainstorming session, the users determined ten categories that entailed 1:1 replacements and new designs. Examples included add-ons to belts and medical kits. The existing add-ons are fragile, break down sporadically, and benefit from on-demand production. Many of these small bits and pieces were physically present during the brainstorming to better assess their AM potential. Another great suggestion was related to explosive shells for training because they are expensive and have long lead times. Furthermore, customizing shells with AM for a specific test would enable better and more thorough training in comparison to the standard solutions available. The other categories included covers for electronic devices, tools, grips, and attachments for communication, video, goggles, helmets, and vests.

The third workshop aimed to identify a single part within the categories. Of the ten categories, we discussed and assessed the covers for electronic devices as having the highest potential—namely phones and tablets. The plethora of options and continuous development of these electronic devices result in regular replacements of both the devices and the associated aftermarket and legacy parts. Furthermore, considering that manufacturers distinguish their products in terms of their physical appearance, users are also forced to use multiple covers and regularly replace them. Moreover, the covers require different grips and attachments to connect to the uniform and other equipment. Determining suitable solutions and sourcing consumes an unnecessarily large amount of the users' time. Therefore, all users agreed regarding the covers and viewed them as having enormous potential because AM would be suitable for making incremental adjustments to an existing design or a new tailored solution for the electronic device—not only for the device itself, but also for grips and attachments to combat uniforms or other equipment.

If we return retrospectively to the initial approach during the first run and apply the Phase 0 assessment, the results would be close to the content in Fig. 6. Therefore, we are confident that Phase 0 would have improved our initial part-identification approach and guided us toward a purer bottom-up approach, thereby fulfilling the purpose of ensuring that the identification process is operationalizable in the organization. Furthermore, besides providing further empirical research on part identification for existing aftermarket and legacy parts, we have some general reflections on part identification, KM, and data availability that move beyond this case. The findings of this paper resonate with Schniederjans et al. (2020), which point to the assisting role of KM in the digitalization of the supply chain and the adoption of Industry 4.0. Our Phase 0 moves beyond speculation and provides an example of how KM can assist in overcoming challenges and barriers and enable Industry 4.0 adoption in the specific context of AM adoption.

This paper contributes conceptual finesses from KM to the field of part identification of AM, which is one example of Industry 4.0 adoption. Prior to our Phase 0 suggestion, the literature on part identification of AM was mostly focused on recombining preexisting methods, and the literature could be accused of being conceptually weak. Our contribution resembles the need for research within the field of lean improvements—a field that focuses on tools and methods, rather than much-needed theoretical underpinnings (Åhlström et al., 2021). For such endeavors, KM also has something to offer, and possibly, this paper can inspire further research within Industry 4.0, lean improvement, and beyond. Given the advance accomplished by this paper, it begs the question of what else can be achieved conceptually concerning Industry 4.0, within lean improvement, and beyond, from the perspective of KM. A common theme in these developments is capability development, knowledge, and data issues. These are all issues for which KM has much to offer, hence our suggestions for future research.

Regarding general suitability of the part-identification approaches, data availability is an enabler for top-down screening, and this paper defines it as follows:

- High data availability = AM knowledge and data are codified and of high quality (i.e., both explicit codified knowledge and tacit knowledge are available).
- Low data availability = AM knowledge and data are not codified and are only available from specific users (i.e., only tacit knowledge is available).

However, further contextual dimensions likely influence the choice of approach. We speculate that some organizations are more susceptible to the top-down approach by default. For example, OEMs are likely to have drawings and codified data because they are the developers. Furthermore, digitally mature organizations are also likely to utilize top-down screening more effortlessly. However, fast-moving industries could face challenges because they do not have the time to codify data (Ferdows, 2006; Søberg, 2010). Furthermore, system integrators and companies that usually source their equipment should embrace a bottom-up approach. A potential solution to improve data availability is to ensure that the supplier includes CAD files and other technical information in its offerings or offers them for purchase. That would enable an alternative for AM-ready organizations to secure the aftermarket and legacy parts when needed. Furthermore, when improving the data foundation for part identification, we speculate that it would also improve the digitalization of the supply chain because more data and information are available.

