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Mapping technology diffusion with AI: A web-based approach for tracking additive manufacturing adoption

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ABSTRACT

Understanding the diffusion of emerging technologies is essential for capturing the benefits of innovation. Yet, traditional science, technology, and innovation (ST&I) indicators are often limited in measuring technology adoption. This study investigates the potential of analyzing corporate websites through web mining and machine learning to measure the adoption of additive manufacturing (AM) technologies. Furthermore, it examines how regional ST&I indicators — specifically patents and publications — shape AM adoption patterns. Despite still being niche, AM adoption in Germany doubled from 0.37% (2022) to 0.74% (2023) of firms. Regional web-based adoption hot spots largely align with patent and publication activity. In addition, our regression analyses reveal a positive and statistically significant relationship between these indicators and AM diffusion based on our AI-based web indicator. These results underline the potential of WebAI methods to complement traditional ST&I indicators.

1. Introduction

New technologies, their adoption and diffusion play a central role in the performance of companies and, therefore, their competitiveness (Aghion et al., 2009; Audretsch & Feldman, 1996; Crepon et al., 1998), driving sustainable economic development and contributing to the substantial rise in living standards the world has seen since the first industrial revolution (Aghion et al., 2021; Helpman & Trajtenberg, 1998; Romer, 1990). Recent developments in digital technologies are transforming the manufacturing and production sector. One important technology in this context is additive manufacturing (AM), which has been adopted in various industries, from the automotive and aerospace industry (e.g., rapid prototyping, small-scale and on-site production, use of lightweight materials) to the biomedical field (e.g., individualized and patient-specific prosthetics) (Campbell et al., 2023; Pose-Rodriguez et al., 2020). AM technologies have resulted in innovations that are expected to stimulate economic growth while addressing major societal and economic challenges (Huang et al., 2013). Therefore, AM is considered a key enabling technology (KET) and plays an important role in the innovation strategy for European policymakers (European Commission, 2012). Draghi (2024a, 2024b) highlights the role of AM in creating a resilient and sustainable economy. Despite its political relevance, data to measure AM adoption and diffusion comprehensively is limited. Data sources that track AM include the KOF Swiss Innovation and Digitalization Survey (Arvanitis et al., 2017), relevant patent classes identified by the European Patent Office (Cavallo et al., 2023), and the annual Wohlers Report (Campbell et al., 2023). Furthermore, most measures are prone to various biases, which can overlook important trends in the diffusion process of interdisciplinary and fast-evolving digital technologies (Hall, 2006, 2020).

Various science, technology, and innovation (ST&I) metrics, including surveys, patent data, case studies, and interviews, provide researchers with valuable information to track the adoption and diffusion of new technologies. However, they are often also limited in coverage and timeliness (Dahlke et al., 2025; Nagaoka et al., 2010; OECD Patent Statistics Manual, 2009; Squicciarini et al., 2013). Advances in Natural Language Processing (NLP) and machine learning

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(ML) offer new ways to measure the technology adoption of companies by analyzing the product offerings, news and publications on their websites on a large scale and in real time (Dahlke et al., 2024; Gschnaidtner et al., 2024; Kinne et al., 2024).

This paper aims to provide an overview of the current state of AM adoption, using traditional ST&I-related indicators, including publications and patents, and a novel web mining-based indicator. The latter was derived by systematically scraping corporate websites and classifying their textual content with a fine-tuned deep learning model to identify AM-related content. The geographical focus of this paper is Germany, which is due to its well-established and widely distributed industrial base, an ideal setting to study transformative technologies. Industries such as automotive, aerospace, manufacturing, and biomedical play a crucial role in the country's overall economic success (Beier et al., 2022; Foders & Vogelsang, 2014). In addition, Germany has a very high proportion of companies that scientifically publish and patent new technological advances and innovations, providing researchers with insights into potential regional spillovers (Blind et al., 2006; EFI, 2015).

Based on our methodological approach, combining large-scale web data and processing through artificial intelligence (AI) methods, we aim to answer two main research questions. The first research question (**RQ1**) asks: Is it possible to measure the adoption of additive manufacturing based on web mining and machine learning?

In addition, this paper also provides an opportunity to understand if and how the availability of patents and publications in a firm's close regional environment influences its own adoption of AM and thus drives the diffusion of the technology. Thus, we arrive at our second research question (**RQ2**): How are traditional ST&I-related indicators, such as publications and patents, influencing the adoption of AM?

Our results show that, although still a niche technology, adopted by 0.74% (2023) of all companies in Germany, AM has already doubled its adoption rate from 2022 to 2023. Adoption hot spots measured through our web-based AM variable can be found in Central, South, and Southwest Germany, while regions with relatively high values of AM patents can be found in Central and Eastern regions. Our results further show that there is a positive and statistically significant relationship between AM-related patent activity and actual AM adoption (as measured by our web indicator), as well as between AM-related scientific publication activity and actual AM adoption in regions. However, differences between those two ST&I-related indicators can be found in regard to their influence after increasing time-lags. Our findings contribute to the literature on innovation and technology diffusion (e.g. Dahlke et al., 2024; Hall, 2006) - in particular of specific technologies such as KETs. Furthermore, our research contributes to recent literature on machine learning-based economic indicators (e.g. Kinne & Lenz, 2021; von Bloh et al., 2020).

2. Background

2.1. Additive manufacturing technology

In this study, we track the adoption of AM, a digital technology that produces physical objects from digital data (Gebhardt & Hötter, 2016). AM is often used synonymously with the term 3D printing. Unlike traditional production technologies such as drilling, milling or injection molding, the AM process involves combining materials layer by layer to create a physical object. AM encompasses a group of production processes that differ in how material is added layer by layer and whether support structures are required during production (Bechtold, 2015; Lavoie & Addis, 2018). The standards ASTM 52900 and VDI 3405 define the main AM processes such as binder jetting, powder bed fusion, fused filament fabrication, and vat photopolymerization. Besides altering the means of production in terms of variable costs, AM affects a company's strategic positioning by enabling on-demand and local production (Ben-Ner & Siemsen, 2017; Choong et al., 2020). Therefore, it also creates opportunities for flexible production and mass customization (Schwierzy & Wenzel, 2024; Weller et al., 2015). Additionally, AM can positively impact the shift towards a circular economy (Despeisse et al., 2017).

The commercialization of AM technology began in the 1980s, with the primary applications being the production of prototypes and spare parts. More recently, AM has also become more important for the production of end-products (Su & Al'Aref, 2018). Its increasing relevance is also reflected in the continuous growth of the AM market, including revenues from AM systems, materials, software, and services. A compound annual growth rate of roughly 25% led to a global market size of 1.3 billion USD in 2010, 12.8 billion USD in 2020, and approximately 20.4 billion USD in 2023 (Campbell et al., 2023).

AM innovations are primarily motivated by increasing flexibility, enabling product customization, and reducing the overall number of production stages and costs (Attaran, 2017; Weller et al., 2015). The relationship between labor and AM technologies is therefore characterized by complementarities rather than labor-saving effects, as is the case with other digital production technologies (Felice et al., 2022). Conventional manufacturing methods are often limited to the production of simple parts which must then be assembled into complex products. In contrast, AM enables the production of fully functional, movable assemblies in one or only a few steps, significantly reducing or even eliminating post-production assembly. This also speeds up the entire production process and allows companies to respond quickly to new trends and innovations (Felice et al., 2022; Leal et al., 2017; Weller et al., 2015). Furthermore, AM technologies enable the production of goods without the need for tools or molds. This provides designers and engineers with a high degree of freedom and flexibility in the design and production processes, allowing for extensive customization and enabling the ability to serve even the smallest market niches (Rayna & Striukova, 2016; Rosen, 2014).

Consequently, AM technologies have received increasing attention from policymakers (e.g. EFI, 2015) and researchers (e.g. Mariani & Borghi, 2019). However, due to data limitations that may not capture actual AM adoption or may not be comprehensive, the analytical focus of previous research has continued to be primarily on traditional ST&I indicators.

2.2. Traditional ST&I indicators

In general, measuring the adoption and diffusion of technologies within industries and regions typically relies on well-established methods that utilize both qualitative (e.g., expert interviews) and quantitative data (e.g., patent analysis and survey data).

Firm-level adoption of a technology is often measured using primary data from large-scale questionnaire-based surveys, where industry experts, end-users, and executives provide direct and valuable insight into the context of use, barriers to adoption, and developments over time. Examples of established and officially recognized surveys to measure the degree of innovation of firms and related R&D expenditure can be found both at national level (Germany: annual Mannheim Innovation Panel (MIP)) (Peters & Rammer, 2013) and at European level (biennial European Community Innovation Survey (CIS), based on the Oslo Manual Union (1997). The KOF Swiss Innovation and Digitalization Survey (Arvanitis et al., 2017) and the annual Wohlers Report (Campbell et al., 2023) are examples of a survey and an industry report specifically aimed at tracking AM technologies.

As an alternative to survey data, researchers frequently rely on patent analysis as a valuable and reliable proxy for inventions and the diffusion of technology (Acs et al., 2002). The number of patents, citations, licensing and co-patenting networks help to identify areas of intense R&D, to track knowledge spillovers in terms of geography or industry, and even to detect the development or invention of new technological fields (Griliches, 1998; Hall et al., 2000). Patents have also frequently been used in the case of AM (e.g. Felice et al., 2022; Trappey et al., 2017).

Besides patents, scientific publications have also often been used to capture knowledge creation. Similar to patents, publication data offers not only comprehensive and direct comparability across countries, regions, and individual actors, but also allows for focusing on specific scientific disciplines (Frietsch et al., 2024). Therefore, scientific publications have also been employed in the context of AM. For example, they have been used to capture knowledge diffusion (Lavoie & Addis, 2018) and assess technological maturity of AM (Lezama-Nicolás et al., 2018).

However, these traditional indicators also have several limitations and drawbacks, particularly in providing timely, comprehensive, and granular information on the state of a technology and its adoption (Nagaoka et al., 2010; OECD Patent Statistics Manual, 2009; Squicciarini et al., 2013). A shortcoming of survey data is the generally small sample size, which leads to limited coverage of the total population of firms. As information on the majority of enterprises remains unknown, statistical extrapolation is necessary to draw general estimates and conclusions. In addition, (voluntary) surveys present challenges such as sampling issues due to incomplete questionnaires, non-response bias, and self-selection, but also self-report bias, as participants' responses may be influenced by social desirability (Dillman et al., 2014; Kinne & Axenbeck, 2020; Kleinknecht et al., 2002; Podsakoff et al., 2003). Similar shortcomings also apply to patent data, as not all firms seek formal intellectual property protection for their innovation activities, either because of lack of resources, legal restrictions, and differences in patent practices between industries (e.g. software industry) and countries, strategic decisions to keep inventions secret (e.g. defensive patenting), or because they do not take the next step of bringing their inventions into applications in products or services, all of which lead to a misleading understanding of the actual diffusion of a technology (Archibugi & Planta, 1996; Arundel & Kabla, 1998; Hall et al., 2000; Shepherd & Shepherd, 2003). Due to the lack of granularity in the data, geospatial innovation processes also often remain hidden (Acs et al., 2002; Arzaghi & Henderson, 2008; Carlino & Kerr, 2015; Catalini, 2018; Kerr & Kominers, 2015; Kinne & Axenbeck, 2020). Another drawback of traditional data and methods is that they are temporally limited, providing only snapshots due to cross-sectional observations (survey data) and time lags (e.g. between the priority date of a patent and the availability of information) of typically more than one year Squicciarini et al. (2013). Carrying out these analyses on a large scale, therefore, requires considerable financial and time resources.

In summary, traditional indicators provide a reliable and valuable source in measuring inventions and developments of new technologies. However, they fall short in terms of full coverage of the firm population, timeliness and granularity of the data (geographical and depth of information) as well as overall costs of implementation.

2.3. Text-based innovation analyses

Advances in the field of NLP are increasingly opening up text data for innovation-related analyses. Constructing innovation-related indicators based on information derived from corporate websites has long been proposed (Katz & Cothey, 2006). In the early days of this research, predating the use of ML, keyword-based approaches were employed. In this context, Gök et al. (2015) demonstrate that analyzing R&D activities in innovative firms using archived websites from the Wayback Machine and keyword filtering can produce reliable results. Arora et al. (2013) analyze the innovation behavior of 20 graphene firms, being one of the first studies to recognize the potential of quantitatively analyzing corporate websites for economic studies. Youtie et al. (2012) and Ackland et al. (2010) employ a keyword-based approach to study the websites of nanotechnology firms.