Top-down and bottom-up approaches result in different outputs of aftermarket and legacy parts. For our first run with top-down screening, the users had basic AM knowledge but limited practical AM knowledge and experience with DfAM. The first run outputted substitution parts rather than redesign parts, in line with previous research, indicating that

DfAM is complicated and challenging when having only basic knowledge (Bracken et al., 2020; Chekurov, 2019). During our second run, a few users had practical AM knowledge and experience with DfAM. The second run mainly provided redesign parts. The output resonates well with previous research that focused on redesign requirements using a bottom-up approach (Lindemann et al., 2015) or excluded redesign while using a top-down approach (Chaudhuri et al., 2021; Knofius et al., 2016).

However, we speculate that users with supply chain backgrounds are more interconnected with top-down approaches due to their focus on codified data and information related to factors such as cost, lead time, and demand. We speculate that design-oriented users connect more with bottom-up approaches because of their tacit design and manufacturing knowledge of AM. The outcome will reflect this because the management-oriented user does not typically have the know-how to redesign parts. Furthermore, the internalization and socialization phases result in more creativity than the externalization and combination phases in the SECI framework (Schulze and Hoegl, 2008). Bottom-up approaches start during the socialization phase, facilitating the creativity needed for a redesign. In contrast, top-down approaches mostly start from the SECI framework's combination phase.

6. Conclusion

This paper infuses KM theory into AM part-identification approaches for aftermarket and legacy parts. First, we investigated and mapped the body of literature on part identification. We then developed a part-identification approach that combines top-down and bottom-up elements during our first run. We analyzed 35,000 aftermarket and legacy parts and successfully identified a suitable AM candidate. However, our top-down screening encountered multiple obstacles, resulting in adjustments to our approach. Upon revisiting the literature, we could see that a lack of data and data quality were common issues. Our suggestion for coping with the challenges links part identification and KM in a Phase 0 assessment. Phase 0 assesses the organization's KM on factors essential for part identification for aftermarket and legacy parts. Phase 0 tailors and operationalizes the AM part-identification approach to the organization rather than the other way around. Phase 0 is our main contribution to overcoming challenges when integrating AM into current operations and supply chains.

During our second run, we had an additional trial with the part-identification approach in a new unit of the case organization based on our Phase 0 assessment. The new approach included purely bottom-up elements through a series of three workshops in which we identified a part candidate within a scoped area without any adjustments to the approach. It was not possible within our case organization, but whenever possible, we recommend using the top-down approach as the preliminary screening method to narrow thousands of candidates to less than 100. Top-down and bottom-up approaches benefit from being combined whenever possible because the approaches fail to excel as standalone.

Practical implications include applying part identification in AM adoption to identify the low-hanging fruit of aftermarket and legacy parts to build a solid business case. The Phase 0 assessment and guidelines on developing the approach assist managers and practitioners in overcoming early challenges and barriers to adopting AM in the supply chain. We recommend using the Phase 0 assessment to tailor the identification approach to the organization as a starting point. For example, if the spare-part inventory is not extensive, the bottom-up approach sufficiently identifies part candidates. Consultancies can provide knowledge in the case of limited AM knowledge within the organization. On the other hand, we recommend checking that the data foundation is adequate before designing an approach if the spare-part inventory is extensive. Otherwise, segregating the inventory into manageable chunks is required, or the organization's data foundation needs to expand (e.g., by including technical data and CAD drawings in purchases). Choosing between top-down and bottom-up approaches might also depend on the company type. For example, if the organization is an OEM, it likely has more data, CAD drawings, and manufacturing knowledge than an organization that mainly sources goods. Likewise, organization type can also affect AM equipment availability.

The current literature (Chaudhuri et al., 2021; Knofius et al., 2016; Lindemann et al., 2015) applies preexisting approaches that fail to consider the organization's KM factors related to part identification for aftermarket and legacy part. The theoretical implications of this paper entail moving beyond prior studies and contributing by infusing part identification with KM considerations. We encountered the same challenge when combining the approaches by Knofius et al. (2016) and Lindemann et al. (2015) in our first run. However, by developing Phase 0 in our second run, we contribute by providing much-needed guidelines on how to cope with the lack of a "one-size-fits-all" approach, which is requested by Chaudhuri et al. (2021) and Frandsen et al. (2020). Therefore, we move beyond current research by providing empirical-based suggestions to tailor and operationalize the part-identification approach of the organization rather than the other way around. Additionally, while (Lindemann et al., 2015) developed their approach with a redesign in mind, we did not. However, our second run outputted parts for redesign, regardless. Thus, our research provides novel insights into how identification approaches are biased toward a specific outcome by default.