The further development of NLP and ML methods has led to significantly more complex approaches in the area of text-based innovation research. The analyses are usually performed on pre-filtered paragraphs, using fine-tuned NLP models that classify texts according to predefined categories or group them using unsupervised topic modeling (Dahlke et al., 2025). Kinne and Lenz (2021) introduce a methodology to predict a company's innovativeness based on its website text. Using Artificial Neural Networks (ANN) trained on data from the German Community Innovation Survey, they classify firms as product innovators. Their findings indicate that this web-based approach is reliable and provides broader coverage compared to traditional benchmarks, such as patent statistics and surveys. Axenbeck and Breithaupt (2021) show that the use of English language and website size are among the most relevant characteristics to predict innovation activities. To overcome the limitations of SIC codes, Marra and Baldassari (2022) classify firms' activities by extracting keywords from corporate websites. By subsequently analyzing textual data, they identify firms' specializations, map industrial proximity through co-occurrence patterns, and provide a more granular and dynamic classification of innovative business activities. Abbasiharofteh et al. (2023) show that characteristics of firm hyperlink networks strongly correlate with their innovation capabilities, especially when linking to geographically distant but cognitively similar firms. Analyzing corporate website texts, Mirtsch et al. (2021) find that innovative firms are more likely to obtain a specific information security certification.

Several studies have also addressed particular technologies via the ML-based classification of website texts. Dahlke et al. (2024) develop a web-based indicator of AI adoption among firms in German-speaking countries, analyzing website text from 1.1 million companies. By constructing a hyperlink network, they incorporate social capital and network embeddedness into AI diffusion models. Their findings highlight three key adoption drivers: proximity to AI hubs, exposure to deep AI knowledge, and integration within the AI knowledge network. Gschnaidtner et al. (2024) investigate the use of blockchain technology in Germany. Kinne et al. (2024) expand upon this approach by incorporating sustainability engagement into their analysis. Both studies show that blockchain applications remain rather niche. Our study contributes to this literature by providing a web-based indicator for AM.

The analysis of corporate websites, however, faces several important limitations. At the firm level, web data may misrepresent actual innovation due to strategic signaling and challenges in distinguishing innovation stages. System-wide analyses are also constrained by representation biases, especially the underrepresentation of smaller or less digitally active firms (Dahlke et al., 2025). Given the described advantages and drawbacks of both traditional and more modern text-based innovation analysis, we propose an approach that combines methods for a more comprehensive and multidimensional analysis of a technology or innovation, as well as its spread and evolution over time.

3. Data & methodology

In the following, we describe the datasets used in our study in detail. Additionally, we present the methodological approach for our regression analysis.

3.1. Data sources & variables

Our final dataset was constructed based on four different databases: textual data from company websites, patents, publications, and regional information from the INKAR database of the German Federal Institute for Building, Urban and Spatial Research (BBSR). Overall, our dataset includes information for all NUTS3 regions in Germany for the time period between 2015 and 2023.

Table 1
Descriptive statistics of main variables.

Variable	Description	Source	Obs	Mean	Std. Dev.	Min	Max
AM Adoption	Number of AM firms	webAI	1194	12.70	22.32	0	400
AM Patent	Number of AM patents	EPO	1194	2.45	5.27	0	85.33
AM Publication	Number of AM publications	SCOPUS	1194	4.99	16.42	0	174.67
Popdens	Population density	INKAR	1194	541.29	712.83	35.34	4868.01
EmpKnowint	Share of employment in knowledge-intensive sectors	INKAR	1194	9.50	6.66	0	47.18
GDPpc	GDP per capita (measured in 1000 euros)	INKAR	1194	40.53	16.84	16.76	164.76

3.1.1. Web-based AM variable

As described in Section 2.3, improvements in the field of NLP and ML have allowed more efficient usage of text data for innovation-related analyses. Therefore, the focus of our analysis was on the large-scale, AI-based analysis of texts from corporate websites.

As the basis for our methodology, we used data from the comprehensive ORBIS database (van Dijk, 2022) to identify all companies with an active website in Germany. It includes relevant information such as address, founding year, and Unified Resource Locator (URL). Based on the address, we conducted geocoding using the Nominatim Application Programming Interface (API) which provided coordinate pairs for each firm if the address was findable in OpenStreetMap (OSM). Our initial dataset comprised 1,111,702 firms. With the help of the cloud-based web scraping tool *webAI*, developed by ISTARI.AI, we then acquired the HTML content of each respective website, accessing the 25 subpages with the shortest URL, through a large-scale web scraping approach, following Kinne and Axenbeck (2020). We scraped data in 2022 and 2023, but only used the latter, more recent dataset for our regression analysis.

To minimize computational effort for the processing of such a large text corpus, pre-filtering of text paragraphs based on potentially relevant keywords is recommended (Dahlke et al., 2025). Since no standardized nomenclature for AM technologies exists, we compiled an extensive list of keywords based on technical terms from industry standards, namely ASTM 52900 and VDI 3405, and current publications. A complete list of keywords used for the search and the respective source can be found in the appendix (see Table 3).

A sample of 3000 text paragraphs that contained at least one relevant keyword was then selected and manually labeled to create a training dataset for our classification model. While previous research (Dehghan et al., 2023; Schwierzy et al., 2022) distinguished different AM usages (*manufacturer*, *service*, *retail*, *information*), we decided to discard these more fine-grained analysis categories and only differentiate paragraphs into *AM* - i.e. a text demonstrating explicit know-how about the technology (e.g. active personnel), products or services related to AM usage - and *not related* - i.e. information about the technology without own application or know-how or entirely unrelated content. The training data was then used to fine-tune an ensemble learner consisting of 10 models, each trained on a different subset of the data to learn distinct patterns. This approach enables the estimation of confidence scores for predictions, where agreement among a greater number of models corresponds to higher confidence in the outcome. Additionally, we optimized the architecture of each individual model within the ensemble via an extensive neural architecture search to enhance overall performance (Jin et al., 2019). Each constituent model received semantic vector representations as input, derived from encoding the training data using pre-trained Sentence Transformers (Reimers & Gurevych, 2019).

All paragraphs identified through keyword filtering on each website were then classified by the fine-tuned model. The number of paragraphs concerning AM was then normalized over the length of the website to approximate the relative importance of the topic of AM for a company, thereby creating an intensity score. The higher this score was, the more central was the topic of AM on this website. A score of 0 represented a company that did not have a single text paragraph on its website demonstrating its own AM know-how. For our dependent variable (*AM Adoption*), we counted the number of firms with an AM intensity > 0 per NUTS3 area.

3.1.2. ST&I variables

In line with previous literature (see Section 2.2), we used patent and publication data as our main sources for measuring scientific and technological activities. For this purpose, we retrieved AM patents from the European Patent Office (EPO) database based on the inventor's location (Version: February 2025). We applied the methodological approach introduced by Pose-Rodriguez et al. (2020) to find the AM-related patents by searching for the respective Cooperative Patent Classification (CPC) codes and keywords. We then counted the number of respective patents per NUTS3 region. To avoid distortions due to erratic trends over time, we followed previous studies (e.g. Laursen & Meliciani, 2010) and used a three-year moving average (*AM patent*).

Furthermore, we used the SCOPUS database by Elsevier to access publication data. To identify relevant AM publications, we performed a semantic analysis of article abstracts associated with German institutions. This process relied on the same technology-specific keywords as the pre-filtering of our website analysis (see Appendix 3). Publications were assigned to NUTS3 regions based on the listed affiliation address of the authors. Publications with multiple assigned locations were counted separately for each assigned region. As with patent data, we used a three-year moving average to avoid distortions (*AM publication*).

3.1.3. Control variables

Moreover, we also controlled for additional regional characteristics through data from the INKAR database of the BBSR. In line with (Grashof & Basilico, 2025), we included the population density of a region to control for urbanization (*Popdens*). In addition, based on the classification by Gehrke et al. (2010), we controlled for the employment structure in regions by considering the share of employment in knowledge and research-intensive sectors (*EmpKnowint*). These include, for example, the NACE industries for the manufacture of chemicals and of computer, electronic and optical products. To consider the overall structural strength or weakness of regions, we also controlled for the regional GDP per capita (*GDPpc*).

An overview about the descriptive statistics of all variables used in our regression models are presented in Table 1. Moreover, the correlation between these variables is rather low (see Table 4 in the Appendix). Thus, multicollinearity was no serious problem for our empirical analysis.

3.2. Methodological approach

Given the panel structure of our final dataset, consisting of regional data ranging from 2015 to 2023, we conducted a panel regression approach at the level of NUTS3 regions in Germany. Following the results of the robust Hausman test (Schaffer & Stillman, 2016; Wooldridge, 2002), we used a fixed effects panel regression. Our dependent variable was a non-negative count variable (i.e., the number of AM firms in each region in each year) and suffered from overdispersion (i.e., the variance being greater than the mean). To account for this, we followed previous studies (e.g. Grashof & Kopka, 2023; Schlegel & Backes-Gellner, 2023; Wessendorf & Grashof, 2023) and used Poisson pseudo-maximum likelihood (PPML) regressions with region and year fixed effects that remain stable in the presence of overdispersion (Fally, 2015). The corresponding standard errors were clustered around labor market regions, as defined by Kosfeld and Werner (2012), in order to control

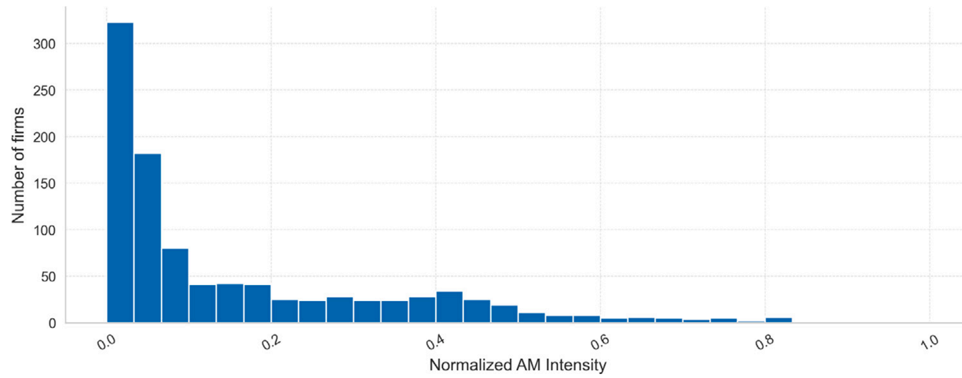
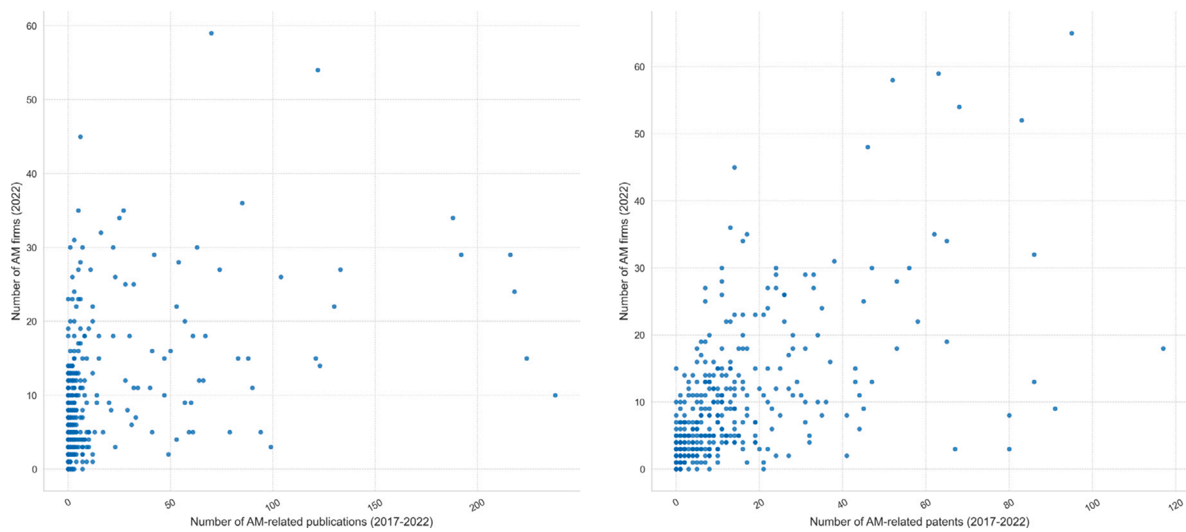


Fig. 1. Histogram of normalized AM intensity (2023).



(a) AM firms vs. publications.

(b) AM firms vs. patents.