As for the study's limitations, the first is the lack of cut-off values on costs in the AHP screening. While we added lower limit cut-off values to lead times and demand rates, there were no upper limits. Suppose that top-down screening is the deciding factor for the identification approach. In this case, the approach should set up parameters and define lower-and upper-limit cut-off values for the dataset. Furthermore, it would also be worthwhile to include system-level screening to decide on which fraction of the inventory to focus for the individual part identification. The second limitation is related to the case study. Since this research only concerns one case/organization, the Phase 0 framework would benefit from being tested in other organizations to validate it further and ensure its applicability. Thus, the generalization is limited to analytical generalization (Yin, 2009) rather than empirical generalization. However, other direct and indirect avenues related to part identification should be investigated for future research.

Influences from supplier type (Andersen et al., 2019) and supply chain evolution dynamics (Maccarthy et al., 2016) constitute elements worthy of further research concerning the operationalization and combination of part identification approaches. The speculations in the discussion of this paper that OEMs and system integrators, respectively, may have different starting points concerning part identification approaches are relevant to discuss further. This would also enlighten our speculation about OEMs being more susceptible to a top-down, data-driven approach than are system integrators. However, such discussion could start on the shoulders of future empirical comparisons focusing on the operationalization of part identification methods across different types of suppliers. Another relevant consideration concerns supply chain evolution dynamics. At different stages of the supply chain life cycle (Maccarthy et al., 2016), the relevance of and the configuration of part identification approaches may differ. However, we will leave any conclusions on whether and how these speculations resonate with relevant empirical evidence for further research.

Our mapping of the literature in Fig. 1 (Section 2.1) further indicates the relevance of future research that contributes to approaches and theorizing, focusing on bottom-up approaches for in-service aftermarket and legacy parts that move beyond our contribution. Furthermore, considering that our case was suitable only for using the bottom-up approach, we would encourage future research investigating Phase 0 and knowledge management-based part identification in an organization with a solid data foundation. Such investigation could elucidate our speculation that top-down approaches are good at finding maintenance parts to be printed as is, whereas bottom-up approaches seem to output more redesigned parts. If that speculation is correct, how can redesign then be incorporated into top-down data-driven approaches? Perhaps by including design-oriented users and bottom-up elements in the validation, as suggested at the end of Section 5.2. Ultimately, part identification for AM should be conscious of the continuous developments in Big Data, machine learning, and the general exploitation of Industry 4.0 technology. These advances most likely will change how to utilize part identification and enable a broader application of data-driven approaches.

Acknowledgments

We would like to show our gratitude to Peter Henriksen for the support in the initial phase of this study, and we are grateful for the generous support provided by Innovation Fund Denmark (grant number 9163-00012B).

Appendix

The initial part-identification approach (first run)

The initial part of the identification approach that we developed was the first run in the case organization. Due to the organization's limited AM capabilities, knowledge, and data, our initial approach combined existing top-down and bottom-up approaches (Knofius et al., 2016; Lindemann et al., 2015). A sample size of 35,000 existing aftermarket and legacy parts necessitated an initial top-down screening, but the approach focused on the workshops due to limited data availability. Our initial approach followed the combined path shown in Fig. 4.

Table 5
Methodological choices for the initial approach (first run).

Type	Note
Quantitative method	AHP
Quantitative sample	Wheel-based vehicles (35,000 parts)
Qualitative method	Two semi-structured interviews
Qualitative method	Two workshops
Qualitative sample	One manager and three users
Quality issue	Lack of codified data

Table 5 presents the methodological choices for the initial approach used during the first run. We used an approach similar to the one that Knofius et al. (2016) suggested for top-down screening, with some slight modifications, including reducing the number of variables. The conceptual design entailed five variables and three go/no-go factors. The five spare-part variables were: (i) cost; (ii) lead time; (iii) demand rate; (iv) supply option; and (v) response time. The three go/no-go factors were: (i) part size, (ii) materials, and (iii) CAD drawings. The AHP uses the variables to calculate a score, whereas the go/no-go factors are binary and discard ineligible parts. For example, if a part size is greater than the printer's build chamber, it receives a score of zero and is discarded.