Fig. 2. Scatterplots illustrating the relationship between the number of AM printing firms and (a) publication counts and (b) patent counts across NUTS3 regions. Outliers above the 0.95 percentile were removed for legibility.

for heteroscedasticity and autocorrelation (Hoechle, 2007; Kopka & Grashof, 2022). The stylized model took the following form:

$$AM\,Adoption_{i,t} = \beta_0 + \beta_1 AM\,Patent_{i,t-1} + \beta_2 AM\,Publication_{i,t-1} + \beta_3 Controls_{i,t-1} + \omega_i + \alpha_t + \mu_{i,t}$$

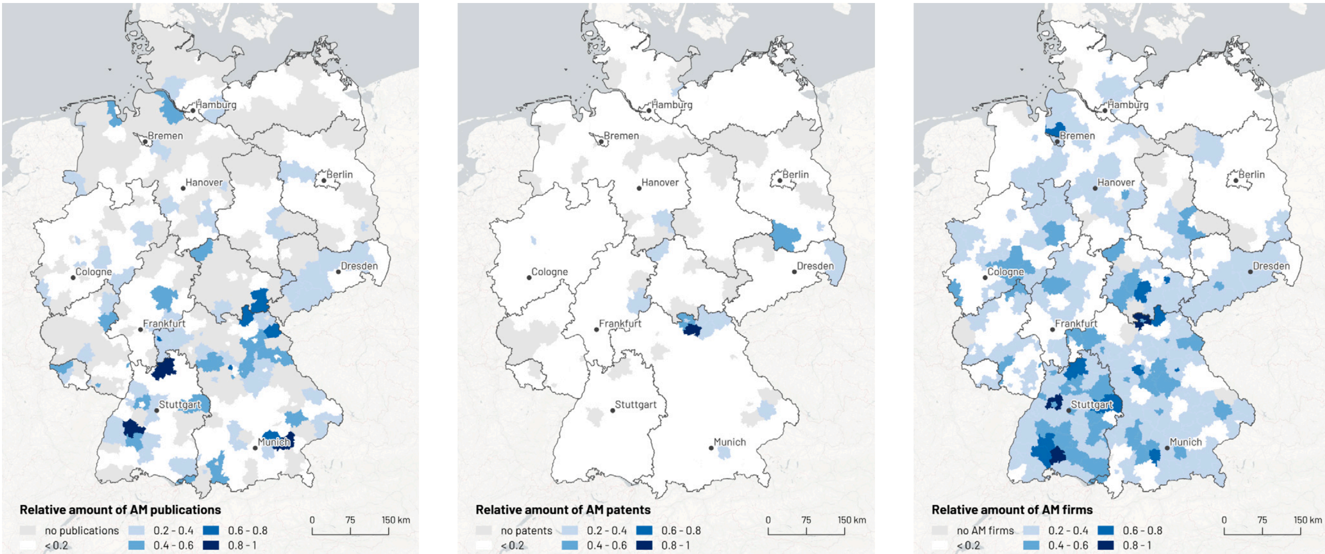
where $AM\,Adoption_{i,t}$ corresponds to the number of AM firms for each NUTS3 region (i) and each time period (t). $AM\,Patent_{i,t-1}$ and $AM\,Publication_{i,t-1}$ are our two main independent variables capturing the "traditional" ST&I activities. They measure the average number of patents and the average number of publications (using a three-year moving window). $Controls_{i,t-1}$ stands for a set of control variables characterizing the region which potentially influence our dependent variable, such as *GDPpc*, the number of employees in knowledge-intensive industries and population density. To mitigate possible endogeneity problems in the regressions, all independent and control variables were lagged by at least one year, denoted by t_1. Since the publication and patent activities may need longer to influence the actual adoption, we also lagged our independent and control variables by two and three years. Moreover, we included region (ω_i) and time (α_t) fixed effects in order to control for unobserved heterogeneity at these two dimensions. Finally, $\mu_{i,t}$ represents the residuals. To further check for reverse causality, we swapped our dependent variable, AM Adoption, with our two main independent variables, AM Patent and AM Publication. As shown in Table 5 in the Appendix, we did not find a statistically significant association in both cases, providing an indication that the problem of reverse causality may not be too severe in the context of our study.

4. Results

4.1. Descriptive results

Based on our web analysis approach, we identified 8273 firms engaged in AM in the year 2023, which was a sharp increase from 4131 firms in 2022. This corresponded to 0.74% of all firms in Germany with an active website. The regions with the highest absolute number of AM firms were Berlin (400), Munich (278), Hamburg (238), Cologne (122), Munich Land (121), Hanover (120), Dusseldorf (112), Stuttgart (111), Frankfurt am Main (102), and Aachen (98) (see 4(c)).

Since our web-based analysis did not just return a binary indicator, it was also possible to analyze the distribution of AM intensities across the German firm population. Fig. 1 shows this distribution, which is clearly right-skewed, i.e. has many very low values. Firms with an AM intensity of 0, i.e. no text paragraph containing a AM-related keyword, are excluded from the plot for reasons of legibility. The distribution mirrors findings from other web-based studies on specific technologies, such as Kinne et al. (2024).



(a) AM publications (2017–2022). (b) AM patents (2017–2022). (c) AM firms (2022).

Fig. 3. Relative concentration of AM activity per NUTS3 region. All values are min–max normalized for comparison across firms, patents, and publications.

As shown in Fig. 3(c), we found most adoption hot spots based on website analysis in Central, South, and Southwest Germany. Particularly, Baden-Württemberg, Bavaria and Thuringia stood out. Northern Germany, on the other hand, had very few NUTS3 regions with relatively high AM adoption. The NUTS3 regions with the highest relative amount of AM firms were Tuttlingen (2.56%), Enzkreis (2.17%), Jena (2.04%), Schwarzwald-Baar-Kreis (2.02%), Sonneberg, Coburg, Amberg, Frankenthal (Pfalz), Ilm-Kreis, and Kronach. Most of these were, however, regions with quite low numbers of overall firms (only three above median). In contrast, the pattern of relative AM patents (see 3(c)) revealed that most regions in Germany had a rather low level of AM patents. Almost all of the regions with relatively high values were located in Central and Eastern regions, where firm densities were considerably lower. The absolute number of AM firms identified via the web indicator was quite similar to the number identified through patent data, with the spatial distribution of hot spots appearing largely consistent. The spatial distribution of AM-related publications was somewhat more similar to the web indicator, with most hot spots being located in Southern Germany. Interestingly, the location of large technical universities was not particularly noticeable on the map. This may be related to the high level of overall publication activity there, which might obscure AM research.

The statistically significant Global Moran's I, using a Queen contiguity spatial weights matrix, of 0.316*** indicated that there was a certain spatial clustering of similar web intensities. Patents had a slightly lower clustering (0.235***), while publications did not show any significant signs of clustering (0.014).

Fig. 2 compares the relationship between the number of AM printing firms in a NUTS3 region with the respective cumulative amount of patents and publications over five years. Most data points in plot (a) are concentrated at low publication counts and firm numbers, while there are a few scattered outliers at higher values. The distribution between the number of AM firms and AM-related patents in plot (b) shows a wider spread along both axes but retains a high concentration around the origin, i.e. many NUTS3 regions with little measurable AM activity.

4.2. Regression results

The results of our main regressions are presented in Table 2. In addition to our control variables, we included $AM\,Patent$ and $AM\,Publication$ with a one year time-lag (Model 1), two year time-lag (Model 2) and three year time-lag (Model 3). We found evidence for a positive and statistically significant association between AM-related patent activities and the actual adoption of this technology in regions. This relationship remained relatively stable over time, although the coefficient became statistically insignificant with a three year time-lag (see Model 3), indicating that the influence of patent activity diminishes over time.

While the relationship between patent activity and adoption was relatively clear for AM, it was less evident for scientific publications. Similar to patent activities, we find a positive and statistically significant (at the 5% level) coefficient of $AM\,Publication$ (see Model 1). For a one year time-lag, we thus found evidence that the regional scientific activities on AM topics, measured via scientific publications, drive the actual adoption of AM in regions. However, unlike in the case of patents, this relationship changed over time. With a two year or three year lag, we found a negative but statistically insignificant coefficient (see Model 2 and Model 3). The relationship between publication activity and adoption of AM in regions was therefore less stable than for patents, which may reflect that the academic direction of AM research sometimes diverges from what is commercially useful.

Regarding our control variables, we found a highly statistically significant and positive influence of population density throughout all our regression models. In line with our descriptive findings (see Section 4.1), a higher urbanization was positively associated with a higher adoption of AM.

5. Discussion & conclusion

The goal of this study was to provide new insights into AM adoption and diffusion, and to contribute to a better understanding of the diffusion of emerging technologies. By using a web-based approach, we tracked the adoption of AM within Germany and showed that the resulting patterns were plausible (**RQ1**). Moreover, we found a relatively robust, positive and statistically significant relationship between patents, publications and AM adoption as measured by our web-based indicator (**RQ2**). While we found on average a positive relationship between the ST&I variables and AM adoption, we also identified some

Table 2
Regression results for advanced manufacturing adoption.

	(1)	(2)	(3)
	AM Adoption	AM Adoption	AM Adoption
AM Patent$_{t-1}$	0.006***		
	(0.002)		
AM Patent$_{t-2}$		0.008***	
		(0.002)	
AM Patent$_{t-3}$			0.002
			(0.005)
AM Publication$_{t-1}$	0.004**		
	(0.002)		
AM Publication$_{t-2}$		−0.001	
		(0.001)	
AM Publication$_{t-3}$			−0.002
			(0.001)
GDPpc$_{t-1}$	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)
EmpKnowint$_{t-1}$	−0.017	−0.018	−0.018
	(0.019)	(0.019)	(0.018)
Popdens$_{t-1}$	0.003***	0.003***	0.002***
	(0.001)	(0.001)	(0.001)
Constant	−0.733	−0.080	1.093
	(0.923)	(0.820)	(0.744)
Time-fixed effects	Yes	Yes	Yes
Region-fixed effects	Yes	Yes	Yes
Observations	1194	1194	1194
Pseudo R2	0.809	0.809	0.809
AIC	4837.96	4838.51	4841.70

Clustered standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01.

interesting variations in our descriptive analyses. Besides the similarities that can specifically be found in comparing the geographical results of our web-based approach with patent data, it was noticeable that there were more regions showing some AM activity through the web indicator than based on traditional data sources. This suggests that different potential uses of the technology are not fully covered by patents or publications. The findings also confirm the need for and usefulness of web indicators for providing a more complete picture of AM adoption. Therefore, our web-based adoption score reflects not only R&D, which is primarily measured through patents, but also actual usage — including users, service providers, and retailers.

As an example, high adoption in certain areas appeared to be driven by longstanding applications in the manufacturing sector (see Fig. 3(c)). Thus, several AM hot spots can be found in traditional manufacturing-driven regions such as Central, South, and Southwest Germany. Jena appears to have its AM engagement driven by users from the optical industry, which has traditionally been strong in the region. In contrast, Tuttlingen is renowned for its manufacturing industry, which includes suppliers to the automotive sector, medical engineering, and the production of parts and materials used in various industrial applications. These industries are known for their widespread adoption of AM (Campbell et al., 2023). These findings about centers of regional adoption align with previous studies on the regional agglomeration of knowledge and innovation (e.g. Audretsch & Feldman, 1996; Pinheiro et al., 2025). However, unlike patents, which primarily capture the inventive dimension, our web-based indicator for AM adoption can identify additional regional agglomerations that are potentially based on other localizing externalities, such as increased demand through reduced consumer search costs or access to specialized labor or inputs (Marshall, 1920).