A division of the organization's equipment was the sample in this case study. Both the parts and participants required for the identification approach were identified in this section. The chosen equipment section was "wheel-based vehicles" and comprised plastic and metal parts for civilian and warfare purposes. We chose this section based on the initial discussion, which indicated wide variation in parts, data accessibility, and heterogeneous demand patterns for part candidates. Further fine-tuning reduced the sample to include only equipment and parts used for warfare because of criticality when compared to civilian equipment.

For the AHP, we defined the organization's goals and weighted both goals and the five variables with a manager using semi-structured interviews. The manager had general knowledge and experience with the sample and was a former user (providing unique insight into the equipment's importance in extreme situations). The last step in the screening process entailed retrieving and analyzing secondary codified data, which covered three years and involved 35,000 parts. A manual screening process removed 25,000 parts of the sample. Examples of eliminated parts include zero-cost items, commodities, and equipment. The parts' overall score was calculated by multiplying the variable's score with previously established weights and adding the weighted scores together to obtain the overall score. Our scoring followed the tenet that AM excels in contexts with long lead times, low/intermittent demand, and high costs (Thomas-Seale et al., 2018; Weller et al., 2015; Wohlers and Campbell, 2017). Therefore, a longer lead time, lower demand, and higher costs make AM relevant and would provide a higher score for the part candidate. For more details on the AHP process, see Knofius et al. (2016).

The screening process revealed two issues regarding data quality: a lack of data and low discrimination between parts' scores. Furthermore, a few instances required estimates or clarifications from users or data owners. Table 6 presents the data availability in the case study. As depicted, the unavailability of data discarded the supply options and response time variables, along with the go/no-go factor of the CAD drawing (Y/N).

Table 6
Data availability in the case study.

Type	Available	Discarded	Missing or estimated
Cost	X		Cases of missing and questionable data—clarified in preparation for the workshop
Lead time	X		Cases of missing and questionable data—clarified in preparation for the workshop
Demand	X		Cases of missing and questionable data—clarified in preparation for the workshop
Supply options		X	Discarded because of insufficient data
Response time		X	Discarded because of insufficient data
Spare part size			Estimated after AHP screening in preparation for the workshop
Spare part material			Estimated after AHP screening in preparation for the workshop
CAD drawing (Y/N)		X	CAD data were not available from the case organization

Preparation for the two workshops during the first run mainly entailed gathering missing data and estimating AM production costs. The quality issues presented in Table 6 resulted in more manual searches and semi-structured interviews than intended. Three users from the wheel-based vehicle division and the manager who assisted with the AHP joined the two workshops for the bottom-up approach, which drew inspiration from Lindemann et al. (2015). The first workshop included an introduction to AM, mainly to ensure that everyone was on the same page in terms of a basic understanding of AM. Otherwise, the workshop focused on a joint discussion about the part candidates. The discussion focused on the potential strategic advantages of printing parts compared to sourcing them. We added two scenarios to the discussion: (i) cost vs. lead time; and (ii) the environment to which the parts would be exposed (e.g., heat, cold, humidity, or sand). The second workshop focused on reducing the candidate list to one.

Phase 0 adjusted part-identification approach (second run)

We developed a new approach for our second run in the case organization based on our Phase 0 assessment. We conducted the second run in a different unit of the organization because our first run strongly indicated that top-down screening was not feasible. Therefore, we adjusted our approach to investigate a new part inventory with new users for the Phase 0 assessment. We decided to use an approach that comprised only a series of three short workshops during the second run. A semi-structured interview with the manager, during which we assessed Phase 0, led to this decision. Table 7 presents the methodological choices for the adjusted approach.

Five users participated in the three workshops, aside from the manager. The five users all represented different areas within this new organizational unit, all of whom had a basic understanding of AM. A few also had practical experience with CAD modeling and printing. We did not pre-scope the inventory as in the first run because there was a lack of codified data. Thus, we sought a broader view and included users from the five different areas represented. Aside from the Phase 0 assessment, the three workshops required little preparation. The first workshop focused on ensuring a common understanding of AM and establishing essential AM factors that were important to users. The second workshop focused on brainstorming various part categories because no top-down screening was used. The third workshop focused on narrowing part categories and selecting a part candidate based on the factors identified during the first workshop.

Table 7
Methodological choices for the adjusted approach (second run).

Type	Note
Qualitative method	Semi-structured interviews
Qualitative method	Three workshops
Qualitative sample	One manager and five users

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