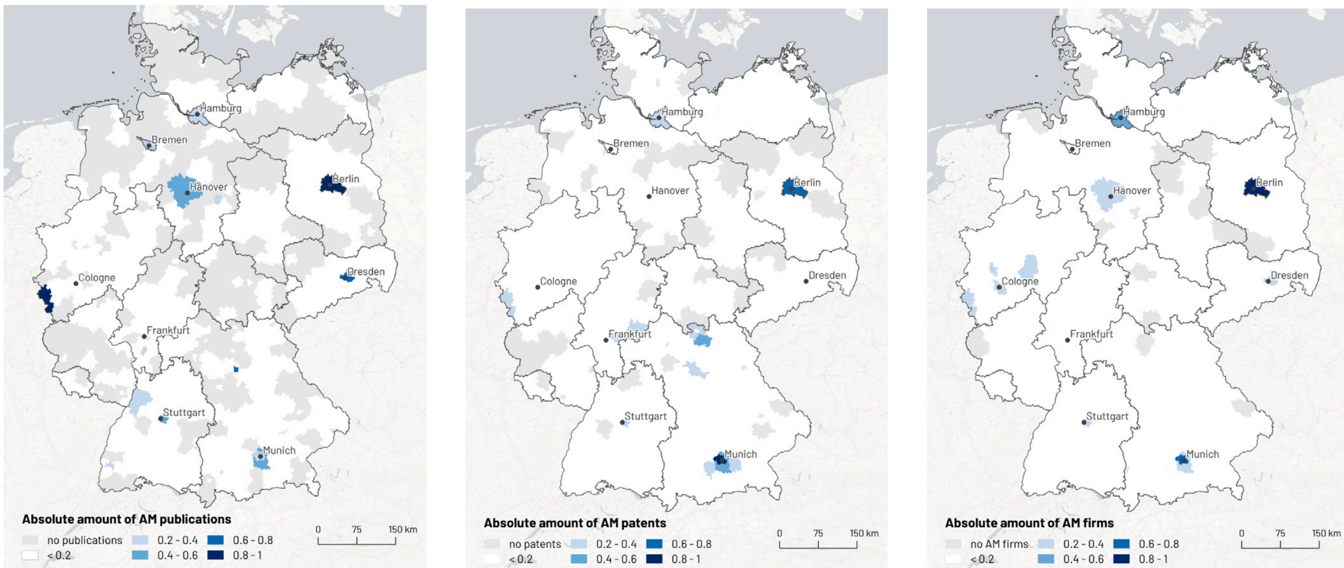
5.1. Limitations

Due to data limitations, we were unable to test for specific underlying mechanisms that lead to the observed patterns directly. Therefore, our empirical findings should not be interpreted as causal links, but rather as associations, despite our econometric efforts to address potential sources of endogeneity. Furthermore, as with traditional ST&I-related data sources such as surveys or patents, it must be acknowledged that research based on website data comes with potential biases (Dahlke et al., 2025). Although our web-based approach has achieved broad coverage, it relied heavily on the content published on corporate websites. Consequently, companies that do not communicate about AM on their websites cannot be identified using our methodology. Additionally, websites primarily serve as marketing and communication tools for companies to present themselves in a positive light. A certain degree of overrepresentation of technological capabilities should therefore be expected and taken into account when interpreting the results. Due to computing limitations, web-based analyses are also subject to a certain *selection bias*, as only a limited number of sub-pages are analyzed on every company website. Despite a clear strategy for extracting the most relevant content on every website, companies with larger websites (typically larger companies) (Kinne & Axenbeck, 2020) face the challenge that not all their published content is represented in the web-based variable, potentially resulting in an underestimation of the role of larger firms in the adoption of a technology (*retrieval bias*). In contrast, we must consider that smaller companies (e.g., start-ups) typically strategically design their websites and exaggerate their capabilities to attract potential investors and customers (*incentive bias*) (Dahlke et al., 2025). Very small or newly established firms that do not yet have a corporate website may have also been excluded from the analysis (Kinne & Lenz, 2021). Due to its nature of being a rather procedural technology, it can be argued that many companies already apply AM in their internal processes but do not specifically communicate about it as it is not a central part of their business model. The use of AM in production steps can thus also be underestimated by website analyses, as these are often not promoted publicly. Furthermore, language-specific and cultural biases in pre-trained NLP models need to be mentioned (Gallegos et al., 2024; Myung et al., 2024). Since our study focused on German-language websites, this bias should, however, not have significantly affected the comparability of our results.

5.2. Contribution and implications

Despite these limitations, our study contributes to the literature on innovation and technology diffusion (e.g. Hall, 2006) by introducing a novel AI- and web-based indicator that measures the adoption of AM. Moreover, we provide empirical evidence on the relationship between this new indicator and more traditional ST&I-Related indicators, as captured by patents and scientific publications. Although we find, on average, a positive relationship in this context, we also demonstrate that our AM adoption indicator extends beyond publication or patent counts by capturing aspects such as technology adoption and the intensity of use, thereby providing a refined measure of technological innovation. In light of our findings, it is therefore reasonable to argue that our web-based measurement of AM adoption can also help to empirically test previous seminal theoretical models on technology adoption (e.g. Rogers, 1983). Particularly in the context of an emerging technology such as AM or AI, this appears to be crucial (Dahlke et al., 2024). Potential negative externalities of (emerging) technologies that may influence the socio-economic development, such as higher energy consumption or ecological sustainability in general, are more likely to be comprehensively identified by capturing the technology adoption rather than technology generation (Kopka & Grashof, 2022). Hence, our web-based indicator provides a foundation for research investigating the broader socio-economic implications of (emerging) technologies.

In addition to the aforementioned research implications, our findings also have practical relevance. Since our web-based AM variable



(a) AM publications (2017–2022). (b) AM patents (2017–2022). (c) AM firms (2022).

Fig. 4. Absolute number of 3D printing-related publications, patents, and firms per NUTS3 region.

provides results at a detailed regional level, policymakers can also use our methodological approach to design more targeted regional innovation policies, as suggested in previous studies (e.g. Grashof, 2021; Tödtling & Trippl, 2005). In particular, our novel web-based indicator enables monitoring of technology diffusion. Therefore, the potential effects of specific funding programs on diffusion patterns can be investigated more directly.

The findings of our study also provide further starting points for future research. For example, subsequent studies could focus on determining the most useful purpose of each indicator, such as scientific publications, patents and our web-based adoption indicator. Similarly, more detailed research is needed on the reasons behind the regional differences in the adoption patterns of KETs, such as AM. Furthermore, the rapid development of Generative AI, particularly Large Language Models (LLMs), is promising for deriving even more fine-grained insights into firm characteristics (Dahlke et al., 2025). However, these approaches still need to be evaluated in the context of AM. While AM has already been investigated in connection with the topic of ecological sustainability (Dehghan et al., 2023), future studies should combine multiple data sources, such as Environmental, Social and Corporate Governance (ESG) reports, to uncover the impact of AM on corporate sustainability. Other studies have shown the high importance of collaboration for innovative processes (Kinne et al., 2024). Indicators based on hyperlink connections have been proposed in the literature to approximate such collaboration networks (Abbasiharofteh et al., 2023; Schmidt et al., 2025). Such an approach could also be evaluated for the topic of AM.

Overall, our web-based indicator and empirical findings therefore help researchers and policymakers identify real-world applications and early adopters of the technology with more precision, thereby contributing to a better understanding of the technology diffusion process.

CRediT authorship contribution statement

Julian Schwierzy: Writing – review & editing, Writing – original draft, Validation, Resources, Project administration, Methodology, Investigation, Conceptualization. **Robert Dehghan:** Writing – review & editing, Writing – original draft, Validation, Resources, Project administration, Methodology, Investigation, Conceptualization. **Sebastian Schmidt:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Nils Grashof:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation. **Hanna Hottenrott:** Supervision, Funding acquisition. **Michael Woywode:** Writing – review & editing, Supervision.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

See Tables 3–5 and Fig. 4.

Table 3
Keywords for semantic search.

Source: Standard VDI 3405		
Additive Manufacturing	Additive Fertigung	Rapid Manufacturing
Rapid Prototyping	Rapid Tooling	Stereolithography
Stereolithografie	Laser Sintering	Laser-Sintern
Selective Laser Sintering	Selektives Laser-Sintern	Laser Beam Melting
Laser-Strahlschmelzen	Laser Forming	Laser Forming
Selective Laser Melting	Selective Laser Melting	LaserCUSING
Direct Metal Laser Sintering	Direktes Metall-Laser-Sintern	Electron Beam Melting
Elektronen-Strahlschmelzen	Fused Layer Manufacturing	Fused Layer Modelling
Fused Deposition Modelling	Filament Deposition	Strangablegeverfahren
Multi-Jet Modelling	Poly-Jet Modelling	3D-Printing
3D-Druck	Layer Laminated Manufacturing	Schicht-Laminat-Verfahren
Laminated Object Manufacturing	Digital Light Processing	Thermotransfer Sintering
Thermotransfer-Sintern		
Source: Standard ISO/ASTM 52900		
Binder Jetting	Freistrahl-Bindemittelauftrag	Directed Energy Deposition
Materialauftrag mit gerichteter Energieeinbringung	Material Extrusion	Materialextrusion
Material Jetting	Freistrahl-Materialauftrag	Powder Bed Fusion
Pulverbettbasiertes Schmelzen	Sheet Lamination	Schichtlaminierung
Vat Photopolymerization	Badbasierte Photopolymerisation	
Source: AMPower GmbH & Co. KG		
Metal Selective Laser Sintering	Laser Beam Powder Bed Fusion	Wire Feed Laser
Powder Feed Laser Energy Deposition	Continuous Fiber Sheet Lamination	Wire Arc
Plasma Arc Energy Deposition	Electron Beam Powder Bed Fusion	Liquid Metal Printing
Fiber Alignment Area-Wise Vat Polymerization	Electron Beam Energy Deposition	Ultrasonic Welding
Metal Filament Fused Deposition Modeling	Nanoparticle Jetting	Friction Deposition
Metal Pellet Fused Deposition Modeling	Metal Lithography	Powder Metallurgy Jetting
Continuous Fiber Thermoplastic Deposition	Electrographic Sheet Lamination	Thermal Powder Bed Fusion
Laser Powder Bed Fusion	Pellet Based Material Extrusion	Mold Slurry Deposition
Continuous Fiber Material Extrusion	Filament Based Material Extrusion	Coldspray
Area-Wise Vat Polymerization	Resistance Welding	Thermoset Deposition
Continuous Fiber Thermoset Deposition	Elastomer Deposition	Vat Vulcanization
Source: Recent scientific articles from journals such as *Additive Manufacturing*, *Rapid Prototyping Journal*, *Materials*, etc.		
Laser Chemical Vapor Deposition	Continuous Liquid Interface Production	Laser Metal Fusion
Selektives Laserschmelzen	Selective Mask Sintering	Selektive Maskensintern
Laser Engineered Net Shaping	ARBURG Kunststoff-Freiformen	Laserpulverformung
Maskless Masoscale Material Deposition	Foam Reaction Prototyping	Tool-Less Fabrication
Werkzeuglose Fertigung	Generative Manufacturing	Generative Fertigung
Digital Composite Manufacturing	Laserstrahlschmelzen	Laser Consolidation
Laserkonsolidierung	Ultrasonic Consolidation	Ultraschallkonsolidierung
Freeform Fabrication	Freiformherstellung	Layer Manufacturing
Schichtbauverfahren	Additive Layer Manufacturing	Additive Schichtherstellung
Additive Layer Manufacturing	Additive Schichtherstellung	Additive Techniques
Ultrasonic Additive Manufacturing	Additive Process	Additive Fabrication
Digital Light Synthesis	Continuous Digital Light Manufacturing	Two-Photon Polymerization
Programmable Photopolymerization	Direct Shell Production Casting	Thermal Polymerization
Directed Light Fabrication	Light Initiated Fabrication Technology	Additive Techniken
Ultraschalladditivherstellung	E-Manufacturing	Hot Lithography
Holographic Interference Solidification	Fused Filament Fabrication	Schmelzschichtung
Masked Stereolithography	Laser Metal Deposition	Laserauftragsschmelzen
Lithography-Based Ceramic Manufacturing	Robocasting	Direct Metal Deposition
Beam Interference Solidification	Ballistic Particle Manufacturing	Bioprinting
Solid Ground Curing	Solid Foil Polymerisation	Film Transfer Imaging
Cold Spraying	Selective Deposition Lamination	Kaltgasspritzen
Digital Manufacturing	Digitale Fertigung	Direct Ink Writing
Stereolithography Apparatus		

Notes: This table lists all AM-related keywords used for the semantic search of article abstracts with German affiliations. The keywords originate from four sources: the standards VDI 3405 and ISO/ASTM 52900, the consulting firm AMPower GmbH & Co. KG, and technical terms from recent literature in journals like *Additive Manufacturing*, *Rapid Prototyping Journal*, and *Materials*.

Table 4
Pairwise correlation matrix.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) AM Adoption	1.000					
(2) AM Patent	0.521***	1.000				
(3) AM Publication	0.590***	0.582***	1.000			
(4) GDPpc	0.284***	0.257***	0.336***	1.000		
(5) EmpKnowint v	0.014	0.005	−0.046	0.177***	1.000	
(6) Popdens	0.463***	0.457***	0.453***	0.491***	−0.123***	1.000

*** p<0.01, ** p<0.05, * p<0.1.

Table 5
Test for reverse causality.

	(1)	(2)
	3DPrintPat	3DPrintPub
3DPrintAdoption$_{t-1}$	0.004	0.002
	(0.006)	(0.002)
Bippc$_{t-1}$	0.00587	0.000174
	(0.0179)	(0.00506)
EmpKnowint$_{t-1}$	−0.0849	0.00951
	(0.0856)	(0.0267)
Popdens$_{t-1}$	−0.00350	−0.000865
	(0.00364)	(0.00109)
Constant	5.783	4.447**
	(4.801)	(1.940)
Time-fixed effects	Yes	Yes
Region-fixed effects	Yes	Yes
Observations	562	492
Pseudo R2	0.535	0.879
AIC	1035.40	1176.73

Clustered standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01.

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